Energy-Harvesting Wireless Sensor Networks (EH-WSNs): A Review

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Wireless Sensor Networks (WSNs) are crucial in supporting continuous environmental monitoring, where sensor nodes are deployed and must remain operational to collect and transfer data from the environment to a base-station. However, sensor nodes have limited energy in their primary power storage unit, and this energy may be quickly drained if the sensor node remains operational over long periods of time. Therefore, the idea of harvesting ambient energy from the immediate surroundings of the deployed sensors, to recharge the batteries and to directly power the sensor nodes, has recently been proposed. The deployment of energy harvesting in environmental field systems eliminates the dependency of sensor nodes on battery power, drastically reducing the maintenance costs required to replace batteries. In this article, we review the state-of-the-art in energy-harvesting WSNs for environmental monitoring applications, including Animal Tracking, Air Quality Monitoring, Water Quality Monitoring, and Disaster Monitoring to improve the ecosystem and human life. In addition to presenting the technologies for harvesting energy from ambient sources and the protocols that can take advantage of the harvested energy, we present challenges that must be addressed to further advance energy-harvesting-based WSNs, along with some future work directions to address these challenges.

CCS Concepts: • **General and reference** → **Surveys and overviews**; • **Computer systems organization** → *Sensor networks*; • **Hardware** → *Renewable energy*;

Additional Key Words and Phrases: Wireless sensor networks, energy harvesting, energy scavenging, self-powered devices

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1 INTRODUCTION

Wireless Sensor Networks (WSNs) consist of spatially distributed, autonomous, wireless, networked sensing devices that can be used to monitor a physical space (Yick et al. 2008; Sharma et al. 2016). WSNs have gained increasing popularity for a range of applications, such as environmental monitoring (Khedo et al. 2010; Bhattacharya et al. 2012; Postolache et al. 2014; Adamo et al. 2015), animal tracking (Szewczyk et al. 2004; Pereira et al. 2008; Amundson and Koutsoukos 2009;

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Radoi et al. 2015), monitoring for disasters such as earthquakes, hurricanes, and floods (Estrin et al. 2002; Akyildiz et al. 2002; Devasena and Sowmya 2015), and health monitoring of civil structures such as bridges and buildings (Lee et al. 2007; Kim et al. 2007; Hu et al. 2013).

Of particular interest in this article are WSNs used for environmental monitoring, including water quality monitoring, air quality monitoring, plant/animal tracking, and disaster monitoring. These environmental monitoring WSNs, also called "field systems," oftentimes consist of a number of sensor nodes distributed in the environment along with a local gateway node that gathers the data for storage or to transmit the data to a remote server. In these systems, the sensor nodes are low-cost, battery-operated devices with the ability to sense the specific environmental parameters required by the application and transfer the collected data to the local gateway for processing and storage. Hence, a sensor node consists of the sensor(s), a wireless transceiver, a micro-controller, memory, and a battery to power the node.

When running on batteries, the limited lifetime of the sensor nodes is one of the main challenges in implementing WSNs for environmental monitoring applications (Potnuru and Ganti 2003; Muthukarpagam et al. 2010). In many of these applications, it is difficult to change the batteries of the nodes regularly, and hence once a sensor node depletes its battery, that node can be considered dead.

Over the years, researchers have focused on designing energy saving techniques to minimize the energy consumption of the sensor nodes at the physical (PHY), medium access (MAC), and routing layers (Muthukarpagam et al. 2010; Khajuria and Gupta 2015). However, even with very energy efficient sensing and communication protocols, once the limited battery energy is exhausted, the sensor node can no longer participate in the network operations (Khajuria and Gupta 2015).

To address the challenge of the limited energy supply to sensor nodes powered by batteries, new WSN platforms that support the harvesting of energy from the immediate surroundings have been developed. These devices are able to capture small amounts of energy that would have been lost as heat, light, sound, vibration, or movement within the environment (Shaikh and Zeadally 2016a). By recharging the battery with energy harvested from the environment, and by developing energy-harvesting aware protocols that support so-called "energy-neutral operation," theoretically, WSNs could have infinite lifetime. Several researchers have explored technologies to harvest energy from natural sources, such as the sun, wind, and water flow, to power the sensor nodes (Shaikh and Zeadally 2016a), while others have explored man-made sources of energy, such as human walking, magnetic fields, high-frequency vibrations, and RF fields (Chandrakasan et al. 1999).

Starting from the early 2000's several researchers have conducted surveys in the area of WSNs and Energy-Harvesting WSNs (EH-WSNs), pointing out the various energy sources, storage technologies, communication network operations, and specific implementation areas where sensor networks are applicable and deployable (Paradiso and Starner 2005; Gilbert and Balouchi 2008; Wan et al. 2011; Sudevalayam and Kulkarni 2011; Ku et al. 2016). Other surveys conducted in this area looked into the energy-harvesting sensor node architecture and relative challenges and limitations of powering the sensor node through energy harvesting (García-Hernández et al. 2007; Seah et al. 2009; Tan and Panda 2010a). Of particular interest is the work presented in Sudevalayam and Kulkarni (2011), which describes the design implications of powering WSNs via energy harvesting. Here, the authors present a survey on energy-harvesting sources, mechanisms, and architectures, discussing the two main sensor node architectures (i.e., harvest-use and harvest-store-use), techniques for converting different energy sources to electrical energy, and different types of energy storage technologies. In addition, the authors provide some examples of real implementations of EH-WSNs.

In this article, we present the state-of-the-art on EH-WSNs. Starting with a description of the available energy sources (such as radiant, mechanical, and thermal) and the technologies used for harvesting energy, we provide an overview of some EH-WSNs that deploy hybrid energy-harvesting systems. We then describe the common wireless sensor node architecture and present the benefits and drawbacks of using different types of energy storage (such as rechargeable batteries and super-capacitors). In addition, we discuss different energy prediction algorithms and energy management techniques to cope with the unpredictability of energy-harvesting rates from the environment, and we discuss their impact on the design of energy-harvesting-aware communication protocols. This article extends the work done by Sudevalayam and Kulkarni (2011), presenting recent developments and techniques in communication protocol design in WSN applications with energy-harvesting capabilities. We present new techniques that do not just consider energy-based metrics (such as the effective energy, cumulative energy usage, energy value), link quality, and duty cycling for route selection, but we also consider previous knowledge of the network and energy count to determine the route based on the energy harvesting of the nodes in a path and the status of future path hops and not only the next hop to select routes. Finally, we present different implementations that use EH-WSNs for environmental monitoring, and discuss the current challenges and future research directions.

The rest of the article is organized as follows. Section 2 provides the motivation for EH-WSNs. In Section 3, we describe the different sources of energy that can be harvested by sensor devices. Section 4 presents the sensor node power system architecture, and the energy storage technologies, energy prediction, and energy management techniques used in EH-WSNs. In Section 5, we discuss the various approaches at the Physical, MAC, and Routing layers developed for EH-WSNs, as well as some tools that have been proposed for simulating and emulating EH-WSNs. In Section 6, we discuss the performance/design requirements in EH-WSNs compared to traditional WSNs, and we give an overview of performance analytical models that guarantee QoS under worst-case scenarios. In Section 7, we discuss some implementations of EH-WSNs in Animal Tracking (AT), Air Quality Monitoring (AQM), Water Quality Monitoring (WQM), and Disaster Monitoring (DM). In Section 8, we present the challenges related to EH-WSNs and provide future research directions in developing energy-harvesting-based wireless sensor networks. Finally, Section 9 concludes the article.

2 MOTIVATION

The existence of life on earth depends upon the availability of quality air and quality water for humans, animals, and plants. For instance, ingesting contaminated drinking water containing harmful chemicals and waste products causes diseases (i.e., diarrhea), and even deaths of humans and animals (Owa 2014; Landrigan and Fuller 2016). Furthermore, according to the WHO, 80% of deaths related to ischemic heart disease are caused by outdoor air pollution. The WHO has also reported that 14% of deaths in recent times were due to chronic obstructive pulmonary disease or acute lower respiratory infections due to air pollution, and 6% of deaths were due to lung cancer also related to outdoor air pollution (WHO 2014). Hence, monitoring air quality is essential to improve lives. Moreover, there is a high cost associated with providing fencing and mustering for animals. Therefore, providing situational awareness of the state of the pasture and of the animals can greatly improve livestock management (Wark et al. 2007).

Due to patients' needs for real-time, low-cost, and flexible health monitoring systems to keep track of their body parameters, sensor nodes can also be integrated into a wireless body area network (WBAN) to enable a proactive personal health management system that has the potential to transform the future of healthcare (Pantelopoulos and Bourbakis 2010; Omer and Al-Salihi 2017).

Another critical area where WSNs can provide safety and save lives is in military applications and hostile areas where deploying soldiers can be risky or dangerous (Azzabi et al. 2017). WSNs can be an integral part of information distribution in various military scenarios such as blast localization, perimeter surveillance and protection, nuclear, chemical, and biological attacks detection, and missile monitoring, which can decrease fatality rate by providing more accurate and real-time data (Đurišić et al. 2012). Furthermore, WSNs can be used for disaster management applications such as floods and earthquakes for detection, monitoring, and rescue operations (Saha and Matsumoto 2007; Aziz and Aziz 2011; Mahamuni 2016).

Supply chain management is critical in various areas such as the food supply chain to reduce loss of perishable food by deploying sensor nodes for temperature monitoring, damage detection, and transportation tracking (Evers et al. 2007; Parreño-Marchante et al. 2014). Furthermore, human errors can lead to a significant revenue loss, hence, automating the supply chain process using WSNs can enhance quality of service, improve efficiency, and increase revenue (Wang et al. 2015). Similarly, inventory management using WSNs can prevent manual process errors and ensure personnel safety by limiting the need to be in dangerous environments such as offshore oil rigs (Vellingiri et al. 2013).

Governments, policy makers, engineers, and scientists around the world are looking for ways to curb these environmental problems. WSNs can be used to monitor the environment to provide information that can aid in finding solutions to these issues. While WSNs provide distributed sensor readings that can be valuable in mapping the environment, there are a number of challenges to their continuous operation. Specifically, as the sensor nodes are battery operated, to achieve consistent monitoring, sensor nodes must be designed to be as energy efficient as possible (Potnuru and Ganti 2003). Thus, energy management is key, requiring protocols that reduce energy dissipation in the physical, MAC and routing layers, as well as energy efficient topology control protocols that simultaneously support the application Quality of Service (QoS) (Kawahara et al. 2009; Muthukarpagam et al. 2010; Swati and Priyanka 2010; Basagni et al. 2013; Gupta and Sikka 2015).

While all of the research on energy-efficient protocols has helped to prolong the lifetime of WSNs, for environmental monitoring applications, it is vital to ensure continuous operation without the need to change batteries. Achieving this goal requires the adoption of novel technologies, such as energy harvesting, which opportunistically acquires energy from solar, wind, mechanical vibrations, magnetic or RF fields to recharge the node batteries. Recent advances in these energy-harvesting technologies, and the commercialization of sensor nodes that support energy harvesting, have led to a new class of WSNs, referred to as Energy-Harvesting WSNs (EH-WSNs). The ability of EH-WSNs to power the sensor nodes through ambient energy sources has led to a shift in the design requirements and goals of these networks, as network lifetime is, ideally, no longer an issue. Instead, the goal in EH-WSNs is to support energy-neutral operation, so that the EH-WSN can operate continuously using the harvested energy.

Energy harvesting provides new opportunities as well as challenges for the design of the protocols and algorithms to support environmental monitoring. In particular, rather than focusing narrowly on reducing the node energy consumption to extend network lifetime, as is the key design metric in traditional WSNs, in EH-WSNs it is important to re-consider the impact of performance metrics such as energy-efficiency, fairness, scalability, and latency in the presence of energy flow into the network. Similarly, physical, MAC and routing protocols need to be re-designed to optimize the rate at which the energy is used, rather than simply minimizing the total energy expenditure.

Given the above, it is important to clearly define the performance metrics and design requirements that impact EH-WSNs, given that energy is no longer limited in the same way. Hence, in this article, we survey the current state-of-the-art techniques for harvesting energy for WSNs as well as the latest protocols and algorithms that optimally utilize this harvested energy to support the application goals and provide continuous environmental monitoring.

Table 1. Energy-Harvesting Sources and their Corresponding Power Densities

Energy Source	Types	Energy-Harvesting Method	Power density
Radiant	Solar	Solar cells (indoors)	$<10\mu W/cm^2$
		Solar cells (outdoors, sunny days)	$15mW/cm^2$
	RF	Electromagnetic conversion	$0.1\mu W/cm^2$ (GSM)
		Electromagnetic conversion	$0.01\mu W/cm^2$ (WiFi)
Mechanical	Wind Flow and Hydro	Electromechanical conversion	$16.2\mu W/cm^3$
	Acoustic Noise	Piezoelectric	$960nW/cm^3$
	Motion	Piezoelectric	$330\mu W/cm^3$
Thermal	Body heat	Thermoelectric	$40\mu W/cm^2$

3 ENERGY-HARVESTING SOURCES

Over the past few years, energy-harvesting technologies have greatly improved in terms of their efficiencies, and devices that can provide continuous power output from different energy sources such as solar energy and vibration have been developed (Instruments 2015a). Furthermore, recent WSN devices are designed to be extremely energy efficient, enabling them to operate using the limited harvested energy for a very long period of time without shutting down, at least not due to energy depletion. There are multiple sources of natural and man-made energy that can be harvested by the sensor node and converted to electrical energy, and each power source provides a different power density, as shown in Table 1.

In the following subsections, we describe the different types of energy that can be harvested from radiant sources (e.g., solar energy and radio frequency waves), mechanical sources (e.g., vibrations, wind, human body motion, and water flow), and thermal sources (e.g., temperature difference between two conducting materials, external heat, and friction sources), and we provide some examples of commercial harvesters (Seah et al. 2009; Tan and Panda 2010b).

3.1 Radiant Energy

Radiant energy is harvested from the sun and from radio frequency waves, for both indoor and outdoor systems. In recent years, energy harvesting from radio frequency and sunlight has been explored extensively in an attempt to utilize this source of energy to power wireless sensor networks for environmental monitoring applications (Morais et al. 2008; Bhuvaneswari et al. 2009; Tabbakh et al. 2010; Alippi et al. 2011; Lim et al. 2013; Zhou et al. 2014).

3.1.1 RF Energy. In RF energy harvesting, rectifying antennas (or rectennas) are used to capture electromagnetic signals emitted from nearby sources like mobile phones or radio stations, which are then converted to regulated DC power using a rectifier circuit to be utilized by small, low power consumption systems such as sensor devices (Ramesh and Rajan 2014). Some RF sources like radio stations transmit high amounts of RF power (up to megawatts), but due to path loss and fading, their signals reach the harvesting antennas at relatively low levels (Lim et al. 2013), thus making the harvesting process challenging. Nevertheless, RF energy harvesters are promising when implemented in urban and suburban areas due to the large amount of ambient energy sources and the relatively small distance between the RF sources and the receiving antenna (Pinuela et al. 2013). Implementing a multi-band antenna array architecture enhances the efficiency of RF energy harvesters and allows energy harvesting even for low-power signals (as low as −29dBm) (Pinuela et al. 2013). Efficient RF energy harvesting requires spectrum analysis and knowledge of the harvester distance and direction from the RF source, as the receiving antenna requires an appropriate level of beam-pointing and polarization matching to ensure that the maximum amount of power is harvested. A survey on wireless networks using RF energy harvesting was provided in Lu et al. (2015), where the authors discussed the state-of-the-art in RF circuit design and implementations as well as describing resource allocation design issues in RF-EHWSNs, and presenting future research directions and practical challenges that still need to be addressed.

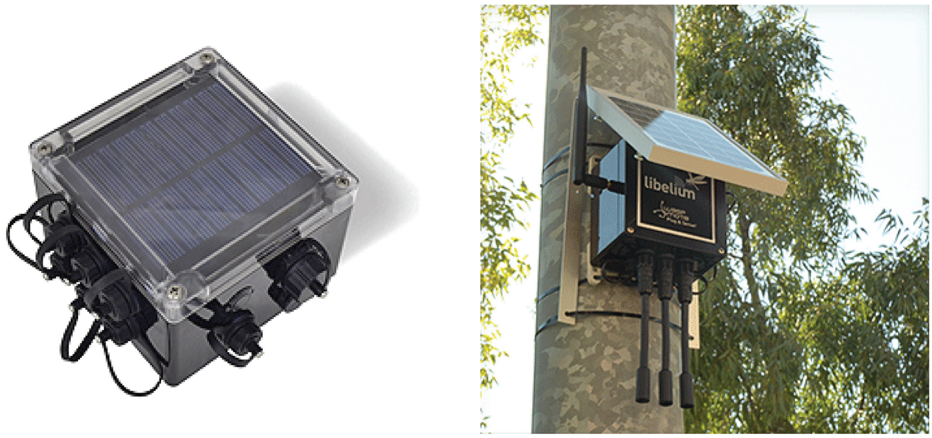
3.1.2 Solar Energy. There are two main approaches for converting sunlight into usable energy: (1) thermal conversion, whereby the energy from the sun is converted into electricity by heating a medium that passes through a turbine generator, and (2) photovoltaic conversion, whereby light is directly converted into electricity and therefore does not require any moving parts or intermediate energy conversion steps (Bube 2012). Solar energy harvesting based on photovoltaic technology provides the highest power density of around $15mW/cm^2$ on bright sunny days (Morais et al. 2008; Bhuvaneswari et al. 2009), as indicated in Table 1. This makes solar an appropriate energy-harvesting technique suitable for environmental monitoring EH-WSNs.

Photovoltaic harvesters have several advantages when employed for EH-WSNs. Since its inception, solar energy harvesting has remained one of the most reliable, convenient, and preferable energy-harvesting sources available in WSNs (Li and Shi 2015). Photovoltaic harvesters produce constant and direct current (DC) to power sensor nodes. Hence, they do not require additional circuit rectification (i.e., converting from alternating current (AC) to DC). Solar energy-harvesting approaches are non-emissive, harmless to the environment, and their current and voltage levels meet the power requirements of wireless sensor nodes (Akbari 2014; Zhou et al. 2014; Shaikh and Zeadally 2016b). Although solar energy is a preferred source for powering sensor nodes in unattended areas, the amount of energy that can be harvested is seasonal and depends on the area where the solar panels are deployed. For example, in environmental applications, sensor nodes might be deployed under shaded areas that do not receive much sunlight even during the day and receive no sunlight during the night. This affects the operational cycle of the sensor nodes.

Indeed, there are several environmental monitoring implementations that harvest solar energy. For example, in Figure 1(a) a solar panel is embedded on the front of the enclosure containing a sensor node to harvest energy for water quality monitoring applications. Another way to attach solar panels to the sensor node is to mount the solar panel on the sensor node, as shown in Figure 1(b), which is especially useful for air quality monitoring applications. An overview of the various commercially available solar cells is presented in Table 2.

There are two design principles proposed for solar energy-harvesting modules due to the limited amount of power generated from these systems: (1) the system should be designed to extract the maximum amount of power at any given point in time, and (2) power management subsystem efficiency should be maximized to effectively utilize the limited amount of energy harvested for use by the sensor nodes. These principles are difficult to adhere to when designing practical applications, because a solar cell active area (i.e., the area of the solar cell through which the light enters the solar cell) varies when used for power generation (Morais et al. 2008). Other limiting design factors include the energy storage unit capacity and power conditioning subsystem features. The latter can lead to a lower solar to electrical energy conversion efficiency if it is not operated at the solar cell maximum power point (i.e., the highest possible power output of a solar cell) (Morais et al. 2008).

A key design consideration with respect to solar energy harvesters, is Maximum Power Point Tracking (MPPT) (Rodriguez and Amaratunga 2007; Simjee and Chou 2008; Dondi et al. 2008;



(a) Embedded solar panel (b) Externally mounted solar panel

Fig. 1. Example of a sensor node with (a) embedded or (b) externally mounted solar panel. Source (Libelium 2016).

Table 2. Comparison of Solar Cells

Solar Cell Type	Efficiency	Advantages	Disadvantages
Monocrystalline	15–24%	High conversion efficiency, the most mature technology, high reliability	High cost, large silicon consumption, complex production process
Polysilicon	14–20.4%	No efficiency recession, can be fabricated on cheap substrates, far lower cost than monocrystalline	Relatively large silicon consumption and cost, complex production process
Amorphous silicon (a-Si)	8–13.2%	Low cost, easiness of mass production, relatively high optical absorption coefficient, very low dark conductivity, good response to weak light	Light-induced recession effect, low conversion efficiency, low stability
Cadmium Telluride (CdTe)	Theoretical: 28%	Ideal band gap, high light absorption rate, high conversion efficiency, stable performance, simple structure, low cost	Limited natural tellurium reserves, high cost of module and base material, toxic cadmium
Copper-indium-gallium-diselenide (CIGS)	Up to 20%	Low cost, nonrecession, good weak light performance, wide applicability of substrate, adjustable optical band gap, strong antiradiation ability	Rare materials, the difficulty of controlling four elements precisely

Adapted from Zhou et al. (2014).

Scarpa et al. 2009; Lu et al. 2010; Chen and Chou 2010; López-Lapeña et al. 2010). To maximize the amount of power harvested from solar cells and to overcome the design challenges imposed by MPP in the design of wireless nodes, new design schemes are proposed to ensure that the maximum power is extracted from a photovoltaic (PV) module at any given time as incident light conditions change and to ensure that the PV module always operates at its MPP.

In selecting the appropriate solar energy harvester for environmental applications, the factors that need to be considered are the solar-harvesting circuitry, the battery technology, data transmission adaptation mechanisms, and the ability for the node to perform MPPT. Also in designing the recharging circuit, features of much concern are power consumption, cost, and its ability to provide unlimited power supply to the sensor node and also to recharge the batteries efficiently (Bhuvaneswari et al. 2009; Shaikh and Zeadally 2016a). Some of these design considerations are provided in the work done by Sudevalayam and Kulkarni (2011), in which a detailed discussion was provided on solar energy-harvesting systems, their energy storage technologies and whether they apply MPPT or not. Another similar work that looked into solar energy-harvesting systems is the work of Bader et al. (2014). In their work, the authors presented an evaluation of some of the recent solar energy-harvesting architectures and common methods for their modeling. Each of these systems were classified based on the input regulation method (i.e., a distinction between systems with voltage level compliance and those that perform MPPT), the output regulation method (i.e., systems that implemented DC-DC boost regulator), and the storage technology implemented in the systems.

DuraCap and OpenWise (Chen and Chou 2010; González et al. 2012) are two of the recent solar energy-harvesting systems. DuraCap (Chen and Chou 2010) is composed of a solar panel, energy storage, system control unit, power regulator, and MPPT circuitry. DuraCap stores harvested energy in three super-capacitors—*the booting super-capacitor* (responsible for cold booting), and two *reservoir super-capacitors* (responsible to provide power for the target device). DuraCap provides two different output voltages: 3.3V and 4.2V. The 3.3V is supplied for use by the system and 4.2V (similar to Li- ion battery) is directly used by the target devices. DuraCap addresses the problem with the traditional DC-DC converter by utilizing a pulse-frequency modulated (PFM) regulator to transfer the harvested energy, which is similar to Everlast. Unlike all the other solar energy-harvesting nodes, all functions in DuraCap are performed by a low-power micro-computer unit (MCU), which uses its ADC to detect the voltage value of the solar panel, super-capacitors, and the current sensor output.

In conclusion, it is important to note that the choice of solar energy-harvesting sensor node with battery only, super-capacitors, or both will allow developers to set up an efficient WSN for environmental monitoring applications that are deployed in harsh areas where it is difficult to change the batteries. Therefore, knowing and considering the important features of these technologies are very relevant in recent times. Design considerations include sensor nodes robustness (in terms of storage, charge and discharge rate), low price, MPPT performance, and data transmission mechanism to achieve a longer lifetime of the WSN. For example, since super-capacitors are more efficient than batteries and offer higher lifetime in terms of charge-discharge cycles, systems that include a layered energy storage mechanism (i.e., by using both super-capacitors and a battery) are good for such environmental applications. Similarly, those that employ multiple super-capacitors like DuraCap will equally be useful in such applications (Bhuvaneswari et al. 2009).

3.2 Mechanical Energy

Another source of energy that can be harvested to power WSNs is mechanical oscillations or vibrations. Typically, mechanical energy is harvested using piezoelectric devices (Seah et al. 2009).

Due to the piezoelectric materials' properties, piezoelectric energy-harvesting devices are known to generate energy at higher voltages without any external voltage supply. For instance, piezoelectric ceramic PZT is known for its high energy conversion rate, while polyvinylidene fluoride (PVDF) is known for its high mechanical strength (Zhou et al. 2014). Other advantages piezoelectric harvesters offer in WSNs include their easiness to model due to their simple structure, low cost, and absence of electromagnetic interference (Wang 2012b; Zhou et al. 2014; Shaikh and Zeadally 2016b). On the other hand, piezoelectric devices require energy-harvesting circuits to regulate the output power leading to energy losses, thereby affecting the overall efficiency of the energy-harvesting system (Zhou et al. 2014). Moreover, it is difficult to integrate piezoelectric devices into a small system (Wang 2012b; Shaikh and Zeadally 2016b).

There are a number of systems that have been developed using piezoelectric devices. For example, in Kahrobaee and Vuran (2013), an underground piezoelectric energy harvester used in an agricultural application was shown to provide encouraging capabilities in harvesting above ground accelerations from a four wheeler center pivot irrigation system.

Energy harvesting from the vibrations of roads caused by automobiles is another promising technique for powering wireless sensor nodes. This approach has been used for monitoring car exhaust fumes (air quality measurements) or measuring traffic flow (disaster traffic management) (Vijayaraghavan and Rajamani 2008, 2010; Zhu et al. 2012). Additionally, harvesting energy from vibrations has been used for disaster relief operations (Hande et al. 2010), where experimental results show that a mechanical vibration energy-harvesting system can provide sustainable energy for operation. A high vibrational acceleration, wide range frequency band, and an adaptive resonant frequency tracker are the main requirements to design a high performance vibration energy-harvesting system.

Wijesundara et al. (2016) proposed a WSN-based system to monitor the location of Asian elephants that harvests the kinetic energy generated by the elephants' movements to power the sensors. The proposed harvester is composed of one moving magnet, two stationary magnets, a polycarbonate tube, and two coils. Through experimentally validated analytical and simulation models of the energy harvester, and measurements of the elephant movement, the proposed prototype was found to be able to generate 88.91 J per day. This energy was able to power a mounted tracking unit (tag), which transmits the elephant's location to a remote monitoring center at least 24 times a day.

Energy can also be harvested from water current depending on the water flow rate, either from water flow with greater pressure (turbulent) or flow at a constant velocity. The energy derived from flowing water is mainly kinetic. Kinetic energy is obtained as a result of pressure fluctuations or by applying pressure to the flowing water using mechanical devices and must be converted into electrical energy. While water flow energy harvesting has not been explored extensively in WSNs, some research has explored how to harvest energy from flowing water. Most of these works used different techniques to harvest kinetic energy. For example, Pobering and Schwesinger (2004) used a fluttering flag to harvest kinetic energy from a turbulent flowing water to electrical energy using a piezoceramic transducer; Wang and Liu (2011) used a shear mode piezoelectric energy harvester to harness energy from pressurized water flow; Ye and Soga (2011) harvested energy using a microturbine from a water distribution system in different bypass pipes; and Sun and Hu (2011) used an electromagnetic vibration generator to harvest energy from the periodic movement of a magnet within a coil box.

Although the works described above harvest energy from water to power small devices such as sensor nodes, they come with limitations such as complexity and large size (Sun and Hu 2011), and high power generation due to the pressure differences between the water and the ambient air (Ye and Soga 2011) causing the system to waste energy when used to power sensor nodes that require only 15mW out of the total 150W generated by the system. Hence, these systems remain impractical to adapt and integrate in smaller devices such as wireless sensor nodes, which are usually used for Water Quality Monitoring (WQM) and other environmental monitoring systems.

3.3 Thermal Energy

Thermal energy harvesting is based on the fact that when there is a temperature difference between two conducting materials, an electric current is generated (Seah et al. 2009). Many environmental studies on thermal powered sensor nodes have been conducted throughout the years. For example, in Woias et al. (2014), a thermoelectric generator (TEG) was mounted to a sheep's collar for tracking purposes. The thermal energy harvester depends on the temperature gradient between the sheep body and the ambient environment. This system was shown to be capable of generating a maximum power of 54μW, which is capable of powering a low-power Very High Frequency (VHF) radio tracking system. Similarly, a thermal powered sensor node model is developed in Davidson et al. (2009). The proposed system benefits from the temperature difference between the ocean water surface that is heated by the sun and the immediate ambient air to monitor water quality. The average output power was shown to be about $5mW/cm^2$ all year long.

Deploying thermal energy harvesters in WSNs depends on the efficiency of the thermoelectric materials (Zhou et al. 2014). To increase the thermal energy harvester output voltage and power levels, multiple arrangements of thermocouples are required, because the individual thermocouple's voltages and power levels are very low. Therefore, thermal energy harvesters are more suitable for large scale power generation such as steam turbines (Gilbert and Balouchi 2008; Shaikh and Zeadally 2016b).

3.4 Hybrid Energy-Harvesting Systems

A few researchers have proposed hybrid energy-harvesting systems that combine multiple types of energy harvesters into a single system. In this section, we review some of these existing hybrid energy-harvesting systems.

3.4.1 Solar/Thermal Systems. A solar/thermal hybrid system was proposed in Li et al. (2008) and Yu et al. (2008) for self-sustained wireless sensor nodes. The system consists of a solar panel and a TEG as energy converters, a Li-ion battery in addition to a super-capacitor for energy storage, and a power management subsystem. The proposed system was experimentally tested and shown to provide continuous support of the node operation for more than 5 years under normal conditions, while it was able to operate for only 7 continuous days in darkness or rain. A hybrid indoors artificial lightning and thermal energy harvesting was proposed in Tan and Panda (2011). The hardware prototype demonstrates a solar cell, a miniature TEG, and a combined power management circuit, and it was shown to harvest an average electrical power of 621μW. A hybrid solar/thermal harvesting system for indoor ammonia gas concentration measurements in an organic fertilizer plant was proposed in Chottirapong et al. (2015). The TEG utilizes the heat difference between the hot side and the cold side of a deodorizer tank. The system was able to generate a minimum of $15mW$ all day and a maximum of $290mW$ in the morning.

3.4.2 Solar/Thermal/Electromagnetic Systems. Virili et al. (2014) designed and fabricated a hybrid electromagnetic/thermal harvesting system. The system is composed of a quarter-wavelength patch antenna that operates in the Industrial, Scientific and Medical (ISM) frequency band 2.4–2.48GHz and that supports a thermoelectric generator (TEG) on top of it. In addition to electromagnetic energy harvesting from the antenna, when the sun's rays hits the TEG, its top side heats up while it cold side is at ambient temperature. This temperature difference allows extra thermal energy harvesting. The TEG was able to generate 20 and $50mV$ for air waves at 50 and 100°C, respectively (Virili et al. 2015). Moreover, the authors enhanced their hybrid system by integrating a solar cell on top of the TEG in Virili et al. (2016). When the sun rays hits the solar cell, it converts solar energy into electric energy, and concurrently the generated heat is transfered to

Table 3. Energy Harvesters Systems

Harvested Energy	Energy Storage	Maximum Energy/Power	Testing Environment	Reference
Solar	Ultra-capacitor	$4.2V$	Experimental	Chen and Chou (2010)
Solar	Battery	$2.09W$	Experimental	González et al. (2012)
Thermal	N/A	$50W/m^2$	Simulation	Davidson et al. (2009)
Solar/ Thermal(Indoors)	Ultra-capacitor	621μW	Experimental	Tan and Panda (2011)
Solar/Thermal	Battery & Ultra-capacitor	290mW	Experimental	Chottirapong et al. (2015)
Thermal/ Electromagnetic	N/A	$50mV$	Experimental	Virili et al. (2014, 2015)
Solar/Thermal/ Electromagnetic	N/A	$34.3mW$, $1.7V$ (Solar) $0.06mW$, $2.5V$ (Thermal)	Experimental	Virili et al. (2016)

the hot side of the TEG, which generates extra harvested electrical energy. A summary of these energy-harvesting systems is presented in Table 3.

3.5 Open Source & Commercial Harvesters

In Table 4, we present the technical specifications of some energy harvesters that are either open source or commercially-developed. From this table, we can see that solar energy harvesters are on the lower end of the price range, while thermal harvesters are on the upper end. Increasing the solar cell size increases the output power of the cell, but the efficiency of solar cells is still not more than 20% (see Table 2). RF energy harvesters are the smallest in terms of size, which is reflected in their output power. The main consideration when selecting the type of energy harvester is to choose the right type based on the ambient energy source available in the deployment site.

4 ENERGY-HARVESTING NODE ARCHITECTURE

Sensor nodes have evolved from large devices into current day small, embedded devices consisting of one or multiple sensing units, a radio transceiver, a processing unit, and a power unit (see Figure 2). Around 2010, sensor nodes with energy harvesters were introduced, which has led to the development of EH-WSNs. In these networks, the sensor node architecture is composed of one or multiple sensing units, a radio transceiver, a processing unit, an energy harvester, one or more energy storage units, a power management system, and possibly an energy predictor (Kochlan et al. 2015; Basagni et al. 2013), as shown in Figure 2.

The energy-harvesting system converts harvested energy into electrical energy for use by the sensor node, either directly (as shown in Figure 3(a)) or indirectly by first recharging the node energy storage (as shown in Figure 3(b)). In the latter, the energy storage is a basic part of the sensor node power unit that stores harvested energy and supplies the node with the required energy to operate. Furthermore, energy predictors are used to estimate the amount of harvested energy that will be available at any given time to a sensor node. Power management techniques have been a

Table 4. Examples of Energy Harvesters

Name	Harvesting Source	Output Voltage (V)	Maximum Output Power (mW)	Dimensions (mm)	Unit Price ($)	References
WISP	RF	1.8	0.3	N/A	N/A	Smith et al. (2006)
PoWiFi	RF (WiFi)	2.4	0.1	N/A	N/A	Talla et al. (2015)
Ningbo Yongjiang Shenzhou Photovoltaic SZGD8855	Solar	3.84	550	88 × 55 × 2.8	9.90	Ningbo Yongjiang Shenzhou Photovoltaic Co. (2015)
KCF Technologies SH-1	Solar	3.3	Depends on load	76.5 × 56.1 × 29.5	N/A	KCF (2014)
Libelium Waspmote Plug and Sense	Solar	6.5	1300	111 × 91 × 3	Included in Kit price	Libelium (2016)
Perpetuum 66001	Vibration	5, 8	27.5	87 × 65 × 6	N/A	PERPETUUM (2013)
MIDE QPK-1001	Vibration	1.8, 2.5, 3.3, 3.6	0.8	54.4 × 22.4 × 0.25	10	MIDE (2014)
Powercast P2110B	RF	up to 6	N/A	14 × 13.5 × 2	35.95	POWERCAST (2015)
EnOcean STM 300	RF	N/A	8.9	22 × 19 × 3	29.75	EnOcean (2012)
STMicroelectronics SPV1050	Thermal	2.6 to 5.3	N/A	3 × 3 × 1	40	STMicroelectronics (2015)
Marlow EHA-L37L37-R01-L1	Thermal	2.3, 3.3, 4.1, 5	5.5	54 × 38 × 38	295	Marlow (2016)

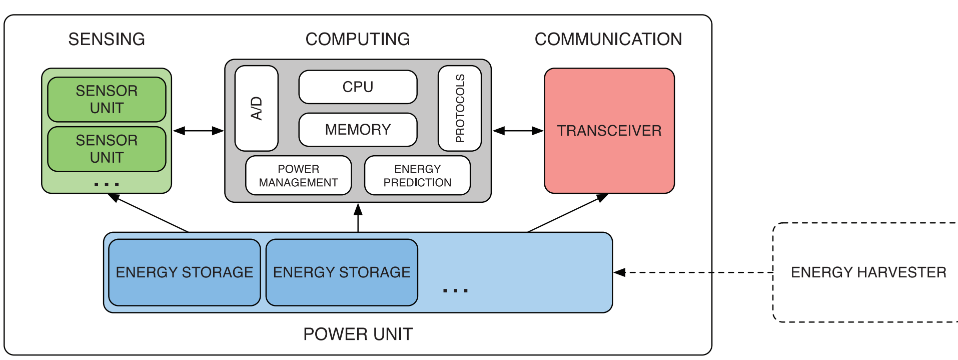
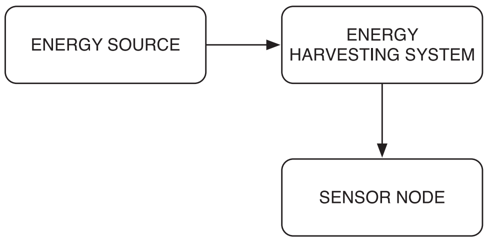


Fig. 2. Wireless sensor node architecture. The same architecture is used for energy-harvesting wireless sensor nodes by connecting an energy harvester (represented in dashed lines) to the power unit.

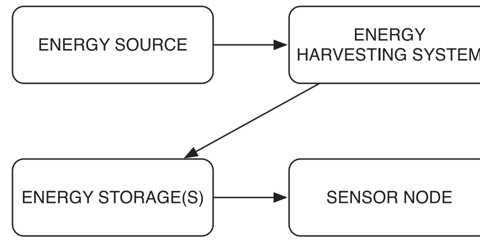
focal research point to achieve energy-neutral operation by using approaches like adaptive duty cycle (Kausar et al. 2014). Energy storage, energy prediction, and power management subsystems will be described in details in the following subsections.

4.1 Energy Storage

Traditionally, sensor nodes have been powered by batteries, typically alkaline, Nickel-Metal hydride (Ni-MH), Lithium-ion (Li-Ion), or Lithium iron disulfide (Li-FeS2) batteries. The alkaline batteries are cheap but have lower capacity and short lifetimes compared to Li-FeS2 batteries (Reddy 2010). The introduction of rechargeable Li-Ion batteries in the early 2000s improved the battery



(a) Harvest-Use Architecture



(b) Harvest-Store-Use Architecture

Fig. 3. A sensor node architecture where the harvested energy is (a) used directly to power the node, and (b) stored for later use in the sensor node. Adapted from Sudevalayam and Kulkarni (2011).

Table 5. Comparison of Super-capacitors Experimentally Tested in Weddell et al. (2011) and Kovář (2013)

Manufacturer	Capacitance (F)	Voltage (V)	Temperature Range (°C)	Diameter (mm)	Length (mm)	Price (USD)
Panasonic	4.7	2.5	−25 to +60	10	20	3.17
Nichicon	4.7	2.7	−25 to +70	10	20	2.80
Elna	1	2.5	−25 to +70	8	22	1.83
Maxwell	5	2.7	−40 to +65	10	20	2.23

capacity and the network lifetime, as the specific energy increased to about 150Wh/kg instead of about 60Wh/kg cycles for Ni-MH batteries (Reddy 2010).

The main technologies used to store harvested energy for powering sensor nodes in EH-WSNs are super-capacitors and rechargeable batteries. In this section, we provide an overview of these different technologies.

4.1.1 Super-capacitors. Super-capacitors are based on the same operational principles as regular capacitors, however they have narrower dielectrics and a larger surface area, which results in a capacitance increase leading to higher energy and power densities than regular capacitors and batteries, respectively. In addition, super-capacitors are charged quicker and they have cycle lifetimes that are typically longer than conventional capacitors. On the other hand, super-capacitors discharge at a higher rate than regular batteries due to leakage, which fortunately can be compensated by the higher charging rate (Halper and Ellenbogen 2006). Table 5 shows a comparison among super-capacitors that were tested experimentally (Weddell et al. 2011; Kovář 2013). Accurate modeling of super-capacitors is important in the design of EH-WSNs, hence much research has been done in modeling their behavior under different assumptions, ranging from modeling the super-capacitor as an ideal device (Jiang et al. 2005) to more accurate models that take into account the super-capacitor internal charge distribution process using a three-branch circuit model (Weddell et al. 2011; Nadeau et al. 2014).

4.1.2 Rechargeable Batteries. Rechargeable batteries are used for energy storage due to their high energy densities (Halper and Ellenbogen 2006). Nickel-Metal Hydride (*NiMH*), Lithium Ion (*Li-Ion*), and Lithium Ion Polymer (*LiPo*, a Li-Ion rechargeable battery in a pouch format) are the most common types of batteries. A comparison of these different batteries is provided in Table 6.

Table 7 provides a high level comparison between super-capacitors and rechargeable batteries. Additionally, a Ragone plot showing the current super-capacitor and rechargeable battery technologies is shown in Figure 4. For systems with limited node size or in case of financial limitations, rechargeable batteries are preferable over super-capacitors due to their lower price

Table 6. Comparison of Rechargeable Batteries

Type	Cycle Life	Charge Time	Self-discharge/ Month	Voltage (V)	Capacity (mAh)	Energy (Wh)	Price (USD)
NiMH	300–500	2-4H	30%	1.25	2500	3.0	60
Li-Ion	500–1000	2-4H	10%	3.6	730	2.7	100
LiPo	300–500	2-4H	10%	3.6	930	3.4	100

Adapted from Battery University (2016).

Table 7. Comparison between Super-capacitors and Rechargeable Batteries

Energy Storing Device	Advantages	Limitations
Super-capacitor	Much higher recharge cycle life High cycle efficiency (>95%) Much longer lifetime compared to batteries Environmentally friendly Broader range of voltage and current Low internal resistance High performance in low temperatures	Expensive Low energy per unit weight Low per cell voltage High self-discharge rate High dielectric absorption
Rechargeable battery	Inexpensive Low self-discharge rate High energy per unit weight	Lower recharge cycle life Much lower lifetime

Adapted from Akhtar and Rehmani (2015) and Group (2016).

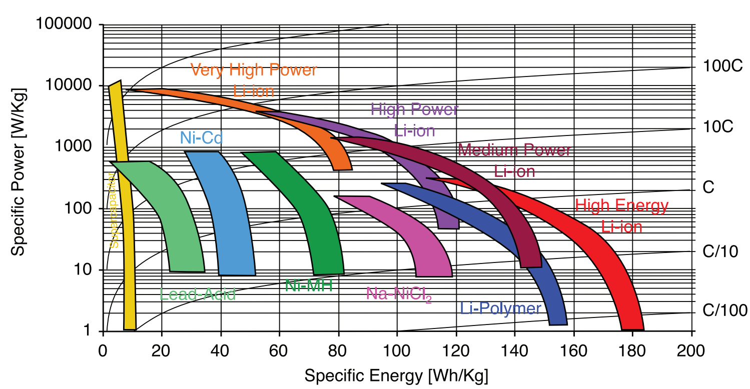


Fig. 4. Ragone plot for super-capacitors and rechargeable batteries technologies. Adapted from U.S. ARMY TARDEC (2014).

and higher energy density. On the other hand, for applications that require a long lifespan or operates in low temperatures, a combination of super-capacitors and rechargeable batteries would be optimal, as the super-capacitors have a much longer lifetime and a large range of operating temperatures (Sánchez et al. 2011; Ongaro et al. 2012). We note that, in recent times, energy storage in WSNs is often a combination of rechargeable batteries and super-capacitors to benefit from both the higher number of charge/discharge cycles of super-capacitors and the high energy density of rechargeable batteries (Kochlan et al. 2015).

Table 8. WSN-based Applications Using Rechargeable Batteries

Application Scenario	Energy Storage Device Used	References
Water Quality Monitoring	12V Battery	Amruta and Satish (2013) and Sowmya et al. (2017)
Wildfire Monitoring	1Ah lithium battery	Lazarescu (2015)
Climate Change Monitoring	150mAh NiMH rechargeable battery (main) 2200mAh Li-ion battery (backup)	Ingelrest et al. (2010)
Bridge Structural Health Monitoring	Lithium-Ion or Lithium-Polymer batteries (10,000mAh capacity)	Jang et al. (2010)
Aquatic Environmental Monitoring	NiMH-cell battery	Alippi et al. (2011)

Table 9. WSN-based Applications Using Both Rechargeable Batteries and Super-capacitors

Application Scenario	Combined Storage Device	References
In-line River Monitoring	Super-capacitors (first buffer unit) Rechargeable batteries (second buffer unit)	Capella et al. (2013)
WSN Enabled Intelligent Buildings	Supercapacitor (main) Rechargeable battery (backup)	Naveen and Manjunath (2011)

In Table 8 and 9, different application scenarios and their respective energy storage devices are presented.

4.2 Energy Prediction

Energy prediction is important for EH-WSNs, because protocols can be optimized if there is some knowledge of not only the existing (stored) energy but also the energy that will be harvested in both the short and long term. However, as the amount and rate of energy that can be harvested from different energy sources are generally dynamic and highly variable, accurate energy prediction can be quite challenging. Different energy sources can be categorized based on their predictability and controllability (Shaikh and Zeadally 2016a). For example, for solar energy, an Exponential Weighted Moving Average (EWMA) algorithm assumes the energy generation at a certain time is an exponentially weighted moving average of the energy harvested at the same time on previous days (Kansal et al. 2007). This model is applicable to stable weather conditions but does not account for frequent meteorological changes, which results in an average error of 28% between the predicted and the actual harvested energy. Weather-Conditioned Moving Average (WCMA) algorithm divides the day into time slots, and at the end of each time slot the energy prediction of the next time slot is provided. The WCMA algorithm includes data from the same time in past days and scales it with respect to the difference in weather conditions between the current day and the past days to achieve a better prediction model, with an average error of 9.8% (Piorno et al. 2009). In Moser et al. (2007), the energy predictor collects information about the received energy at the current time and combines it with an exponentially decaying old data from past days. A comparison between these algorithms shows that the WCMA algorithm provides the best energy prediction with the lowest error; however, it requires more storage memory and longer prediction time (Bergonzini et al. 2009).

Sharma et al. (2010a) designed their algorithm to benefit from local weather forecasting data by creating a model that translates weather forecast data into an energy-harvesting prediction. Although weather forecasting can provide more accurate data than algorithms that take only the past days into account, this algorithm requires high overhead to transmit the weather prediction data to the sensor nodes. In Noh and Kang (2011), an algorithm based on EWMA is proposed. To overcome EWMA's inability to account for varying weather conditions, a scaling factor (which is the ratio between the predicted and the actual energy harvested) is calculated at the end of each time slot and used to adjust the predicted energy for the future time slot.

In Cammarano et al. (2012), the proposed Profile energy prediction model (Pro-Energy) algorithm collects a day-long profile that contains information about the energy harvested at each time slot throughout the day, and then classifies the day into a typical profile: sunny, cloudy, or rainy. At each time slot, Pro-Energy predicts the harvested energy based on the day profile most similar to the current day. Pro-Energy is composed of three components, the prediction module, which is responsible for short and long term energy prediction, the profile analyzer, which selects the most similar profile to the current day, and the profile pool, which contains a collection of different energy profiles. Pro-Energy achieves a 60% improvement in prediction accuracy compared to EWMA and WCMA. Furthermore, the authors proposed an enhanced version of this protocol called Profile Energy prediction model with Variable-Length Time slots (Pro-Energy-VLT) in Cammarano et al. (2013). Instead of the common design of dividing a day into fixed-length time slots, Pro-Energy-VLT assigns a variable length time slot based on the average daily harvesting rate computed using historical data. The newly proposed protocol outperformed Pro-Energy, WCMA, and EWMA, achieving a lower prediction error up to 10%, 40%, and 50%, respectively. Moreover, Pro-Energy-VLT achieves a higher performance in terms of energy and memory saving. In addition, increasing the number of time slots results in a lower prediction error, as this allows a better estimation of the fluctuating energy source. These results were obtained using real-life experiments using Telos B nodes interfaced with solar panels and wind micro-turbines (Cammarano et al. 2016).

In general, solar prediction models provide a reasonable indication of the energy to be harvested from solar energy. However, solar energy is the most predictable energy source when compared to the other sources described in Section 3, and accurate prediction models for the other energy sources are still needed.

4.3 Power Management

As described above, the amount of energy harvested is variable, e.g., for solar energy harvesting, no energy will be harvested at night. This variability in the available energy for EH-WSNs has led to the idea of designing either the individual node or the larger network to operate at an energy equilibrium, also called energy-neutral operation (ENO) (Sharma et al. 2010b). Energy-neutral operation refers to a state where the energy consumed by a node is always less than or equal to the energy harvested from the operating environment (Kansal et al. 2007; Sharma et al. 2010a; Fafoutis and Dragoni 2011; Baghaee et al. 2014). Designing an EH-WSN to support energy-neutral operation theoretically leads to infinite network lifetime (Kansal et al. 2007; Fafoutis and Dragoni 2011).

Given its importance, various approaches have been proposed to achieve ENO and can be classified into predictive approaches that predict the energy and adjust the node operations accordingly to satisfy ENO, or reactive approaches that monitor the node energy generation level and adjust some aspect of the node operation in response to the harvested energy (Buchli et al. 2014). Existing energy-neutral systems are designed to use analytical models and protocols to schedule tasks in accordance with the amount of energy harvested from the environment (for both predictive and reactive approaches) (Kansal and Srivastava 2005; Vigorito et al. 2007).

Power management schemes such as Dynamic Power Management (DPM), On-Demand Medium Access Control, joint energy-harvesting and operation scheduling, energy synchronized communication and the harvesting-aware utility-based sensing rate allocation algorithm (Gu et al. 2009; Fafoutis and Dragoni 2011; Sharma et al. 2010b; Zhang et al. 2011; Shu et al. 2017) enable task (e.g., communication or sensing tasks) scheduling to meet ENO. Furthermore, techniques such as duty cycling and adaptive sensing (Alippi et al. 2009; Hsu et al. 2006), adaptive control (Vigorito et al. 2007), topology control (Tan et al. 2015; Yoon et al. 2015; Wang et al. 2016b), cooperative transmission (Zhang et al. 2016a), frame length optimization (Li et al. 2017), adaptive throughput, and mean delay optimal energy-neutral policies have been proposed for EH-WSNs to maximize the performance of the network given the rate of energy that is harvested by the sensor nodes (Sharma et al. 2010b; Fafoutis and Dragoni 2011).

Adaptive duty cycling or control are mechanisms that allow the energy-harvesting sensor nodes to autonomously adjust their duty cycle (that is, waking up the sensors) according to the energy availability in the operating environment. In this case, the nodes are assumed to have prior knowledge of the energy profile (Hsu et al. 2006).

Since energy storage devices have a limited capacity and are prone to energy leakage, it is not always beneficial to maximize conserved energy, especially when excessive energy could be harvested (Gu et al. 2009). Gu et al. (2014) rely on this fact to propose an energy synchronization communication (ESC) protocol that aims to minimize the communication delay in EH-WSNs through dynamically synchronizing the nodes' activity patterns or working schedule with the available energy budget and simultaneously achieving energy-neutral operation.

Topology control is another method to manage the energy consumption of the WSN by properly adapting the node transmission power and number of neighbors (Santi 2005). In Tan et al. (2015), the behavior of sensor nodes are defined as an ordinal potential game in which a Nash equilibrium is proven to exist. In this game theory approach, the energy status and harvesting capabilities of the sensor nodes are considered, and consequently the high and low harvesting power nodes cooperate together to optimize the network topology and achieve network connectivity. In Yoon et al. (2015), a hierarchial topology control approach is implemented in which the sensor nodes are arranged in layers based on their residual energy levels. Since nodes closer to the sink require more energy to aggregate data, this approach shifts the network load into high residual energy levels. In Wang et al. (2016b), a localized topology control approach selects the node's neighbors based on their distance and their remaining energy levels, which is modeled as a Bernoulli random process to take into account the energy-harvesting capabilities of the sensor nodes.

In Dynamic Power Management (DPM), which is another technique for power management, the main focus is on reducing the power consumption while maintaining the network performance at a reasonable level by switching the nodes to different energy states. In DPM, to save power, the nodes go into the sleep mode whenever they are not needed, and they are woken up when they are required to process the data or send or receive the packets. In this way the node lifetime is increased by reducing its power consumption. It is important to note that an efficient sleep mode transition algorithm is essential. In Sinha and Chandrakasan (2001), several sleep states are defined for each node based on which components are put in the sleep mode. In the deeper sleep states, more components of the node are in sleep mode, and thus less power is consumed. However, this translates into an higher latency for waking up the node. In Chen et al. (2013), the authors present a multi-hop wake-up radio-based sensor node that improves the wake-up range while achieving low power consumption for energy-harvesting sensor nodes. Their implementation consists of a low-power wake-up radio circuit combined with a WISP-Mote, which allows both an ID-based and a broadcast-based wake-up mechanism.

To reduce the energy used for sensing operations, adaptive sensing can be employed to dynamically regulate the amount of data sensed in a given period of time (Alippi et al. 2009; Sharma et al. 2010b; Zhang et al. 2013, 2016b; Yoon et al. 2016). Cooperative spectrum sensing is proposed in Zou et al. (2016) to balance the network energy consumption by optimizing the nodes' sleeping schedules. Cooperative transmission and relay selection is a widely used concept in sensor networks to provide better energy efficiency (Cui et al. 2004). Zhang et al. (2016a) proposed a cooperative transmission scheme that aims at balancing the node's residual energy levels. Based on the initial energy in the source, channel gain and source's energy-harvesting rate, the node that achieves the maximum sensors' residual energy is chosen as a relay to cooperate with the source node. This protocol is shown to provide better residual energy balancing compared to the largest E_r (LERS) scheme, where the relay with the highest initial energy is chosen, and the minimum energy consumption scheme (MECS) in which the node that minimizes the total energy consumption is chosen as the relay node (Berbakov et al. 2013).

There are three main design considerations discussed in Kansal et al. (2007) for energy neutrality in WSNs. These include the size of the energy buffer, the operational performance level when in energy-neutral mode, and the measurement capabilities required in the hardware for harvesting the energy. Typically, the energy buffer could be a a battery or a super-capacitor used to store the harvested energy depending on the energy generation profile. In an energy-harvesting system, it would be ideal to have an energy buffer that could store any amount of energy without any inefficiency in the charging process and one that does not leak energy over a period of time when the sensor node is in use. In practice, it becomes difficult to harvest energy without these inefficiencies and leakages. Hence, the implementation of energy neutrality in such systems is paramount. The performance level will be determined based on the power-management strategies employed.

Measuring the amount of energy harvested from the environment and the variability in the energy supply can be helpful when employing power management schemes to manage the amount of energy used for sensing, communication, and data processing in energy-harvesting sensor network systems. In Baghaee et al. (2014), the combination of vibrational energy harvesting, rechargeable batteries and adjusting the sensor node duty cycle has been shown to empirically achieve energy neutrality. In addition, an energy-neutral clustering protocol is proposed in Peng et al. (2015) to maintain the network operation and achieve energy neutrality. The uncertain nature of the amount of harvested energy results in a more challenging protocol design, as this requires more sophisticated prediction models. When designing an EH-WSN, a design goal is to maximize the network performance while meeting ENO. Achieving this goal depends on the energy harvested by multiple distributed nodes rather than simply at individual nodes, as the network load should be allocated based on the energy harvested by the entire network (Kansal et al. 2007).

Although the energy harvested from the environment can be quite variable in nature, a long term data collection and analysis for the amount of energy harvested may lead to a high performance protocol design that will operate and achieve energy-neutral operation over the long run rather than for a short period of time. In contrast to providing nodes with energy using static chargers through wireless energy transfer, energy harvesting using mobile chargers have received much attention due to their ability to provide stable energy supply to the nodes, which has lead to a new type of WSN called Wireless Rechargeable Sensor Networks (WRSNs) (Baroudi and Al-Roubaiey 2014; Fu et al. 2016). Although WRSNs can potentially decrease the uncertainty of harvested energy, there are different challenging areas that still need to be explored such as localization, synchronization and velocity control of mobile chargers (Fu et al. 2013; Shu et al. 2015, 2016).

5 COMMUNICATION PROTOCOLS FOR EH-WSNS

In WSNs, communication protocols are used to efficiently collect sensor data from distributed sensors and deliver this data to a local base station. The main purpose of these protocols is to effectively utilize the energy supplied to the node for sensing, computation, and communication/networking.

In traditional WSNs, as the energy is limited by the batteries, energy efficient protocol design is a key component for designing systems that achieve long lifetimes.

Over the years, there have been a number of protocols developed to try to minimize the energy required to send data throughout the network, at the physical, link (MAC), and network layers, as well as protocols for topology control and network connectivity to ensure sufficient data are collected and the network remains connected (Lynch and Loh 2006; Nack 2010; Potnuru and Ganti 2003). In these traditional WSNs, the important performance metrics are application quality of service (QoS) and energy-efficiency (network lifetime). Hence, protocols such as routing protocols seek to achieve the required QoS while at the same time reducing energy dissipation as much as possible. To achieve this, energy is often considered as the metric to optimize, for example, in selecting next hop neighbors in routing (Singh et al. 2010; Nack 2010).

On the other hand, EH-WSNs obtain energy from the harvester to continuously power the sensor nodes. Hence, rather than making decisions to minimize energy drain, in EH-WSNs the ultimate goal is to design protocols that effectively manage the use of this variable energy to support application QoS goals. For example, in EH-WSNs, energy may not be considered as a routing metric, because the design will no longer focus on energy efficiency of the sensor nodes and the overall network, but instead it will focus on the active time a node can operate with the minimum amount of energy harvested in a specified time interval. Additionally, physical layer issues related to the modulation scheme and power transmission are of much interest in EH-WSNs. Different communication protocol parameters that must be adapted for EH-WSNs are presented in Sudevalayam and Kulkarni (2011).

Meeting these new goals for EH-WSNs requires different types of optimizations of existing protocols as well as new designs that consider the variable energy supply of the node. In the following sections, we overview the various protocol changes needed to support EH-WSNs at the physical, MAC, and routing layers.

5.1 Physical Layer

Data transmission and reception are the most energy-consuming operations in wireless sensor nodes (Carmona et al. 2014) and, to maintain a certain bit error rate, the transmission power must increase as the distance between the communicating nodes increases (Nanavati and Deshpande 2015). Furthermore, higher transmission power can increase the interference with other nodes. As a result, the transmission power must be adjusted appropriately to find an optimum operating point that can result in a high packet delivery ratio or achieve energy-neutral operation (Yildiz et al. 2016). Sudevalayam and Kulkarni (2011) provided a discussion on how to adjust the node's transmission power based on its current and predicted effective energy in addition to the node's energy consumption to achieve ENO. In Fan and Liu (2016), an energy synchronized transmission control scheme (ESTC) is proposed, in which each node adjusts its transmission power based on its energy budget and traffic load.

In this article, we describe the latest advances in power adjustment protocols and present two additional techniques developed to enhance the system performance by changing the number of transmitting and/or receiving antennas and the usage of adaptive source and channel coding in addition to adaptive modulation schemes.

5.1.1 Power Adjustment Based on Link Quality Parameters. In the literature, many algorithms are available to adjust the transmit power based on link quality parameters such as received signal strength and link quality indicator (Yildiz et al. 2016; Carmona et al. 2014). For example, Abo-Zahhad et al. (2015) provided the optimal transmission power that minimizes the energy per bit for different modulation schemes as a function of the distance. Lin et al. (2006) proposed a protocol for WSNs in which the nodes' transmission power is controlled based on the link quality of the neighbors. In this adaptive transmission power control algorithm, each node receives feedback packets carrying the link quality information. Based on the collected link quality information, each node determines a suitable transmission power to reach a particular neighbor and, when the quality of the transmission link changes, the node adjusts its transmit power accordingly.

In Aprem et al. (2013), the authors proposed a protocol that adapts the transmission power based on the current Channel State Information (CSI). In automatic repeat request (ARQ)-based packet transmissions, the sender node may receive either an ACK packet indicating a successful transmission or a NACK packet indicating an unsuccessful one. In Aprem et al. (2013), each ACK/NACK packet includes the CSI, which is then used by the transmitter to adjust the transmit power for the next data packet. For instance, if the channel is in good condition, the sender may reduce the transmit power for the next transmission to save energy. Conversely, if the CSI shows a low link quality, a higher transmission power is chosen for the transmission of the next packet.

Building off of this work, an optimal power allocation algorithm for EH-WSNs is presented in Sinha and Chaporkar (2012). Assuming that the transmitter has the full CSI, the transmission power that maximizes the link throughput is calculated by formulating the power allocation problem as a Markov Decision Process (MDP). They consider different states for the channel and the battery, and their model decides the optimal transmit power for that specific state so that the maximal overall throughput can be achieved. Every state represents the energy in the battery and also the channel fade coefficient. The actions that can be taken at each state is based on the amount of transmit power that is allocated to the node. Moreover, they assumed that the battery has a limited capacity and can be recharged through a renewable source like the wind or solar. Their aim is to find the optimal transmit power such that the reward function, which is defined based on the channel's capacity, is maximized.

5.1.2 Multi Antenna-Based Protocols. Multi-Input Multi-Output (MIMO) radio antenna technology is another approach to adjust the transmission power to improve energy efficiency in wireless networks. In such networks, various dynamic antenna selection schemes can be used for communication: Multi-Input Multi-Output (MIMO), Multi-Input Single-Output (MISO), Single-Input Multi-Output (SIMO), and Single-Input Single-Output (SISO). Each of these schemes has different power consumption, and different protocols that adapt both the number of antennas and the transmit power for the data communication have been proposed in the literature. In Ayatollahi et al. (2015), the authors employed an adaptive multi-antenna protocol in which the number of antennas for sending and receiving the data and thus the transmit power is adjusted according to the channel bit-error-rate, the transmission distance, and the available energy in the nodes' buffers. Among four dynamic antenna selection schemes, the one that provides the highest lifetime for the system is chosen on a per-packet basis.

In Zhang and Ho (2013), a novel multi-antenna broadcast channel (MIMO-BC) system for simultaneous wireless information and power transfer (SWIPT) energy in a three-node network is proposed, and the authors show fundamental trade-offs in designing future SWIPT systems. In their system, all three nodes (one transmitter and two receivers) are equipped with multiple antennas, of which, one of the receiver nodes is responsible for harvesting the energy and transferring it to the other nodes, while the second receiver decodes the data sent by the transmitter. At the receiver-side, the authors proposed two receiver designs. In the first design, the receivers switch between harvesting and transferring the energy and receiving the data packets. In the second design, the received signal is split into two separate signals with different power levels, with each signal being sent to one of the receivers.

5.1.3 Joint Source-Channel Coding Based Protocols. In EH-WSNs, since the amount of harvested energy is variable and unpredictable, sensor nodes should employ adaptive source coding, adaptive channel coding and modulation scheme selection (Bai and Nossek 2013; Motlagh et al. 2015; Castiglione and Matz 2014; Yao et al. 2012). However, modulation scheme selection and adaptive source-channel coding in which source encoders and channel encoders are jointly designed, can be very challenging without robust energy prediction models that estimate the amount of available energy in the future (Zhai et al. 2005; Castiglione et al. 2011). Due to the prediction-based nature of energy-harvesting problems, some of the algorithms assume that either the full knowledge of the harvested energy in the future is known at the transmitter, or both the history and the future harvested energy are available prior to the communication.

The problem of minimizing the mean squared error of estimated source symbols at the receiver side in an energy-harvesting estimation system is explored in Zhao et al. (2013). Here, the authors consider two cases, when the transmitter only knows the amount of harvested energy in the past and also when the transmitter knows the harvested energy in the past, present, and the future.

The throughput of energy-harvesting transmitters is analyzed by employing discrete M-ary Quadrature Amplitude Modulation (MQAM) and coding rates in Bai and Nossek (2013). Bai and Nossek (2013) assumed that the energy arrival in a specific time duration is fully known at the transmitter to maximize the total throughput. According to their simulation results, the throughput of the system with the coded transmission is better than the uncoded one when the distance between the transmitter and the receiver is more than 50 meters. In Yao et al. (2012) the source packet generation rate is optimized by choosing the number of packets that allow the system to achieve ENO. Here, the authors proposed a source coding rate algorithm that first transmits the most valuable data packets.

In Castiglione et al. (2012), an energy management model is proposed that focused on allocating the energy to the channel encoders and source encoders based on different parameters such as available energy, quality of the wireless channel, and the state of the data queue. This protocol simultaneously achieves maximal average distortion and ensures the stability of the queue that connects the source and the channel encoders. For networks with more than two nodes, they employed TDMA-based scheduling policies to ensure the stability of the data queues at the nodes.

In Motlagh et al. (2015), an adaptive source-channel coding system with an energy-harvesting transmitter is proposed in which the channel codewords change according to the variation of available battery energy, their main goal being to minimize the distortion at the receiver side. They found a lower bound for the average distortion in a system with a constant transmission power and infinite battery capacity. A similar problem for the case of a finite and rechargeable battery in the energy-harvesting nodes is discussed in Castiglione and Matz (2014). Here, the authors proposed a joint energy management scheme for channel and source encoders, and proved that using this algorithm, a near-optimal level of distortion can be achieved with respect to the battery size.

5.2 MAC Layer

Optimizing communication protocols is a cornerstone in the design of EH-WSNs, hence the importance of an efficient MAC layer design (Shahzad and Sheltami 2015). MAC layer synchronous protocols that rely on sharing nodes' sleeping schedules are unsuitable for EH-WSNs, since the nodes' charging periods (in which the node is considered to be unavailable for communication) may coincide with the wake up periods (Huang et al. 2013). Asynchronous schemes can be categorized into transmitter initiated schemes, in which the receiver wakes up periodically and checks for a preamble from the transmitter, and receiver initiated schemes where the receiver sends periodic beacons implying that it is ready to receive data (Bachir et al. 2010). Existing MAC protocols for EH-WSNs fall primarily into three categories: adaptive duty-cycle-based protocols, CSMA type protocols, and polling-based protocols. The main idea behind the first two categories of protocols were discussed in the Sudevalayam and Kulkarni (2011) survey; nevertheless, we provide the latest advances in these protocols categories and, in addition, we discuss polling-based techniques, which were not included in the aforementioned survey.

5.2.1 Adaptive Duty Cycle Based Protocols. Several EH-WSN MAC protocols that use an adaptive duty cycle have been developed; however, the protocols differ in the criteria that controls the node duty cycle. In the Energy Adaptive MAC (EA-MAC) protocol, the RF harvested energy adapts the node duty cycle (Kim and Lee 2011a). This protocol was developed for a star network in which the sink node is always awake to transmit RF energy to power the source nodes and receive data from them. When the node energy reaches a threshold, it awakens and competes for the channel to send its data based on the unslotted CSMA/CA algorithm in the IEEE 802.15.4 protocol and then goes back to sleep. The authors extended their work to provide analytical model of the algorithm in Kim and Lee (2011b). Karthi et al. (2015) proposed an energy-harvesting WSNs MAC protocol based on the IEEE 802.15.4. IEEE 802.15.4 beacon-enabled mode that uses a super-frame structure that consists of fixed active and non-active periods. In the active periods, the nodes access the channel according to the CSMA/CA protocol. Conversely, in the proposed protocol, if the node's remaining energy is less than a certain threshold, the protocol reduces the node's duty cycle to its minimum value. Otherwise, the proposed protocol adjusts the active and non-active periods according to the battery discharge characteristics, the node's harvested and consumed energy.

On Demand MAC (OD-MAC) is a receiver initiated protocol that uses a solar energy prediction model (i.e., the EWMA protocol described in Section 4.2) to set the node's initial duty cycle (Fafoutis and Dragoni 2011). Then at each slot, the node checks its actual harvested energy, and based on the difference between this value and the predicted energy, it reduces or increases its duty cycle to achieve energy-neutral operation. Load and Energy Balancing MAC (LEB-MAC) (Liu et al. 2014) is an asynchronous, receiver initiated protocol that sets the duty cycle of the nodes in a distributed manner. Based on the node harvesting energy rate, the node sets its duty cycle and sends this information along with the next time it is expecting to wake up to its neighbors. When the neighbor nodes receive this information, they combine it with their own energy-harvesting rate to synchronizes the duty cycles (Liu et al. 2014).

ERI-MAC is a receiver initiated duty cycle with carrier sensing MAC protocol developed for EH-WSNs (Nguyen et al. 2014). ERI-MAC depends on a receiver-initiated mechanism, which has been proven to be energy efficient in WSNs and widely used in adaptive duty cycling protocols. The protocol also applies a packet concatenation mechanism by aggregating similar small packets into a larger packet. This provides energy efficiency by reducing the control packets overhead. In their previous work, Byun et al. (2013) assigned low-priority packets a fixed queuing time-out before sending them. They have extended their work in ERI-MAC by dynamically changing the time-out according the energy-harvesting rate and the node's energy consumption. When the energy consumption is higher than the energy harvested, the node switches to a sleeping mode until its batteries are recharged above a certain threshold.

Two MAC protocols that adapt the node duty cycle based on the the current and expected energy are presented in Yoo et al. (2012). The authors first proposed the Duty-cycle Scheduling based on Residual energy (DSR) protocol, in which the node adjusts its duty cycle based only on its residual energy. Afterwards, the Duty-cycle Scheduling based on Prospective increase in residual energy (DSP) protocol was developed that takes into account the effect of future harvesting rates on the residual energy. A similar approach was proposed in Varghese and Rao (2014), in which the authors developed two protocols, the Exponential Decision MAC based on Current Residual protocol energy (ED-CR), and the Exponential Decision based on Prospective Increase in Residual energy (ED-PIR) protocol. The main difference between these approaches is that Yoo et al. (2012) proposed a linear decision graph to adapt the duty cycle while an exponential decision graph is implemented in Varghese and Rao (2014). ED-PIR achieves a better performance in terms of energy consumption, end to end delay and packet delivery ratio compared to DSP and to the non energy-harvesting receiver initiated protocol (RI-MAC) in which the receiver nodes wake up periodically to receive data.

An adaptive duty cycle protocol developed for periodically powered indoors WSNs is proposed in Le et al. (2015). The protocol applies the Zero Energy Interval predictor (ZEI) proposed in Castagnetti et al. (2012) to determine the harvesting and non-harvesting periods. Then, it adjusts the node's duty cycle according only to its residual energy in the non-harvesting periods. On the other hand, the protocol adapts the node's duty cycle based on the harvested energy in addition to saving a portion of the collected energy to be utilized in non-harvesting periods. Similarly, Oueis et al. (2016) proposed an adaptive duty cycle MAC protocol for indoors and outdoors photovoltaic EH-WSNs that takes into consideration the battery's residual energy and its variation. The protocol compares the node's remaining energy in two consecutive time slots, and if there is an increase/decrease in this value, which corresponds to a charging/discharging state, the protocol increases/decreases the duty cycle.

FarMAC is a multi-source protocol developed for WSNs rechargeable by RF wireless power transfer (WPT) (Shao et al. 2016). In addition to the charging sink nodes, the protocol categorizes nodes into Energetic Sensor Devices (ESDs), which is ready to transfer its data directly, and lethargic sensor devices (LSD) that need energy replenishment before being able to conduct data transmission; the LSD devices are provided with a higher channel access probability. In the first stage, ESDs switch to a sleeping mode while LSDs use a CSMA/CA protocol to contend for channel access, and the winner node communicates with a specific sink node to compute its required charging time and then switch to a sleeping mode. Afterwards, the sink node sends a Data Query (DQ) packet to the ESDs that contend for the channel and the winner replies with a Data Request (DR), which in turn responds with a Data Request Clear (DRC) packet. Afterwards, wireless power transfer and data collection are executed concurrently.

5.2.2 CSMA/CA Based Protocols. The RF-MAC protocol was developed to work with sensor nodes that harvest energy from multiple RF transmitters (Naderi et al. 2014). When the node residual energy reaches a minimum threshold, it sends an RF request with its ID to the transmitters to replenish its energy, and a shorter inter-frame spacing (DIFS) is assigned to this energy request to assure it is given a higher priority than data exchange. When the node is ready to send its data, it contends for the channel based on a slightly modified CSMA/CA protocol. In particular, RF-MAC provides nodes with a higher harvesting rate a higher priority to access the channel by assigning them shorter back-off times.

Energy Level MAC (EL-MAC) is an energy aware MAC protocol that was developed for energy-harvesting secondary users in cognitive radio networks, nevertheless it could be applied in EH-WSNs. In this protocol, the node channel access probability is set to be inversely proportional to its residual energy by assigning a smaller contention window to low energy nodes. This process ensures that low energy nodes have high probability to access the channel and then go back to sleep mode to save energy otherwise lost in channel sensing. Furthermore, this process lowers the probability of collisions by decreasing the number of contending nodes (Kim et al. 2014).

5.2.3 Polling Based Protocols. Polling is a common MAC protocol used in many EH-WSNs implementations. The simplest polling approach proposed for EH-WSNs is ID polling, where the sink node polls each of the nodes based on their ID regardless of the number of active nodes in the network or the node's harvested energy rate. This approach is simple but can result in polling inactive nodes, which leads to a low network throughput (Eu et al. 2011).

To overcome this problem, a Probabilistic ID polling protocol that depends on the number of active nodes in the network to determine a contention probability was proposed in Eu et al. (2011). In this protocol, the active nodes receive a broadcasted periodic polling packet from the sink node and generate a random number between 0 and 1. If this number is higher than the contention probability, then the node will defer from sending and wait for the next polling packet. Otherwise, it will send its data, and in the case of collisions, the sink node lowers the contention probability. The authors also provided analytical models for slotted CSMA, unslotted CSMA, ID polling, and probabilistic polling MAC schemes. They have shown that probabilistic polling achieves higher performance in terms of network throughput, fairness and scalability.

Probabilistic polling protocol was extended to achieve a multi-hop WSN in Fujii and Seah (2011), by enabling sensor nodes to poll other nodes beyond the sink's range and dynamically update their tier number in a multi-tier manner. The sink node polls the nodes in its transmission range, and then each polled node either sends its data back to the sink or rebroadcasts the same probabilistic value to a higher tier nodes. When a node gets polled by a lower tier node, it sends its data and the data it received from higher tier nodes, and this process is repeated until the data reaches the sink through intermediate tiers. Unlike the previous protocols, the authors used commercial devices as testbed validation of their approach.

In EH-WSNs different nodes may harvest different amounts of energy, hence assigning the same contention probability for all nodes regardless of their energy state can be considered unfair to nodes with low energy levels based on Jain's fairness index. EH-MAC is a multi-hop, asynchronous, receiver initiated polling scheme that provides nodes with lower charging rates more transmission opportunities by integrating their harvested energy rate into their contention probability (Kunikawa et al. 2015). This approach succeeded in increasing the network fairness but slightly lowers network throughput compared to ID polling and probabilistic polling.

5.3 Routing Layer

Sensor nodes' energy is the main consideration in routing protocol design for WSNs and EH-WSNs, as out of energy nodes affect the routing decisions and cause a degradation in the network performance. In designing an energy aware routing protocol for WSNs, minimum hop count schemes might not be optimal as they may lead to energy depletion of nodes in the shortest path at a higher rate than other network nodes. Hence, traditional routing protocols have been modified to include energy aware parameters. For example, Distributed Energy-Harvesting Aware Routing Algorithm (DEHAR), is an energy-aware routing protocol that includes the concept of energy distance, which is a combination of the hop count between the source and destination and the energy consumed in this path, to find the optimum route instead of only using the hop count (Jakobsen et al. 2010). To select the shortest path in energy-harvesting applications, some protocols are designed to perform the route selection based on the residual energy of the sensor node, while some EH-WSN routing protocols implement an energy consumption prediction model. There is a paradigm shift from energy aware routing protocols (EARPs) to energy-harvesting aware routing protocols (EHARPs), as in EH-WSNs, routing protocols should focus on achieving the required QoS when the ambient energy is not available or limited (Wu and Liu 2013). In the following, we discuss the advanced schemes for routing in EH-WSNs that include incorporating the energy-harvesting rate into the route cost, updating the traditional geographic routing that depends on the nodes' location, and clustering-based routing protocols improved for EH-WSNs.

5.3.1 Offline Routing Protocols. In offline routing protocols, nodes' routing tables are constructed based only on previous knowledge of the network. Kollias and Nikolaidis (2015) implemented a seasonally aware routing protocol that builds the nodes' routing tables based on their solar energy-harvesting rates and the created paths from previous years. These types of protocols are fairly simple and do not waste energy in overhead for creating routes. For energy-harvesting sources that are periodic or at least predictable, this type of routing protocols could be beneficial. The drawback of this approach is that if a node dies, an offline routing protocol cannot recover. To enhance the performance of EH-WSNs, routing protocols must go online to mitigate the affect of energy unpredictability. Two types of online protocols are discussed in this article, multi-hop-based and clustering-based EH-WSNs routing protocols.

5.3.2 Route Cost Based Protocols. Multi-hop routing protocols are based on finding the route cost using a cost function that takes into account energy-harvesting parameters. For example, Ad hoc On-Demand Distance Vector (AODV) is modified in Gong et al. (2014) to support energy harvesting by replacing the hop count field with an energy count field to find the route with the minimum cost based on the energy harvesting of the nodes in the path. Similarly, Pais et al. (2011) proposed a routing protocol with a routing cost function that includes the hop count between source and destination, the source residual energy and the source's harvested energy in the last time slot as its parameters. This routing algorithm is improved in Cheng et al. (2015) by taking into account the status of future path hops and not only the next hop.

Peng and Low (2013) proposed an energy-neutral routing (ENR) protocol based on directed diffusion. In ENR, each node admits or rejects packet relay requests based on its energy-harvesting status, which aims at fairly distributing the network traffic load to achieve ENO. Smart Energy-Harvesting Routing (SEHR) proposed a cost function that formulates the energy consumption based on the sent data type in addition to the node's energy and the expected energy-harvesting rate (Bai et al. 2015). SEHR selects routes using three main strategies including real-time node power estimation, which is based on the amount of energy harvested and the energy drain rate, the node mobility and stability, and finally the protocol prioritizes routes based on the data types available for transmission.

These protocols do not take into account the waste of harvested energy due to finite-energy storage capacities, which is considered in the energy-harvesting wastage-aware (EHWA) routing algorithm (Martinez et al. 2014b). EHWA selects the best route by computing the cost associated with current residual battery level of a node to obtain a resultant energy. The route with the maximum total resultant network energy is selected to transmit packets from source to destination. The authors extended their work by jointly optimizing multiple routing requests instead of optimizing each route separately with the objective of maximizing the total remaining energy in the network (max-total) or maximizing the minimum residual energy (max-min) by formulating this as a linear programming (LP) optimization problem (Martinez et al. 2014a). To maximize the total remaining energy, the shortest path is chosen, while the longer paths can be used when maximizing the minimum remaining energy to avoid low-energy nodes. This protocol works under the assumption that the required routing request information is available on demand. The jointly optimized protocol shows higher residual energy levels compared to both the max-total and max-min approaches.

5.3.3 Geographic Routing Based Protocols. Energy-harvesting opportunistic routing (EHOR) is a protocol developed for linear EH-WSNs. For each sender, EHOR divides the possible set of forwarding neighbors into regions and gives transmission probabilities to each region based on its distance from the sink, with the nearest region to the sink assigned the highest probability (Eu et al. 2010). The number of regions depends on the average energy-harvesting rates and the number of possible forwarding nodes, and for each region, only one node is chosen to forward packets to the sink to decrease the probability of collision. Afterwards, the authors developed adaptive routing protocol (AOR), which is a routing protocol for a general two dimensional EH-WSNs (Eu and Tan 2012). Opportunistic Routing algorithm with Adaptive Harvesting-aware Duty Cycling (OR-AHaD) is a one dimensional EH-WSNs routing protocol (Beheshtiha et al. 2012). Similar to EHOR, the nodes are organized in zones, and nodes residing in zones closer to the sink have greater transmission priority based on their residual energy. In contrast to EHOR, OR-AHaD implements coordination messages between nodes and takes into account the estimated energy-harvesting rate in the near future to adjust the nodes' duty cycles, which results in a better performance in terms of goodput compared to EHOR.

Beaconless geographic routing protocols have been developed to overcome the challenges of conventional geographic routing protocols by reducing the cost of transmitting beacons and the maintenance of keeping neighbor information (Heissenbüttel et al. 2004). Instead of sending control messages, the Energy-Efficient Beaconless Geographic Routing with Energy Supply (EBGRES) protocol starts sending the data packets itself (Jumira et al. 2013). EBGRES divides the network into subregions based on their progress towards the destination node and uses a three way handshake (DATA/ACK/SELECT) and a discrete dynamic forwarding delay scheme is applied to select the next node. Moreover, the selected node will make forwarding decisions based on the energy harvesting and the node's duty cycle.

Stability-Aware Geographic Routing in Energy-Harvesting wireless sensor networks (SAGREH) is a geographically based routing protocol that selects routes based on the location information, the residual and solar harvested energy, and the link quality of neighboring nodes, to enhance the route selection reliability and increase the network lifetime (Hieu et al. 2016). The authors used Packet Reception Rate (PRR), which is defined as the ratio of the number of receivers within a certain distance from the transmitter to the average number of receivers within the same distance as a link quality indicator to select the most stable multi-hop path between the transmitter and receiver. The proposed protocol surpasses the EHWA routing algorithm (Martinez et al. 2014b) in terms of average hop count, packet delivery ratio, and average consumed energy.

5.3.4 Clustered Network Based Protocols. Clustering is a valuable technique to enhance the network efficiency and balance the energy consumption of all nodes, and it has been used in WSNs to improve the network performance for large scale networks. In EH-WSNs, different approaches must be implemented for clustering to benefit from the energy-harvesting properties of the sensor nodes. The differences between clustering algorithms in WSNs and EH-WSWNs include choosing the cluster-heads, selecting the cluster-head rotation frequency, and determining how the communication is achieved between the sensor nodes and their assigned cluster-head or between the cluster-heads themselves.

The node harvesting rate and its energy status are used to modify the probability of electing the node as a cluster head in EH-WSN clustering protocols (Bozorgi et al. 2015; Meng et al. 2012). In addition to choosing the cluster-head based on the energy-harvesting rates of the nodes, selecting the optimum cluster-head position enhances the network performance, since the cluster-head position affects the energy consumption of the nodes inside the cluster (Zhang et al. 2013). Furthermore, an energy-neutral clustering protocol is proposed in Peng et al. (2015) to maintain the network operation and achieve energy neutrality. This protocol is based on scheduling a group of sensor nodes within a cluster to be the cluster head (CH) for specific time slots to share the traffic load and reduce the CH re-selection overhead, which achieves a perpetual network operation.

A genetic-based algorithm called Energy-harvesting genetic-based unequal clustering-optimal adaptive performance routing algorithm (EHGUC-OAPR), is proposed in Wu and Liu (2013). EHGUC-OAPR is composed of a set-up phase and a steady state phase. During the setup phase, sensor nodes send their location, remaining energy and harvesting energy rate to the base station, which implements a genetic algorithm to form unequal size clusters and choose cluster heads. Then, the OAPR algorithm is executed to establish a routing path between cluster heads. After the set-up phase, the base station broadcasts the information about the cluster heads and the routing paths to all sensor nodes. Discrete particle swarm optimization (DPSO), which is another optimization algorithm, is implemented in Li and Liu (2015) to select cluster heads. This proposed algorithm uses the EWMA algorithm to predict the nodes' energy-harvesting rates.

5.4 Cross-Layer Protocols

Castagnetti et al. (2014) proposed a joint duty-cycle and transmission global power management protocol that optimizes the nodes' wake up periods and transmission power based on the harvested energy and link quality. They have applied the closed-loop power manager proposed in Castagnetti et al. (2012) to compute the transmission wake-up periods. The protocols used a combination of the exponentially weighted moving-average (EWMA) energy prediction model and the last received signal strength indicator (RSSI) from the base station to adjust the node's transmission power.

Han et al. (2015) proposed a cross-layer multi-path protocol that is based on geographic routing. At the physical layer, instead of using the maximum power, the nodes collaborate to adjust their transmission power according to their residual energy as proposed in Abdu and Salamah (2011). The connected k-neighborhood (CKN) sleep scheduling algorithm is applied at the MAC layer to dynamically adapt the nodes' duty cycles according to their residual energy levels to allow the nodes to recharge their storage. In each epoch, the node runs the CKN algorithm and collects information about the 2-hop neighbors' locations, residual energy, energy harvested and consumed rates to schedule the state of the next epoch, whether to be in active or sleep mode. In the routing layer, a 2-hop multi-path protocol named Two-Phase geographic Greedy Forwarding (TPGFPlus) is proposed in which the next hop is determined based on its progress to the destination, the node's harvesting rate, and the node's residual energy levels.

A MAC/Routing cross-layer protocol for wireless sensor nodes with RF energy-harvesting capabilities is proposed in Sasikala and Kumar (2016). The sensor nodes toggle between transceiver mode or harvesting mode based on the energy-harvesting time and the node's active time. After the path between a sender and the receiver node is established, the node checks for data availability. If the node's residual energy is higher than a certain threshold, then it sends an RTS signal, at which point all of its neighbors will go to harvesting mode for a certain duration except the intended receiving node. If the residual energy at the receiver is higher than a certain threshold, then it will reply with a CTS, at which point all of the receiving node's neighbors will switch to harvesting mode. On the other hand, if the node has data to send but it does not have enough energy, it switches off to recharge and after few cycles, if its energy is still below a certain threshold it transmits an energy request packet.

5.5 Simulation and Emulation Tools

As described in the previous sections, when using an energy-harvesting source, the objectives of the communication protocols are fundamentally different than those of using a traditional energy source: rather than focusing on minimizing the maximum energy and adapting the operations according to the residual energy, algorithms need to shift the optimization to the maximum rate at which the energy can be used (Kansal et al. 2007).

As a result, the need for a simulation framework for evaluating the performance of energy aware wireless networks has been widely recognized. Different generic network simulators are compared in Merrett et al. (2009), showing that no existing simulators natively provided models for the energy source and the energy harvester, nor for simulating the energy consumptions of the different elements that compose the wireless node. To overcome these limitations, Merrett et al. (2009) proposed WSNsim, one of the first simulators to include a set of flexible and extensible hardware and environment models to enhance the design of energy-aware sensor nodes. However, WSNsim is not available to the research community. Subsequently, an extension to ns-3 to support energy aware networks has been proposed (Wu et al. 2011). The framework in Wu et al. (2011) is designed and implemented with the objective of adding support for different energy sources and device energy consumption models into ns-3 simulations. A generic energy model for OMNeT++ has been presented in Chen et al. (2009), which allows the accurate evaluation of the energy consumption and network lifetime of sensor networks, taking into account the energy consumption of both the radio transceiver and the CPU.

While these solutions provide viable simulation environments for energy-aware wireless networks, they do not include support for the simulation of EH-WSNs. As a result, the increasing interest in evaluating the performance of energy-harvesting wireless systems brought forth several contributions to fill this gap. In particular, GreenCastalia, an energy-harvesting framework for the Castalia simulator (Castalia 2016) that allows the simulation of networks of embedded devices with heterogeneous harvesting and energy source capabilities, has been presented in Benedetti et al. (2013). Minakov and Passerone (2013) presented PASES, a standalone, flexible, and extensible design space exploration framework that allows an accurate analysis of the performance and energy consumption of WSNs, from the application to the hardware level. This framework requires detailed power models of the node architecture to provide statistics about the power consumption and to determine the optimal hardware configuration. A complete ns-3 modeling of a practical WSN architecture with energy-harvesting capabilities has been described in Sánchez et al. (2011). However, the focus of Sánchez et al. (2011) was to simulate the performance of the particular system under consideration, and the relative ns-3 implementation is not available to the research community. A complete framework for the simulation and emulation of EH-WSNs has been proposed in Dall'Ora et al. (2014). The framework allows the reuse of the same code written for the simulations in real-world WSN deployments and, for this reason, relies heavily on the architecture of a specific wireless sensor node.

More recently, an extension to the ns-3 energy framework presented in Wu et al. (2011) that introduces the concept of an energy harvester has been proposed in Tapparello et al. (2014). Using this framework, different energy harvester models can be developed as independent ns-3 objects, and can then be connected to the current and future energy source implementations. In addition to the definition of the general interface, the framework includes the implementation of two simple models for the energy harvester: a basic energy harvester, where the energy provided by the harvester varies over time according to a customizable generic random variable, and an energy harvester that recharges the energy source with an amount of energy gathered from a dataset of real solar panel measurements.

Ekho, a tool to record and emulate energy-harvesting conditions is presented in Hester et al. (2014). Ekho is generally applicable to a wide range of harvesting technologies, and uses a novel method to explore and record an energy-harvesting environment by modulating the load using a precisely controlled digital potentiometer. The energy-harvesting environment (Solar, RF) is processed and stored to be later replayed through a custom analog front-end that serves as a current source.

6 PERFORMANCE METRICS AND MODELING OF EH-WSNS

A metric is a measure for quantitatively evaluating the performance of a system (Khan et al. 2012; O'Donohoe 2008). In computer networks, metrics are important as design factors, and the network performance is generally evaluated based on specific metrics for each network layer (Akkaya and

Fig. 5. Design metrics for traditional WSNs and for EH-WSNs.

Younis 2003). In traditional wireless sensor networks, the most important metrics contributing to the design and performance evaluation are quality of service (QoS) and network lifetime (Akyildiz et al. 2002; Yahaya et al. 2009). Network lifetime is the time span from the deployment of the WSN to the instant when the network is considered nonfunctional (Chen and Zhao 2005). With respect to QoS, network lifetime can be determined based on how long the network is able to meet the QoS requirements of the end user/application. Thus, network lifetime is the time until which the network stops providing the required QoS in a given network.

QoS seeks to evaluate how the network meets the needs of the application. QoS is application-specific and can be measured in different ways. For example, in environmental monitoring systems, minimizing the probability of false alarm (PFA) and maintaining a high probability of detection (PD) are essential for reliability, as this leads to more accurate results that are used for decision making (Dutta et al. 2005). As another example, in determining the QoS in an application for tracking animals, the interest may be in the expected accuracy of the location of the animal in a given time (Perillo and Heinzelman 2005).

While application QoS is an applicable metric in EH-WSNs, unlike traditional WSNs, EH-WSNs can be operational with a continuous energy supply, through energy-neutral operation. Alternatively, EH-WSNs can also harvest and store energy that the sensor nodes can use to perform sensing, processing, and communications operations at a later time, which makes the network lifetime no longer a design requirement for EH-WSNs. In EH-WSNs, instead, designers and application developers are concerned with the network uptime (i.e., the percentage of time during which the network remains active and provides the required application QoS). Hence, as shown in Figure 5, this is the main difference between performance metrics for traditional WSNs and for EH-WSNs.

Guaranteed Qos under worst-case scenarios are required in some applications that implement EH-WSNs. Therefore, performance modeling and analysis of the network must be executed, which can be challenging due the probabilistic nature of the network load and energy-harvesting patterns. Schmitt and Roedig (2005a) proposed one of the first analytical frameworks to perform traffic analysis under worst-case scenarios using deterministic network calculus. The proposed framework also demonstrated the interdependencies between the node power consumption, buffer requirements and information delay. Moreover, an extension of their framework to compute the worst-case topology in terms of delay and buffer requirements, to provide performance analysis for multiple sinks, and for cluster-tree WSNs were proposed in Schmitt and Roedig (2005b), Schmitt et al. (2006), and Koubaa et al. (2006), respectively. Even though these models provided a basic framework for traffic analysis, they did not take into account the energy constraint of WSNs.

To overcome the limitations in these frameworks, a stochastic network calculus (SNC) approach that models the harvested and consumed energy using stochastic charging and discharging rates was proposed in Wu et al. (2012). This framework provided the upper and lower bounds on the node residual energy levels, the stochastic performance of the network delay, and an analysis of multiple energy sources in the system. This model does not take into account overflow due to the finite-energy storage capacity, and energy underflow when the battery runs out of energy. Wang and Simon (2016) extended this work by incorporating energy-harvesting rate, energy overflow and depletion using the SNC approach by modeling the node's energy resources as the amount of service that can be provided for the incoming traffic. When receiving traffic, the node checks it resources and only accepts it if there are enough tokens. Otherwise, the traffic is discarded. Upper and lower bounds on network delay, wasted energy, and lost packets were derived using SNC.

7 IMPLEMENTATIONS OF ENERGY-HARVESTING WSNS

In the previous sections, we discussed the unique features of EH-WSNs, including the sensor node architecture, energy storage technologies and capacities, energy-neutral operation, energy prediction models, and communication protocols. The main difference between traditional WSNs and EH-WSNs relates to the network lifetime: whereas traditional WSNs are constrained with energy, and hence optimize for network lifetime, EH-WSNs are designed with an emphasis placed on the percentage uptime of the network, because they can operate via energy neutrality or achieve essentially infinite lifetime when deployed in environments with a constant energy supply.

In this section, we present recent implementations of Energy-Harvesting Wireless Sensor Networks (EH-WSNs) for the following environmental applications: Animal Tracking (AT), Air Quality Monitoring (AQM), Water Quality Monitoring (WQM), and Disaster Monitoring (DM). In these environmental applications, different application-specific protocols are designed to meet the criteria set for the system to achieve high performance.

7.1 Animal Tracking

EH-WSNs are used for animal tracking to provide information about different animals species (Zhang et al. 2004; Sorber et al. 2013; Woias et al. 2014). Information gathered in these systems include data on the animals' habits, behaviors, and habitat conditions; this information can help researchers develop a better understanding of the status and dynamics of wildlife resources, and hence can provide the basis for the effective protection, sustainable use, and scientific management of wildlife resources (Zhang et al. 2014). In such applications, the QoS metrics may include the expected accuracy of the target location estimates provided by the sensor network (Perillo and Heinzelman 2005) as well as the fairness of the system based on the per-node packet delivery rate (Sorber et al. 2013).

Energy-harvesting technologies have been used in tracking animals with projects such as ZebraNet for tracking Zebras (Zhang et al. 2004), TurtleNet for studying the Gopher tortoise (Sorber et al. 2013, 2013), tracking Cervus elaphus (a type of deer) in their environment to keep them from becoming an endangered species (Zhang et al. 2014), tracking sheeps (Woias et al. 2014), and elephants tracking in Wijesundara et al. (2016). Energy-harvesting-based sensor nodes are fitted to these animals to gather sensor data and transfer this sensed data to a mobile base station or to other nodes within a specified range (Gilbert and Balouchi 2008). To power these sensor nodes, the main sources of energy for these implementations are rechargeable batteries and solar energy or vibration energy. For example, a Li-Ion (2A-hr, 45g) battery was recharged using a solar panel for the ZebraNet, TurtleNet and Cervus eaphus implementations (Zhang et al. 2004, 2014), while the sensor nodes of JumboNet were powered through a kinetic energy harvester (Wijesundara et al. 2016).

Generally in environmental systems, the energy of the system is largely consumed by the radio and the GPS during sensing, transmission, and reception. To minimize energy consumption in such applications, different approaches have been adopted. In Zhang et al. (2004), to minimize the energy

(a) Collar mounted on a zebra

(b) Collar mounted on an elephant

Fig. 6. Wildlife monitoring through wireless collars for (a) ZebraNet (Zhang et al. 2004) and (b) JumboNet (Wijesundara et al. 2016).

consumption and to maximize the performance of different components on the sensor devices, separate power supplies were designed for each module, which were turned off independently of each other. However, in Sorber et al. (2013), an adaptive sensing technique was used to adjust the application behavior to match the sensor nodes' energy budget so that the sensor nodes do not exhaust their battery energy. Although these systems provide mechanisms to minimize the amount of energy consumed by the sensor nodes, no specific energy prediction model has been proposed to forecast the amount of energy that can be harvested for future use.

We provide a detailed description of ZebraNet to illustrate the use of solar harvesters and sensor nodes for tracking animals in their natural environment. ZebraNet was designed to monitor and track the movement of zebras in Kenya to support research work by biologists in the Mpala Research Center (Zhang et al. 2004). The system consisted of sensor nodes built into collars that were placed on the zebras. The sensor nodes had integrated GPS to locate the animals to determine patterns in migration as well as habitats. The system used a total of 14 solar modules, each producing a maximum of 7mA at 5V. The extra harvested energy was used to recharge a 2mA-H lithium-ion battery, which was utilized at night and during periods where there was low or no sunlight (especially during bad weather conditions). The batteries provided up to 72h of normal operation without recharge, and charging normally took place when the voltage was near 4.2V. Figure 6(a) shows a sensor node with a solar energy harvester placed around the neck of a zebra to track its movement (Zhang et al. 2004).

Zebras are mobile, and they spread over long distances covering several kilometers. To track these zebras, ZebraNet collars are placed around the necks of a selected number of zebras, creating a sparse network. In this sparse network, nodes communicate through pairwise connections between two zebras within a single hop when the collars come in contact with each other. Data is transferred to a manned mobile base station periodically from several zebras. The radio connectivity is maintained within a range of 1–5km. The radio is activated every two hours to search for nodes in range and allows for data transmission of recorded positions to the immediate neighbor. The radios are powered off after 5min of activation to conserve energy. Information propagation is performed either by the use of flooding or history-based protocols within the network and the base station (BS). When a flooding-based routing approach is used, the nodes communicate data to their neighbors whenever they meet, and when the history-based routing protocol is used, each node is assigned a probability of sending data to the base station based on its history of successful communication with the base station (Boukerche 2008). This routing technique allows the BS to receive the data from all of the collared zebras in range (Zhang et al. 2004).

Table 10. Air Quality Monitoring EH-WSN Implementations

Location	Harvesting Source	Harvesters	Sensors	Energy Storage	Harvested energy	References
Indoors/ Outdoors	Vibration Thermal RF Solar	V25W Volture TG12-2.5-01L Powercast P211 Solems solar cell	NE4-CO NE4-NO2 NE4-NO NE4-H2S NE4-CL2 NE4-NH3 SHT21 MPL3115A2	1F super-capacitor	137.3J	Touati et al. (2015)
Organic fertilizer plant	Thermal Solar	TEC1-12706 Solar cell	NH3	1F super-capacitor Li-Ion battery	290mW	Chottirapong et al. (2015)
Urban	Solar	5W Solar cell	CO PM	Lead-acid battery	9.5Wh/day	Wang et al. (2012)
Urban	Wind	Airscrew	Air temperature and velocity	Super-capacitor	45mW for 9m/s wind speed	Sardini and Serpelloni (2011)

7.2 Air Quality Monitoring

Human activities affect the quality of air, since high volumes of smoke are emitted from factories and cars, which increases the emissions of greenhouse gases such as carbon dioxide (CO_2) leading to the increasing effects of global warming (WHO 2014). The utilization of EH-WSNs in air quality monitoring (AQM) aids in the detection of air pollutants such as particulate matter (PM), carbon dioxide (CO_2), ozone (O_3), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2) (Morelli et al. 2016; Sardini and Serpelloni 2011; Touati et al. 2015; Chottirapong et al. 2015; Wang et al. 2012). EH-WSNs for air quality monitoring can be installed indoors or outdoors, with the main difference being in the amount of energy harvested from the environment. For outdoor AQM systems, solar cells is an obvious energy-harvesting technique but must be accompanied by energy storage, management and prediction to provide high efficiency and overcome the obstacles in harvesting solar energy, such as varying weather conditions.

A thermal solar hybrid energy-harvesting implementation for air quality monitoring is provided in Chottirapong et al. (2015). The authors looked at the possibility of harvesting energy from organic fertilizer plant waste to monitor air pollution in terms of ammonia gas concentration. The first part of the system is the energy harvester. A thermoelectric generator (TEG) is used to convert the difference between the hot and cold sides of a gas deodorizer tank—used for treating the polluted air—from heat energy into electrical energy. To increase the power to operate the ammonia sensor and the transmission module in the morning, solar cells are proposed. BQ25570, which is an Ultra Low Power Harvester Power Management IC with Boost Charger (Instruments 2015b), is used as the power conditioner for interfacing DC sources, which stabilizes the output voltage that is stored in a combined 1F super-capacitor and Li-Ion battery to provide continuous voltage levels. The last part is the energy management in which an MSP430G2231 (Instruments 2013a) Texas Instruments low power consumption micro-controller is used. The results show that the TEG and the solar cells provide up to 15mW and 275mW, respectively, while the consumption of the nodes is only about 55mW, which allows the system to be working all day. The STM32W RF module standard version DZ-ZB-GA is used as a radio frequency transmission module, which operates using the ZigBee protocol (IEEE 802.15.4). Table 10 provides examples of existing EH-WSNs used for air quality monitoring.

7.3 Water Quality Monitoring

In recent times, water bodies have suffered from damaging human activities such as mining, manufacturing, and the production of goods. Harmful chemicals and waste products from homes and industrial activities are dumped into various water bodies, thereby polluting them (Owa 2014).

Thus, water quality monitoring remains an interesting application area where EH-WSNs can be used to monitor different conditions to ensure safe drinking water. Self-autonomous wireless sensor networks with sensor nodes that harvest energy from their operating environment can provide water quality monitoring in rural and residential areas. Energy can be harvested from solar, thermal, and mechanical sources to support this type of environmental application, which requires constant energy for measuring parameters such as temperature, pH, conductivity, turbidity, and dissolved oxygen (DO). Apart from monitoring drinking water for humans, water quality monitoring can be performed to improve life in aquatic environments. For example, WQM can be used to monitor the temperature, pH, and DO in fish farms to maintain constant conditions for the fish.

To monitor water quality, devices have been designed to harvest energy from flowing water using piezoelectric polymers, including use of a flag-shaped piezoelectric polymer harvester and micro-structured piezo-bimorph generator (Pobering and Schwesinger 2004), Intellisonde probe (to measure water flow, temperature, and pressure) (Ye and Soga 2011), and an energy-harvesting eel (Taylor et al. 2001). Although these technologies have not yet been fully harnessed and implemented for monitoring water quality in a WSN environment, advances in the manufacturing of wireless sensor nodes are expected to increase to support the implementation of these technologies for water quality monitoring.

An example WQM system with energy-harvesting implementation is provided in Wang (2012a). In their work, the authors proposed an energy-harvesting system for monitoring and management of aquaculture (i.e., fishery water quality monitoring) to collect, process, and transmit environmental parameters on fish farming. The wireless sensor network was designed to detect water temperature, pH, Dissolved Oxygen, Electrical Conductivity, and water level. WQM sensors, such as the pH sensor and the turbidity sensor, were installed to sense specific phenomenon, and the collected data were transmitted to a remote WQM station for data processing. The system used two different sets of nodes. The sub-node included one printed circuit board (PCB) and a set of 500mAh Li-M_nO_2 coin batteries. The main node was encapsulated with a 4000mAh rechargeable Li-Ion battery inside a water proof case and consisted of four PCB boards: main board, interface board, sensor board and sensor area network (SAN) board. ZigBee communication standard was used by the nodes to transfer data among them, and GSM/GPRS was used as the standard for communicating between the nodes in the pumping station and the control center.

7.4 Health Monitoring

Wireless sensor nodes can be deployed for preventive healthcare as a wireless body area network (WBAN), to monitor the human body functions and physical attributes, which arguably can enhance an individual's health through continuous monitoring and reduce the cost of health monitoring (Cavallari et al. 2014; Noel et al. 2017). Energy harvesting from various sources such as biochemical and biomechanical sources from the human body, in addition to scavenging ambient energy, enables WBANs to be more practical by reducing their system size and cost (Akhtar and Rehmani 2017).

The human body wastes about 100W in heat, which can be harvested by thermoelectric generators (TEG), and utilized to power WBANs (Saida et al. 2016). As an example, an experimental study of the thermal human properties of the human body with an attached thermoelectric harvester (TEH) is carried out in Leonov (2013), and shows that the TEH device is capable of powering low-power health monitoring devices such as wireless electrocardiography through body heat harvesting. Similarly, an autonomous wearable sensor node with a bendable amorphous PV panel to harvest solar power, a super-capacitor to store energy, and an ultra low-power circuitry is proposed in Toh et al. (2014). RF transmissions from commercial telecommunications, especially the 900/1800MHz cellular system, represent a reliable ambient energy that could be harvested to power wearable biomedical sensors (Borges et al. 2015). For instance, a battery-less sensor with efficiency tracking RF energy harvester and a whip antenna has been proposed in Xia et al. (2014). Practical experiments show that the system can successfully measure and transmit abdominal temperature to a base station for a distance up to 9m.

7.5 Structural Health Monitoring

Monitoring the performance of structures is important as it can provide advanced warning on damages and potential collapses. Furthermore, using WSNs for structural health monitoring (SHM) was found to be superior compared to conventional wired systems due to their low cost, ease of implementation and their effective data management (Jang et al. 2010; Banerji et al. 2016). In this section, we provide three diverse examples of SHM systems based on the type of harvested energy and the structure.

A solar powered WSN was proposed in Jang et al. (2010) to monitor the structural health of a cable stayed bridge using 70 Imote2 sensor nodes to cover the 484m Jindo bridge length. The system uses 9V-350mA solar panels to power a lithium-polymer rechargeable battery with a total capacity of 10,000mAh. Moreover, in Cahill et al. (2014), a piezoelectric material is used to detect any damage in a reinforced concrete beam through voltage shift, which is simultaneously used to power the wireless sensor node. Based on experimental tests, it was found that the output voltage from the energy harvester is capable of detecting localized damage in the structure. Furthermore, an SHM system to monitor concrete and steel deformation using a vibrating wire strain gauge in an underground train tunnel is implemented in Cammarano et al. (2013). The system uses six Telos B motes with micro wind turbines to harvest energy, which is stored in a super-capacitor. The results show that the energy harvested by each node varies significantly based on its location in the tunnel, and its value ranges from 5 to 132mJ, which allows at least one strain measurement per day.

7.6 Disaster Monitoring

Natural disasters like earthquakes and flooding cause severe impact on humanity in terms of life, financial costs, and emotional turmoil (Rasaneh and Banirostam 2013). Preventing, managing, or at least mitigating their effects is a major challenge due to the unpredictable, short-span, and high-impact nature of these disasters. This has led to some research focusing on using vibration-based energy-harvesting WSNs to monitor or even manage the effects of natural disasters (Hande et al. 2010; Mihajlovic et al. 2015; Cheng et al. 2013). A flooding monitoring system that harvests energy from a 2V, 150mA solar panel that charges a 0.47F super-capacitor is implemented in Mihajlovic et al. (2015). A BQ25570 power management IC is used as the power conditioner with an MSP430G2553 (Instruments 2013b) Texas Instruments low power consumption micro-controller. The results show that a maximum of 0.3W can be harvested with this setup. The design of the network was based on clustering. Three main sensor nodes were used in the clustering setup (i.e., vibration, temperature, and acoustic sensor nodes) (Rasaneh and Banirostam 2013). In each cluster, cluster-heads and the base station have more computing power and energy. The Event-Driven Energy-Harvesting (EDEH) MAC protocol was used to address channel contention under stringent energy constraints. The protocol used a large backoff exponent and spread access of devices

Table 11. Disaster Monitoring EH-WSN Implementations

Type	Harvesting Source	Harvesters	Sensors	Energy Storage	Harvested energy	References
Disaster Relief Operations	Vibration	Quickpack QP20W	—	Rechargeable Li-Ion battery	150μW	Hande et al. (2010)
Earthquake	Vibration	MIDE PEH25W	Accelerometer	10uF Capacitor	0.2mW	Cheng et al. (2013)
Flooding	Solar	Solar cell	6L7020-A20 Pressure, temperature and humidity	0.47F Super-Capacitor	0.3W	Mihajlovic et al. (2015)

over a longer time, which reduces the chance of collision at the cost of an increased delay. Table 11 provides examples of EH-WSN implementations for disaster monitoring.

8 CHALLENGES AND FUTURE RESEARCH DIRECTIONS

While much work has been done on EH-WSNs, as described in this article, there are still a number of challenges that require future research to address.

8.1 Challenges

8.1.1 Universal Harvester Design. Energy-harvesting techniques still have drawbacks that affect their net performance, i.e., solar energy does not work at night or during bad weather conditions, vibration energy harvesters produce very low power unless there is a considerable size vibration, RF energy harvesting works on limited bands only and its power declines rapidly with distance, and thermal energy harvesting only works well when there is a large heat difference. Hence, there is a need to design a multi-source harvester that can harvest energy from various environmental sources to comply with the sensor nodes' energy needs (Shaikh and Zeadally 2016a). Furthermore, due to the variability of the available energy from the environment, designing a power conditioning subsystem that can adapt to this unpredictability is a major challenge in the design of energy harvesters (Yang et al. 2014).

8.1.2 Energy-Harvesting Modeling. Although a practical recharge model for WISP tags is developed based on extensive experimental data in He et al. (2013), stochastic statistical modeling of harvested environmental energy remains a challenging task, as in most cases natural resources can be variable and unpredictable (Gunduz et al. 2014). Implementing learning algorithms such as the Q-learning algorithm that models the harvested energy rate, channel conditions and data arrival as Markov processes can lead to an optimal transmission strategy (Blasco et al. 2013). However, as the number of nodes increases, a longer learning time would be required to reach this optimal strategy. In addition, achieving an optimal transmission state for all the nodes leads to more complex algorithms as the data arrival rate at the nodes is coupled with the transmission rate of other nodes (Gunduz et al. 2014).

8.1.3 Network Energy Optimization. Sensor nodes may have different energy consumption levels based on their location, transmission power, and the network architecture used (e.g., clusters, chain, tree, etc.). In a single-hop network, nodes that are farther from the sink will require more transmission power to get their data to the sink, while in a multi-hop network, nodes that are closer to the sink will need more power to route sensed information from other nodes to the sink. Although existing protocols such as the work in Huang and Neely (2013), have attempted to manage power and balance energy consumed by nodes in the network, network energy optimization still remains a challenge in energy-harvesting WSNs, where nodes have different energy-harvesting rates that should be considered when managing the network.

8.2 Future Directions

8.2.1 Network Wide Protocol Design. Existing WSN protocols are designed to efficiently manage the amount of energy consumed by sensor nodes, while EH-WSN protocols are designed to improve the network uptime, under fairness, throughput, and delay constraints. To meet these requirements under variable energy-harvesting rates, sensor nodes must collect information about the other sensors in the network. Some protocols proposed for EH-WSNs have been shown to achieve energy-neutral operation for individual nodes by optimizing parameters in the physical, MAC, and network layers. Nevertheless, due to their intrinsic complexity, protocols for network-wide optimization of EH-WSNs have not been fully explored. As a result, research on novel protocols that can achieve Network Neutral Operation (NNO), instead of individual node ENO, can greatly benefit the overall system performance.

8.2.2 Prediction Models. Due to the dynamic nature of the energy-harvesting sources, researchers pay much attention to the amount and the rate of energy that can be harvested over time to predict the network uptime. Prediction models such as Genetic Machine Learning Approach (GMLA) (de Araújo et al. 2014), an optimized Markov model using Oriented Birth-Death (OBD) (de Araújo et al. 2012), and Data Driven Link Quality Prediction (DDLQP) (Liu and Cerpa 2014) have been proposed for link quality prediction in mobile WSNs. Also, solar energy prediction models such as Exponentially Weighted Moving-Average (EWMA) (Piorno et al. 2009; Moser et al. 2007), SunCast (Lu and Whitehouse 2012), and Pro-Energy (Cammarano et al. 2012) are designed based on the solar energy availability. There are also prediction models proposed for energy harvesting that use wind as the energy source. Examples of wind energy prediction models include the adaptive AC-DC converter and a hybrid voltage rectifier using linear regression (Porcarelli et al. 2015) and Combinational Prediction Model (CPM) for short-term wind farm output power based on meteorological data collected by a WSN (Ma et al. 2014). These prediction models are designed to predict the amount of energy to be harvested at the node and not the entire network. These models are also utilized at different levels of the protocol stack to estimate the amount of energy to be harvested by the node to achieve ENO. Hence, communication protocols should be designed to combine different energy prediction models for different nodes to achieve Network Neutral Operation (NNO), and network-wide prediction models should be thoroughly investigated by researchers.

8.2.3 Energy-Harvesting Wearable Devices. Conventional human activity recognition (HAR) relies on an accelerometer, which consumes relatively high amounts of energy and can be a bottleneck in situations where small amounts of energy is harvested (Khalifa et al. 2015). Hence, researchers have started to explore the possibility of using the harvested kinetic energy to classify human activities based on the fact that each activity generates a different amount of energy. Enhancing the design of EH-HAR devices to match the accuracy of conventional HAR that use accelerometer in classifying various human motions, is still an open area to explore.

8.2.4 Energy-Harvesting Channel Capacity. In WSNs without energy harvesting, the available energy for transmission is deterministic and Shannon's capacity formula can be used to design efficient communication systems. On the other hand, for energy-harvesting communication systems, the available energy for information transmission can be unpredictable and is modeled as a stochastic process (Shaviv et al. 2016). Several of the research studies in EH-WSNs have focused on the capacity of EH channel with a finite battery (Shaviv et al. 2016; Mao and Hassibi 2017; Chen et al. 2017), whereas other studies have focused on channels in which energy is harvested in binary units (either 0 or 1 unit) and is stored in a unit-sized battery (Tutuncuoglu et al. 2013, 2017). For instance, Shaviv et al. (2016) proved that, in an EH channel with a battery size larger than the maximum energy that can be harvested, the information-theoretic capacity of the EH channel is approximately equal to the capacity of an AWGN channel with an average power constraint equal to the average energy-harvesting rate.

Since the harvested energy is unpredictable and can be insufficient for information transmission at some instances, channel capacity limits pose a major challenge in recent EH systems. Hence, further theoretical research work is required for determining the channel capacity of these systems under different energy-harvesting processes and for deriving efficient communication policies in multi-user settings.

8.2.5 Joint Transmitter-Receiver Network Performance Analysis for EH systems. In EH-WSNs, energy scheduling at the transmitter side has been at the center of discussion by some researchers, since it is mostly assumed that the power at the receiver is constant in supply using some conventional power source (Satpathi et al. 2016). Due to this limitation, researchers have begun studying the performance of energy-harvesting receivers (EHRs), information decoding and processing costs, which led to some energy-harvesting transmitter-receiver schemes provided in Arafa and Ulukus (2015) and Satpathi et al. (2016). Nevertheless, understanding the energy issues at the receiver side, in addition to developing decoding and transmission policies, still remains an open area for further exploration.

8.2.6 New Communication Technologies (Non-RF Technologies). Communication is an important aspect of WSNs. Communication in WSNs can be local (i.e., between nodes and the sink) or remote (i.e., between the sink and a remote monitoring center). There are a number of conventional communication technologies (or protocols) that are used in WSNs include ZigBee, WiMax, WiFi, LTE, GPRS, and GSM. In addition, there are newer technologies that could also be explored like Visible Light Communication (VLC), underwater optical/acoustic communication, wireless underground communication, and Narrow-band Internet of Things (NB-IoT). NB-IoT is a radio access technology that aims to enhance the GSM and LTE standards for IoT applications in addition to providing coverage extension and enhancing battery lifetime (Wang et al. 2016a). Implementing these technologies in EH-WSNs might require the design of new communication protocols. To fully implement these new technologies, researchers should look into new ways to design the physical layer protocols to accommodate these technologies within the context of energy harvesting.

9 CONCLUSIONS

Wireless sensor networks play a pivotal role in monitoring the environment. Over the years, energy management techniques have been shown to prolong the lifetime of sensor devices in monitoring the environment, but the amount of energy required by sensors to operate for a long time still remains a challenge. Hence, the use of energy harvesters to support the existing power management schemes is essential. In this article, we have provided a comprehensive study of the current state-of-the-art techniques for harvesting energy to increase the lifetime of sensor nodes in WSN environments. We first discussed the energy-harvesting sources that are currently used to support WSNs operation and then presented the technologies used for harvesting the different energy sources. In addition, we discussed the unique features of EH-WSNs and their different energy prediction and management techniques, with a particular emphasis on their impact on the design of energy-harvesting-aware communication protocols. Finally, we presented recent implementations of EH-WSNs for environmental applications. Despite the large body of work in this area, there are still several challenges that need to be addressed to make EH-WSNs mainstream.

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