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Energy harvesting in wireless sensor networks: A comprehensive review

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A B S T R A C T

Recently, Wireless Sensor Networks (WSNs) have attracted lot of attention due to their pervasive nature and their wide deployment in Internet of Things, Cyber Physical Systems, and other emerging areas. The limited energy associated with WSNs is a major bottleneck of WSN technologies. To overcome this major limitation, the design and development of efficient and high performance energy harvesting systems for WSN environments are being explored. We present a comprehensive taxonomy of the various energy harvesting sources that can be used by WSNs. We also discuss various recently proposed energy prediction models that have the potential to maximize the energy harvested in WSNs. Finally, we identify some of the challenges that still need to be addressed to develop cost-effective, efficient, and reliable energy harvesting systems for the WSN environment.

Contents

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1. Introduction

The notion of a widely interconnected, adaptive, and dynamic ubiquitous computing environment has been proposed for decades [1]. Only recently has Wireless Sensor Networks (WSNs) technology started to receive recognition as a key enabling technique for the emerging pervasive computing areas [2]. The fusion of sensing and wireless communication has led to the development of WSNs. Due to their rapid growth, WSNs have been proposed for a plethora of applications, including environmental monitoring [3], fire detection [4,5], object tracking [6], vehicular adhoc networks [7], and body area networks [8,9]. As a result, commercial use of WSNs is expected to increase dramatically in the very near future.

Generally, a WSN is composed of a large number of static sensor nodes with low processing and limited power capabilities that often communicate over unreliable, short-range radio links [10–12]. Additionally, sensor nodes have limited storage capacity, batteries, and multiple on-board sensors that can take readings, such as temperature and humidity. Sensor nodes are deployed in an ad-hoc manner and cooperate with each other to form a wireless sensor network [13,14]. Since the communication range of sensor nodes is limited, they often adopt hop-by-hop communication to exchange data. Typically, a powerful base station, known as a *sink*, is also an integral part of a WSN [10]. The sink mediates between the sensor nodes and the applications running on a WSN. Currently, WSNs are also beginning to make extensive use of mobile elements, which are used to transport data from one place to another opportunistically [15] or to plan their movement [16,17]. Fig. 1 depicts a commonly used WSN scenario for various applications.

A sensor node typically consist of three basic subsystems: (i) a sensing subsystem to acquire data, (ii) a processing subsystem for processing data locally, and (iii) a wireless communication subsystem for communicating data. Also, a power source (usually a battery with a limited energy budget) is used to power the sensor nodes subsystems. Furthermore, for most of the applications, it is very difficult, if not impossible, to recharge the batteries due to the deployment of the nodes in difficult and hostile terrain or due to the large number of nodes deployed in the environment. Despite these constraints, the applications running on WSNs require the sensor nodes to be functional and to fulfill their requirements for several months or even years. These requirements highlight the need to extend the lifetime of WSNs by prolonging the life of their sensor nodes either by applying different energy minimizing techniques or providing energy harvesting mechanisms for the sensor nodes.

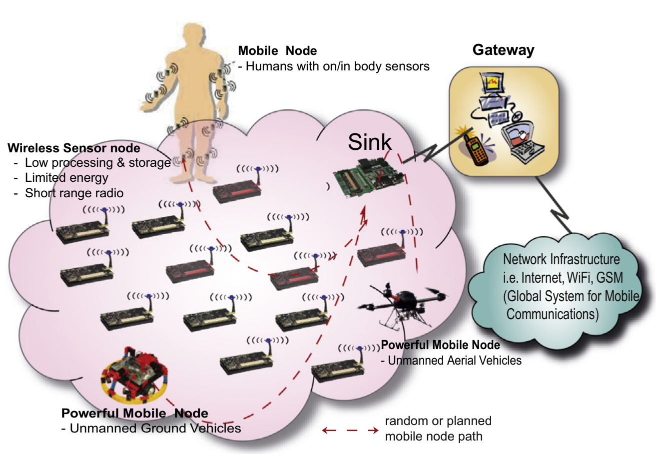


Fig. 1. A typical WSN scenario.

Among the three subsystems of a sensor node, the communication subsystem consumes more energy on average than the processing and sensing subsystems [10]. Generally, the sensing subsystem consumes the lowest amount of energy depending on the type of sensor used (e.g., for temperature and light). However, in some cases, the sensors may consume a substantial amount of energy (e.g., when using a Global Positioning System (GPS) module [18]). In order to address the power consumption of the processing and storage subsystem, many operating systems have been developed such as TinyOS [19] and Contiki [20]. The main objective of such operating systems is to provide the required I/O services in an energy efficient manner [21]. Since the communication subsystem consumes the most energy, many approaches proposed in the literature aim to minimize the communication cost. Some of these approaches include the use of in-network processing [22], location awareness [12], data prediction, or to send data when needed [23] to reduce the communication costs. To save additional energy, the sensor nodes may go into a sleep mode by disabling all their subsystems (i.e., duty cycling) when they have no task to perform [14]. However, if the sensor nodes must wake up from the sleep mode frequently, then the energy savings may not be optimal since having the sensor nodes transition to and from sleep mode also requires energy. Table 1 compares the energy consumption of some of the widely used sensor node platforms.

Mobility in WSNs can also help to reduce energy consumption if mobility incurs low overheads [17,30]. Generally, mobility expends more energy on the mobile node, i.e., motors and other hardware require more energy. The main assumption of mobile WSNs is that the mobile nodes do not have energy constraints. They traverse the network and return back to the sink to recharge. Moreover, for some applications, mobility may be inherent in the network (e.g., moving people or cars).

Thus, various mechanisms can be implemented to consume less energy. In any case, energy consumption is a critical issue in WSNs that must be addressed properly.

The rest of the paper is organized as follows. Section 2 reviews why energy harvesting is important for WSNs. The classification of energy management in WSNs is presented in Section 3. Section 4 discusses recently proposed energy prediction models for energy harvesting. Future opportunities and challenges are discussed in Section 5. Finally, we present some concluding remarks in Section 6.

2. Motivations for energy harvesting in WSNs

It is a well-known that one of the major problems WSNs face is energy [31,10,12,2,32]. When the energy of a sensor node is depleted, it will no longer fulfill its role in the network unless either the source of energy is replaced or some harvesting mechanism is introduced to fill the energy gap. The major existing energy source used by the sensor nodes is battery power, but many problems are associated with batteries. First, the current leakages that consumes the battery even if not in use. Second, extreme weather conditions may break down the batteries, resulting in chemical leakages that can cause various environmental problems [33]. Finally, the battery's energy density is limited, and that may hinder the sensor node operation over a long period of time [34]. There are many WSN application scenarios where the lifetime of the sensor node ranges from months to several years based on the application requirements. Therefore, the lifetime of the sensor nodes must end several years before their batteries drain and they become idle due to the lack of power supply. To work uninterrupted in most cases, sensor nodes require a continuous power supply, whether that supply is in an active mode to transmit and process data or an inactive mode when sensor nodes go to sleep as shown in Fig. 2.

Table 1
Energy consumption of widely used sensor node platforms.

	IRIS [24]	MicaZ [25]	IMote2 [26]	SunSpot [27]	Waspmote [28]	WiSMote [29]
Radio standard	802.15.4/ZigBee	802.15.4/ZigBee	802.15.4	802.15.4	802.15.4/ZigBee	802.15.4/ZigBee/6LoWPAN
Microcontroller	ATmega 1281	ATMEGA 128	Marvell PXA271	ARM 920 T	Atmel ATmega 1281	MSP430F5437
Sleep	8 μA	15 μA	390 μA	33 μA	55 μA	12 μA
Processing	8 mA	8 mA	31-53 mA	104 mA	15 mA	2.2 mA
Receive	16 mA	19.7 mA	44 mA	40 mA	30 mA	18.5 mA
Transmit	15 mA	17.4 mA	44 mA	40 mA	30 mA	18.5 mA
Idle	–	–	–	24 mA	–	1.6 mA
Supply	2.7–3.3 V	2.7 V	3.2 V	4.5–5.5 V	3.3–4.2 V	2.2–3.6 V
Average	–	2.8 mW	12 mW	–	–	–

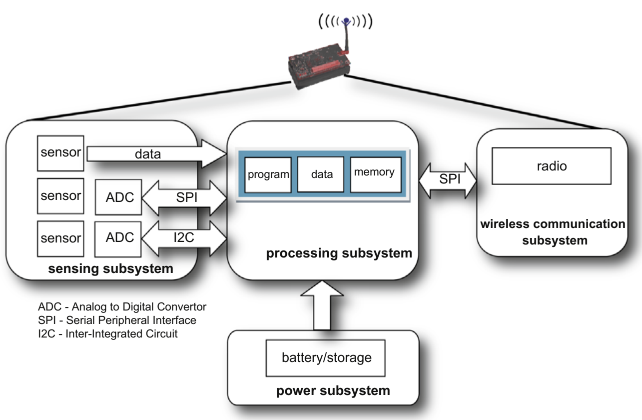


Fig. 2. Sensor node architecture with battery as main source.

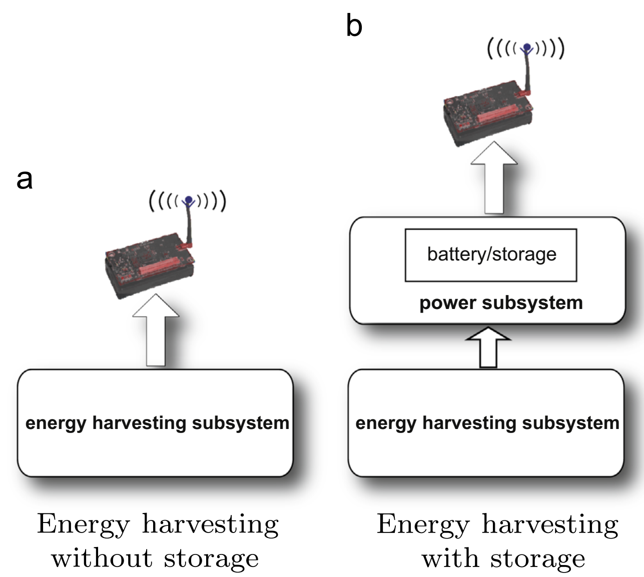


Fig. 3. Architecture of energy harvesting wireless sensor node.

Generally, the failure of a few nodes is not a significant problem for the proper functioning of a WSN, but the loss of those nodes certainly affect performance and overhead. Eventually, the network cannot overcome the loss of the nodes or fulfill the application's desired requirements. Over time, the connected nodes will drain the energy stored in the storage elements. The sensors, processing, communication, and data transmission frequency of the sensor nodes greatly impact the lifetime of the battery. All of these factors encourage the use of energy harvesting in WSNs. A WSN should be self-powering, long lasting, and almost maintenance free.

Accordingly, energy harvesting can be described as a mechanism used to generate energy from a networks ambient surroundings to provide an uninterrupted power supply for a specific sensor node and for the overall WSN. Furthermore, we can categorize two types of energy harvesting systems: (1) where ambient energy is directly converted to electrical energy to power the sensor nodes (no battery storage is required as depicted in Fig. 3(a)), and (2) where the converted electrical energy is first stored before being supplied to the sensor node as shown in Fig. 3(b). For the time being, WSN applications will continue to use disposable and long-lasting batteries. That being said, for applications requiring high power over the lifetime of the network, the energy harvesting techniques will enforce the usage of rechargeable batteries. The greatest potential, however, rests in a new class of battery-free nodes enabling applications that previously would have been possible due to the maintenance cost of repeated replacement of batteries.

Energy harvesting is ideal for applications that need to survive for longer time periods, i.e., those that are deployed once and then always available, such as environmental monitoring applications [35–37]. Other applications that can benefit from energy harvesting are those that require the transportation of large amounts of data to the sink, as is the case in multimedia applications WSNs [38], structural monitoring data [39,40], etc. Essentially, all types of WSN applications can benefit from energy harvesting mechanisms to prolong the lifetime of the networks.

3. Classification of energy harvesting techniques in WSNs

For energy harvesting various energy sources have been considered. To choose an energy harvesting source, one of the main criteria is to determine whether or not it can provide the required power level for the sensor node. In general, power dissipates during voltage conversion, and the dissipation increases as the input/output ratio of the voltage increases. Therefore, it is important to ensure that the generated power is at a suitable voltage and current level. In order to achieve the desired power level, either the source of the energy is increased or the energy harvesting device is scaled accordingly. For example, in the case of Radio Frequency (RF), increasing the power of the source will fulfill the desired demand. Furthermore, increasing the PhotoVoltaic (PV) cell area will collect more light, resulting in the generation of more power. However, in certain circumstances, the sources/converters cannot be scaled so easily. For example, energy derived from industrial vibrations cannot generally be scaled up without increasing the vibration effect on the machine, which may not be desirable. Thus, while it may be possible to scale up the harvesting device, many WSN applications require nodes to be small and lightweight. Accordingly, the power density metric is used widely by the researchers to compare different energy harvesting techniques [41]. Therefore, developers must keep this tradeoff in mind

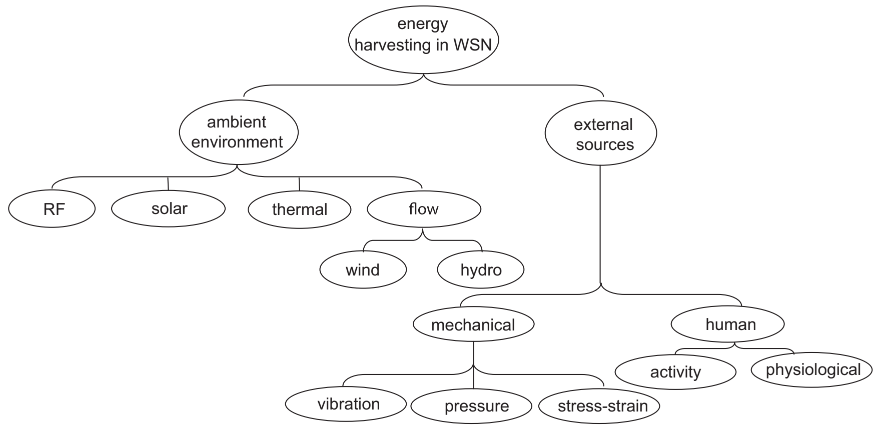


Fig. 4. Taxonomy of energy harvesting sources in WSNs.

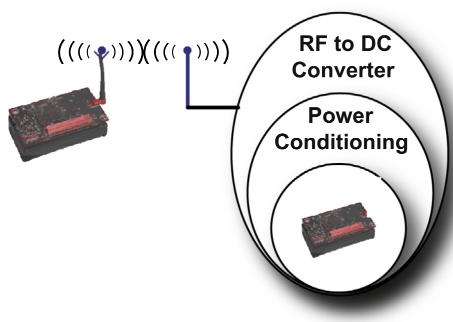


Fig. 5. Generalized RF energy harvesting system for WSNs.

when selecting an appropriate energy harvesting system for a particular application.

We classify the energy harvesting sources into two broad categories: ambient sources and external sources. Ambient sources are readily available in the environment at almost no cost. On the other hand, external sources are deployed explicitly in the environments for energy harvesting purposes. These categories are further subdivided as shown in Fig. 4.

3.1. Ambient sources

3.1.1. Radio Frequency-based energy harvesting

For RF-based energy harvesting, received radio waves are converted to DC power after conditioning as shown in Fig. 5. Converting the RF signals into DC power can be achieved through several approaches, such as single-stage vs. multistage, depending on the desired application requirements (i.e., power, efficiency, or voltage). The source power, antenna gain, distance between source and the destination, and energy conversion efficiency are some of the factors that impact the amount of power harvested. Typically, RF to DC conversion efficiency is between 50% and 75% over a 100 m range of input power [42].

RF energy harvesting has two models: the sensor nodes can use two radios, one for RF harvesting and the other for communicating with other sensor nodes, or the sensor nodes can employ only a single radio that can be used for both purposes. In order to optimize the solution, it is better to have a single radio for a WSN scenario. This also helps to reduce the software complexity and overall size of the code.

In WSNs, intentional sources (e.g., the sinks) transmit power or, in other words, the application has control over the availability of power. The intentional sources can provide power continuously, on a scheduled basis, or on demand and can be used to provide power to activate sensor nodes or to keep the sensor nodes fully charged. Furthermore, the sensor nodes can anticipate and provide the basis for RF energy harvesting for other sensor nodes in the surrounding area. The intermediate sensor nodes can act as sources of power on a regular or sporadic basis, but they generally cannot be controlled since continuous data transmission is not suitable for WSNs. In WSNs, RF energy harvesting also takes advantage of one-to-many wireless power distribution; in such distribution, a transmission from one sensor node can provide power to all nodes that receive or listen the transmission. It should be noted that regulations regarding safety and health concerns do limit the output power of RF [43].

The RF energy harvesting can be used in multiple ways to implement a power system [44], such as (a) direct power (no energy storage), (b) battery-free energy storage (i.e., supercapacitor), (c) battery-recharging, and (d) battery activation. When the harvested power is very low, there is a need to increase the power to ensure that the sensor nodes can operate properly. In [45], a Multistage Villard Voltage Multiplier (MVVM) circuit is used to provide direct power after harvesting. A MVVM circuit is used to boost the achieved power to desired power levels using RF harvesting. In [46], a Multistage Dickson Charge Pump (MDCP) is used to enhance the power gathered using RF harvesting and to store the energy in a capacitor. In [47], the authors seek to improve upon MDCP by introducing a smart voltage regulator to enhance the efficiency of RF–DC conversion. The Cockcroft–Walton Multiplier (CWM) is used in [48] and a multistage CWM is used in [49] to increase the harvested power.

Radio Frequency IDentification (RFID) tags can be viewed as a very basic RF energy harvesting solution available on the market. In passive RFID systems, the RFID reader sends the RF signals to query an RFID tag, and the tag responds with its identification by powering itself from the inductance of the loop antenna [50,51]. The Wireless Identification and Sensing Platform (WISP) [52,53] demonstrates one possible means of integrating RFIDs with WSNs and utilizing RF energy harvesting. Recently, STMicroelectronics developed contactless memories with RF energy harvesting capabilities [54] to exchange data across Near Field Communication (NFC) enabled smartphones and RFID systems as shown in Fig. 6(a). Similarly, Texas Instruments developed the TMS37157 device (Fig. 6(b)) for short range, battery-free, two-way communications [55]. The device operates by scavenging the RF energy transmitted from the base station and working at 2.4 GHz. Powercast produces RF energy harvesters for charging both batteries and capacitors [56] with a maximum efficiency of 75% (as shown in Fig. 6(c)). In [57], an ambient RF energy harvesting sensor node was developed (as shown in Fig. 6(d)). For sensor node operation, a minimal RF input power of −18 dBm (15.8 μW) is needed. In [58], the authors

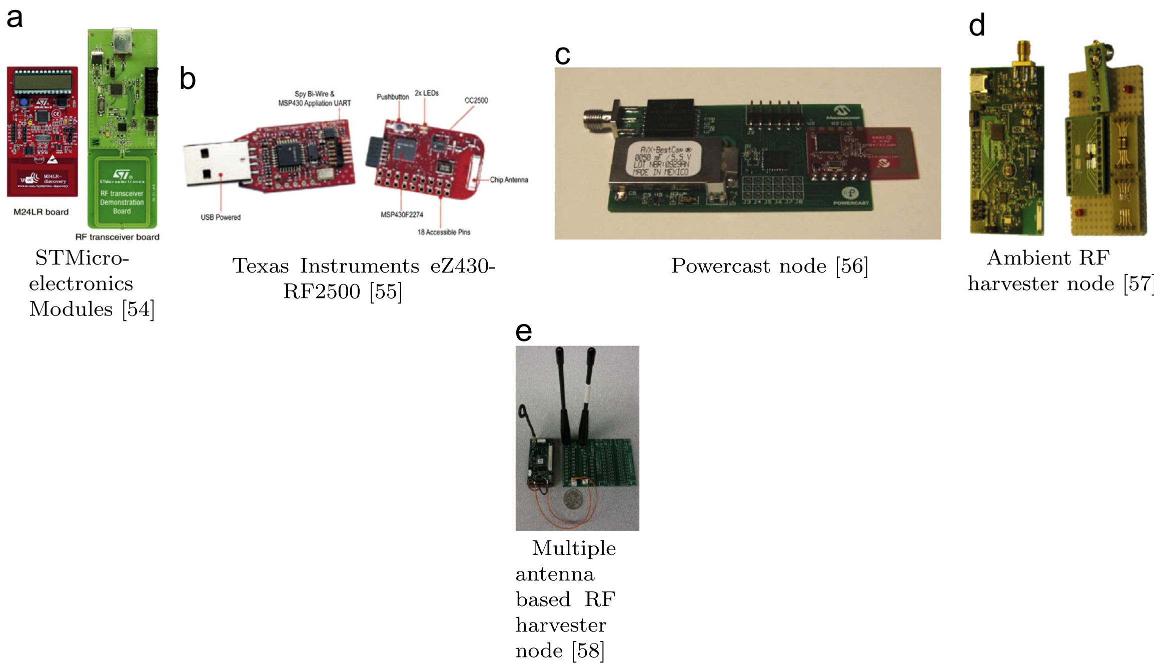


Fig. 6. RF energy harvesters for WSNs.

proposed a new model of RF energy harvesting that uses multiple antennas to increase the amount of energy harvested. They also demonstrated how one could power the commercially available Mica2 sensor node with their RF energy harvester using MVVM as shown in Fig. 6(e).

RF energy harvesting can be used both indoors and outdoors for a number of WSN applications. Applications include agricultural monitoring [59], smart homes, structural health monitoring, location tracking, and environmental monitoring. For indoor applications, RF energy harvesting has more potential since interiors often have either low-light conditions or no light, making solar energy harvesting methods unreliable. Similarly, thermal gradients and vibrations are also not likely to be available indoors. Thus, RF energy harvesting is an appropriate choice for indoor WSN applications.

In order to make full use of RF energy harvesting, the protocols running on sensor nodes need to be aware of adapted energy harvesting mechanisms to derive an optimal solution. In [60], the authors discuss a duty cycle approach for RF energy harvesting sensor nodes and propose an adaptive scheme based on the available harvested energy. In [61], the authors proposed a data delivery scheme, that takes into consideration RF energy harvesting, is proposed. The data delivery scheme aims to optimize the usage of the small amounts of harvested energy through a sink-synchronized protocol. The design has been implemented and experimentally validated utilizing commercially available RF energy harvesting devices.

3.1.2. Solar-based energy harvesting

Given its abundance in the environment, solar energy is an affordable and clean energy source that could eliminate the impending energy problem in WSNs. Due to the limitations of solar energy harvesting systems during the night, developers must ensure the highest possible efficiency during daylight hours to guarantee the viability of solar power. The photovoltaic effect can be observed when certain semiconductor materials are exposed to sunlight and convert solar rays into DC power. A solar cell is a semiconductor electrical junction device that is usually composed of silicon. When sunlight strikes a solar cell with appropriate energy, the electrons and holes are separated, and electrons start

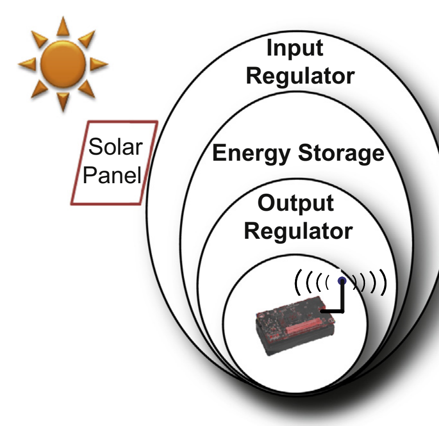


Fig. 7. Generalized solar energy harvesting system for WSNs [62].

to move towards the attached load via an input and output regulator. Generally, solar energy harvesting uses a harvest-store-utilize system with different options for storage, i.e., super-capacitors, batteries, or a combination of both, as shown in Fig. 7. A solar system can produce outputs from μW to MW depending on the surface area of the solar cell and the amount of illumination. In [63], the authors reported on the efficiencies of different solar cells at various illumination levels. For a typical outdoor (bright and sunny) illumination level of 500 W/m^2, efficiencies vary from approximately 15% to 25% for polycrystalline silicon and amorphous silicon cells respectively [64]. For typical indoor illumination levels of 10 W/m^2, efficiencies vary from approximately 2% to 10% for amorphous silicon and crystalline silicon/gallium indium phosphide respectively.

Generally, solar energy harvesting is more appropriate in outdoor environments, but some indoor environments, such as hospitals, stadiums, and industrial buildings, may benefit from it as they typically have more lighting than other indoor environments [65].

There are several implementations of solar energy harvesting sensor nodes that are different from each other based on the type of solar panels, battery type, and complexity of the circuit for recharging. The Indoor Router Node (IRN) [65], Battery Less Solar

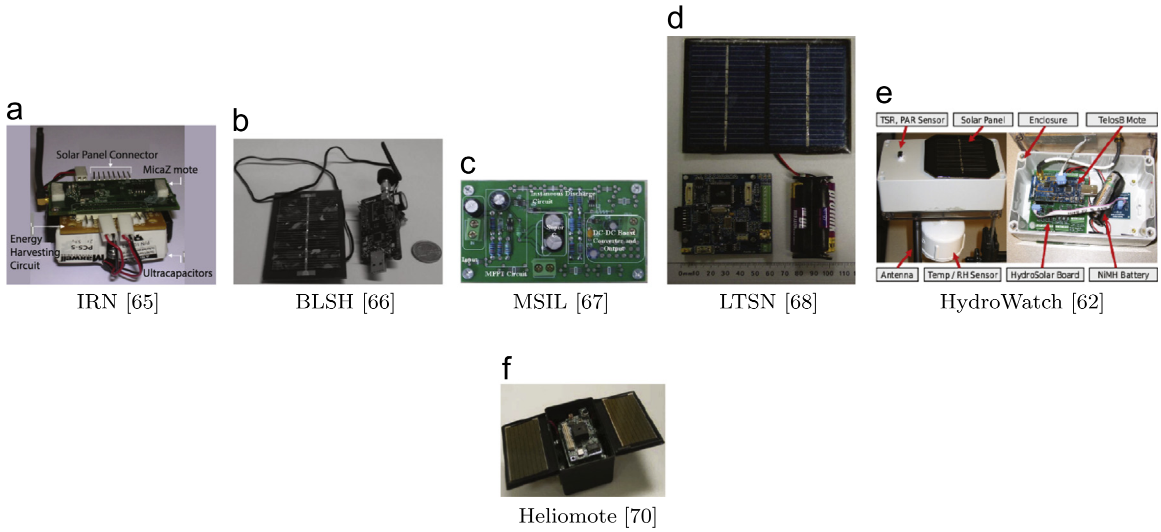


Fig. 8. Solar energy harvesters for WSNs.

Table 2
Characteristics of various solar harvesting sensor nodes [71].

Node	Solar panel size (inxin)	Solar panel power (mW)	Energy availability	Storage type	Sensor node
IRN [65]	3.75 × 2.5	400	–	Capacitor	MicaZ
BLSH [66]	44 × 44	50	–	Capacitor	Tmotesky
MSIL [67]	Any panel	–	–	Capacitor	Humidity sensor
LTSN [68]	4.5 × 3.5	1200	2100	Battery	Fleck1
HydroWatch [62]	2.3 × 2.3	276	139	Battery	TelosB
Heliomote [70]	3.75 × 2.5	190	1140	Battery	Mica2

Harvester (BLSH) [66], Micro-Scale Indoor Light (MSIL) energy harvesting system [67], Long-Term Solar Powered Node (LTSN) [68], HydroWatch [62,69], and Heliomote [70] are examples of some platforms (Fig. 8) that use the harvest-store-utilize architecture with either battery, super-capacitors, or both as the storage. A comprehensive review of solar based sensor nodes is presented in [71]. Table 2 summarizes the characteristics of various nodes and shows that existing nodes use different sizes of solar panels to generate more power for charging either the capacitor or batteries. Furthermore, existing solutions can be applied to commercially available off the shelf sensor nodes.

Due to their wide availability, solar energy harvesting systems are used in various WSN applications [72–75]. Many approaches for data transmission adapt to solar energy harvesting mechanisms by changing the transmission range [76], scheduling the transmissions [77], synchronizing communication [78], routing [79], and adapting MAC [80]. Several approaches [81,82] can optimize both the energy management and lifetime of the network, which is the primary objective of the WSNs. Whether it is duty cycling [83] or a mobile WSN [84,73,82], the approaches need to adapt to the solar energy harvesting mechanisms.

3.1.3. *Thermal-based Energy Harvesting*

As shown in Fig. 9, converting heat energy into electrical energy using Seebeck effect requires a load to be attached across the heated and cold faces of a Thermo Electric Generator (TEG) for thermal energy harvesting. Many large scale devices exist (e.g., generation of electricity from heating radiators [85]). On a smaller scale, the major interest is generating power from human body temperatures. A thermoelectric harvester has a long life, stationary

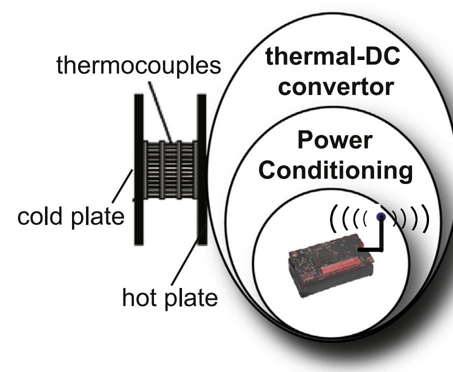


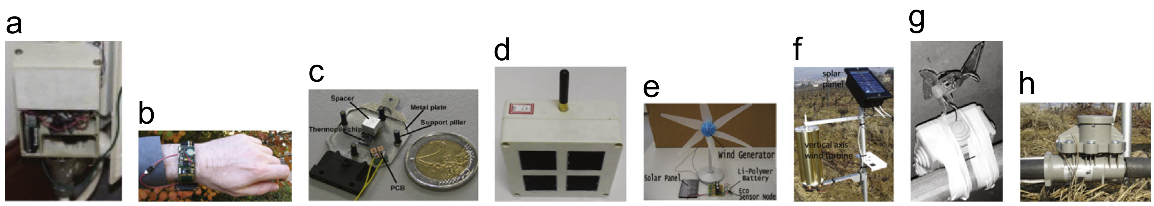
Fig. 9. Generalized thermal energy harvesting system for WSNs [62].

Table 3
Characteristics of various thermal harvesting sensor nodes.

Node	Seebeck temp. (hot/cold) °C	Thermal power (mW)	Storage type	Sensor node
Room heater TEG [85]	55/21	150	Both	ZigBee
Flex TEG [92]	22/16	100	–	Custom
Wearable TEG [93]	36/30	0.026	Battery	Custom
SPWTS TEG [94]	–	0.02	–	Custom

parts, and highly reliable characteristics. However, the low efficiency (5–6%) of thermal harvesting is a major hindrance for its widespread adoption. Recently, with the development of new thermoelectric materials and efficient modules, more than 10% efficiency has been achieved [86–89]. Micro-fabricated devices can achieve power densities of 0.14 $\mu W/mm^2$ for a 700 mm^2 device [90] and 0.37 $\mu W/mm^2$ and 0.60 $\mu W/mm^2$ for 68 mm^2 and 1.12 mm^2 devices, respectively [91], for the temperature difference of 5 K which can be typically achieved in wireless body area networks. However, for higher temperature differences (for example, if a building has heaters) principally the power density can be scaled by the square of the difference in temperature [64].

Table 3 provides insight into various thermal energy harvesting nodes. For existing commercial sensor nodes, the power TEGs generate is clearly not sufficient at a low difference of temperatures. In [85], thermal energy is obtained from the room heaters to



Room heater TEG [85] Flex TEG [92] Wearable TEG [93] SPWTS TEG [94] Ambi-max [95] VAWT [96] μ AFH [97] Commercial hydrogenerator [96]

Fig. 10. Thermal and flow energy harvesters for WSNs.

control the ZigBee-based node used to monitor the temperature of the room as shown in Fig. 10(a). Flex TEG [92] and Wearable TEG [93] are examples of WBAN (Fig. 10(b) and (c)). A Self-Powered Wireless Temperature Sensor (SPWTS) [94] can power itself when the temperature rises (Fig. 10(d)).

Furthermore, in [98], the energy harvesting is done using pyroelectric cells based on Lead Zirconate Titanate (PZT) and Poly-Vinylidene Fluoride (PVDF) films to run a low power RF transmitter [99]. Generally, due to a low pyroelectric coefficient, the PVDF cells produce less energy [100].

3.1.4. *Flow-based energy harvesting*

Flow based energy harvesting generally use turbines and rotors that convert rotational movement into electrical energy using electromagnetic induction principal [101,95] as shown in Fig. 11.

3.1.4.1. Wind-based energy harvesting. Although wind energy is also freely available and provide a good alternative power source (1200 mWh/day) [71], the turbines are generally bulkier than is required for WSNs. AmbiMax [95] uses wind energy harvesting along with solar energy harvesting as shown in Fig. 10(e). The rotor frequency is supplied to a Frequency–Voltage (FV) converter to produce the voltage. AmbiMax has a length 200 mm and a blade radius of 155 mm, which is significantly larger than the form factor of sensor nodes. In [101], an anemometer shaft turns an alternator along with a pulse buck–boost converter in order to convert the rotation motion into voltage. In [102], a micro turbine used under low wind speed conditions harvested sufficient energy to ensure the proper operation of a TI eZ430-RF2500T sensor node. A DC–DC boost converter with resistor emulation is used to achieve an average electrical power of 7.86 mW at an average wind speed of 3.62 m/s. In [103], a similar approach using a buck–boost converter and optimal power point tracking circuit is used for wind energy harvesting. In [96], Vertical Axis Wind Turbines (VAWT) harvest energy using a boost DC–DC converter as shown in Fig. 10(f).

The Air-Flow Harvester (AFH) in [97] (Fig. 10(g)) consists of a two-stage architecture: a passive-Schottky-diode full-wave rectifier and a buck–boost converter, which recharges a supercapacitor used as a local energy buffer. The airflow transducer used in this work is a small, plastic, four-bladed, horizontal axis, micro-wind turbine, which produces a sinusoidal power signal whose amplitude and frequency is dependent on the air speed.

A novel method to harvest wind energy using PZT piezoelectric material is proposed in [104,105]. In [104], the harvested energy of 917 μJ powers the RF transmitter to transmit 5 12-bit words in 100 ms.

3.1.4.2. Hydro-based Energy Harvesting. Hydropower (waterpower) harnesses the energy of moving or falling water. Currently, several small (350-1200W) commercial off the shelf units can be installed in streams and rivers. Furthermore, people can harvest the energy of moving liquids, such as water or liquid nutrients, in pipes with a small hydrogenerator [96]. In [96], a commercial hydrogenerator by Vulcano (Fig. 10(h)) was used as an energy harvester. The

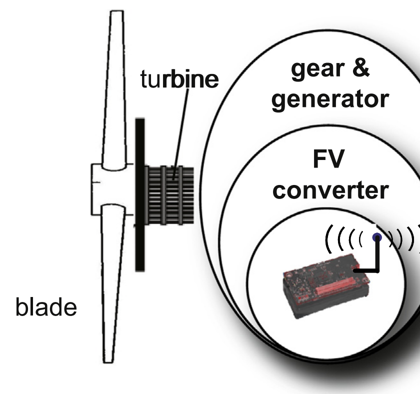


Fig. 11. Generalized flow energy harvesting system for WSNs.

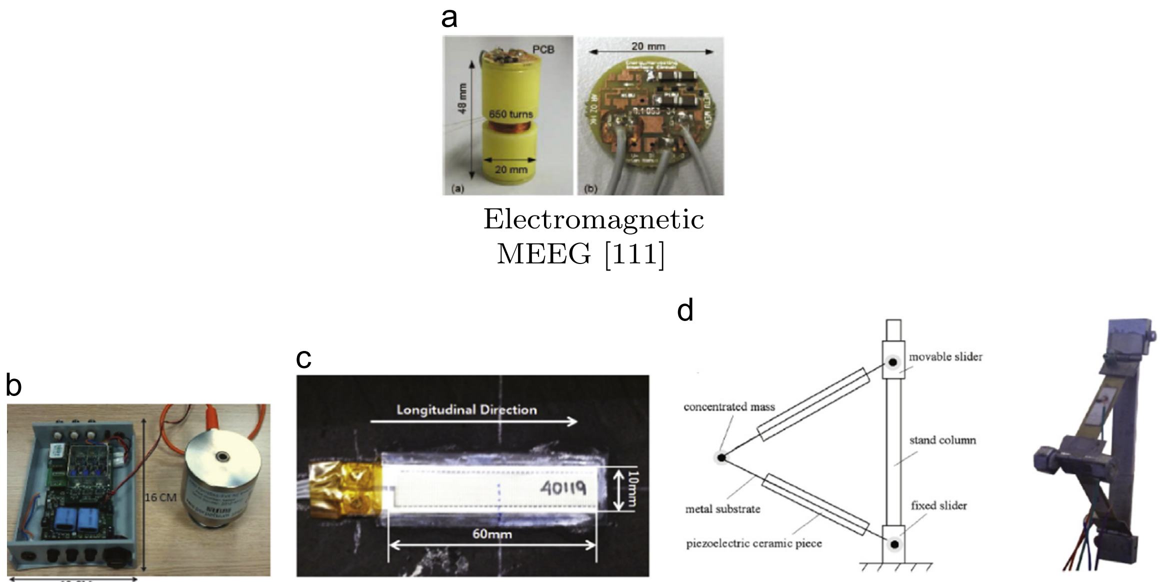
hydrogenerator output power is almost constant (approximately 18 mW) and is independent of the water flow value. Another alternative is the use of seawater batteries made up of electrodes. The seawater acts as the electrolyte and activate the electrodes to generate the energy [106]. The performance and longevity of seawater batteries depend on the hydrodynamic conditions at the deployment location. Accordingly, they are deployed where deep-sea hydrodynamic flows exist or attached to a moving device or object so that water can flow through the electrodes. In addition, the Microbial Fuel Cell (MFC) is yet another alternative for underwater energy harvesting. It exploits the metabolic activities of bacteria (such as micro-organisms from water) to generate electrical energy directly from biodegradable substrates [107].

3.2. *External sources*

3.2.1. *Mechanical-based energy harvesting*

To harvest energy from vibrations, pressure, and stress–strain, one needs to use a suitable Mechanical-to-Electrical Energy Generator (MEEG). Generally, a MEEG uses either electromagnetic, electrostatic, or piezoelectric mechanisms to harvest energy [108,64]. The pressure variations can be converted to energy using either piezoelectric or electrostatic generators, which provide the highest density of power [109,100].

In electromagnetic energy harvesting, vibrations are required to move a magnet across a coil to generate a current. In contrast, electrostatic convertors use vibrations to pull the plates of a charged capacitor against the electrostatic attraction, resulting in electrical energy due to the capacitance change. Conversely, when stressed using vibrations, piezoelectric materials can produce an electric potential difference that can be extracted as electrical energy. For a MEEG, the harvested energy increases with device volume, i.e., for 100 cm^3 in volume, a device generates 10 mW, and a device with a volume less than 0.01 cm^3 can generate less than 10 mW. In [110], a device with a volume of 150 mm^3 achieved 45 μW for a 0.6 m/s^2 acceleration at 50 Hz.



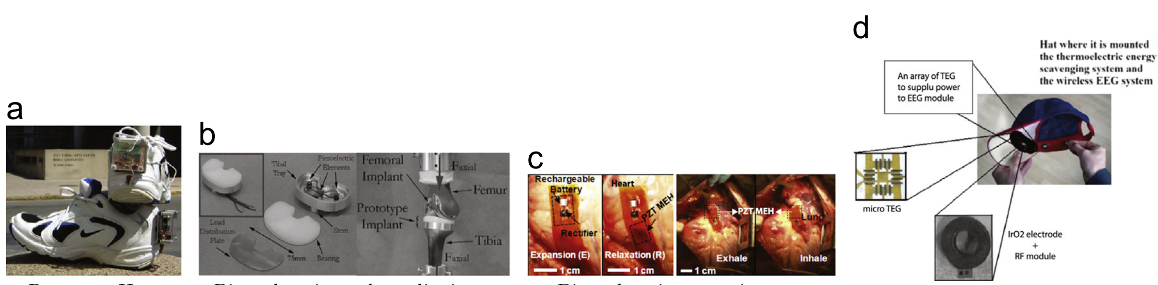
Electromagnetic MEEG [111]

AEM MEEG [112]

Piezoelectric MEEG [113]

μ Piezoelectric MEEG [114]

Fig. 12. Mechanical energy harvesters for WSNs.



Rotary Harvester [116]

Piezoelectric orthopedic implant [120]

Piezoelectric organ implant [121]

μ TEG [123]

Fig. 13. Energy harvesters for WBAN.

In [111], the electromagnetic harvester uses 10 Hz vibrations to charge the battery of a MicaZ mote. A two-stage Dickson rectifier gathers the generated energy. Fig. 12(a) shows the fabricated energy harvester module and the assembled rectifier. The proposed harvester first charges the capacitor, which in turn charges the batteries of the senor node. In [112], a hybrid energy harvesting system for Acoustic Emission Monitoring (AEM) is proposed to power the ZigBee based sensors using supercapacitors as the storage medium (Fig. 12(b)). The energy is harvested from three sources namely thermoelectric, vibrational (based on the electromagnetic phenomenon), and a photovoltaic. The proposed energy harvesting system is deployed on an air compressor in a large-scale cold storage facility. By using electromagnetic harvesting from machine vibrations at 25–48 mg magnitudes and 49.3–49.7 Hz frequencies, 1.56 mW is harvested.

In [113], a piezoelectric energy harvester is developed to harvest energy from the acceleration of tires (Fig. 12(c)). The self-powered WSN node used for the application was tested while driving vehicles. The 1.37 μW/mm3 of power harvested was sufficient to power the developed node. A micro piezoelectric vibration energy harvester is proposed in [114] (Fig. 12(d)). The output power achieves 115.2 mW when the load resistance is 200 kΩ. A detailed discussion of piezoelectric vibration energy harvesting for WSNs is given in [115].

3.2.2. Human-based energy harvesting

Among other WSN applications, the healthcare sector is of prime importance due to the necessity of monitoring patients continuously to ensure that medical professionals can take appropriate and timely actions. Accordingly, the Wireless Body Area Network (WBAN) have been receiving a lot of attention recently; in these networks, sensor nodes are deployed on or inside of the human body to monitor physiological parameters continuously. Due to their deployment on humans, the nodes need to be operational for long periods of time and ideally for the lifetime of the humans being monitored. Thus, harvesting energy from the human is preferable to alternative sources of power. Fortunately energy can be harvested from humans in a variety of ways, such as through locomotion or changes in finger position, body heat, and blood flow. Broadly speaking, human-based energy harvesting can be categorized as activity based harvesters and inherent physiological parameters based harvesters. Traditional harvesters as well as the other energy harvesters for WSNs discussed previously can be used for human based energy harvesting, but the main challenge will be to miniaturize them to make them easier for human adoption, Though infrequent, human movements are generally non-periodic and contain high acceleration, e.g., 100 m/s^2 at 2 Hz while jogging. Furthermore, the average human walk generates up to 7W per foot of power. Researchers have used several types of generators, such as shoe-mounted rotary harvesters [116] (Fig. 13(a)), piezoelectric materials [117–119], and electroactive polymers, to convert human movement into power. The highest power achieved has been in the range of 0.210 W [118].

The use of piezoelectric materials is gaining interest in implants, including orthopedic implants [120] (Fig. 13(b)), which generate around 4.8 mw raw power. In contrast, the motion of the heart, lungs, and diaphragm [121] (Fig. 13(c)) generate a power density of approximately 1.2 μW/cm^2.

In [122], a micro TEG used on a human arm produced 34 mW of power. Similarly, in [123], an EEG module was powered using TEG to produce a power of 18 μW (Fig. Fig. 13(d)).

4. Energy harvesting modeling

The amount and the rate of the energy harvested over time are two critical parameters that anyone developing an energy harvesting system should consider before the design stage [124,125]. Generally, the behavior of the energy source is dynamic in nature. For example, in solar energy harvesting, the energy source is predictable and non-controllable; therefore, developers can forecast the amount of energy harvested and the availability of the source [126,127]. Accordingly, energy sources can be distinguished with respect to the characteristics of predictability and controllability. For controllable energy sources, there is no need for prediction as the harvestable energy will be available whenever required. For non-controllable energy sources, the energy will be harvested whenever available. Furthermore, if the energy source can be predicted for non-controllable energy sources, then it will be easy to forecast the next availability of the energy source to harvest the energy. Table 4 provides an overview of different energy sources and their corresponding characteristics.

Such a forecasting mechanism will enable the energy harvesting system to decide how to utilize the available energy and how much to store for future use. Next, we provide an overview of the different energy forecasting mechanisms presented in the literature.

Predicting RF energy for harvesting is tied to predicting the quality of the links. The quality of the links affects the reliability of communication between the sensor nodes, which in turn enables the energy harvesting mechanisms to harvest energy from the RF signals. In [128], a Genetic Machine Learning Approach (GMLA) for link quality prediction is proposed to forecast the RF connectivity time in mobile environments. GMLA consists of a classifier classification and Markov chain model of RF links. The Markov model parameters can be adapted at runtime, thereby making the GMLA approach appropriate for generic environments. Fig. 14 depicts the GMLA approach and shows the prediction and classifier selection processes.

In [129], the reviewed an optimized Morkov model is presented for link quality prediction using the Oriented Birth-Death (OBD) model. The authors added orientation to the original Birth-Death model to introduce the tendency of the future states of the link; i.e., the model considers if the link tends to increase or decrease the signal strength to make a prediction for mobile WSNs.

For static WSNs, a Data Driven Link Quality Prediction (DDLQP) approach is defined using link features in [130]. DDLQP consists of three steps: data collection, off-line modeling, and online prediction. In the data collection phase, link quality indicators, such as Receiver Signal Strength Indicator (RSSI), Link Quality Indicator (LQI), and Signal-to-Noise Ratio (SNR), are collected and then used to train the system in the off-line phase. During the prediction phase, the authors used three machine learning methods: the Bayes classifier, logistic regression, and artificial neural networks. They showed that logistic regression performs better than other prediction techniques.

In [126], the authors propose a Solar Energy Forecasting Model (SEFM) based on the Exponentially Weighted Moving-Average (EWMA) with the assumption that the energy source at a particular time of a day is similar to previous days. The whole day is divided into fixed length time slots (30 min), and the amount of energy available on previous days is maintained as a weighted average where the contribution of older data decreases exponentially. The EWMA adapts very well to the normal day-night cycle

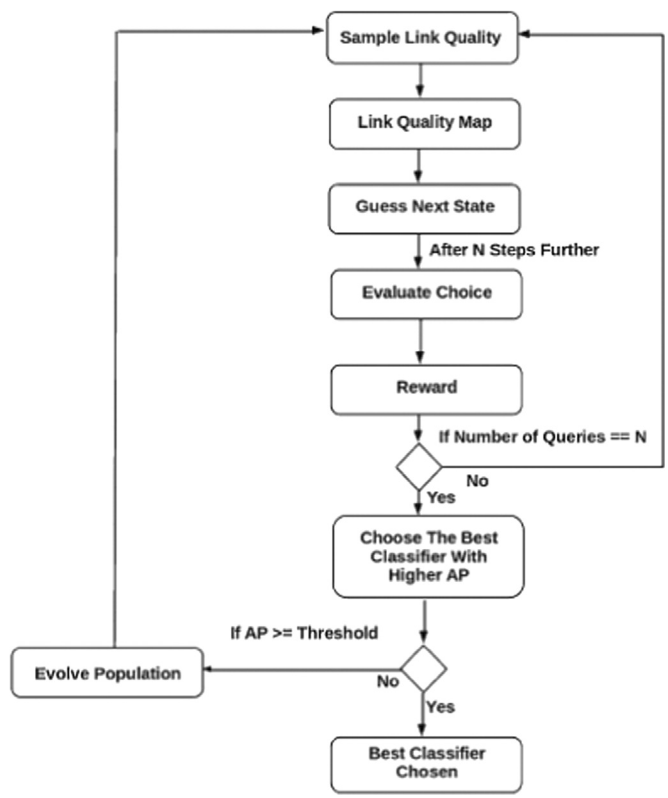


Fig. 14. GMLA [128].

Table 4
Characteristics of various energy sources.

Energy source		Predictable	Unpredictable	Controllable	Non-controllable
RF		✓		✓	
Solar		✓			✓
Thermal			✓	✓	
Flow	Wind	✓			✓
	Hydro	✓			✓
Mechanical	Vibration		✓	✓	
	Pressure		✓	✓	
	Stress–strain		✓	✓	
Human	Activity		✓	✓	
	Physiological		✓		✓

and produces accurate results. If, however, the weather changes frequently, the EWMA is less accurate. Put more formally, if $x(i)$ is the generated energy in slot i, then the historical average for each slot is $\bar{x}(i) = \alpha\bar{x}(i-1) + (1-\alpha)x(i)$, where α is a weighting factor (taken as 0.5) and $\bar{x}(i)$ is the historical average value for slot i.

To overcome the deficiencies of the EWMA approach, the authors in [131] proposed the Weather-Conditioned Moving Average (WCMA). The WCMA is able to take into account both the current and past days weather conditions, obtaining a relative mean error of only 10%. The WCMA algorithm uses an E matrix of size DxN that stores N energy values for each D past day, i.e., $E(d,n+1) = \alpha E(d,n) + GAP_k(1-\alpha)M_D(d,n+1)$, where α is a weighting factor, $M_D(d,n+1)$ is the mean of D past days at $n+1$ sample of the day ($M_D(d,n) = \sum_{i=d-1}^{d-D} E(i,n)/D$), and GAP_k factor measures the solar conditions in the present day relative to the previous days. To overcome the corner cases of the WCMA, especially those due to sudden changes in the environment with $\alpha = 0.5$, the authors in [132] proposed a feedback system known as the Phase Displacement Regulator (PDR). The PDR significantly reduces the WCMAs prediction errors.

In [133], the authors proposed a prediction scheme similar to the EWMA based on assumptions made about the periodic solar energy availability. The system receives tuples $(t, E_S(t))$ for all time slots $t \geq 1$ ($E_S(t)$ is harvested energy) and delivers N predictions (intervals of equal size L) for energy harvesting. Accordingly, at time t, the predictor produces estimations $\tilde{E}(t,k) = \tilde{E}_S(t + k \cdot L, t + (k+1) \cdot L)$ for all $0 \leq k < N$. The prediction scheme combines the energy harvested in the current time slot with the energy availability during past time slots.

To overcome short-term varying weather conditions, which are not handled properly in previous approaches, the authors in [134] introduced a scaling factor to minimize the prediction errors as $\xi_n = x_{n-1}/y_{n-1}$ where x_{n-1} is harvested energy and y_{n-1} is the predicted energy during slot $n-1$ using the EWMA. The value of ξ_n is then used to fine-tune future predictions.

SunCast [135] propose the use of regression analysis to map and predict future sunlight. It uses a three-stage process to predict the sunlight: (1) first, it calculates the similarity between the real-time data and historical data; (2) then, it uses regression to map the trends in the historical data and real-time data; (3) finally, it combines the weighted historical data to predict sunlight using quadratic optimization. SunCast is limited to predictable environmental factors such as sunrise and sunset. The rapid daylight changes, such as those caused by the clouds, are unpredictable.

Pro-Energy [136] utilizes both solar and wind energy prediction to cope with the problem of energy availability in an energy harvesting system. The main idea is to utilize the available energy profiles from previous days. The harvested energy profile of a typical day is also stored in a vector. Once per time slot, Pro-Energy predicts the available energy by looking at the stored profile most similar to the current day. The Euclidean distance is used to find the similarity between the profiles using first t elements, where t is the current time slot. Compared to the EWMA and WCMA, Pro-Energy performs well due to its ability to utilize the energy profiles of previous days to make fewer errors. In [137], the authors propose the Pro-Energy with Variable-Length Time slots (Pro-Energy-VLT), an extension of Pro-Energy to improve the accuracy of predictions keeping memory and energy overhead low. The authors, having argued that using equal-length time slots may not provide the best results, proposed an adaptive scheme to fine-tune the time slots according to the dynamic behavior of the energy source. They showed a 50% reduction in memory overhead compared to Pro-Energy.

In [138], the authors analyzed weather forecast data and energy harvesting data to formulate a model, known as Cloudy Computing, that predicts solar and wind energy. The inconsistency of weather patterns leads to the poor performance of traditional EWMA-based approaches. Thus, cloudy computing integrates the fine-grained weather details from the weather forecast data to predict energy availability more accurately.

Table 5
Performance comparison of various prediction schemes for solar energy [139].

	Memory (B)	Time (μs)	Average error (%)
EWMA	96	9	28.6
WCMA	384	51	9.8
ETHZ	96	14	29.9
Neural network	520	711	67.2

The authors in [139] compared different solar energy prediction schemes. They showed that it is possible to design a prediction scheme that has a low memory footprint and requires less computation. They also introduced a neural network based approach for solar energy prediction where supervised learning is carried out with error back propagation. Based on their study, Table 5 shows the statistics of various prediction schemes.

In [97], the authors proposed wind energy prediction using linear regression in which the prediction variable is the time (t = average duration of the wind harvesting events) and the response variable is the estimated power at $t(p^t)$. For the set of the last n power observations, $\{(t_{i-n}, p^t_{i-n}), \cdots (t_i, p^t_i)\}$. The goal of the simple linear regression is to find the equation of the straight line that will provide the best fit for the observed data points.

In [140], the authors proposed a Combinational Prediction Model (CPM) for short-term wind farm energy harvesting using meteorological data. For prediction purposes, the CPM combines a Back Propagation Neural Network (BPNN) with a Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The meteorological data is used as input for the BPNN, whereas the GA and the PSO are used to adjust the BP's weight and threshold values dynamically. Then, the trained GA-BPNN and PSO-BPNN are used to predict wind power through a combination method as $P_{\sum} = P_{GA-BPNN} + P_{PSO-BPNN}/2$. A comprehensive review of wind energy generation prediction is available in [141].

In [142], the authors used neural networks for River Flow Prediction (RFP). The authors proposed an adaptive cascade-correlation algorithm to present the data to the Artificial Neural Networks (ANN) to train them. A Generalized River Flow Prediction (GRFP) model using an ANN is proposed in [143]. In order to improve the efficiency of the ANN when the input data for training is limited, the GRFP proposes a guidance system for the cascade-correlation learning architecture. For Flow Prediction in Horizontal Pipelines (FPHP), the authors in [144] proposed the Least Square Support Vector Model (LSSVM). The inputs of this model are the superficial velocities of oil and water, pipe diameter, pipe roughness, and oil viscosity. For further reading on this topic, [145] provides an effective review of predicting water resource variables using an ANN.

In contrast prediction techniques, [146] proposes a Prediction FREe Energy Neutral (P-FREEN) power management system using Budget Assigning Principles (BAPs) to maximize the amount of harvested energy that a sensor can use in the presence of battery energy storage inefficiencies. P-FREEN implements BAPs on the observed rate of energy harvested and the residual battery energy level. The computational complexity of P-FREEN is lower than the existing prediction mechanisms, and it performs well during simulations.

Table 6 summarizes the different prediction techniques various approaches use for energy forecasting.

Table 6
Summary of prediction techniques for energy forecasting.

Energy source	Approach	Prediction mechanism
RF	GMLA [128]	Classifier-Morkov chain model
	OBD [129]	Morkov model
	DDLQP [130]	Logistic regression
Solar	SEFM [126]	EWMA
	[131]	WCMA
	[133]	EWMA
	[134]	EWMA with scaling factor
	SunCast [135]	Regression analysis
Solar+Wind	Pro-Energy [136]	Energy profiles (EP)
	Pro-Energy-VLT [137]	EP with adaptive time slots
	Cloudy Computing [138]	Weather forecast
Wind	[97]	Linear rigression
	[140]	CPM
Hydro	RFP [142]	ANN
	GFRP [143]	ANN
	FPHP [144]	LSSVM

5. Open research challenges

WSNs are emerging as a key technology for the Internet of Things and related applications for indoor and outdoor environments. Energy harvesting mechanisms for WSNs are flourishing and becoming more attractive as microelectronics and MEMS advance.

Generic harvester: One of the key challenges is to harvest energy from multiple sources, which requires the development of advanced power management techniques. A generic plug and play energy harvester that can harvest energy from multiple sources is needed in order to fulfill sensor nodes energy requirements. By having such a generic harvester, it may be possible to eliminate energy storage systems to power the nodes.

Miniaturization: The large-scale deployment of WSNs with bulky harvesting systems will not be economically viable or suitable for pervasive environments. Therefore, in future the main focus should be on the development of nano-scale miniaturized energy harvesting systems. Accordingly, microelectronics will be utilized to provide robust, miniaturized, low power, and low-cost micro-computing systems that can be interfaced to the already miniaturized electronics. As discussed in earlier sections, the biomedical field has made some effort to use very small energy harvesting systems in implants. While sufficient for powering the implants, the small amount of energy these miniaturized systems produce cannot be used directly for other application scenarios such as monitoring. Thus, there is a need for small-scale harvesting systems that can produce sufficient energy to power the node, sensors, and other associated interfaces.

Protocol adaptation: Traditionally, the focus of WSNs has been on energy efficient networking protocols to maximize the lifetime of the network [12]. With the introduction of energy harvesting systems the WSN objectives need to be redefined, e.g., instead of energy efficient protocols it should be information centric protocols which maximize the information based on amount of energy harvested. Redefining the objectives will lead to a careful adaptation of the various protocols and strategies involved in delivering information from the environment to the user. Topology control protocols may use high power transmissions in order to deliver information successfully from one hop to another. Given that this requirement will require more energy to be harvested, topology control protocols need to be adapted according to harvested energy. Typically, WSN MAC protocols trade delay for energy usage. For energy harvesting WSNs, it is important to determine how to maximize throughput and minimize delays. Furthermore, cross layer analysis of communication links can promote efficient utilization of the energy harvesting schemes. Routing protocols also need to be adapted to take advantage of the availability of new energy harvesting systems in the network. The optimization problem of routing must be revisited carefully since the majority of the existing works in WSNs assume a limited energy budget for routing purposes. Accordingly, to ensure reliability where retransmission of data is frequent, transport protocols must adapt to provide application level requirements.

Although some works have investigated protocol adaptation for energy harvesting WSNs [147,71,148], developers still need to develop a generic framework for the dissemination of information in energy harvesting WSNs.

Efficient prediction techniques: The existing prediction techniques are generally simple, but they can lead to substantial prediction errors. Despite their shortcomings, they are used to avoid expending excessive power for processing because the harvested power is also limited (e.g., harvested solar energy). Thus, researchers should devote more attention to developing efficient and less error prone prediction algorithms to improve power management.

Simulation environments: To the best of our knowledge, simulation environments that can cover all aspects of energy harvesting in WSNs are almost non-existent. Such a simulation environment will be a valuable tool to evaluate the impact of proposed energy harvesting systems on large-scale networks.

Energy-efficient reliable systems: All energy harvesting systems will benefit from more reliable and ultra-energy efficient sensors and nodes. Beyond having anti-fouling coatings on the surfaces, reliable sensors must strive for consuming very low power (ideally no power) and should be highly reliable over the system lifetime. The sensor nodes also raise the challenge of calibration and cleaning over the entire system lifetime. Thus, nodes not requiring calibration or cleaning would resolve many of the reliability challenges. Having such sensors will reduce both the amount of energy needed and the size of the energy system, which will increase the system lifetime.

Energy storage: Large-scale and long-lasting applications will impact battery parameters, such as self-discharge, charge cycles, and environmental conditions. Therefore, future researchers should devote additional effort to further investigate and assess the performance and reliability of conventional and rechargeable battery technologies [149]. Researchers should also further explore the tradeoffs between using batteries and capacitors as storage devices.

The ultimate goal of energy harvesting systems for WSNs is to shift the paradigm from the battery-operated WSN to an autonomous energy harvesting WSN that only relies on energy harvested from the ambient environment.

6. Conclusion

Energy harvesting in WSNs continues to receive a lot of attention by various stakeholders involved in their design and implementation given the strong potential of energy harvesting techniques in meeting the energy demands of future WSN deployments. In this work, we developed a comprehensive classification scheme for energy harvesting techniques in WSNs. More specifically, we focused on energy harvesting techniques that leverage the ambient environment and external sources to generate energy for WSNs. For each class and sub-class of energy harvesting techniques we have identified, we thoroughly reviewed the energy harvesting mechanism, the harvester hardware design, the amount of energy harvested, and the efficiency of the harvester. It is worth noting that each energy source has different harvesting capabilities and, as a result, the harvester hardware design is also different for each category which ultimately determines the efficiency of the harvester. In order to address the issue of intermittent outages of harvested energy, we surveyed in detail the various models aimed at predicting future energy cycles. We found that the current state-of-the-art in this area of modeling is still immature and only very basic prediction techniques have so far been utilized. Finally, we identified several open research challenges that still need to be addressed in the future including the need to focus miniaturized generic harvesters which can be used in different environments with dynamic energy sources.

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