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Power Supply Issues in Battery Reliant Wireless Sensor Networks: A Review

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***Abstract* - Wireless sensor networks (WSNs) have enabled numerous embedded wireless applications in different areas, such as military/battle field, environmental monitoring, and intelligent building systems. They consist of a large number of nodes that need to operate normally for months to years to complete designated tasks. Due to the small dimension of a sensor node, the power supply attached to the sensor node has to be very limited in size. Thus energy conservation becomes a challenging issue in WSN design. Meanwhile, it is a challenge for researchers and developers to obtain long operating hours without sacrificing the system performance. A variety of mathematical models have been studied to serve as analytical tools in quantifying battery discharge characteristics. However, batteries, as the primary power supply, still fail earlier in some applications than their projected working time. To further analyze the factors that affect battery discharge, and understand the characteristics of WSN power supply, this paper surveys both physical and network communication parameters that can affect battery lifetime and cause the difference between the simulation and application results. Furthermore, it offers readers a glimpse of applying new technology-driven WSNs with energy harvesting techniques, such as photovoltaics or piezoelectric generators.**

***Index Terms*—Battery, energy harvesting, wireless sensor networks, renewable energy**

1. INTRODUCTION

Wireless sensor networks (WSNs) consist of spatially-distributed autonomous sensors to monitor physical and environmental conditions, such as temperature, sound, and pressure that cooperatively pass their data through the network to a main location [2, 3]. Because of the flexibility of WSNs, they have enabled numerous embedded wireless applications, such as environmental monitoring, air pollution monitoring, and forest fire detection. Recently, interest in deploying WSNs for building environmental monitoring, construction monitoring, heating, ventilation, and air conditioning control, lighting control, and security access control has increased.

A wireless sensor node is made up of four basic components as shown in Fig. 1: a sensing unit, a processing unit, a transceiver unit with an internal antenna or connection to an external one, and a power unit. Once a node is deployed, it automatically collects data from its surroundings based on the sensor functionality and then establishes itself within the network topology to transfer collected data to a base station. The base station aggregates and analyzes the reported data and decides what the corresponding node should do. Various key design issues are involved in WSNs to make them perform as desired. Such research has targeted WSN dynamics and node deployment, transmission media and communication, data delivery models, node capabilities, power consumption, data aggregation, fault tolerance, scalability, and network topology. A major challenge for WSNs, however, lies in the node energy constraint. The energy source for sensor nodes is typically two AA batteries. On the other hand, expected lifetimes of batteries should range from months to years, since it is undesirable to recharge or replace the batteries of thousands of sensor nodes frequently. When a node is depleted of energy, it can no longer fulfill its role unless the source of energy is replenished. Therefore, it is generally accepted that the usefulness of a wireless sensor (or wireless sensor node) expires when its battery runs out. The energy exhaustion of any node indicates that the network needs to be reorganized or fixed.

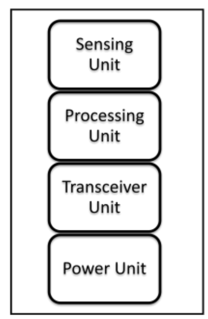

Fig. 1. Components of a wireless sensor node

We include a variety of battery related topics in this review paper. Meanwhile, insights about battery types, key factors that can affect battery's lifetime and new technology that can substitute the traditional power supply are discussed as well. The next section describes the related work on wireless sensor battery research. Available batteries as a source to wireless sensors are introduced in Section III. In Section IV, battery modeling methods for analysis of the discharge behavior of a wireless sensor's battery are discussed. Section V describes the main factors that can affect battery discharge characteristics. New technologies that may potentially replace the traditional battery in wireless sensor nodes are discussed in Section VI. Finally, Section VII concludes this paper.

1.1 Related Work

The majority of work on wireless sensor research relies on generic battery models which place little emphasis on actual hardware platforms and batteries. Park *et al.* [4] are among the first to experimentally examine the battery discharge characteristics of sensor nodes. They conduct experiments with a commercial lithium-ion cell and examine its sensitivity to the load profile of a sensor node. However, they consider only a

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limited set of WSN parameters. For example, they assume fixed transmission power levels and do not consider the influence of ambient temperature. Secondly, they do not evaluate the impact of battery characteristics on network-level trade-offs. One of their important findings is that the capacity extracted from the battery is significantly degraded by the voltage converter that is typically used to supply power to the sensor node. A similar conclusion is drawn from the deployment study in [5]. Panthachai and Keeratiwintakorn [6] propose an energy model for data transmission based on the size of the payload, in bytes, for sensor nodes. The work has measured the exact energy usage via a high-precision digital oscilloscope when sensor nodes are used in a variety of scenarios.

Conventional low-power design techniques emphasize reduced battery energy consumption in the circuit architecture of a single node [7]. In some of the prior work, the power consumed in radio frequency (RF) and analog activities are either ignored or represented by constant values [8-10]. This treatment may lead to erroneous energy evaluations since the RF and analog sections process analog signals with high-frequency content and typically consume more energy compared to the digital part. Different aspects of low-power wireless communication transceivers have been addressed in recent years to lower sensor energy usage. These include energy efficient modulation scaling [8, 9], delay controlled transmission schemes [10-12], energy efficient routing [13-15], and power management-based task scheduling for digital communication processors [16], etc.

Measuring the battery lifetime through real experiments is time-consuming. Thus numerous simulation tools have been proposed in recent years to estimate it [17, 18]. Two major ones are NS-2 [19] and SWAN [20]. In addition, a variety of simulation strategies have been proposed to exploit battery characteristics for designing more "battery friendly" systems and communication protocols [21-25]. Similar work is discussed in [26] where an energy model of sensor nodes is developed. A drawback of this model is that it does not consider payload size. Note that these simulation methods utilize a simple energy model that assumes key characteristics of packet transmission. Many efforts have been made to extend the lifetime of WSN by using energy efficient protocols such as [27-30] The rationale behind these work includes taking paths with maximum available power, minimum energy, minimum hop, maximum available power; however, these models lack of detailed analysis of the lifetime of sensors, and the relationship between the lifetime of individual sensor and that of the whole sensor network. Battery models are complex and difficult to parameterize to match real-world data. To achieve a good generalized fit between measured and simulated results, we still need a variety of laboratory data.

Researchers have been working on how to predict the longevity of a WSN mathematically. Mathematical models providing upper bounds on lifetime have been developed in [31-35]. However, none of these models have been experimentally validated using real sensor nodes. One of the reasons for this deficiency is the relatively long lifetime of batteries, which makes the comparison of theory and practice a tedious task that might take weeks or months. Ritter *et al.* [36] present a hardware methodology by using special capacitors with very large capacities, so-called Gold-Caps, which enables short-term experiments with durations no longer than a few hours. Some research [37] use Gold-Caps on embedded sensor boards to measure the longevity of small sensor networks and compare these results to those of a mathematical model. The model computes bounds on the lifetime of a continuously operating WSN. It concentrates on the energy consumption of routing since communication is the most expensive activity in terms of energy consumption, generally far more expensive than sensing and computing [38]. Their research shows that the measured lifetime of the WSN agrees well with the lifetime predictions by their mathematical model.

The issue of powering a node becomes critical when one considers the prohibitive cost of wiring power to it or replacing its batteries. Unfortunately, battery technology did not improve much in terms of energy density and size in the last decade, especially for such low-power applications as WSNs [39]. Most prior work in the literature did not consider the role of battery characteristics in determining sensor node lifetimes. In fact, the published results from actual deployments indicate that in practice, a node's lifetime is often far lower than the expected lifetime due to the premature exhaustion of batteries [5].

2. BATTERY AS A SOURCE TO WIRELESS SENSORS

Due to the small dimensions of sensor nodes, batteries have to be designed with a small size in mind. Thus, the available energy resources – whether batteries, energy harvesting, or both – limit their overall operation [40]. On the contrary, wireless sensors need to operate for long periods of time in most settings to continuously collect corresponding data. To ensure long time operation, the energy of the battery must be used wisely. There are numerous battery types available for wireless sensor nodes. When comparing different battery technologies, several criteria should be considered. They include energy density (charge stored per unit weight of the battery), cycle life (the number of discharge/charge cycles prior to battery disposal), environmental impact, safety, cost, available supply voltage, and charge/discharge characteristics. Next we summarize the properties of the typical battery technologies and describe battery technologies developed over the last two decades to meet the increasing demand for smaller, lighter and higher capacity batteries [41].

2.1 Nickel-Cadmium

Nickel-cadmium has been used for long periods as a mature technology to power wireless sensors. A rechargeable nickel-cadmium battery also works commonly in residential buildings as a power supply for appliances. A nickel-cadmium cell contains a cadmium anode, nickel-hydroxide cathode, and alkaline electrolyte. Batteries made from them offer high currents at relatively constant voltage and are tolerant to physical abuse and inefficient usage cycling [42]. A Nickel-cadmium battery can sustain high discharge rates without adversely affecting battery capacity. Nickel-cadmium cells producing 1.2 V are expensive because of the cost of cadmium. Moreover, cadmium is toxic and not environmentally-friendly.

2.2 Nickel Metal Hydride

Nickel Metal Hydride (NiMH) is the workhorse of rechargeable batteries. The significant difference compared to nikel-cadmium battery is that it tends to maintain its characteristics through many recharges. It is similar to Alkaline but relatively heavier with lower energy density, meaning that a typical AA-sized NiMH battery starts at 1.2V instead of the conventional 1.5V for an alkaline AA battery. Its behavior can be described in terms of a second-order polynomial; similar to the model used for alkaline battery. NiMH performs better at low temperatures. It does not drain fast as current draw increases. It also has a wide working temperature range, and can be deployed to high-temperature environments under which lithium-based cells may explode.

2.3 Alkaline

Alkaline batteries are the most commonly used ones in wireless sensor networks. They have a fixed energy rating and therefore, a limited life. For example, one particular sensor node operating at 1% duty cycle on standard 3000 milliampere-hour (mAh) AA batteries would require battery replacement every 17.4 months; at an operational duty cycle of 10%, the batteries must be changed every week [43]. With the same voltage, alkaline batteries have a higher energy density and longer shelf-life, compared with zinc-carbon batteries. Their usage life is 5 to 6 times longer than the zinc-carbon batteries. The nominal voltage of a fresh alkaline cell is 1.5 V. Multiple voltages may be achieved by arranging cells in series. The effective zero-load voltage of a nondischarged alkaline battery varies from 1.50 to 1.65V, depending on the composition of manganese dioxide in the cathode and zinc oxide in the electrolyte [44]. The average voltage under load depends on discharge and varies from 1.1 to 1.3V. The fully discharged cell has a remaining voltage in the range of 0.8 to 1.0V. Alkaline batteries typically have a sloping discharge curve. Most devices are designed to operate within a voltage range (for example from 1.6V to 0.9V per cell) to accommodate this sloping discharge characteristic. The sloping discharge in alkaline batteries is primarily due to the increase in battery internal resistance due to reaction byproducts forming on the electrode surfaces and the decreased availability of the fuels i.e., water.

2.4 Reusable Alkaline

While disposable alkaline batteries have been used for many years, reusable alkaline-manganese technology has been developed as a low-cost alternative in which energy density and cycle life are not as good as nickel-cadmium batteries. While the initial energy density of reusable alkaline batteries is higher than that of nickel-cadmium ones, it has been found to decrease rapidly with cycling.

2.5 Zinc-carbon

Zinc-carbon batteries are widely used because of their relatively low cost. They produce 1.5 V working voltage and are not rechargeable. They are composed of a manganese-dioxide-and-carbon cathode zinc anode, and zinc chloride as the electrolyte. Their main drawback is the outer shell. The protective casing of the battery is made of zinc. The casing serves as the anode for the cell can develop holes if the anode does not oxidize evenly. In some cases, the developed holes allow leakage of the mildly acidic electrolyte, which can further damage the device being powered. Therefore, the application of this kind battery must be limited to non-critical applications.

2.6 Lithium Polymer

This technology enables ultra-thin batteries (<1 mm thickness). Lithium is a chemical element with high electro positivity. As a result, “the specific energy of some lithium-based cells can be five times greater than that of an equivalent-sized lead-acid cell and three times greater than that of alkaline batteries” [45]. Compared to lead-acid cell and alkaline batteries, lithium polymer batteries are lighter in weight, have lower per-use costs; they produce a starting voltage of 3.0 V and exhibit a higher and more stable voltage profile. However, lithium polymer batteries are more dangerous compared to lead-acid cell and alkaline batteries because they can explode if lithium is in contact with water. For this reason the lithium and lithium ion cells are made in small sizes. Some lithium-based cells are rechargeable and can provide 3.7 V.

Different batteries have their own discharge characteristic as stated in [42]. he nickel-cadmium batteries have been popular in battery-powered devices such as phones, toys and hand tools owing to their high current, relatively constant voltage and the ability to tolerate physical abuse. However, they do suffer from a memory effect, since they lose capacity if recharged before completely discharged. It needs to take several cycles of discharge and recharge to restore the battery to nearly full memory. Small amounts of mercury are used as an additive in zinc-carbon batteries to suppress the formation of internal gas that can lead to leakage, possible ruptures, or short shelf life without mentioning the environmental hazard. In addition to that, their capacity is low. Therefore, zinc-carbon batteries have been replaced by alkaline batteries in most applications. Alkaline batteries have high energy density, high rate capability, very long shelf life, and good performance over a wide range of temperatures. They have been used in many home applications such as flashlights, watches, calculators, cameras, fire and smoke detectors, and communications devices. The lithium batteries represent a relatively new technology with superior specific energy and cycle life and possess no memory effect They have been commonly used in electronic products, such as cell phones, hearing aids, computers, and intend to displace nickel-cadmium batteries in hand-held power tools. They are considered by many to be the best choice for plug-in electric vehicle applications. For WSN applications, common batteries, such as ordinary zinc-manganese dioxide ones are not recommended because of their low capacity and high self-discharge characteristics.

On the other hand, alkaline batteries are preferred because of their high-capacity, low self-discharge rate, and low cost.

3. BATTERY MODELING

Battery characteristics are experimentally found to have an impact on sensor node lifetime and influence numerous design decisions relating to the gathering, processing, and transmitting of sensor data in WSNs. To better understand battery discharge characteristics and predict battery lifetime, several research efforts have demonstrated the need to examine the problem from a quantitative standpoint, and a variety of battery modeling work has been recently conducted. The complexity of a battery technology is due to the nonlinear battery discharge characteristics. The operation of the battery depends on many factors, such as the materials used in battery electrode (cathode and anode) and the rate of diffusion of active materials in electrolyte. The battery capacity, measured in Ampere hours (Ah) or milliAmpere-hours (mAh), represents the amount of energy stored in a battery. Battery models should estimate the battery lifetime with great accuracy without complex measurements, which can hamper the use of these models in practical applications. Existing models should be compared based on their accuracy, computational complexity and configuration effort.

Accuracy – How close the predicted values of the battery variables of interest, e.g., lifetime and voltage, match experimental data;

Computational complexity – Time required to derive the results; and

Configuration effort – The number of parameters in the model.

Accuracy, computational complexity and configuration effort are three important factors in assess the battery models. People would like to use a model with simple computation complexity and less configuration effort, but great accuracy. However, it is not always the case. To obtain relative reasonable modeling results, people have to comprise within the above factors. A model with easy computation complexity may give a rough prediction results at the beginning and appropriately for marketing people to initiate the budget. On the other hand, to better analysis the network performance, researchers need a complex model to accurately forecast the network lifetime. It surely useful for hardware designers as energy consumption could be reduced at the physical layer, benefits can be obtained with lower radio duty cycles. Techniques aimed at reducing the idle mode leakage current in CMOS-based processors are also noteworthy.

3.1 Physical Models

Physical models, as tools to optimize a battery's physical parameters, have great utility for battery designers with great accuracy. However, to produce prediction results, physical models work slowly. The configurations of the model are complicated with limited analytical insight for system designers [46]. Fuller *et al.* [47] develop an isothermal electrochemical model that describes the charge and discharge of a lithium (anode)/polymer (electrolyte)/insertion (cathode) cell for a single cycle. This model derives a number of differential equations that provide cell potential values as a function of time by applying concentrated solution theory.

3.2 Empirical Models

Empirical models can produce wireless sensor battery lifetime prediction results quickly with easy configurations. However, the results are least accurate. These kinds of models attempt to capture non-ideal discharge behavior using relatively simple equations in which the parameters match empirical data [17]. Syracuse and Clark [48] use statistical methods to model the discharge behavior of lithium-oxyhalide cells and name the model a Weibull fit model. For a fixed load and temperature, they note battery voltage values at various stages of discharge. Then they involve three more coefficients to the voltage values to express voltage as a function of delivered capacity, or charge lost. They estimate the coefficients for different load/temperature combinations similarly, and model the coefficients' variation as a quadratic surface. They use a similar method to predict battery lifetime as a function of load and temperature. Pedram and Wu [49] develop a battery efficiency model to compute efficiency—the ratio of actual capacity to theoretical capacity—as a linear quadratic function of the load current. Bounds on the actual power consumed for different current distributions with the same average current are derived. They further approved that these bounds depend on the maximum and minimum current values. Their research show that with δ-function current distribution, a circuit with bi-modal current distribution exhausts the battery more rapidly compared to one with the same average current but a uni-modal operation. This conclusion is clearly showed in their table 1 and 2. By further look into each table, the battery lifetime, namely DOS, is longer if the discharge current is pulse profile compared to the uniform current profile. This model accounts for rate dependence and can handle variable loads. With minor modifications, researchers can apply that model to maximize the lifetime of multi-battery systems, to minimize the discharge delay product in an interleaved dual-battery system design, and in static task scheduling for real-time embedded systems. The two most important properties of a battery are its voltage (expressed in volts V) and its capacity (mostly expressed in Ampere-hour, Ah); the product of these two quantities gives the energy stored in the battery. For an ideal battery the voltage stays constant over time until the moment it is completely discharged, and then the voltage drops to zero [50]. The capacity in the ideal case is the same for every load for the battery. Reality is different, though: the voltage drops during discharge and the effectively perceived capacity is lower under a higher load.

In the ideal case it would be easy to calculate the lifetime of a battery [50]. The lifetime (L) in the case of a constant load is the capacity (C (A•h)) over the load current (I (Ampere))

$$L = \frac{C}{I}$$

This above relation cannot hold for real battery lifetime prediction because of various nonlinear effects. Therefore, a simple approximation for the lifetime under constant load can be made with Peukert's law [51]:

$$L = \frac{a}{I^b}$$

where a > 0 and b > 1 are constants that depend on the battery. This relation, however, does not hold for a variable load. Thus, by following Peukert’s law, all load profiles with the same average current would have the same lifetime. However, this prediction is experimentally examined and proved to be wrong because batteries can recover some capacity when the load is removed [50]. Due to the charge recovery process that takes place in the battery during the idle, research shows that battery efficiency can be improved by using a pulsed current discharge instead of a constant current discharge time periods [52]. This conclusion is in line with Pedram and Wu [49].

3.3 Abstract Models

Abstract models attempt to provide an equivalent representation of a battery instead of modeling discharge behavior either by describing the electrochemical processes in the cell or by empirical approximation [17]. To obtain battery lifetime prediction results, abstract models employ lookup tables that require considerable effort to configure. Abstract models have limited utility for automated design space exploration; and they lack of analytical expressions for many variables of interest.

The above models are compared based on their accuracy, computational complexity and configuration effort as shown in Table 1.

Table 1: Battery Models

Modeling Method	Accuracy	Computational Complexity	Configuration Effort
Physical models	most accurate	very complex and slow to yield results	hardest
Empirical models	least accurate	quickly produce predictions	easiest
Abstract models	acceptable accuracy	require much effort	hard

3.4 Other Models

Lahiri *et al.* [16] classify the analytical models, based on electrical circuits, stochastic and electrochemical techniques. The analytical models use algebraic expressions to calculate the residual capacity of the battery through current discharge and physical properties of the battery. Rong and Pedram [53] propose that a 30% error in predicting the battery capacity of a lithium-ion battery can result in up to 20% performance degradation for a dynamic voltage and frequency scaling algorithm. To solve the problem, they proposed an analytical model based on voltage, current, and physical parameters of the battery. However, more than fifteen physical parameters need to be configured to estimate the battery lifetime with a constant load current. Rao *et al.* [46] propose a Markov process-based stochastic model that uses probabilities as a function of battery physical characteristics for NiMH batteries. This model considers the electrochemical features during the battery discharge processes.

3.5 Remarks

WSN designers, while using traditional energy optimization approaches, tend to assume that a battery is in an ideal operation mode. In other words, it has a constant voltage throughout the discharge, and has a constant capacity for all discharge profiles. However, these assumptions are not valid. Panigrahi *et al.* [54] find that the energy delivered by a battery depends heavily on its discharge profile, and it is generally not possible to extract all of the energy that is stored in a battery. Therefore, it becomes necessary for the process scheduler of a battery-operated system to take the discharge profile and non-linearity of a battery into account for optimal performance. Such a task demands a fast and accurate battery model that can predict the total energy delivered by the battery depending on the discharge profile. Physical models can provide a detailed description of the physical processes occurring in a battery. It is the most accurate one among all available models. However, its configuration process is too complex. It also takes a long time to obtain calculation results through this model. Empirical models consist of ad-hoc equations describing battery behavior with parameters fit to match experimental data. It is considered as the least accurate model with the easiest configuration. This characteristic makes it work well in rough computation of battery lifetime. Abstract models represent a battery as electrical circuits, discrete-time equivalents, and stochastic process models. Their accuracy falls between the empirical and physical models. They need moderate configuration effort to obtain a result. They enable the analysis of the discharge behavior of the battery under different design choices [4].

4. FACTORS AFFECTING BATTERY DISCHARGE

A battery has a finite life due to the occurrence of chemical or physical changes to, or the loss of, the active materials of which they are made. These changes are usually irreversible and they affect the electrical performance of the cell. Meanwhile, other factors such as discharge rate, temperature, transmission power, and communication distances affect the lifetime [55]. This section describes the factors influencing battery life.

4.1 Chemical Changes

Batteries are electrochemical devices that convert chemical energy into electrical energy or vice versa by means of controlled chemical reactions between a set of active chemicals. Unfortunately the desired chemical reactions on which the battery depends are usually accompanied by unwanted chemical reactions that consume some of the active chemicals or impede their reactions. Even if the cell's active chemicals remain unaffected over time, cells can fail because of unwanted chemical or physical changes to the seals keeping the electrolyte in place. At low discharge currents, inactive reaction sites get uniformly distributed throughout the volume of the cathode. However, during intervals when the discharge current is large, the outer surface of the cathode is covered with inactive sites, making many internal active sites unreachable. These rate capacity effects lead to an overall reduction in battery capacity at higher rates of discharge [56].

4.2 Thermal Effects

The effect of ambient temperature on battery efficiency depends strongly on the specific battery chemistry. Performance of the battery is primarily dependent on how fast critical fuels, water, and hydroxyl ions can move and react in the battery. Maximum battery performance will not be achieved at cold or extremely hot temperatures. As the temperature decreases, usually a temperature below room temperature (around 25 ℃), chemical activity in the cell and full charge capacity decreases, and internal resistance and the slope of the discharge curve increases. This will result in a lower battery performance and shorter battery life cycle. Therefore, the general provision for optimal performance is to maintain the ambient temperature around 25 ℃.

4.3 Depth of Discharge

When current is drawn from the battery, positively charged ions are consumed at the cathode-electrolyte interface and are replaced by new ions that diffuse through the electrolyte from the anode. When the current drawn is sufficiently large, the rate of diffusion fails to keep up with the rate at which ions are consumed at the cathode. As a result, the concentration of positively charged ions decreases near the cathode and increases near the anode, degrading the battery’s output voltage. However, if the battery is allowed to idle for a period of time, the concentration gradient decreases (due to diffusion), leading to an apparent charge recovery. As a result, its capacity and lifetime increase [47].

5. NEW TECHNOLOGY FOR SENSOR ENERGY DEMANDS

Wireless sensors are mainly powered by batteries that need to be replaced when they are fully discharged. Thus, changing batteries becomes the largest and most expensive part for WSNs. Therefore, the typical power management goals for a battery-powered device are to minimize the energy consumption or to maximize the lifetime achieved while meeting required performance constraints. While many nodes in a WSN will be battery-powered, they can also be powered by energy scavenged from the surroundings. Energy sources that are being considered to power nodes include light, vibrations, acoustics, and thermal sources. A detailed comparison of these technologies is given by [38]. Table 2 compares the power generation potential of some energy harvesting techniques. Among them, solar energy harvesting through photovoltaic conversion and vibration energy harvesting through piezoelectric elements provide the highest power densities. This fact makes them the options of choice to power WSNs that consume power on the order of several mW. Nodes powered by such a source can process data, and receive and transmit packets without consuming battery energy. However, the design of an efficient energy harvesting module involves complex tradeoffs due to the interaction of several factors such as the characteristics of the energy sources, chemistry and capacity of the energy storage device(s) used, power supply requirements, power management features of the embedded system, and application behavior. It is therefore essential to thoroughly understand and judiciously exploit these factors to maximize the energy efficiency of the harvesting modules. Moreover, the power output from these natural sources is highly nonlinear in nature and depends upon a variety of factors. Harvesting energy for low-power (and possibly embedded) devices like wireless sensors presents a new challenge as the energy harvesting device has to be comparable in size (i.e., small) to the sensor nodes.

Table 2: Power densities of energy harvesting technologies [1]

Harvesting technology	Power density
Solar cells (outdoors at noon)	15 mW/cm^2
Vibration energy through Piezoelectric (shoe inserts)	330 $\mu W/cm^2$
Vibration (small microwave oven)	116 $\mu W/cm^2$
Thermoelectric (10^oC gradient)	40 $\mu W/cm^2$

5.1 Solar power

Solar power is the most common and mature technology among the different forms used for energy harvesting. A complete energy harvester must include a transducer, an energy conditioning unit, and an energy storage unit. Solar energy harvesters offer a large variety of transducers, but only a few solar battery chargers are designed for sensor nodes. From Table 2, it is clear that solar energy is the most efficient natural energy source available for WSNs used for outdoor applications. For indoor applications, however, photovoltaics (PV’s) are able to generate energy only when there is sufficient sunlight or artificial light. A system [57] has been developed to address the needs of WSNs deployed in indoor environments (e.g., hospital and industrial) where lights are operational at close to 100% duty cycle. Several distinguishing factors in designing PV-powered WSNs are identified including the use of hardware or software, battery protection, different storage technologies, and the design of solar powered platforms. Many factors can affect PV-based WSNs, such as dynamic duty cycle adjustment to match sensor operation to available power, the use of a two-stage energy storage to reduce the number of charge-discharge cycles, photo cell output point matching, and dynamic adjustment of the cell inclination angle to increase incident light. Jeong *et al.* [58] conduct empirical and mathematical analysis of two micro-solar power systems, i.e., Trio [59] and Heliomote [60]. These two platforms are identified as leading examples of different approaches in designing PV-based WSNs. More advanced power supply sources for wireless sensors combine the PV and traditional battery, which maximize the WSNs’ lifetime, are proposed in [61]. Under this circumstance, rechargeable batteries are shallow discharged, and may be continuously charged when the sun light is available. Consequently, the resulting WSNs can sustain their life for much longer time than traditional ones.

5.2 Mechanical

Vibrational, kinetic, and mechanical energy generated by movements of objects can also be harvested. Vibration harvesting seems the most active area and an increasing number of devices are becoming available. Vibrations are present all around us and are especially prominent in bridges, roads, and rail tracks, with frequencies typically ranging from 20 Hz to 150 Hz. Some vibration harvesters are complete energy harvesters, but others lack storage or even alternative current (ac)/direct current (dc) conversion. One device that includes the energy conditioning and storage units for any kind of energy transducer has also been marketed [62]. The storage unit is only intended for short-term supply. One method of harvesting vibrational energy is through the use of a piezoelectric crystal. In [63], a vibration harvesting micro-power generator is used to scavenge environmental vibrations for use in a sensor node. Traffic sensors can also be solely powered by the short duration vibrations when a vehicle passes over the sensor [64]. Experimental results have shown that when a piezoelectric pushbutton is depressed, sufficient energy is harvested to transmit two complete 12-bit packages of information wirelessly [65]. Similarly, a system that harvests energy from the forces exerted on a shoe during walking has been demonstrated [66] and indoor locations, like staircases, are potential locations to harvest vibrational energy for powering wireless environmental sensors, as shown in [67].

5.3 Thermal

Thermal energy harvesting uses temperature differences or gradients (e.g., between the human body and the surrounding environment) to generate electricity via the thermoelectric effect. Thermal harvesters include only the energy transducer; the energy conditioning and storage blocks must be externally added. Devices with direct contact to the human body can harvest the energy radiated from the human body by means of thermo-generators [68]. To address the needs of telecommunications and other embedded applications, micro-structured thermoelectric devices have been designed [69]. Due to the lack of moving parts in thermal energy harvesting devices, they tend to last longer than vibration-based ones.

5.4 Remarks

For short lifetime, batteries are a reasonable solution. However, for long lifetime, energy scavenging should be taken into account. Energy harvesting devices are becoming commercially available. The EnOcean Alliance [70], a consortium of over 60 companies, was formed to promote WSNs powered by scavenged power sources previously mentioned. Energy scavengers using small photovoltaic PV modules have been recently proposed to enable perpetual operation of WSNs. A solar energy harvesting development kit [71] can be used to create solar-powered WSNs. WSNs for outdoor environmental monitoring are a class of systems where solar-powered battery is the most appropriate. Energy harvesting techniques can solve the problem by supplying and converting energy from the surrounding environment and refilling an energy buffer formed by a battery stack or by super capacitors. Unfortunately the low energy budget available does not help to perform an efficient replenishment of the storage devices. Indoor solar sensors are frequently employed to manage lighting levels. However, they are much less useful for powering wireless devices, since the power available from indoor lighting is typically at the level of 10 to 100 $\mu W/cm^2$, and its usefulness depends in part on the spectral composition of the light. In dim office lighting, or areas with no light, they are inadequate to provide a reliable power source. Thus, if adequate light energy is available in the environment in which the node will operate, solar cells offer an attractive solution. If the projected lifetime is more than a few years, and sufficient light energy is not always available, vibration conversion can be an alternative. Low-level mechanical vibrations are available in many environments, and therefore, have a potentially wider application domain than some of the other sources. They can occur in common household and office environments as a potential power source. The potential power available from their conversion is enough to be of use. Vibration-based energy harvesters that can replace batteries and be used to power WSN nodes are commercially available [62]. Power scavenged from thermal gradients is also of interest if the necessary thermal gradients are available. It is, however, difficult to find high enough, e.g., greater than a 10 ℃ thermal gradient in a volume of 1 cm^3. WSNs that are powered by ambient energy harvesting are promising for many sensing applications as they eliminate the need to replace batteries. It is a hot topic to study how power needs in a WSN can be met completely by harvested power due to the dependence upon many environmental and operational factors. Recently, hybrid power supply system becomes available and ready to be applied to WSN. These systems can provide a backup power supply source, thus prolong the entire network lifetime [61].

6. CONCLUSIONS

An effort has been made to give an overview of power supply issues for WSNs in this paper. Since most wireless sensors utilize attached finite-capacity energy sources as direct power supplies, the energy budgets become very limited, and efficient energy utilization becomes one of the key points in the context of battery-powered embedded networks. A variety of battery models are compared and analyzed in this paper as a mathematical model can act as an analytical tool to roughly tell the lifetime and discharge characteristics of the battery, and can further help in choosing/designing proper power sources for WSNs. A more accurate model needs to combine possible effects from both battery chemical reaction features and wireless sensor work load in general. In real applications, batteries typically last for a shorter period of time compared to the mathematical model prediction result. Therefore, this work has surveyed other important factors that also play important roles in the battery lifetime of WSNs. These research results can help people design energy-aware communication protocols to save overall WSN energy consumption. Increasing interest has been shown in energy harvesting techniques for WSNs as alternative to primary batteries. Multiple options to power wireless sensors from the environmental energy harvesting are available. Thus, new alternative battery and energy technologies can lead to replacement of traditional batteries in powering WSNs. More research and applications are expected to emerge.

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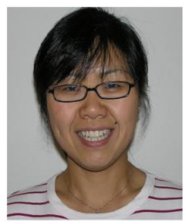

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