Wireless Sensor Networks – Energy Perspective with Compressive Sensing

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***Abstract*— Wireless sensor networks are getting more importance with the technological progression of all realms of life. The critical issue of energy expenditure and management of wireless sensor networks (WSNs) has been discussed in this paper. Together with the normal procedures for saving the energy by using renewable energy sources, the study talks over the use of compressive sensing (CS) framework in WSNs to increase the energy efficiency. The energy efficient performance of different CS algorithms are discussed with necessary estimations. It is clear that for a sufficiently sparse sensor signal, a substantial amount of energy can be hold back by using CS methods.**

Keywords*— *Sensor Network, Renewable Energy, Compressive Sensing, Sparsity, Efficiency

I. INTRODUCTION

Wireless Sensor Networks became an inexorable part of daily life, possessing amazing potential aimed at numerous applications. A WSN comprises of low-energy and low-cost, tiny sensor nodes. They cooperatively observe physical parameters and regulate actuators. A network may consists of thousands of randomly deployed self-configurable nodes that operate autonomously in interaction with surroundings to form a multi-hop topology. They implement sensing, computation, communication and actuating. Figure 1 is an overview of various WSNs showing their immense potential for diverse applications.

Along with the rise in popularity of WSNs, the design and implementation challenges also show an intense upsurge. Recently, because of wide applications, potential and distinctive challenges, WSNs became a broiling research arena. The crucial organizational challenges of the WSNs are data reduction, energy efficiency, stability and prolonged lifetime. The battery capacities of nodes are limited and replacement is impractical. Considering WSNs, energy efficiency issue is very severe at both sensor node level and the network infrastructure level. The sensors basically become useless without energy and they cannot be added to the utility of WSN. Typically WSNs are having limited power storage capabilities. The proper WSN design should consider effectual management of the existing energy and possibility of the addition of some energy harvesting methods. But because of the dense arrangement of sensor modules at harsh environment and due to limitations in hardware, computation and communication requirements, a compromise in the energy expenditure plan has been made. WSNs' energy management concerns with three fundamental aspects. They are energy harvesting, storage of harvested energy and controlling of energy consumption. The paper deals with these three aspects. The first part of the paper describes the optimization of the networks with the application of various renewable energy harvesting sources. A detailed study is conducted on the existing energy harvesting sources and the storage technologies, which are applicable to the WSNs' arena. The second part explains the controlling of energy consumption and energy saving with the new concept of Compressive Sensing (CS). The energy expenditure can be reduced by decreasing the processing, communication and storage overheads with CS concept.

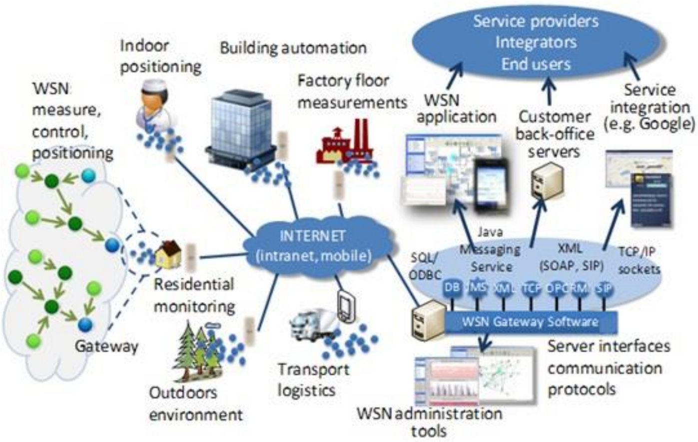

Fig. 1. Overview of WSNs

II. ENERGY HARVESTING WITH RENEWABLE ENERGY RESOURCES

There are numerous methods available to harvest various energies in the ambient environment. The effective and efficient application of proper method or a combination of suitable methods can serve the power hungry WSN nodes for a long life. This involves two steps. They are the selection of proper renewable energy source and the selection of proper energy storage technology. The key sources of ambient energy suitable for use with WSNs are solar, mechanical, thermal, acoustic, dynamic fluids and magnetic energy.

A. Solar Energy

Solar power is the matured and most common form of the renewable sources of energy. In a solar system, solar cells transform sunlight to electrical power as per the photovoltaic principle [1]. Depending on the materials used, solar cells can be of four categories. They are silicon solar batteries, polymer solar batteries (PPVC), multi-compound solar cells and nano-crystalline solar cells. The silicon solar batteries are more popular among these and they possess the principal share in production and market. The proficiency of solar cells depends on several factors like solar insolation, seasonal effects, snow cover and dense cloud periods, elevation and latitude, shadow by obstructions, installed position and angle of solar panel, energy conditioning capability, characteristics of cells and the chemistry and capacity of energy storage components [2].The efficiency comparison of various categories is depicted in Table 1.

TABLE I. SOLAR CELLS - EFFICIENCY COMPARISON

Type	Efficiency
Silicon solar batteries	Up to 24%
Multi-compound solar cells	Up to 30%
Polymer solar batteries (PPVC)	Below 5%
Nanocrystalline solar cells	More than 10%

B. Mechanical Energy

When an object is imperiled to any movement or mechanical deformation, mechanical energy is generated. This can be transformed to electrical form by different methods like electrostatic, electromagnetic and piezoelectric conversion [3]. The vibration is the chief rampant energy source available in many environments like bridges, buildings, vehicles, roads, ships, and even in human or animals as blood current and body pulse. The common vibration frequency range is 60Hz-200Hz

1) Electrostatic (Capacitive) Energy Harvesting: This system produces voltage by varying capacitance. There should apply an initial voltage to the capacitance, before outputting the energy from the system, [4]. Then by the external vibrations, the charge quantity in the capacitor will change, which generates a charge flow in the circuit, by providing electrical power to the sensors.

2) Electromagnetic Energy Harvesting: This is centered on the principle of electromagnetic induction. The parameters important in this harvesting are magnetic induction, coercive force and magnetic flux density. Four common types of magnets are used in the system. They are ceramic, Alnico, SmCo and NdFeB. NdFeB is the more common material as it possess the highest magnetic field intensity and large coercive force. It will not undergo any demagnetization with the generator vibration. The extracted power is related with electromagnetic damping. This damping depends on coil turns, flux gradient, load impedance and coil impedance. All these parameters are connected with the size. [5]. By sputtering, electroplating and through other deposition technologies, the micro-magnets can be fabricated.

3) Piezoelectric Energy Harvesters: When subjected to pressure, piezoelectric materials generate electricity [6].The piezoelectric harvesting technology utilizes this inherent property. Major Piezoelectric materials include piezoelectric mono-crystal, piezoelectric polymers, piezoelectric composites and piezoelectric ceramics. Among these, piezoelectric ceramic PZT is used commonly in the generators. For better performance and improved efficiency, the piezoelectric materials should possess greater electromechanical coupling coefficient, low loss and high piezoelectric constant strain.

C. Thermal Energy

There exist numerous ambient heat sources around us, like geo-thermal [7], engine exhaust, industrial waste heat, the heat of sun etc. Thermoelectric energy harvesting system utilizes the temperature gradient between the two ends of semiconductor PN junction to generate power. Thermoelectric materials exhibit mainly three temperature-dependent properties: thermal conductivity, electrical conductivity and Seebeck coefficient [8]. The generated voltage in thermoelectric generators (TEGs) is proportionate with temperature difference and the quantity of thermoelectric elements.

D. Dynamic Fluid Energy

Dynamic fluid energy comprises flowing water and wind power. The fluid's kinetic energy is transformed to electrical form by two approaches. The first method is by using mechanical parts like micro turbine systems. The second method employs non-mechanical parts, similar to mechanical energy harvesting techniques. Here the flowing wind or water brings mechanical vibration which is transformed to electrical energy by electromagnetic [9], piezoelectric [10, 11] or electrostatic principles [12].

1) Micro Wind Harvester: The forced convection or ambient air flow [13] is utilized for energy harvesting for WSNs in outdoor, inaccessible or remote locations [14]. The wind harvesting methods include electromagnetic wind generators, piezoelectric wind harvesters, micro wind turbines and micro wind belt generators.

2) Flowing Water Energy Harvesting: The kinetic energy of the water flow due to the fluctuating water pressure, is rehabilitated to electrical form by energy harvesters [15]

E. Acoustic Energy

Spreading of the sound waves on an object surface, causes the object vibration. This acoustic energy is harvested to electrical energy. The existing acoustic power spectrum comprises the transverse, longitudinal, bending, shears or hydrostatic waves. The major components of acoustic harvesting system contains a mechanical power spectrum input, a proper acoustic impedance matching, a biased piezoelectric transducers for energy conversion from mechanical to electrical form and a matched electrical load [16]. The power contained by acoustic energy is huge for high decibel levels.

F. *Magnetic Energy*

The magnetic energy, an inexhaustible and renewable power source, is ubiquitous on the earth. The magnetic effect of electric current is utilized to produce magnetic energy for delivering to wireless sensors. A changing magnetic field is produced around the power lines while transmitting alternating current.

III. BATTERY TECHNOLOGIES IN WSNS

Even though technologies are trying hard for scaling down weight and size of sensor networks' batteries, batteries remains still as a significant fraction of total weight and size of nodes. As size and energy storing capacity are strictly related, batteries are pigeonholed by power and energy densities. Energy density designates the amount of energy stowed in a region of space or given system per unit volume. Power density represents extent of unit volume power. Ragone plot in Figure 2 relates performances of various electrochemical devices. It shows that ultra-capacitors deliver high power, but with limited storage capacity. However Fuel Cells store large energy, but have a comparatively low output power.

Relative time taken for charging in or draining out is indicated with sloping lines in Ragone plots. Lithium batteries have reasonable time for this. An ideal energy reservoir must provide high power and energy densities. But usually batteries feature ample energy density, but inadequate power density. The three traditionally used main WSNs technologies are Nickel Metal Hydride (NiMH), Lithium and Alkaline batteries. In practice, single sort of storage element cannot simultaneously fulfil all favoured characteristics of a perfect energy storage system. Hence a hybrid solution is much efficient and preferred to overcome the bounds of single power reservoir.

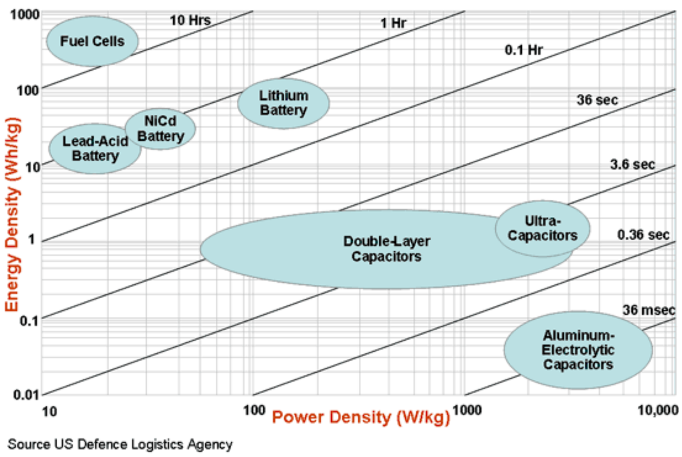

Fig. 2. Ragone Plot – Comparison of Battery Technologies

IV. CONTROLLING THE ENERGY CONSUMPTION

Here the general energy requirement of the WSNs is estimated during the normal signal processing activities. The method of CS is employed to save the energy. How to achieve energy saving in WSNs with CS is explained in this section.

A. *Sensor Networks - Energy Estimate*

The energy expended by a sensor module is approximated as the sum of the energies used for sensing, computation and communication. Here the operational energies during one sampling period are focused. The energy for communication - Ecomn, is the key constituent of the operational energies in WSNs. The main components of Ecomn are sleeping, listening, transmission, reception and switching energy.

The total energy in Nyquist measurement (conventional sampling) with N number of samples, E_{totN} can be expressed with Equation 1

$$E_{totN} = Esensing + Ecomp + Ecomn \qquad (1)$$

Esensing is the energy for sensing and Ecomp is the computational energy required [17] [18].

Some of the prevailing techniques for energy management are listed below

- Usage of alternative sources of energy like piezo, solar, thermal etc. to cater these the sensor nodes which are having limited power supply.
- Equip with rechargeable power units to enable greater flexibility for the nodes.
- Optimize the transmission medium like optical medium, which support less power consumption.
- Putting the power supply to sleep mode when not in use and using the sensors with zero stand-by power.
- Reduce the computational requirements to maximum possible limits
- The communication of a module with its neighboring nodes and base station should be optimized to lessen the power consumption including transmission and reception power, communication rate, medium of communication, type of modulation etc.
- Design of power aware and application specific protocols and algorithms, which will have the consideration of obtaining high level for performance parameters, maintaining power efficiency.
- Optimizing the transceiver efficiency to obtain trade-off between the power consumption and antenna efficiency.
- Effective use of sleep mode for the communication unit to curtail the power consumption

B. *Relevance of CS in Signal Processing*

In a normal sensor network, the entire scenario of signal processing starts with the initial step of sampling. Here the analog signal will be converted in to the digital format by taking samples of the signal. The sampling theorem governs the process, which needs a sampling rate of twice the maximum frequency of the signal to have an effective rebuilding of the input signal known as the Nyquist rate [19], [20]. As the sensed signals are generally sparse, this rate is too high and creates huge data which makes overheads in processing, communication and storage. Most of this data will be thrown out after the transform coding stage. Managing this high volume of data needs more energy in sensing, computation and communication. So one of the practical way to lessen the energy expenditure is to decrease the managing data volume by adopting to some kind of sub-Nyquist sampling technique. The CS can play a vital role for this.

Compressive sensing present a state-of-the-art scheme to capture compressible signals at a very low rate which is well below the rate specified by Sampling Theorem. This technique employs non-adaptive and linear projections which can conserve the structure of the sparse signal. Using various reconstruction algorithms, through an optimization process, the original signal will be regenerated from these projections [21] [22]. The idea of CS relays on the sparsity concept. The signal is considered sparse if it has only a limited non-zero values in comparison with its overall length [23]. For sparse data, only these non-zero coefficients need to be stored or transmitted in many cases; the rest can be assumed to be zero. A signal x is K-sparse when it has at most K non-zeros. Sparse signal models of this kind can achieve higher levels of compression. For CS, if the initial signal is sparse in a known frame, the same signal can be recovered from a smaller number of compressive measurements [24].

C. Estimation of Energy Expenditure with CS

In this study, the estimation of the energy disbursed by a sensor module during CS measurement in a sampling period is calculated and it is compared with a normal Nyquist measurement. The analysis is performed with some of the major reconstruction algorithms. They are Basis Pursuit (BP),Orthogonal Matching Pursuit (OMP), Compressive Sampling Matching Pursuit (CoSaMP), Subspace Pursuit (SP), Belief Propagation (BPn), Expander Matching Pursuit (EMP) and Sparse Matching Pursuit (SMP) [25] [26] [27] [28] [29]. At the first step, the number of compressive measurements (M) required for CS reconstruction is calculated for each algorithm for different values of sparsity (K). Here the sample Nyquist rate (N) is taken as 100. The estimated values are listed in table 2. In CS, the sensor node measures only M measurements. This M is lower than N as it is a subset of the later. As per CS theory, M will be very low if signal is having high sparsity (value of K should be low).Using this value, the energy saving can be estimated.

TABLE II. M FOR DIFFERENT K VALUES

Algorithm	Equation for M	For K=5	For K=10	For K=20	For K=30
BP	K log N	23	46	92	139
OMP	K log N	23	46	92	139
CoSaMP	K log N	23	46	92	139
SP	K log N/K	15	23	33	37
EMP	K log N/K	15	23	33	37
SMP	K log N/K	15	23	33	37
BPn	K log N	23	46	92	139

The energy used up in a sensor module will be the sum of the energies used for sensing, communication and computation [30]. N −M measurements, computations and communications can be kept back in the process, if CS method is adopted. So the total energy savings in Compressive Sensing (E_{CS}) can be approximated with Equation (2)

$$E_{CS} \approx (N - M)(E_{sensing} + E_{comp} + E_{comn}) \quad (2)$$

D. Results

The energy saving factor is (N-M)/N, which is the fraction of energy saved with CS method compared with Nyquist method for a single node. The energy savings factor (N-M)/N is calculated for different recovery algorithms with a fixed sparsity and N value – 100 and expressed in percentage. Table 3 and Figure 3 shows the percentage saving in total energy for different K values for the testing algorithms.

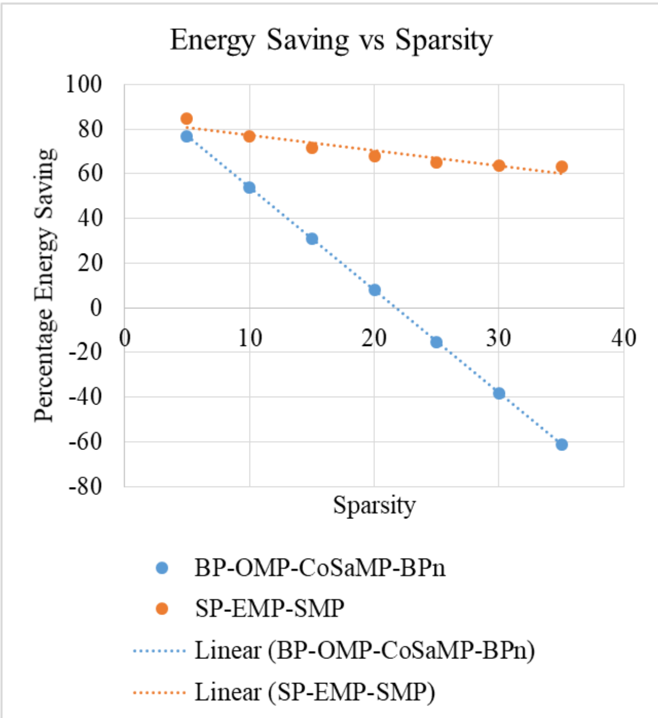

Fig. 3. The Percentage Energy Saving for Different Sparsity Values

TABLE III. M FOR DIFFERENT K VALUES

Algorithm	Percentage Saving in Energy for Different Sparsity (K)						
	K=5	K=10	K=15	K=20	K=25	K=30	K=35
BP	77	54	30.9	8	-15.1	-38.2	-61.2
OMP	77	54	30.9	8	-15.1	-38.2	-61.2
CoSaMP	77	54	30.9	8	-15.1	-38.2	-61.2
BPn	77	54	30.9	8	-15.1	-38.2	-61.2
SP	85	77	71.5	68	65.3	63.9	63.3
EMP	85	77	71.5	68	65.3	63.9	63.3
SMP	85	77	71.5	68	65.3	63.9	63.3

V. ANALYSIS AND DISCUSSIONS

The analysis and discussion is divided in to two sections. The first section deals with the renewable energy sources and the second section deals with energy consumption controlling with CS.

A. *Energy Harvesting Methods*

The renewable energy harvesting methods will replace the batteries in future to realize the independent power supply of the wireless sensor nodes. In addition, there are some other advantages in employing them like noise reduction, elimination of cross-talks,etc. All these power sources are renewable, clean, and available limitlessly in the environment. Table 4 shows comparison of the power density for different renewable energy sources. Solar energy generates comparatively higher power.

TABLE IV. POWER DENSITY COMPARISON FOR DIFFERENT SOURCES

Harvesting Method	Power Density (/cm3)
Solar Energy (Outdoor – Bright Day)	15mW
Solar Energy (Outdoor – Cloudy Day)	0.15mW
Solar Energy (Indoor)	10-100µW
Vibrations (Piezoelectric)	330µW
Vibrations (Electrostatic Conversion)	0.021µW (105 Hz)
Vibrations (Electromagnetic Conversion)	306 µW(52 Hz)
Thermoelectric (5 ° C Gradient)	40 µW
Wind Flow	16.2 µW (5m/s)
Acoustic Noise	960nW-100dB
Magnetic Field Energy	130 µW - 200 µT, 60 Hz

But these methods are having some limitations also. They have low conversion efficiency and power output as evident from table 4. Most of the energy sources are not stable. There should be enough ambient energy to ensure continuous operation of the device. When compared with the cost of batteries, the micro-power generators are costly. The size of the system should be reduced to maximum level to match with sensor nodes to adapt with different applications. The energy harvested from a single method is normally small and extremely unstable with working conditions, time and location. Generally, many different available energy sources exists simultaneously in the harvesting environment. So integration of different types of energy harvesting modules for one sensor node is advisable to guarantee a stable flow of necessary energy from environment.

B. *Energy Consumption Control*

Based on the value of M, the selected algorithms can be divided in to two groups for the sake of analysis. Group one consists of BP, OMP, CoSaMP and BPn. Group two have SP, SMP and EMP. From Figure 3 and Table 3, it can be clearly observed that as K increases, the saving of energy decreases for both classes. For group 1 algorithms, the energy saving performance is higher at low value of sparsity. When K =5, the saving in energy is 77%. But when K=10, the energy saving shows a considerable declining and the value is 54. For K=20, the energy saving is very low. It is only 8%.

For group 2 algorithms, the decrease in E_{CS} is lesser compared to group 1. When the K value increases to more than 20, the compression performance of the group 1 algorithms is reversed and it became negative value. This negative value indicates that the M is greater than Nyquist rate (M>N). The energy expenditure needed for this will be more than that needed for Nyquist rate measurements. So group 2 algorithms are more efficient than others. It is because of the fact that their M values are low. The algorithms with low M values are better than others as they need lesser measurements for reconstruction. Even at fairly high value of K, they exhibit compression and subsequent reduction in energy expenditure.

If CS is instigated for multiple nodes, then this needs to multiply with hop counts compared to baseline non-compression-based N communications. Applying this approach at the multi-node level, N^2-MN communications can be saved compared with baseline N^2 communications. Here M is the sampling nodes out of N available nodes. These savings come at the cost of additional computational energy cost in obtaining the measurement matrix, which is normally neglected, being very small.

VI. CONCLUSION

Energy management is a vast topic and will continue to be a critical issue for WSNs. In this paper, two different methods for optimizing energy usage were examined - usage of renewable energy harvesting methods and reducing the energy usage. The growing energy requirements for WSNs can be satisfied to a certain extent with the latest battery technologies and renewable energy sources. These sources offer great advantages over the conventional methods. But still most of the technologies are in the primitive stages only. It require proper integration of different harvesting sources to ensure the uninterrupted power for WSNs. Along with this, the reduction of the processing data can contribute considerably to the saving of energy. From the study, when the number of measurements are reduced due to CS, there can be considerable reduction in energy expenditure. For low values of sparsity (for highly sparse signals), the percentage saving in energy will be maximum. So for the same sensor network, keeping all the network elements same, the consumed energy will be decreased considerably by using CS framework. Subsequently the battery life, battery replacement cost, hardware life etc. will be having advantages. So by applying CS techniques in sensor networks, the energy expenditure can be managed effectively. There are other factors like routing and access control protocols, localization, time synchronization, coverage control, duty cycle scheduling: incremental activation, which influences the energy management, which are not considered directly in this paper. But all the effect of these factors will be decreased by the reduction of data using the CS technique.

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