Volume 4, Issue 3, March 2014 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Energy Efficiency in Wireless Sensor Network: A Review

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Abstract — In wireless sensor networks (WSNs) improving the lifetime of is directly related to the energy efficiency of computation and communication operations in the sensor nodes. Compressive sensing (CS) theory suggests a new way of sensing the signal with a much lower number of linear measurements as compared to the conventional case provided that the underlying signal is sparse. This result has implications on WSN energy efficiency and prolonging network lifetime. In this paper, the effects of acquiring, processing, and communicating CS-based measurements on WSN lifetime are analyzed in comparison to conventional approaches. the energy dissipation characteristics of WSNs utilizing the concepts of compressive sensing is investigated and compared to two other well known conventional approaches (DANP and DATC). Our results show that compressive sensing prolongs network lifetime significantly in comparison to conventional approaches provided that the acquired signals are highly sparse (e.g., $K/N \leq 0.10$) and node density in the network is not too low (e.g., $Rnet \leq 150$ m and $\zeta = 50$).

Keywords— Compressive sensing (CS), energy efficiency, mixed integer programming, network lifetime, wireless sensor networks (WSN

I. Introduction

A wireless sensor network is a network which consists of a number of sensor nodes that are wirelessly connected to each other. These small, low-cost, low-power and multifunctional sensor nodes can communicate in short distances. Sensor nodes consist of sensing, data processing, and communication components. Large number of these sensor nodes collaborated forms a wireless sensor networks [1].A WSN usually consists of tens to thousands of such nodes that communicate through wireless channels for information sharing and cooperative processing. To ensure scalability and to increase the efficiency of the network operations sensor nodes are often grouped into clusters [2] [3].
The sensors must be placed in exact locations since there are a limited number of nodes extracting information from the environment. The deployment of these nodes and cables is costly and awkward requiring helicopters to transport the system and bulldozers to ensure the sensors can be placed in exact positions. There would be large economic and environmental gains if these large, bulky, expensive macro-sensor nodes could be replaced with hundreds of cheap micro-sensor nodes that can be easily deployed. This would save significant costs in the nodes themselves as well as in the deployment of these nodes. These micro-sensor networks would be fault-tolerant as their sheer number of nodes can ensure that there is enough redundancy in data acquisition that not all nodes need to be functional. By using wireless communication between the nodes would eliminate the need for a fixed infrastructure.
Wireless micro-sensor networks represent a new paradigm for extracting data from the environment. The conventional systems use large expensive macro-sensors that are often wired directly to an end-user and need to be accurately placed to obtain the data. Like the oil industry uses large arrays of geophone sensors attached to huge cables to perform seismic exploration for oil. These sensor nodes are very expensive and require large amounts of energy for operation. The most difficult resource constraint to meet is power consumption in wireless sensor networks. The use of wireless sensor networks is increasing day by day and at the same time it faces the problem of energy constraints in terms of limited battery lifetime. As each node depends on energy for its activities, this has become a major issue in wireless sensor networks. Failure of one node can interrupt the entire system or application. Every sensing node can be in active, idle and sleep modes. In active mode, nodes consume energy when receiving or transmitting data. In idle mode, the nodes consume almost the same amount of energy as in active mode. While in sleep mode, the nodes shutdown the radio to save the energy. Energy constraints end up creating computational and storage limitations that lead to a new set of architectural issues. A wireless sensor network platform must provide application. Support for a suite of application-specific protocols that drastically reduce node size, cost, and power consumption for their target applications.

Following steps can be taken to save energy which is caused by communication in wireless sensor networks.
- To schedule the state of the nodes (i.e. transmitting, receiving, idle or sleep).
- By changing the transmission range between the sensing nodes.
- Using efficient routing and data collecting methods.
- Avoiding the handling of unwanted data in the case of overhearing.

In WSNs, the only source of life for the nodes is the battery. Communicating with other nodes or sensing activities consumes a lot of energy in processing the data and transmitting the collected data to the sink. In many cases (e.g.

surveillance applications), it is undesirable to replace the batteries that are depleted or drained of energy [4]. Many researchers are therefore trying to find energy-aware protocols for wireless sensor networks in order to overcome such energy efficiency problems as those stated above.

All the protocols that are designed and implemented in WSNs should provide some real-time support as they are applied in areas where data is sensed, processed and transmitted based on an event that leads to an immediate action. A protocol is said to have real-time support if and only if, it is fast and reliable in its reactions to the changes prevailing in the network. It should provide redundant data to the base station. The base station or sink using the data that is collected among all the sensing nodes in the network. The delay in transmission of data to the sink from the sensing nodes should be small, which leads to a fast response.

II. Compressive Sensing in WSN

Wireless Sensor Networks (WSNs) are comprised of spatially distributed sensor nodes, where each node contains units for sensing, processing, and communicating data. In general, sensor nodes are assumed to have limited processing power and highly constrained energy resources. A typical WSN topology includes a base station - a powerful entity more capable than the ordinary sensor nodes with a significantly higher energy budget. Ordinary sensor nodes transfer processed or raw sensed data to the base station, which performs the final information aggregation and extraction tasks. In conventional signal processing techniques for true reconstruction at the base station, ordinary sensor nodes sample data at the Nyquist rate, generating raw measurements of the signal. Depending on the sophistication of the sensor, the signal can be transformed to a new domain where most of the signal energy can be represented by a small number of coefficients (*i.e.*, the signal is compressible or sparse). Later these coefficients and their locations are encoded and then transmitted to the base station. Alternatively, each sensor node can also transmit its raw measurements to the base station without any processing. For example, in an image acquisition operation, the sensor first acquires raw data, which corresponds to measuring each pixel value. If the image is compressible in discrete cosine transform (DCT) space, the raw image can be transformed to the DCT domain.

In this way only a small number of DCT coefficients and their locations are saved. These coefficients constitute most of the energy in the image. The rest of the coefficients are discarded without deteriorating the perceived quality of the image significantly. Either the raw image pixels or the DCT coefficients may be transmitted depending on the selected technique. Apart from these conventional techniques, the theory of Compressive Sensing (CS) proposes a novel signal acquisition and recovery method. Briefly, CS theory states that if a signal is sparse or compressible in a certain basis, then it can be reconstructed from a smaller number of linear measurements in comparison to the conventional case by solving a 1 based convex optimization problem. The required numbers of measurements are linearly related to the underlying signal sparsity level. An example image reconstruction result is presented in. Using CS for WSN applications, the sensor nodes can directly acquire a small number of measurements as linear projections of the raw signal and directly transmit these CS measurements to the base station without any further processing in the sensor node. In this way, the signal can be acquired at its information rate and data is compressed while being sensed. This technique also eliminates the need to acquire data that is discarded after doing the transform coding.

Although CS needs to transmit much less data compared to transmitting the whole raw data, it actually transmits more measurements as compared to the transform coding case. Hence, using a fair energy dissipation model (including both communication and computation energy costs), a comparison between conventional and CS based techniques can be performed to understand the conditions under which CS can improve energy efficiency, and enable longer lifetimes for WSNs.

In conventional signal processing, a sensor acquires the signal at least at its Nyquist rate for proper reconstruction. Let's represent this acquired discrete signal as one dimensional vector x ∈ RN. Any vector in RN can be represented as a linear combination of basis vectors as

x= x=

where ψ is the basis matrix with i th column ψi . The signal x is called K-sparse if only K of the coefficients in transform domain vector s is nonzero. The compressibility of most practical signals is the basic point for transform coding. A wireless sensor node, depending on its sophistication, can either transmit all N measurements without any processing or it can transform the signal to a new domain where it can be represented with K _ N coefficients. In transform coding, the full signal x ∈ RN is acquired; all transform coefficients are calculated by s = _T x; the largest K coefficients are located and the rest are discarded. Finally, only the largest K coefficients and their locations are encoded and transmitted

III. Proposed Methodology

Improving lifetime is directly related to Energy efficiency which is the most required quality in a sensor network where each node consumes some energy with each transmission over the network. The proposed work defined the same direction to improve the network life. This work is about to perform the energy effective routing so that the network life and network throughput will be improved.

In this work the effects of acquiring, processing, and communicating Compressive Sensing-based measurements on WSN lifetime are analyzed in comparison to conventional approaches. The energy dissipation models for both CS and conventional approaches are built and used to construct a mixed integer programming framework that jointly captures the energy costs for computation and communication for both CS and conventional approaches. The numerical analysis is performed by systematically sampling the parameter space (i.e., sparsity levels, network radius and number of nodes).

The problem taken for this research work is divided into some objectives which are as follows.

- Study of Wireless Sensor Network.
- Study of different energy efficient protocols in WSN.
- To minimize the energy consumption of sensors.
- To improve network lifetime and network throughput.

The proposed model of the work is shown below:

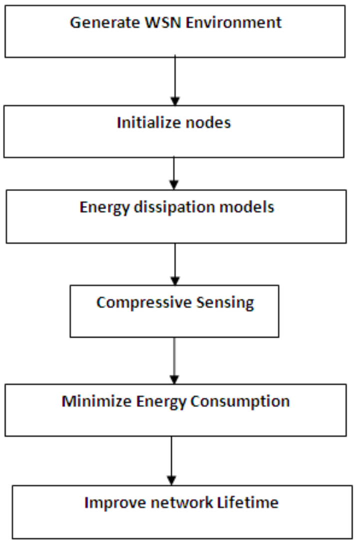

Figure 1: Basic Model

IV. Simulation setup

We implemented our programs based on the MATLAB. Nodes were generated randomly at random position. Nodes were generated at random time as if few nodes were entering into the topology.

Node Characteristics:

1. Link Layer Type: Logical Link type (LL)
2. MAC type: 802_11
3. Network Interface type: wireless
5. Channel type: wireless

To evaluate and compare the effectiveness of the Compressive sensing and Conventional schemes in Wireless Sensor network, we performed extensive simulations in MATLAB. Each simulation is carried out under a constant mobility.

We develop an energy dissipation model for three approaches:

- Data Acquisition and No Processing (DANP) approach
- Data Acquisition and Transform Coding (DATC) approach
- Data Acquisition and Compressive Sensing (DACS) approach

Energy dissipation in a typical WSN node can be categorized into two groups: (i) energy dissipation due to computation – ECMP and (ii) energy dissipation due to communication – ECOM. Energy dissipation for transmitting one bit of data at power level l is denoted as El t x and the maximum transmission range at power level l is denoted as Rl max. If the distance between node-i and node- j is larger than Rl max (i.e., di j > Rl max) then they cannot communicate using power level l. Energy dissipation for receiving one bit of data is constant and denoted as Erx . Each data packet has a header length of 168 bits and the maximum packet size is 2040 bits, thus, the maximum data payload per packet is 1872 bits. Acknowledgement packet length is 160 bits (L A = 160).

Energy dissipation for computation is comprised of three main components:

- data acquisition energy dissipation – EACQ
- background energy dissipation – EBCK
- energy dissipation for processing – ESP

Therefore, computation energy dissipation can be expressed as a sum

$$ECMP = EACQ + EBCK + ESP$$

Power consumption for sensing (including the power consumption of both the CPU and the sensor board) is measured as PACQ = 15.01 mW. Acquisition of an N-byte raw signal requires N CPU operations. At an operation frequency of 7.4 MHz the Atmega 128L can execute 7.4 Machine Instructions per Second (MIPS) 3. Hence, the energy dissipation for acquiring an N-byte signal is obtained as follows:

- EACQ = NPACQ DOP

V. RESULTS

We first perform numerical analysis with various sparsity levels to determine the required number of measurements for CS to reconstruct the acquired signal. The l1-magic packet is used to solve the signal recovery problem. It is a collection of MATLAB routines for solving the convex optimization programs central to compressive sampling. We first use these results together the developed computation and communication energy dissipation models to investigate the effects of DANP, DATC, and DACS on network lifetime without considering data routing (i.e., communication and computation energy dissipation characteristics for a single sensor node is investigated). Later, we systematically explore and compare the aforementioned processing approaches' effects on WSN lifetime by sampling the parameter space through the constructed MIP model, which can model both computation and communication energy dissipation terms within a unified framework.

We use the General Algebraic Modeling System (GAMS) for numerical analysis of MIP models. GAMS is a highlevel modeling system for mathematical programming and optimization. It consists of a language compiler and integrated high-performance solvers. GAMS is used widely for complex, large scale modeling applications.

To determine the energy consumption of a wireless node employing CS for a given signal of dimension N and sparsity level K, the required number of measurements M for correct reconstruction is needed. CS theory defines this measurement number M as in the order of K log N [7]. In the literature, the required number of measurements for correct reconstruction with CS is a studied topic and phase transition curves explaining these relations are obtained. For the sake of completeness, we perform numerical analysis to determine M as a function of K and N. A signal of length N = 512 is taken with sparsity levels K varying between 20 to 200. For each sparsity level K, M compressive measurements are produced using a random Bernoulli/Rademacher (random ± 1) measurement matrix of dimension M × N. Measurement numbers between 20 and 512 are tested and the signals are reconstructed using the minimization problem. These numerical experiments are run 500 times with independent random sparse signal and measurement matrix selections and the number of correct reconstructions are counted. Figure 2 shows the correct reconstruction ratio as a function of number of measurements for different sparsity levels.

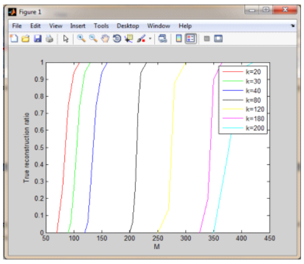

Figure 2: True reconstruction ratio as a function of number of measurements for different sparsity levels.

Figure 3 presents normalized network lifetime as a function of the number of nodes when the network radius is fixed to 100 meters for different sparsity levels. DACS has the highest network lifetime throughout the whole parameter space. Especially for sparser signals (e.g., K/N = 0.05) network lifetimes obtained with DACS is much larger than the lifetimes obtained with other approaches (e.g., DACS approach can result in a lifetime improvement of up to 4 times over DATC approach for ζ = 50 and K/N = 0.05). However, as the sparsity level increases the difference between the network lifetimes obtained with CS and with other approaches decreases (e.g., network lifetimes of DACS and DANP are within 15% neighborhood of each other for K/N = 0.20). Network lifetime increases for all approaches with increasing number of nodes, since increasing the number of nodes for a fixed network radius Rnet increases the node density, which creates more paths towards the base station (i.e., number of neighbor nodes increase). Larger network lifetimes can be obtained with richer routing options available in strongly connected networks. Furthermore, increasing the node density decreases the average hop distance. Note that transmission energy dissipation increases as the distance between the transmitter and the receiver increases. In summary, Figure 5.2 shows that:

1) WSN lifetime is significantly prolonged by DACS in comparison to conventional approaches (DATC and DANP) for all values of the number of nodes in the network. Efficiency of compressive sensing in reducing computation energy dissipation is the key factor in superior energy efficiency of DACS.

2) Lifetime gains obtained by DACS is higher for lower *K/N* because, energy dissipation for DACS increase as the ratio *K/N* increase.

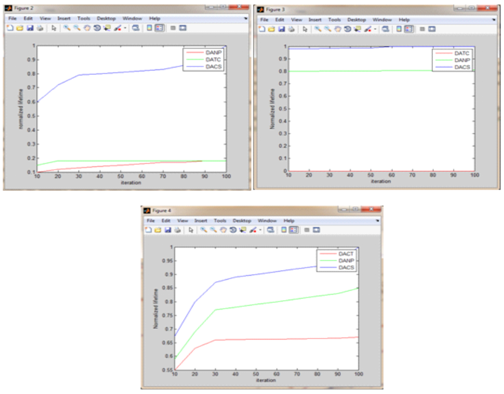

Figure 3: Normalized network lifetime as a function of *ζ* with *R*net = 100 m. (a) *K/N* = 0.05. (b) *K/N* = 0.10. (c) *K/N* = 0.20.

Figure 4 presents normalized network lifetime as a function of network radius for varying sparsity levels (ζ = 50). For all values of K/N except K/N = 0.20, DACS network lifetime is larger than the lifetimes obtained with other approaches provided that Rnet ≤ 150 m (e.g., DACS approach can result in a lifetime improvement of up to 4 times over DATC and DANP approaches for Rnet = 100 m and K/N = 0.05). DATC outperforms DACS for larger values of network radius (i.e., Rnet ≥ 250 m for K/N = 0.05, Rnet ≥ 200 m for K/N = 0.10, Rnet ≥ 150 m for K/N = 0.15, and Rnet ≥ 150 m for K/N = 0.20) with respect to network lifetime. DANP has longer network lifetime values for smaller network radii and high K/N (Rnet ≤ 50 m for K/N = 0.20). Network lifetime decreases as Rnet increases because the average hop distance increases, which results in increased communication cost. Furthermore, increasing network area while keeping the number of nodes constant leads to a decrease in the number of neighbors per node. This limits the energy balancing capabilities of the network. In summary, Figure 5.3 shows that DACS provides longer network lifetimes in denser networks with lower K/N because in such circumstances lower energy dissipation of DACS on computation can compensate its higher communication energy dissipation resulting in lower overall energy dissipation.

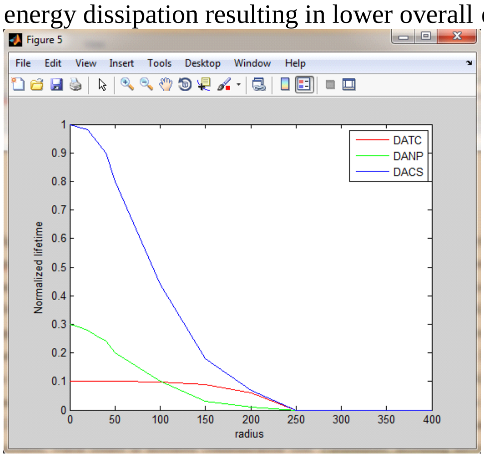

Figure 4: Network Lifetime

VI. Conclusion

In this work, the energy dissipation characteristics of WSNs utilizing the concepts of compressive sensing is investigated and compared to two other well known conventional approaches (DANP and DATC). A model to quantify the energy dissipation in sensor nodes due to data acquisition, computation, and communication for the compared methods is developed. By using the created energy dissipation models an MIP framework is built. The MIP framework models both computation and communication aspects within a unified framework. A systematic exploration of the parameter space, including sparsity level, node density, and network size, to characterize the energy dissipation and network lifetime performances of CS-based (DACS) and conventional (DANP and DATC) approaches is performed. Our results show that compressive sensing prolongs network lifetime significantly in comparison to conventional approaches provided that the acquired signals are highly sparse (e.g., K/N ≤ 0.10) and node density in the network is not too low (e.g., Rnet ≤ 150 m and ζ = 50).

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