Prolonging Wireless Sensor Network Lifetime by Optimal Utilization of Compressive Sensing

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***Abstract*—In a typical Wireless Sensor Network (WSN) application, sensor nodes gather data from the environment and convey the collected data towards the base station. It is possible to perform certain signal processing operations on raw data on each sensor node before transmission so that the amount of transmitted data bits is reduced. The amount of transmitted data usually depends on how much processing is performed on each node. Less processing results in more data to be transmitted and vice versa. However, more complex computation operations dissipate more energy. Hence, utilization of signal processing operations should be evaluated carefully by considering both their computation costs and the amount of data reduction they achieve. It is also possible to employ different signal processing techniques at different nodes, hence, optimal assignment of signal processing algorithms can be assessed at the network-level (*i.e.*, all nodes adopts a single signal processing technique during the entire lifetime) or at the node-level (*i.e.*, allowing different nodes to implement different solutions during lifetime). In this study, we develop a novel Mixed Integer Programming (MIP) framework to quantitatively investigate the effects of utilizing traditional transform coding (TC) based and compressive sensing (CS) based signal processing techniques (network-level and node-level) on WSN lifetime. We explore the parameter space consisting of network size, node density, and signal sparsity level through the numerical evaluations of the proposed novel MIP model.**

***Index Terms*—compressive sensing, wireless sensor networks, energy efficiency, network lifetime, mixed integer programming.**

I. Introduction

A Wireless Sensor Network (WSN) is comprised of numerous battery powered sensor nodes and a sink node (base station) [1]. Sensor nodes gather raw data from the environment and convey the collected data towards the base station either by using other sensor nodes as relays (multi-hop) or direct transmission to the base station [2]. Due to the limited energy budget of sensor nodes, massive amount of data flowing through the network can be reduced by applying proper signal processing schemes so that over-utilization of energy by sensor nodes is avoided and the lifetime of WSN is maximized [3].

A typical sensor node is capable of data processing by using various signal processing techniques [4]. One of the commonly utilized signal processing scheme is the traditional Transform Coding (TC) which is used to transform the original signal into a new domain where most of the signal energy can be represented by a small number of coefficients. Then, these coefficients with their locations are encoded and transmitted to either the base station or other sensor nodes [5]. On the other hand, in the novel theory of Compressive Sensing (CS) [6], [7], the signal can be reconstructed with much lesser number of linear measurements as compared to TC as long as the underlying signal is sparse, allowing the entire signal to be determined from relatively lesser number of measurements.

There are many studies on the applications of CS based data processing in WSNs [8]–[13]. It is shown that CS based data acquisition and processing can reduce communication cost and extend the lifetime of WSNs. Although the amount of data acquired with CS is lower than the amount of raw data bits, it is higher than the amount of data bits produced by TC techniques. However, the computation energy for TC techniques is higher than the computation energy for CS. Therefore, there is a trade-off in utilizing TC and CS techniques for prolonging WSN lifetime. This analysis can be elaborated by performing a network-level (*i.e.*, all nodes adopts a single algorithm during the entire lifetime) strategy. In [5], the effects of acquiring, processing, and communicating CS-based measurements on WSN lifetime are investigated in comparison to conventional techniques. Energy dissipation models for both CS and conventional techniques is developed via a Mixed Integer Programming (MIP) framework which jointly incorporates the energy costs for computation and communication for both CS and conventional approaches. The results reveal that CS prolongs network lifetime significantly in comparison to conventional approaches for sparse signals when the node density is high.

The MIP model with the objective of maximizing the lifetime, proposed in the earlier work can be used to analyze the trade-off exemplified above on network-level. However, there is an issue which has not been investigated yet. Instead of adopting a single processing technique applied to all nodes in the network during the entire lifetime (*i.e.*, network-level strategy), a hybrid solution can be implemented in which different nodes may use different processing options during the lifetime (*i.e.*, node-level strategy). Hence, the research question we investigated in this study can be posed as follows: *How much improvement in network lifetime can we attain with a node-level strategy in comparison to a network-level strategy?* To our best knowledge, this important research question has never been addressed in the literature before.

To answer this research question, we build a novel MIP framework to model the aforementioned hybrid scenario and further quantify the trade-offs in employing CS instead of conventional signal processing techniques in WSNs from energy efficiency and network lifetime perspectives. We perform numerical analysis by systematically exploring the parameter space (*i.e.*, sparsity level, network radius, and number of nodes).

II. System Model

In this section, we present the energy dissipation model, the network model, and the MIP framework.

A. Energy Dissipation Models

Sticking to the ideas provided in the previous work [5], we refer DANP (Data Acquisition and No Processing) and DATC (Data Acquisition and Transform Coding) as the conventional approaches while DACS (Data Acquisition and Compressive Sensing) is referred as the CS based approach.

There are commonly two types of energy dissipation in a sensor node: (i) computation energy – E_{CMP} and (ii) communication energy. Energy dissipation for computation (E_{CMP}) is comprised of three main components as:

1) data acquisition energy dissipation – E_{ACQ}
2) background energy dissipation – E_{BCK}
3) energy dissipation for processing – E_{SP}

In DANP strategy, the energy dissipation for computation contains signal acquisition only. In DATC, a transformation using a transform basis is obtained for signal decomposition, yielding N transform coefficients. To obtain a K-sparse approximation of the signal with N transform coefficients, the K largest values with corresponding locations should be found. Locations and values of the K largest coefficients represent the signal. The DACS model assumes an N dimensional signal acquired as in the conventional case but the M compressive measurements are generated using a multiplication process with a random $M \times N$ Bernoulli (random ± 1) matrix. More information on the derivation of computation costs for these strategies is available in [5].

We use the energy dissipation model for Mica2 motes equipped with CC1000 radios presented in [14]. Energy consumption of the transceiver and corresponding transmission ranges are presented in Table I. Energy dissipation for transmitting one bit of data at power level l is denoted as E_{tx}^{l} and the maximum transmission range at power level l is denoted as R_{max}^{l}. If the distance between node-i and node-j is larger than R_{max}^{l} (*i.e.*, $d_{ij} > R_{max}^{l}$) then communication cannot be established between these nodes using power level l. Energy dissipation for receiving one bit of data is constant and denoted as E_{rx}.

TABLE I: Transmission energy consumption (E_{tx}^{l} – μJ/bit) and range (m) values for the Mica2 motes equipped with CC1000 radios as a function of power level (l) [14]. Channel bandwidth, ς, is 38.4 Kbps [15]. Energy dissipation for reception (E_{rx}) is 0.923 μJ/bit. Values are computed using the data provided in [14].

l	E_{tx}^{l}	R_{max}^{l}	l	E_{tx}^{l}	R_{max}^{l}
1	0.672	19.30	14	0.844	38.86
2	0.688	20.46	15	0.867	43.67
3	0.703	21.69	16	1.078	46.29
4	0.706	22.69	17	1.133	49.07
5	0.711	24.38	18	1.135	52.01
6	0.724	25.84	19	1.180	55.13
7	0.727	27.39	20	1.234	58.44
8	0.742	29.03	21	1.313	61.95
9	0.758	30.78	22	1.344	65.67
10	0.773	32.62	23	1.445	69.61
11	0.789	32.62	24	1.500	73.79
12	0.813	34.58	25	1.664	78.22
13	0.828	36.66	26	1.984	82.92

B. Network Model

We use a disk shaped network consisting of ζ sensor nodes which are uniformly placed within the disk and a base station at the center with a coordinate of $(0, 0)$. The network topology is represented by a directed graph $G = (V, A)$ where V denotes the set of all nodes, including the base station (node-1). We also define set W, which includes all nodes except the base station (*i.e.*, $W = V \setminus \{1\}$). $A = \{(i, j) : i \in V, j \in V - \{i\},\ d_{ij} \leq R_{max}^{26}\}$ is the ordered set of arcs. Note that the definition of A implies that no node sends data to itself or to a node that is separated from it beyond the maximum transmission range R_{max}^{26}. We define set $\mathcal{K}$ which represents both traditional and CS based techniques (*i.e.*, $\mathcal{K}$ ={DANP, DATC, DACS}). The total number of k-type data packets transmitted by node-i to node-j is represented as an integer variable f_{ij}^{k}. The total number of acknowledgement packets transmitted in response to data packets are represented as g_{ij}^{k}.

In our framework, we assume that all nodes are roughly time synchronized and time is organized into equal rounds ($T_{rnd} =$ 500 s). We also assume that a TDMA-based MAC layer is in operation and a time-slot assignment algorithm outputs a conflict-free transmission schedule.

Each sensor node generates a constant amount of k-type of data (s_i^k) and all generated k-type data is conveyed to the base station at each round. Each data packet has a header length of 20 bytes ($L_H = 20$ bytes) and the maximum packet size is 255 bytes ($L_P = 255$ bytes). Thus, the maximum data payload per packet is 235 bytes ($L_D = 235$ bytes). Acknowledgement packet length is 20 bytes ($L_A = 20$ bytes). If N bytes of data is sent without any compression (*i.e.*, DANP stategy) then in each round node-i creates s_i^{DANP} data packets (*i.e.*, $s_i^{DANP} = \lceil N/L_P \rceil$). If DATC is utilized then $s_i^{DATC} = \lceil 2K/L_P \rceil$. For DACS, $s_i^{DACS} = \lceil M/L_P \rceil$, respectively. Analogously, packet size of uncompressed data is calculated as $L_P^{DANP} = \lfloor N/s_i^{DANP} \rfloor + L_H$. For DATC, $L_P^{DATC} = \lfloor N/s_i^{DATC} \rfloor + L_H$. For DACS, $L_P^{DACS} = \lfloor N/s_i^{DACS} \rfloor + L_H$, respectively.

C. MIP Framework

In our framework, we assume that each sensor node can utilize only one optimum algorithm chosen from set $\mathcal{K}$ during the entire lifetime. The optimization problem for maximizing the network lifetime (*i.e.*, the product of number of rounds and

Maximize H
Subject to:

$$\sum_{(i,j)\in A} f_{ij}^k - \sum_{(j,i)\in A} f_{ji}^k = \begin{cases} H_i^k \times s_i^k & \text{if } i \in W \\ -\sum_{t\in W} H_i^k s_t^k & \text{if } i = 1 \end{cases} \quad \forall i \in V, \forall k \in \mathcal{K} \tag{1}$$

$$g_{ji}^k = f_{ij}^k \ \forall (i,j) \in A, \ \forall k \in \mathcal{K} \tag{2}$$

$$\sum_{(0,j)\in A} f_{1j}^k = 0 \ \forall k \in \mathcal{K} \tag{3}$$

$$\begin{aligned} &\sum_{(i,j)\in A} \sum_{k\in\mathcal{K}} L_P^k f_{ij}^k E_{tx,ij}^{opt} + E_{rx} \sum_{(j,i)\in A} \sum_{k\in\mathcal{K}} L_P^k f_{ji}^k \\ &+ E_{rx} L_A \sum_{(j,i)\in A} \sum_{k\in\mathcal{K}} g_{ji}^k + L_A \sum_{(i,j)\in A} \sum_{k\in\mathcal{K}} g_{ij}^k E_{tx,ij}^{opt} \\ &+ \sum_{k\in\mathcal{K}} H_i^k \times E_{CMP}^k \leq \varrho \ \forall i \in W \end{aligned} \tag{4}$$

$$\begin{aligned} &\sum_{(i,j)\in A} \sum_{k\in\mathcal{K}} L_P^k f_{ij}^k + \sum_{(j,i)\in A} \sum_{k\in\mathcal{K}} L_P^k f_{ji}^k + L_A \sum_{(j,i)\in A} \sum_{k\in\mathcal{K}} g_{ji}^k \\ &+ L_A \sum_{(i,j)\in A} \sum_{k\in\mathcal{K}} g_{ij}^k + \sum_{(j,l)\in A} I_{jl}^i (\sum_{k\in\mathcal{K}} L_P^k f_{jl}^k \\ &+ L_A \sum_{k\in\mathcal{K}} g_{jl}^k) \leq \varsigma \ H \ T_{rnd} \ \forall i \in V \end{aligned} \tag{5}$$

$$H_i^k \leq a_i^k \times \mathcal{M} \ \forall i \in W, \ \forall k \in \mathcal{K} \tag{6}$$

$$\sum_{k\in\mathcal{K}} a_i^k = 1 \ \forall i \in W \tag{7}$$

$$\sum_{k\in\mathcal{K}} H_i^k \geq H \ \forall i \in W \tag{8}$$

$$H_i^k \geq 0 \quad \forall i \in W, \ \forall k \in \mathcal{K} \tag{9}$$

$$f_{ij}^k \geq 0 \quad \forall (i,j) \in A, \ \forall k \in \mathcal{K} \tag{10}$$

$$g_{ij}^k \geq 0 \quad \forall (i,j) \in A, \ \forall k \in \mathcal{K} \tag{11}$$

$$a_i^k \in \{0,1\} \quad \forall i \in W, \forall k \in \mathcal{K} \tag{12}$$

Fig. 1: MIP framework

the round duration) is presented in Figure 1. The objective of our problem implies that the network lifetime ends when the first node in the network exhausts its energy. To maximize the lifetime, all nodes are forced to dissipate their energies in a balanced fashion (their battery energies are depleted almost simultaneously). Each node chooses the optimal transmission power for each flow. Note that unitless variable H gives the network lifetime in terms of number of rounds and the actual network lifetime can be expressed by the product $H \times T_{rnd}$ (in seconds).

Equation (1) is used for flow balancing at each sensor node (*i.e.*, $\forall i \in W$) and the base station for each k-type data. The sum of k-type data flows relayed to node-i plus the k-type data generated at node-i is equal to the sum of k-type data flows relayed out to the rest of the network. Note that $H_i^k \times s_i^k$ gives the total amount of k-type data generated at node-i during lifetime. In addition, Equation (1) forces all k-type data generated by the sensor nodes to be terminated at the base station so that the total amount of data generated in the network is $H_i^k \times \sum_{i\in W} s_i^k$. Equation (2) states that the number of acknowledgement packets data on arc (j,i) is equal to the number of k-type data packets on arc (i,j). Equation (3) is used to guarantee that there are no k-type data packets flowing out of the base station. Equation (4) states that for all nodes except the base station energy dissipation for communication and computation for all type of k algorithms is bounded by the energy stored in batteries (ϱ). Each sensor node is assigned equal initial energy ($\varrho = 25$ KJ).

The optimal transmission energy takes a value from a finite set denoted as S_L (*i.e.*, there are only 26 power levels to choose from) and is found by using Equation (13) as

$$E_{tx,ij}^{opt} = \underset{l\in S_L, \ d_{ij} \leq R_{max}^l}{\text{argmin}} \left(E_{tx}^l \right). \tag{13}$$

To take channel bandwidth limitations into consideration in a broadcast medium, we need to make sure that the bandwidth required to transmit and receive at each node is limited by the channel bandwidth. Such a constraint should take the shared capacity into consideration. We refer to the flows around node-i (both data and acknowledgement), which are not flowing into or flowing out of node-i and affect the available bandwidth to node-i, as interfering flows. Equation (5) guarantees that for all nodes including the base station the aggregate rate of incoming and outgoing flows for each k-type packets, and interfering flows is upper bounded by the channel bandwidth. This constraint is a modified version of the sufficient condition given in [16], [17].

The interference function (I_{jl}^i) is presented in Equation (14). If node-i is in the interference region of the transmission from node-j to node-l, then the value of interference function for node-i (I_{jl}^i) is unity, otherwise it is zero. Generally speaking, interference range is equal to or greater than transmission range (*i.e.*, $\gamma \geq 1$). This means depending on the value of γ, node-j's transmission to node-l can interfere with node-i even if the distance between node-j and node-l is less than the distance between node-j and node-i.

$$I_{jl}^i = \begin{cases} 1 & \text{if } \gamma d_{jl} \geq d_{ji} \ \forall j \in V \setminus \{i\}, \forall l \in V \setminus \{i,j\} \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

Equation (6) is used for each node to choose the optimal algorithm during the entire lifetime. In this equation, H_i^k denotes the number of rounds that node-i utilizes k algorithm. When $a_i^k = 0$, node-i cannot utilize algorithm-k (*i.e.*, node-i utilizes k algorithm for 0 rounds). This is achieved by the constraint presented in Equation (9) which allows H_i^k to get the correct value of 0. However, when $a_i^k = 1$, H_i^k value is upper bounded by a sufficiently large number ($\mathcal{M}$). Equation (7) forces node-i to choose only one algorithm from set $\mathcal{K}$. Equation (8) with the objective function (*i.e.*, maximize H) are used to maximize the minimum required lifetime. Equation

(10) and Equation (11) state that all flows are non-negative. Equation (12) ensures a_k^i to take binary values.

III. Analysis

In this section, we present the results of numerical analysis to characterize the relative performances of node-level and network-level strategies presented in Section II. We use the General Algebraic Modeling System (GAMS) with CPLEX solver for the numerical analysis of the developed MIP model.

A signal of length $N = 1024$ Bytes is taken with sparsity levels K varying between 20 to 200. The required number of measurements of CS for each sparsity level is estimated from the numerical experiments as $M \approx 1.5K \log N$. Actual packet sizes for DACS, DATC, and DANP strategies are calculated for K by using the method given in Section II-B.

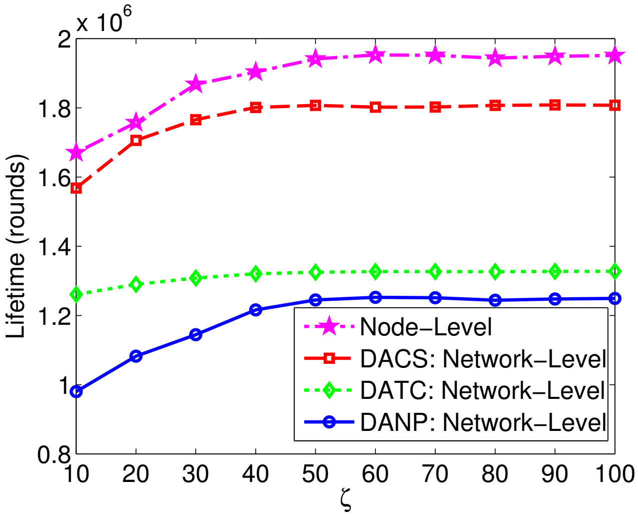
We use a disk topology with radius R_{net}. Sensor nodes are uniformly distributed within the disc. The base station is at the center of the disc. The number of deployed nodes (ζ) is varied between 10 and 100 nodes. Each problem is solved for 100 random topologies and the average network lifetimes in terms of rounds are presented for sparsity levels of $K/N = 0.05$, 0.10, 0.15, and 0.20.

Figure 2 presents network lifetimes for all strategies as a function of the number of nodes (ζ) in the network for different sparsity levels of $K/N = 0.05$ (Figure 2a), $K/N = 0.10$ (Figure 2b), $K/N = 0.15$ (Figure 2c), and $K/N = 0.20$ (Figure 2d). R_{net} is taken as 100 m. In Figure 2 lifetime values for the network-level strategies which utilize DACS or DATC decrease as the network sparsity decreases (*i.e.*, lower K/N values). For example, network lifetimes of DACS with $\zeta = 50$ are 1.80×10^6, 0.99×10^6, 0.66×10^6, and 0.50×10^6 for $K/N = 0.05$, $K/N = 0.10$, $K/N = 0.15$, and $K/N = 0.20$, respectively, whereas, DATC lifetimes with $\zeta = 50$ are 1.33×10^6, 1.21×10^6, 1.09×10^6, and 1.01×10^6 for $K/N = 0.05$, $K/N = 0.10$, $K/N = 0.15$, and $K/N = 0.20$, respectively. The reason for such behavior is that the amount of data to be conveyed to the base station increases for increasing K/N which increases the communication cost. Since DANP strategy is independent of signal sparsity, lifetime evaluated for this strategy does not change as a function of K/N. The lifetime values of the node-level strategy also decrease as $K/N =$ increases because a subset of sensor nodes utilize DACS and DATC (*e.g.*, node-level strategy lifetimes with $\zeta = 50$ are 1.94×10^6, 1.35×10^6, 1.31×10^6, and 1.29×10^6 for $K/N = 0.05$, $K/N = 0.10$, $K/N = 0.15$, and $K/N = 0.20$, respectively).

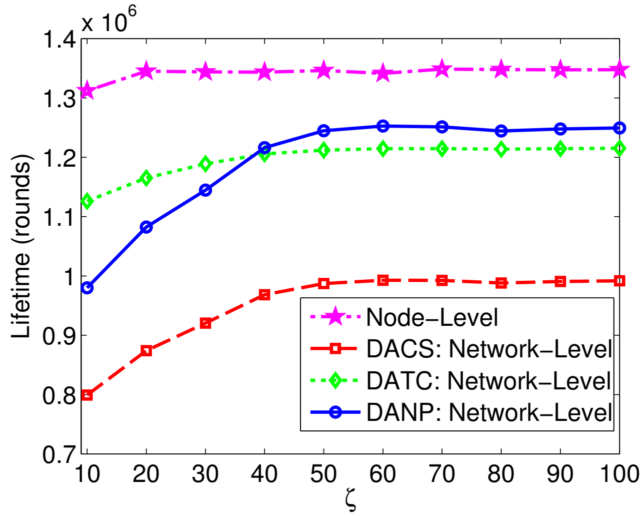
Network lifetime increases for all approaches as long as $\zeta \leq 50$ because increasing the number of nodes for a fixed network radius R_{net} decreases the average distance between the nodes, therefore, the communications cost reduces. Furthermore, increasing the node density creates more paths towards the base station (*i.e.*, number of neighbor nodes increase). However, as the node density reaches a certain point, further increase do not reduce the communication energy cost because the minimum transmission energy level has a certain range (*i.e.*, transmitting to 19.30 m or 1.00 m dissipates the same energy).

For all sparsity levels and network sizes, node-level strategy outperforms all network-level strategies. For example, network-level DACS strategy lifetimes are within (92.29%-97.06%), (60.92%-73.60%), (43.54%-51.00%), and (34.22%-39.04%) bands of the node-level strategy. DATC strategy lifetimes are within (67.95%-75.47%), (85.83%-90.53%), (80.48%-84.26%), and (76.99%-79.49%) bands of the node-level strategy. DANP strategy lifetimes are within (58.67%-64.15%), (74.70%-93.38%), (79.56%-95.87%), and (83.03%-97.53%) bands of the node-level strategy. In fact, the basic design philosophy of the node-level strategy is to utilize the best signal processing technique for each individual node rather than adopting a single technique for all nodes. Therefore, the performance of the node-level strategy is, by construction, not worse than any network-level strategy. Furthermore, the performance of the node-level strategy cannot be achieved by any network-level strategy because the node-level strategy always adopts more than one signal processing technique. As a general trend, for sparser signals, node-level strategy employs DACS for nodes closer to the base station because DACS uses less energy on computation but more energy on communication and for nodes farther than the base station, DATC is utilized because DATC dissipates more energy on computation, however, it creates the least amount of traffic to be conveyed to the base station. As the level of sparsity decreases, closer nodes to the base station starts to employ DANP instead of DACS because the energy dissipation of DACS on computation increases and the amount of data to be communicated increases.

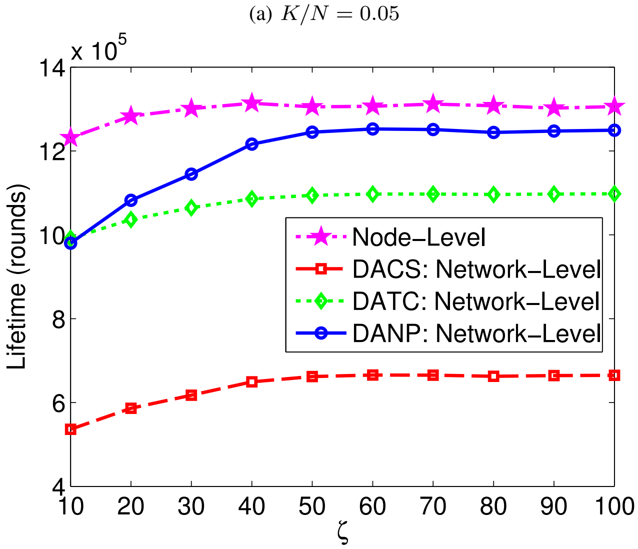
Figure 3 presents network lifetimes as a function of network radius (R_{net}) for different sparsity levels. Number of nodes is taken as 50 (*i.e.*, $\zeta = 50$). Network lifetime decreases for all strategies as R_{net} increases because the average distance to reach the base station increases which gives rise to the communication energy dissipation. Network lifetimes obtained with DACS are close to the node-level strategy provided that the sparsity level is high ($K/N = 0.05$) and the network radius is low ($R_{net} \leq 100$ m). For both low sparsity levels and large network radii, DACS gives the lowest network lifetime values. For example, DACS network lifetime values for ($K/N = 0.05$ and $R_{net} = 50$ m) and ($K/N = 0.20$ and $R_{net} = 250$ m) are 99.73% and 21.21% of the node-level strategy, respectively. DANP gives the best lifetime values among the network-level strategies if the signal sparsity level is not high ($K/N \geq 0.10$) and the network radius is not large ($R_{net} > 100$ m). For example, DANP network lifetime values for ($K/N = 0.20$ and $R_{net} = 50$ m) and ($K/N = 0.05$ and $R_{net} = 250$ m) are 100.00% and 17.21% of the node-level strategy, respectively. Regardless of the sparsity level, DATC gives the best network lifetime values among the network-level strategies as long as $R_{net} \geq 150$ m because as the average distance from the sensors to the sink increases the energy cost of communication dominates over the energy cost of computation and DATC is the strategy that reduces the amount of data to be transported,



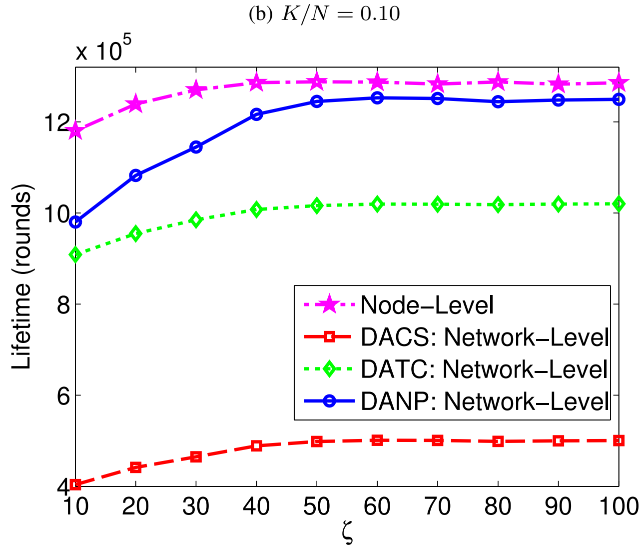
(a) $K/N = 0.05$



(b) $K/N = 0.10$



(c) $K/N = 0.15$



(d) $K/N = 0.20$

Fig. 2: Lifetimes for all strategies for various sparsity ratios (K/N) wrt. ζ when $R_{net} = 100$ m.

most.

IV. Conclusion

The target of this study is to characterize the potential benefits of utilizing compressive sensing in conjunction to traditional transform coding (*i.e.*, node-level strategy) as opposed to the utilization of a single signal processing technique for all nodes exclusively (*i.e.*, network-level strategy). To assess the impact of both computation energy costs and communication energy cost, we utilized a detailed and accurate energy dissipation model. We built a MIP framework to analyze the network lifetime values achievable by the node-level strategy and the network-level strategies. Through the numerical evaluations of the novel MIP model, we explored a wide parameter space. Our results reveal that node-level strategy outperforms all network-level strategies in terms of network lifetime achieved throughout the entire parameter space. In fact, node-level strategy can increase the network lifetime up to more than 200% when compared to the Compressive Sensing based network-level strategy (*i.e.*, DACS).

References

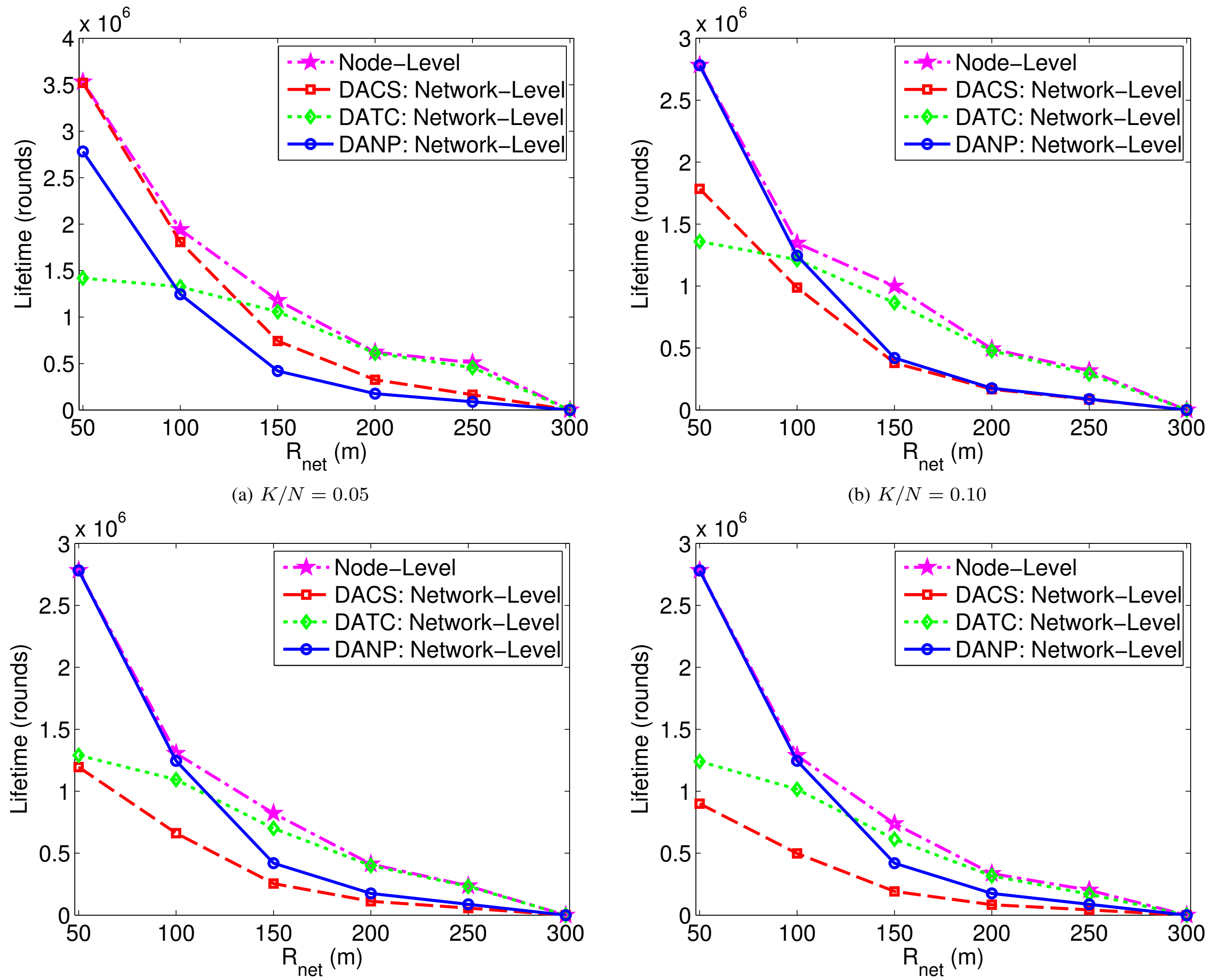
[1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: a survey," *Computer Networks*, vol. 38, pp. 393–422, 2002.

[2] K. Akkaya and M. Younis, "A survey on routing protocols for wireless sensor networks," *Ad Hoc Networks*, vol. 3, pp. 325–349, 2005.

[3] Z. Cheng, M. Perillo, and W. Heinzelman, "General network lifetime and cost models for evaluating sensor network deployment strategies," *IEEE Transactions on Mobile Computing*, vol. 7, pp. 484–497, 2008.

[4] B. Tavli, K. Bicakci, R. Zilan, and J. M. Barcelo-Ordinas, "A survey of visual sensor network platforms," *Multimedia Tools and Applications*, 2011.

[5] C. Karakus, A. Gurbuz, and B. Tavli, "Analysis of energy efficiency of compressive sensing in wireless sensor networks," *IEEE Sensors Journal*, vol. 13, no. 5, pp. 1999–2008, 2013.



(a) $K/N = 0.05$

(b) $K/N = 0.10$

(c) $K/N = 0.15$

(d) $K/N = 0.20$

Fig. 3: Lifetimes for all strategies for various sparsity ratios (K/N) wrt. network radius (R_{net}) when $\zeta = 50$.

[6] D. Donoho, "Compressed sensing," *IEEE Transactions on Information Theory*, vol. 52, pp. 1289–1306, 2006.

[7] E. J. Candes, J. Romberg, and T. Tao, "Robust uncertainty principles: Exact signal reconstruction from highly incomplete frequency information," *IEEE Transactions on Information Theory*, vol. 52, p. 489509, 2006.

[8] M. Mahmudimanesh and N. Suri, "Robust compressive data gathering in wireless sensor networks with linear topology," in *Proceedings of the IEEE International Conference on Distributed Computing in Sensor Systems (DCOSS)*, 2014, pp. 179–186.

[9] M. T. Nguyen and K. Teague, "Tree-based energy-efficient data gathering in wireless sensor networks deploying compressive sensing," in *Proceedings of the 23rd Wireless and Optical Communication Conference (WOCC)*, 2014, pp. 1–6.

[10] X. Wu, Y. Xiong, P. Yang, S. Wan, and W. Huang, "Sparsest random scheduling for compressive data gathering in wireless sensor networks," *IEEE Transactions on Wireless Communications*, no. 99, pp. 1–1, 2014.

[11] M. T. Nguyen and K. Teague, "Compressive sensing based data gathering in clustered wireless sensor networks," in *Proceedings of the IEEE International Conference on Distributed Computing in Sensor Systems (DCOSS)*, 2014, pp. 187–192.

[12] C. Zhao, W. Zhang, X. Yang, Y. Yang, and Y.-Q. Song, "A novel compressive sensing based data aggregation scheme for wireless sensor networks," in *Proceedings of the IEEE International Conference on Communications (ICC)*, 2014, pp. 18–23.

[13] G. Cao, F. Yu, and B. Zhang, "Improving network lifetime for wireless sensor network using compressive sensing," in *Proceedings of the IEEE 13th International Conference on High Performance Computing and Communications (HPCC)*, 2011, pp. 448–454.

[14] J. Vales-Alonso, E. Egea-Lopez, A. Martnez-Sala, P. Pavon-Marino, M. V. Bueno-Delgado, and J. Garca-Haro, "Performance evaluation of MAC transmission power control in wireless sensor networks," *Computer Networks*, vol. 51, pp. 1483–1498, 2007.

[15] K. Bilinska, M. Filo, and R. Krystowski. (2007) Mica, Mica2, MicaZ. [Online]. Available: wwwpub.zih.tu-dresden.de/ dargie/wsn/slides/students/MICA.ppt

[16] M. Cheng, X. Gong, and L. Cai, "Joint routing and link rate allocation under bandwidth and energy constraints in sensor networks," *IEEE Transactions on Wireless Communications*, vol. 8, pp. 3770–3779, 2009.

[17] H. Cotuk, B. Tavli, K. Bicakci, and M. B. Akgun, "The impact of bandwidth constraints on the energy consumption of wireless sensor networks," in *Proceedings of the IEEE Wireless Communication and Networking Conference (WCNC)*, 2014.