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Toward cluster-based weighted compressive data aggregation in wireless sensor networks

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ABSTRACT

Conventional Compressive Sampling (CS)-based data aggregation methods require a large number of sensor nodes for each CS measurement leading to an inefficient energy consumption in Wireless Sensor Networks (WSNs). To solve this problem, we propose a new scheme in the network layer, called "Weighted Compressive Data Aggregation (WCDA)", which benefits from the advantage of the sparse random measurement matrix to reduce the energy consumption. The novelty of the WCDA algorithm lies in the power control ability in sensor nodes to form energy efficient routing trees with focus on the load-balancing issue. In the second part, we present another new data aggregation method namely "Cluster-based Weighted Compressive Data Aggregation (CWCDA)" to make a significant reduction in the energy consumption in our WSN model. The main idea behind this algorithm is to apply the WCDA algorithm to each cluster in order to reduce significantly the number of involved sensor nodes during each CS measurement. In this case, candidate nodes related to each collector node are selected among the nodes inside one cluster. This yields in the formation of collection trees with a smaller structure than that of the WCDA algorithm. The effectiveness of these new algorithms is evaluated from the energy consumption, load balancing and lifetime perspectives of the network. A comprehensive numerical evaluation is performed which shows that the performance of the proposed WCDA and CWCDA algorithms is significantly better than some existing data aggregation methods such as plain-CS, hybrid-CS and the Minimum Spanning Tree Projection (MSTP) schemes.

1. Introduction

1.1. Background

Q2 Wireless Sensor Networks (WSNs) are commonly recognized as a new technology consisting of a large number of independent wireless sensor nodes with a spatial distribution to support a wide variety of applications, including natural environment monitoring, medical services, surveillance and ocean pollution detection [1,2]. In a large-scale proactive WSN, each sensor node performs periodically some operations such as computing, sensing and self-organizing to transmit specific data to the sink node through multiple paths [3]. In such a configuration, sensors are typically powered by limited lifetime batteries, which are hard to be replaced or recharged. Other resource constraints in WSNs are short communication range, low bandwidth, limited processing/storage and in particular, the energy consumption. Energy consumption is mainly addressed in the following three stages: sensing, data processing, and data transmission. Generally, sensing and data processing have less energy consumptions than that of data transmission. Indeed,

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any reduction in the transmission cost can prolong the WSN's lifetime. Thus, minimizing the total energy consumption is of high importance in designing WSNs [4]. Numerous research works have addressed the energy efficiency challenge in WSNs from different perspectives, including energy conserving sleep scheduling [5], topology control [6], mobile data collectors [7], and data aggregation [8]. Central to this study is to deploy proper data aggregation and routing methods in a WSN to enhance both the energy consumption and the network's lifetime with taking the effect of load balancing into account.

With focus on the spatial correlation properties of sensed data in real WSNs, the number of data transmissions can be reduced by compression techniques to achieve a relatively high accuracy of recovery at the sink node. The spatial correlation of sensed data leads to an inherent sparsity of data in a proper basis such as Discrete Cosine Transform (DCT) domain or wavelet domain [9]. This means that a few number of data samples are nonzero or equivalently, a basis can be found in which the sensed data is sparse. To address the sparsity of such signals, Compressive Sensing (CS) theory [10,11] is employed as a newly emerged signal processing technique for efficiently compressing signals and accurately reconstructing of sparse and compressible signals. Unlike the Nyquist criterion, in CS theory, signals can be recovered using much fewer measurements than their original dimensions. More precisely, considering the inherent sparsity features and the spatial correlation of input signals in a correlated WSN, a CS-based data aggregation method forms a random measurement matrix via non-adaptive linear measurements to compress the corresponded data, and then reconstructs these signals through an optimization process [12].

1.2. Related work

In recent years, the attention of researchers has been devoted to utilizing CS-based data aggregation methods to increase the network's lifetime by reducing the amount of data transmissions and balancing the traffic load throughout the whole WSN (e.g. [13–17]). The first study on the decentralized CS-based data aggregation method in WSNs was framed in [13]. The technique in [13] simultaneously computes random measurements of the sensed data and broadcasts them throughout the network using a simple gossiping algorithm. This line of work was further expanded in [14] by incorporating an efficient Compressive Data Aggregation (CDA) method to improve both transmissions cost and the network's lifetime in large-scale WSNs. The authors in [14] analyze the network's capacity using the CDA method and prove that the capacity is proportional to the sparsity level of sensed data. In this method, the total data transmissions are decreased only when the number of required measured samples is small enough. Nevertheless, it is shown numerically in [14] that an increase in the number of measured samples leads to an increment in the number of network's transmissions when compared to the non-CS method. Reference [15] introduces an adaptive data aggregation method which applies CS on the local spatial correlation among data of neighboring sensor nodes. In [16], the authors propose a CS-based data aggregation scheme to reconstruct data at the sink node. The results show that the proposed data aggregation method depends on the network's structure, while the compression matrix design is related to the sensed data. However, the scheme in [16] cannot automatically match the features of complex spatio-temporal correlation data. Reference [17] introduces a hybrid-CS data aggregation algorithm to achieve a high throughput in a WSN. The authors in [17] claim that since the measurement matrix is not sparse enough, applying a plain-CS may not yield a significant improvement in the throughput, while, it can result in a high throughput in the hybrid-CS method.

So far, the interaction between routing and CS-based data aggregation has been a barrier toward the progress in the field of energy consumption in WSNs [18,19]. These techniques utilize both routing and CS-based data aggregation methods to reduce the data traffic. In [18], the authors present a CS-based scheme which considers both routing and compression methods to minimize the energy consumption required for data collection in a WSN. However, this study does not consider the minimization of the energy consumption for transmission of each CS measurement. Most recent data aggregation methods which rely on dense random measurements have not highlighted this fact that a large number of elements in the random measurement matrix may be zero. Reference [20] addresses this issue and proposes a distributed sparse random measurement by which the significant information of a compressible signal can be reconstructed. The authors in [20] claim that each CS measurement only needs a combination of some sensed data instead of using all of them. In addition, it is shown in [20] that using the sparse random measurement considerably reduces the energy consumption of WSNs. However, the transmission cost in the gathering process of measured samples in multihop WSNs is not considered in this study. Routing and CS are also jointly addressed in [21] in which the routing path is iteratively built through a greedy choice to minimize the coherence measurements error. Since, the proposed routing paths are not the shortest ones, additional transmission cost would be imposed on the network. It is shown in [22] that the data compression capability of sensor nodes and the routing strategy affect the transmission cost of the network. Since both schemes in [21,22] are based on sparse random measurements, they improve the energy consumption of WSNs. However, these methods suffer from the fact that the formation of routing trees in collecting of each CS measurement is not optimal, and this degrades the energy efficiency of WSNs. Reference [23] addresses this issue and proposes the Minimum Transmission data aggregation Tree (MTT) which forms a spanning tree based on the CS measurement matrix. Every node shares its sensed data for CS measurements only in a couple of times using the sparse random measurement matrix. The proposed algorithm in [23] forms the data aggregation tree based on the shortest path and the number of times that the nodes transmit their own data. Reference [24] proposes a tree-based energy efficient routing method to reduce the energy consumption of the WSN by considering the sensor transmission range and the probability of occurrence of non-zero elements in the measurement matrix. Following the same model as in [20], the authors in [25] introduce the Minimum Spanning Tree Projection (MSTP) which incorporates a compressive data aggregation method and the sparse random measurement to reduce the number of transmissions and mitigates the energy consumption of whole network. Each projection node collects data of interest nodes and sends them to the sink node through a shortest path. The MSTP uses the Breath-First-Search (BFS) algorithm to form a spanning tree with the minimum number of transmission packets. The authors in [25] consider the "same transmission cost" for all sensor nodes and model the "unweighted network graph". In fact, regardless of energies required to send data in different distances and without considering the power control ability of sensor nodes, reference [25] assumes that all the nodes have the "same communication ranges".

Most of the works on the CS-based data aggregation consider tree-type routing methods in which a large number of sensor nodes take part in each CS measurement. It is shown in [26] that clustering is an efficient mechanism that surpasses the tree-based routing methods in terms of the traffic load balancing and improves both energy consumption and the network's lifetime. Reviewing the studies on the CS application in WSNs and to the best of our knowledge, there exists a few research works that investigate the CS theory for cluster-based WSNs [27,28]. In [27], the authors present centralized and distributed clustering algorithms for WSNs, in which cluster heads transmit data to the sink node through a backbone tree using a hybrid CS mechanism. However, the work in [27] has ignored the fact that the sparse random measurement can be utilized in each cluster to decrease the number of transmission packets. Reference [28] addresses this issue and presents a cluster-based data aggregation method with sparse random measurements in a star topology-based WSN. However, the star topology used in each cluster leads to an increase in the intra-cluster energy consumption.

1.3. Contributions

Taking the above challenges into account, the key contributions of this work are summarized as follows:

- *Part I: Weighted Compressive Data Aggregation (WCDA) algorithm:* The main objective in the first part of this paper is to minimize the energy consumption of the network by utilizing the CDA and the sparse random measurement matrix (normally contains many zero elements) when compared with Non-CS and some classical CS-based data aggregation methods. To address this problem, a new algorithm, namely Weighted Compressive Data aggregation (WCDA), is proposed that aggregates the data from each node and efficiently sends them to the sink node. The novelty of our proposed WCDA algorithm lies in the power control ability in sensor nodes and weighted network graph which distinguish our work from the scheme in [25]. In the proposed WCDA method, each transmit node adjusts its power level based on the Euclidean distance to the destination node to prevent more energy loss in the network. It is numerically shown that employing the WCDA algorithm can significantly reduce the network's energy consumption for the data transmission between sensor nodes by forming efficient routing trees and employing the load-balancing.
- *Part II: Cluster-based Weighted Compressive Data Aggregation (CWCDA):* In the second part we modify the WCDA algorithm by jointly utilizing the CS-based data aggregation and the clustering to further reduce the energy consumption in the whole WSN. Note that the classical CS-based data aggregation methods such as plain-CS, hybrid-CS and the MSTP [25] are based on the tree routing which suffer from this fact that a large number of sensor nodes must be involved in each CS measurement. However, in the Cluster-based Weighted Compressive Data Aggregation (CWCDA) scheme, we apply the WCDA algorithm to each cluster in order to reduce significantly the number of involved sensor nodes during each CS measurement. In this case, candidate nodes related to each collector node are selected among the nodes inside one cluster. This yields in the formation of collection trees with a smaller structure than that of the WCDA algorithm. The effectiveness of these new algorithms is evaluated from the energy consumption, load balancing and lifetime perspectives of the network. A comprehensive numerical evaluation is performed which shows that the performance of the proposed WCDA and CWCDA algorithms is significantly better than some existing data aggregation methods such as plain-CS, hybrid-CS and the Minimum Spanning Tree Projection (MSTP) schemes. Because the cluster-based data aggregation method generally has better traffic load balancing than the tree data aggregation method.

1.4. Paper organization

The rest of this paper is organized as follows. In Section 2, the network model is described and the main assumptions and performance metrics required for our algorithms are introduced. Section 3 introduces the basic concepts of CS theory and gives an overview of the CS-based data aggregation method in order to present the detail of the WCDA algorithm. Section 4 deals with introducing the proposed CWCDA algorithm. Section 5 reports our experiment and simulation results. Finally, in Section 6, an overview of the results and some conclusion remarks are presented.

Notations: Throughout this paper, we use normal letters for scalars. Matrices and vectors are set in bold capital and lower-case letters, respectively. $[.]^T$ indicates the transpose operator. In the vector domain, the concept of $\ell_p - norm$ is defined as $\|\mathbf{x}\|_p = (\sum_{i=1}^{n} |x_i|^p)^{1/p}$. $\mathbb{R}^n$ means the $n-$dimensional real coordinate space. Finally, the ceiling notation $\lceil x \rceil$ is the smallest integer not less than x.

2. Model description and assumptions

2.1. Model description

In this work, we consider a multi-hop WSN consisting of n stationary and location-aware sensor nodes, denoted by $\{s_1, s_2, \ldots, s_n\}$, which are distributed randomly throughout an $A \times A$ square area. The network contains the sink node denoted by s_0 in a preassigned location that collects data from all sensor nodes. The system is modeled by a weighted bidirectional graph $\boldsymbol{G}(\boldsymbol{V}, \boldsymbol{E})$ in which vertices set $\boldsymbol{V}$ represents the sink node and all the sensor nodes, and edge set $\boldsymbol{E}$ represents bidirectional wireless links between nodes. For each link $i, j \in \boldsymbol{V}$, if a link exists, those nodes are in the communication range of each other, or equivalently, a direct communication between them is possible. We denote $w(i, j)$ as the *transmission cost* defined by the Euclidean distance between two nodes i, j. For each single-hop link $i, j \in \boldsymbol{V}$ with the Euclidean distance d_{ij}, the sensor node s_i transmits one data packet x_i of size L bits toward node s_j, where L is a fixed parameter for all the nodes. Assuming that all $s_i, i = 1, \ldots, n$, have data packets for transmission at the beginning of each round, the main task of a data aggregation method is to aggregate adequate information for recovering the n-dimensional signal vector $\mathbf{x} = [x_1, \ldots, x_n]^T$ at the sink node to minimize the energy consumption of the network. In this paper, we assume that all interferences from different sources are controlled by the orthogonal signaling (e.g., Walsh–Hadamard codes [29]) in the network. In addition, we suppose that no packet is lost during each transmission.

2.2. Performance metrics

To analyze and evaluate the performance of the underlying network, we use various performance metrics such as the energy consumption of each link, the load balancing, the First Node Dies (FND), and the tree's cost defined as follows.

- **Energy consumption:** We follow the same energy consumption model as in [30] for the link $i, j \in \boldsymbol{V}$ defined as

$$E_{T_i}(L, d) = E_{elec} \times L + \epsilon_{amp} \times L \times d_{ij}^2, \tag{1}$$

$$E_{R_j}(L) = E_{elec} \times L, \tag{2}$$

  where $E_{T_i}(L, d)$ and $E_{R_j}(L)$ for all $i, j \in \boldsymbol{V}$ represent the energy consumption for sending and receiving one packet x_i of size L bits, for node i as the transmitter and node j as the receiver, respectively, E_{elec} represents the consumed energy in receiving/sending of one-bit message via electrical circuits, and ϵ_{amp} denotes the energy consumption of the transmission amplifier. It is assumed that each sensor node can adjust its power level based on the distance from its corresponding destination. For such an energy model, we ignore the energy consumption of baseband signal processing blocks such as source coding and pulse-shaping, as these energy consumptions are quite small compared to the energy consumption of the RF circuitry [31].
- **Load balancing:** Let Γ_i represents the number of packets transmitted by node s_i in each round. To quantify the performance of the load balancing of the proposed algorithms, we use the load variance metric denoted by $\mathcal{S}_n^2$ for a given Γ_i of node s_i as follows:

$$\mathcal{S}_n^2 = \frac{1}{n}\sum_{i=1}^{n}(\Gamma_i - \overline{\Gamma})^2, \tag{3}$$

  where $\overline{\Gamma}$ denotes the average of the number of packets transmitted by node s_i in each round, obtained by

$$\overline{\Gamma} = \frac{1}{n}\sum_{i=1}^{n}\Gamma_i. \tag{4}$$

  Clearly, lower $\mathcal{S}_n^2$ leads to more traffic load balancing.
- **Network's lifetime:** The lifetime means the time duration that a network is operational and can perform its assigned tasks. In this work, we consider the First Node Dies (FND) as a performance metric to calculate the lifetime of the network which is defined as the number of rounds in which all nodes transmit their data to the sink node until the first node runs out of its energy. For such a definition, the main goal is to minimize the load variance of sensor nodes in order to maximize the network's lifetime.
- **Tree's cost:** The tree's cost is defined as the sum of the links' lengths of the tree. For instance, if a tree includes $\mathcal{L}$ links and d_j denotes the length of jth link, then the tree's cost will be obtained as $\sum_{j=1}^{\mathcal{L}} d_j$.

3. Weighted Compressive Data Aggregation (WCDA) algorithm

In this section, we propose a new data aggregation method, namely Weighted Compressive Data Aggregation (WCDA), for the network model introduced in Section 2. The main idea behind our proposed algorithm is to use both CS theory and sparse random measurements in the underlying weighted WSN graph in order to minimize the energy consumption and control the traffic load of the network. Before proceeding to the main part of this section, some primary concepts of CS theory and the sparse random measurements are briefly explained. We also discuss about the applications of CS theory in WSNs and describe in short some existing CS-based data aggregation methods for the upcoming fair comparison.

3.1. Compressive sampling theory

Compressive sampling theory is a promising methodology in digital signal processing for reconstructing sparse signals with very few measurements under a certain basis [10]. Indeed, CS theory offers a possibility of high resolution capture of compressible signals from relatively few data measurements, typically below the number of data obtained from the optimal Shannon/Nyquist sampling theorem. CS theory declares that signal vector $\mathbf{x} = [x_1, \ldots, x_n]^T$ is k-sparse, if it has at most k non-zero coefficients in which x_i's represent the signal samples and n denotes the signal's dimension. Typically, signals in some WSN applications are not sparse, but they have a sparse representation $\mathbf{x} = \boldsymbol{\Psi}\boldsymbol{\alpha}$ on the basis of compression $\boldsymbol{\Psi}_{n\times n} = [\boldsymbol{\psi}_1, \ldots, \boldsymbol{\psi}_n]$ with column vectors $\boldsymbol{\psi}_i$ where $\boldsymbol{\alpha} = [\alpha_1, \ldots, \alpha_n]^T$ is the sparse equivalent of the original signal $\mathbf{x}$. CS theory states that if signal $\mathbf{x}$ on basis of $\boldsymbol{\Psi}$ has a k-sparse representation so that $\mathbf{x} = \sum_{i=1}^{k} \alpha_i \boldsymbol{\psi}_i$ and $k \ll m$, under certain conditions and using $\mathbf{y} = [y_1, \ldots, y_m]^T = \boldsymbol{\Phi}\mathbf{x}$, the original signal can be recovered from just $m = \mathcal{O}(k \log n)$ samples instead of collecting all samples of signal $\mathbf{x}$ [10]. For $m \times n$ measurement matrix $\boldsymbol{\Phi} = [\boldsymbol{\phi}_1, \ldots, \boldsymbol{\phi}_n]$, the row vectors $\boldsymbol{\phi}_i$ should have large incoherent with the compression basis $\boldsymbol{\Psi}$, or the Restricted Isometry Property (RIP) for the measurement matrix $\boldsymbol{\Theta}_{m\times n} = \boldsymbol{\Phi}_{m\times n}\boldsymbol{\Psi}_{n\times n}$ is established. It is shown in [11] that measurement matrix $\boldsymbol{\Phi}$ satisfies the RIP of order $2k$ if $\delta_k \in (0, 1)$ so that the following statement is true

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for the signal $\mathbf{x}$ with a k-sparse representation:

$$(1-\delta_k)\|\mathbf{x}\|_2^2 \le \|\mathbf{\Phi x}\|_2^2 \le (1+\delta_k)\|\mathbf{x}\|_2^2. \tag{5}$$

Existence of the RIP for random matrices such as Gaussian matrix with uniformly and independently distributed elements and Bernoulli matrix with ± 1 elements has been proved in [11]. The reconstruction process is equivalent to finding the signal's sparse coefficient vector $\boldsymbol{\alpha}$, which can be cast into an ℓ_1- *norm* convex optimization problem that recovers the signal $\mathbf{x}$ using the CS measurements $\mathbf{y} = [y_1, \ldots, y_m]^T$ [12]:

$$\min_{\boldsymbol{\alpha}\in\mathbb{R}^n} \|\boldsymbol{\alpha}\|_{\ell_1} \quad \text{subject to} \quad \mathbf{y} = \mathbf{\Phi\Psi}\boldsymbol{\alpha} = \mathbf{\Theta}\boldsymbol{\alpha}. \tag{6}$$

It is worth mentioning that the practical performance of the CS theory depends on the amount of the signal sparseness and the recovery algorithms. Also, in this theory, increasing the number of CS measurements will enhance the quality of the data recovery [10].

3.2. Application of compressive sampling in WSNs

The ultimate goal of our WSN model is that each node s_i transmits its measured data x_i to the sink node s_0 such that a vector $\mathbf{x} = [x_1, \ldots, x_n]^T$ is formed at s_0. In the Non-Compressive Sampling (*Non-CS*) data aggregation method, shown in Fig. 1a, each child $s_i, i \in \{1, \ldots, \nu-1\}$, sends a sample to νth node, so that the output link of this node sends ν packets to its parent through a preassigned path. Clearly for the Non-CS method, the nodes near to the sink node suffer from the heavy data traffic and lose their energies quickly leading to the network's lifetime degradation. One heuristic solution to alleviate this bottleneck problem is to apply the CS theory in the above data aggregation process. The main idea behind this CS-based data aggregation is illustrated in Fig. 1b, where at the beginning of each round, the node $s_i, i \in 1, \ldots, n$, extends its data to an m-dimensional vector $\mathbf{u}_i = x_i\boldsymbol{\phi}_i$ with $m \ll n$, and sends the extended vector to its parent. For this method, suppose that m is predefined and known in the whole network, and each node s_i is aware of its own m-dimensional coding vector $\boldsymbol{\phi}_i$. Then, each parent node adds its extended data to that of its children, and this procedure is repeated until all the aggregated data arrive at the sink node s_0. Eventually, the sink node collects all CS measurements $y_i = \sum_{j=1}^{n} x_j\phi_{ij},\ i = 1, \ldots, m$, and then the recovery algorithm is used to reconstruct the n raw samples.

Applying the principles of CS theory directly on the data aggregation process, namely *Plain-CS* shown in Fig. 1a, every node requires to send m packets to its parent, thus, the traffic load on each link will always be the same and it equals to m. Therefore, the sink node receives an m-dimensional vector instead of n-dimensional vector as in the Non-CS method. Then, the sink node recovers $x_i, i = 1, \ldots, n$, by a preassigned recovery algorithm. The above Plain CS-based data aggregation method benefits from the fact that the decoding process in each node is carried out in a distributed manner by some simple and low computational cost operations such as addition and multiplication. In fact, the main computational load is pushed to the decoding phase on the sink node s_0 which is limitless in terms of the energy consumption. In the Plain-CS method, the total number of data packet transmissions for data collection from all nodes is equal to mn. It is evident that with an increase in m, the number of transmitted packets inefficiently increases. In addition, the Plain-CS method leads to an unnecessary increase in the traffic load in early stages of the transmission. As a result, applying CS theory naively on each node may not be the best choice in the Plain-CS method.

In another data aggregation method, namely the *Hybrid-CS* algorithm proposed in [17], if the number of transmission packets is larger than CS measurements, i.e., $\nu > m$ the links between the nodes carry out dense random measurements, otherwise, as long as the number of output samples is less than m, the sensor employs the Non-CS method which only relays data packets (see Fig. 1a). It is shown in [17] that the Hybrid-CS method outperforms both Non-CS and Plain-CS schemes in terms of the energy efficiency.

One challenge faced in the aforementioned data aggregation methods is that they have utilized the *dense* random measurement matrix, while they have missed the fact that matrix $\mathbf{\Phi}$ may contain many zero entries. On the other hand, in the data aggregation using *sparse* random measurements, the measurement matrix includes many zero elements. In the sparse case, each sensor node participates in the CS measurement only if its respective ϕ_{ij} is non-zero, while for the aforementioned Plain-CS and Hybrid-CS methods with dense random measurements, all sensors involve in CS measurements. It is shown in [20] that the transmission cost per sample measurement is reduced from $\mathcal{O}(n)$ for dense random measurements to $\mathcal{O}(\log n)$ for sparse random measurements. The authors in [20] state that there is a compromise between the number of non-zero elements in each row of measurement matrix $\mathbf{\Phi}$ and the number of rows it contains. However, the problem in [20] is that a minimum tree's cost for overall network cannot be guaranteed, because for each random measurement, a large number of transmissions is required to collect data at the measurement node without any proper path. Another challenge for the aforementioned schemes is that they suffer from the lack of power control ability in sensor nodes and use energy inefficient routing algorithms in the network.

3.3. Proposed WCDA algorithm

According to the challenges discussed in section 3.2, we propose an efficient data aggregation method, namely Weighted Compressive Data Aggregation (WCDA) algorithm, which benefits from the advantages of sparse random measurements and the power control ability in sensor nodes. The proposed WCDA algorithm forms energy efficient routing trees with focus on the load-balancing issue to improve both lifetime and energy efficiency of the network.

Let start by briefly describing the features of the sparse random measurement matrix $\mathbf{\Phi}$ introduced in [20] which normally contains many zero elements. The measurement matrix $\mathbf{\Phi}$ must satisfy two following conditions:

(1) In order to distribute non-zero elements uniformly in each row of measurement matrix $\mathbf{\Phi}$ with dimension $m \times n$ and maximize its sparseness, the number of non-zero elements in each row of $\mathbf{\Phi}$ must be as $\kappa = \lceil n/m \rceil$.

(2) It is necessary to have no column with all zero elements in measurement matrix $\mathbf{\Phi}$, because each column of matrix $\mathbf{\Phi}$ corresponds to a sensor node. Thus, if a column of matrix $\mathbf{\Phi}$ has full zero elements, then the data from its

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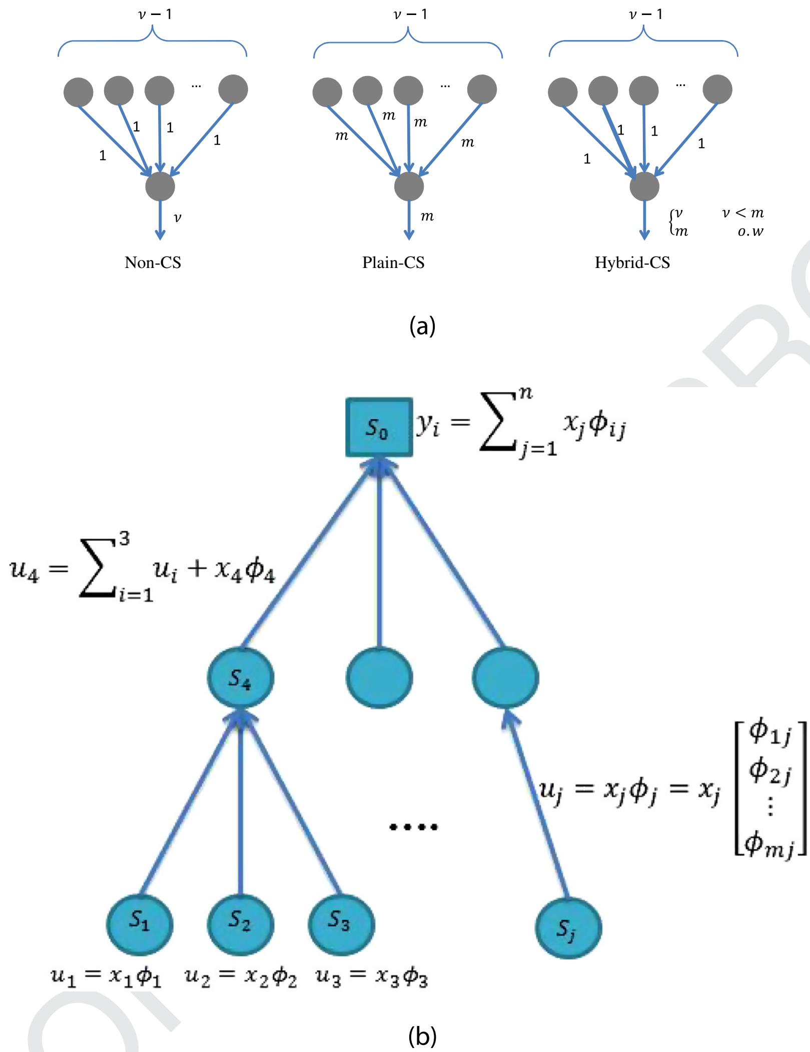

Fig. 1. (*a*) Comparison of three data aggregation methods in multi-hop WSNs. The link labels represent the number of transmission packets on each link during one data aggregation round, and (*b*) A typical structure of the CS-based data aggregation method in multi-hop WSNs.

corresponding sensor node is discarded. Each sensor node $s_i, i = 1, \dots, n$, needs to store a column of measurement matrix $\mathbf{\Phi}$, denoted by vector $\boldsymbol{\phi}_i$, in its memory.

To satisfy the above conditions, the distribution process of elements in each row of measurement matrix $\mathbf{\Phi}$ is performed as follows (see the typical matrix $\mathbf{\Phi}$ with dimension 4×12 in (7) as well):

- **Step 1:** Uniformly distribute $\kappa = \lceil n/m \rceil$ non-zero elements in the first row, while the remaining $n - k$ entries are considered zero.
- **Step 2:** Uniformly distribute κ non-zero elements among the remaining $n - i\kappa$ entries in the i^{th} row, $i = 1, \dots, m$, in which the remaining entries in the i^{th} row are those have considered zero in all previous rows.
- **Step 3:** $i + 1 \leftarrow i$
- **Step 4:** Repeat step 2 till all m rows of measurement matrix $\mathbf{\Phi}$ are filled.

$$\mathbf{\Phi}x = \begin{bmatrix} \phi_{1,1} & 0 & 0 & 0 & 0 & \phi_{1,6} & 0 & 0 & 0 & \phi_{1,10} & 0 & 0 \\ 0 & 0 & 0 & \phi_{2,4} & \phi_{2,5} & 0 & \phi_{2,7} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \phi_{3,8} & \phi_{3,9} & 0 & \phi_{3,11} & 0 \\ 0 & \phi_{4,2} & \phi_{4,3} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \phi_{4,12} \end{bmatrix} \tag{7}$$

Recall that each node s_i measures one sample x_i which has a spatial correlation with its adjacent nodes. According to the CS theory, the sink node s_0 requires only m random CS measurement $y_i = \sum_{j=1}^{n} x_j\phi_{ij}, i = 1, \dots, m$, to recover all samples of the sensor nodes. For this purpose, m nodes are chosen uniformly as *collector nodes*, denoted by $\{r_1, r_2, \dots, r_m\}$, to collect CS measurements in the network. Each collector node r_i aims to collect one random CS measurement y_i and transmits y_i to the sink node. Toward this goal, the ith row of measurement matrix $\mathbf{\Phi}$, denoted by $\boldsymbol{\phi}_{r_i}$, is allocated to $r_i, i = 1, \dots, m$. For the ith collector node, the corresponding nodes with $\phi_{ij} \neq 0$ (in the ith row of $\mathbf{\Phi}$) are defined as the *candidate nodes* $a_k, k = 1, \ldots, \kappa$. We denote $\mathcal{T}_i, i = 1, \ldots, m$, as the *collection tree* corresponding to collector node r_i as its root. This tree is spread using the proposed WCDA algorithm until all the candidate nodes are included.

The pseudo-code of our WCDA algorithm is outlined in Algorithm 1. The network graph $\boldsymbol{G}(\boldsymbol{V}, \boldsymbol{E})$, the collector nodes and the sparse random measurement matrix $\boldsymbol{\Phi}$ act as the inputs of the WCDA algorithm. In each round of performing the WCDA algorithm, one heuristic matrix belonging to the collection tree $\mathcal{T}_i$ with three rows is created, in which the first, second and third rows indicate the tree nodes, the parent of each node and the Euclidean distance between each node and its parent, respectively. The procedure of the proposed WCDA algorithm is perform as follows:

- **Step 1: Initialization:** The candidate nodes corresponding to collector node r_i, represented with the set Int_i, are placed in the set *intTmp*. To form $\mathcal{T}_i$, the collector node r_i with the zero tree's cost is considered as the only node without parent. If r_i is one of the candidate node, it is removed from the set *intTmp*.
- **Step 2: Single-hop candidate node:** The collection tree is extended by adding the candidate nodes which can be connected to the current tree with a single-hop. This process is carried out during the *While* loop in the lines 5–18 of Algorithm 1. The candidate node is connected to the current tree via the link by which the tree's cost is minimized. The parent of the candidate node a_i is defined as the node that connects a_i to the current tree. Then, the nodes connected to the tree with the only single-hop connection are removed from the set *intTmp*. Thus, the set *intTmp* shows the remaining candidate nodes which are still not connected to the tree. If this set is empty, the failure criteria of the infinite loop in the line 4 has been met and there is no need to run the rest of the algorithm; otherwise, go to Step 3.
- **Step 3: Multi-hop candidate node:** Among the remaining candidate nodes located in a multi-hop connection of the current tree, the nearest one will be connected to the tree via the shortest path. This process is run by two nested loops in lines 23 and 24 of the pseudo-code. Since the network graph is weighted, we use the *dijkstra* algorithm [32] to find the shortest path $\mathcal{P}$ from the candidate node in a multi-hop route to the current tree. All existing nodes in the path $\mathcal{P}$ is added to the tree by the *for* loop in the line 29 of Algorithm 1. Then, the candidate node connected to the tree by a multi-hop route is removed from the set *intTmp*.
- **Step 4: Data aggregation:** The above steps are repeated until all the single-hop and multi-hop candidate nodes are connected to the tree. After forming the collection tree $\mathcal{T}_i$ and noting that each node s_j in $\mathcal{T}_i$ knows its parent and children nodes, compute $u_j = x_j\phi_{ij}$. Then, according to the CS-based data aggregation, each node s_j aggregates u_j with its children's data and sends the aggregated data packet to its parent node. Once the collector node r_i receives the random CS measurement $y_i = \sum_{j=1}^{n} x_j\phi_{ij}$, it sends y_i to the sink node in the form of a data packet through the shortest path between the collector nodes and the sink node. The WCDA algorithm is performed for all collector nodes so that collection tree $\mathcal{T}_i, i = 1, \ldots, m$, for each collector node r_i is formed. Similarly, other collector nodes aggregate their measured samples and send them to the sink node. Finally, m collection trees are formed in the network, each constitutes one of the random CS measurements y_i. In this step, the proposed WCDA algorithm uses the *dijkstra* algorithm [32] to find a possible shortest path.

Algorithm 1 WCDA.

Inputs: $\boldsymbol{G}(\boldsymbol{V}, \boldsymbol{E})$, $\{r_1, r_2, \ldots, r_m\}$, $\boldsymbol{\Phi}$
Outputs: $\mathcal{T}_i, i = 1, \ldots, m$

1: **for** $i = 1$ *to* m **do**
2: $intTmp \leftarrow Int_i$
3: $tree \leftarrow [p_i\ -1\ 0]^T$
4: **While** (intTmp is not empty)
5: **Do**
6: **for** $C = 1$ *to* N_{intTmp} **do**
7: **for** $k = 1$ *to* N_{Tree} **do**
8: **if** adj(*intTmp(C)* , *tree(1,k)*) **then**
9: $dist \leftarrow [distance(intTmp(C), tree(1,k))\ tree(1,k)]^T$
10: **end if**
11: **end for**
12: **if** $N_{dist} > 0$ **then**
13: $m \leftarrow find\ min(dist)$
14: $tree \leftarrow [intTmp(C)\ dist(2,m)\ dist(1,m)]^T$
15: $remmove(intTmp, C)$
16: **end if**
17: **end for**
18: **While** ($N_{dist} > 0$)
19: **if** $N_{intTmp} = 0$ **then**
20: **Break while**
21: **end if**
22: $Cst \leftarrow \infty$; $\mathcal{P} \leftarrow []$;
23: **for** $l = 1$ *to* N_{intTmp} **do**
24: **for** $k = 1$ *to* N_{tree} **do**
25: $Cst \leftarrow min(Cst, Cost($*dijkstra* shortest path $(tree(1,k), intTmp(l)))$
26: $\mathcal{P} \leftarrow path(min_{Cst})$
27: **end for**
28: **end for**
29: **for** all Nodes n in path P **do**
30: $tree \leftarrow [n\ pred(n)\ distance(n, pred(n))]^T$
31: **end for**
32: $remove(intTmp, min_{Cst})$
33: **end While**
34: $CollectionTree(i) \leftarrow tree$
35: **end for**
36: return $CollectionTree(i), Cst$

To get more insight into the described WCDA algorithm and to compare that with the MSTP algorithm [25], let consider a network with 24 sensor nodes shown in Fig 2. In this network, nodes 12, 14 and 24 are uniformly selected as the collector nodes. According to the sparse random measurement matrix $\boldsymbol{\Phi}$ with dimension 3×24, the candidate nodes of the first collector node (i.e., root 24) are the nodes 12, 13,

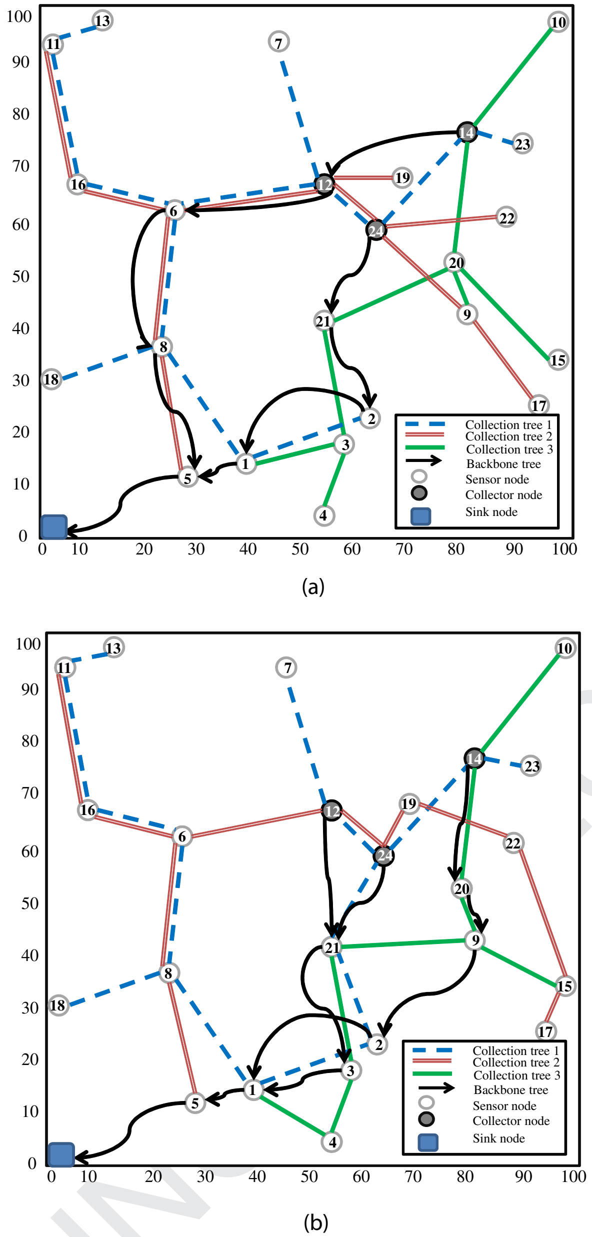

Fig. 2. A typical WSN with $n = 24$ and $m = 3$, (a) MSTP algorithm, and (b) Proposed WCDA algorithm.

8, 14, 7 and 23. In both WCDA and MSTP algorithms, the first collection tree $\mathcal{T}_1$ considers the node 24 as its root and is spread until all the candidate nodes are included. The nodes 12 and 14 are the single-hop candidate nodes of $\mathcal{T}_1$, which are directly connected to node 24 in the first step of both algorithms. The next candidate nodes in both algorithms are 23 and 7 which must be connected to the current tree via a node having the shortest path. Accordingly, node 23 to node 14 and node 7 to node 12 are connected. In the next step, one of two multi-hop collector nodes 2 or 8 should be added to the current tree. Since, the MSTP algorithm is performed based on the number of hops, it does not discriminate between nodes 8 and 2, thus, it connects the node 8 to the current tree via the Breath-First-Search (BFS) algorithm [33]. In this case, an efficient path cannot be selected based on the energy consumption. However in our WCDA algorithm, the node 2 is connected to the current tree earlier the node 8, as node 2 has a smaller Euclidean distance with the current tree than node 8. This selected shortest path results in a higher energy efficiency than the corresponded path node 8 as will be shown in Section 5. After forming the collection trees $\mathcal{T}_1$, $\mathcal{T}_2$ and $\mathcal{T}_3$, the collector nodes 12, 14 and 24 aggregate the data of their candidate nodes based on the CS-based data aggregation process and send them to the sink node through the shortest path. This backbone tree is shown with the directional lines ($\longrightarrow$) in Fig 2. As seen in this figure, the proposed WCDA algorithm aims to select the efficient paths to minimize the energy consumptions in (1) and (2). Numerical results show that the energy consumptions in the WCDA and MSTP algorithms are 0.0611 and 0.0994 Jules, respectively. We see that our proposed WCDA algorithm displays 38.53% more energy efficient than the MSTP algorithm which suffers from the lack of a power control ability. Our WCDA algorithm benefits from this advantage that one specific node does not need to set its power level at the maximum, once it sends data to its nearest node and adjusts its power based on the Euclidean distance. This leads to more efficiently improvement in the formation process of the collection trees than the MSTP scheme.

4. Cluster-based Weighted Compressive Data Aggregation (CWCDA)

The existing CS-based data aggregation methods (e.g., Plain-CS, Hybrid-CS, MSTP) rely on routing trees, in which a large number of sensor nodes are deployed in each CS measurement. Thus, these methods consume more energy which yields they are not practically feasible in WSNs. On the other hand, since candidate nodes in the WCDA algorithm are uniformly selected, some of them may be far from each other. For such a situation and to create each CS measurement $y_i, i = 1, \ldots, m$, a collection tree with lots of links is formed which increases the tree's cost. The above challenges motivate us to propose an energy efficient method, namely Cluster-based Weighted Compressive Data Aggregation (CWCDA), to make a significant reduction in the energy consumption in our WSN model. The main idea behind this algorithm is to apply the WCDA algorithm to each cluster in order to reduce significantly the number of involved sensor nodes during each CS measurement. In this case, candidate nodes related to each collector node are selected among the nodes inside one cluster. This yields in the formation of collection trees with a smaller structure than that of the WCDA algorithm.

In the proposed CWCDA algorithm, we divide the WSN into n_C local non-overlapping clusters, denoted by $\mathcal{C} = \{c_1, \ldots, c_{n_C}\}$, using the simple and well-known K-means algorithm [34], in which the sink node separately aggregates the data of all clusters. For this algorithm, when the clustering process is performed uniformly, the number of sensors in each cluster for a large value of n is approximated by n/n_C. The maximum communication range of each node in cluster c_k, denoted by R_{c_k}, is obtained when the graph is continuous

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in each cluster. Before describing the CWCDA algorithm, we go through the properties of the Block Diagonal Matrix (BDM) which is formed based on the cluster-based data aggregation.

4.1. Block diagonal matrix (BDM)

The block diagonal matrix presented in this paper is a matrix with a total of n_C sub-matrices $\mathbf{\Phi}_k, k = 1, \ldots, n_C$, each $\mathbf{\Phi}_k$ has the individual size $m_k \times n_k$, whereas other nondiagonal entries of the BDM are all zero. Suppose the signal $\mathbf{x} \in \mathbb{R}^n$ is partitioned into n_C vectors $\mathbf{x}_k \in \mathbb{R}^{n_k}$ and for each $k \in \{1, \ldots, n_C\}$, sub-matrix $\mathbf{\Phi}_k : \mathbb{R}^{n_k} \to \mathbb{R}^{m_k}$ collects the CS measurements $\mathbf{y}_k = \mathbf{\Phi}_k \mathbf{x}_k$. The total CS measurement vector $\mathbf{y} = [\mathbf{y}_1^T, \ldots, \mathbf{y}_{n_C}^T]^T \in \mathbb{R}^m$ is given by

$$\mathbf{y} = \mathbf{\Phi}\mathbf{x} \Leftrightarrow \begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \\ \vdots \\ \mathbf{y}_{n_C} \end{bmatrix} = \begin{bmatrix} \mathbf{\Phi}_1 & 0 & \cdots & 0 \\ 0 & \mathbf{\Phi}_2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \mathbf{\Phi}_{n_C} \end{bmatrix} \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \vdots \\ \mathbf{x}_{n_C} \end{bmatrix}. \tag{8}$$

In this paper, we suppose that $\mathbf{\Phi}_k$ is a sparse random measurement matrix which is formed according to the procedure explained in Section 3.3. It is shown in [35] that the BDM $\mathbf{\Phi}$ satisfies the RIP condition and it can be considered as an effective measurement matrix. Reference [35] demonstrates that the random sampling BDM can be used for the signal recovery by the CS theory. The number of CS measurements m depends on the compression basis $\mathbf{\Psi}$ in which the signal is sparse. If the measurement matrix has a low coherence with the compression basis (e.g., Fourier basis or DCT basis), increasing n_C results in a more sparse measurement matrix, while n_C does not increase with m. In other words, if the measurement matrix has a high coherence with the compression basis, m would be considered as a linear function of n_C. With respect to the structure of this measurement matrix, the BDM $\mathbf{\Phi}$ can be converted to a sparse random measurement matrix after permutation of their rows and columns [35]. Thus, a BDM with sparse random measurements blocks can also satisfy the RIP condition.

In the proposed CWCDA algorithm, the measurement matrix created in the sink node is not in the shape of the traditional dense random measurement matrix with the Gaussian or Rademacher elements. In fact, the CS-based data aggregation method creates a BDM consisting of several sampling sub-matrices $\mathbf{\Phi}_k, k = 1, \ldots, n_C$, each $\mathbf{\Phi}_k$ belongs to the kth cluster. We denote n_k and m_k as the number of nodes and the CS measurements for kth cluster, respectively. Since, m_k is a linear function of the number of nodes n_k in cluster c_k, it concludes that $m_k = (n_k/n) \times m, k = 1, \ldots, n_C$. Similar to the WCDA algorithm described in Section 3.3, in the CWCDA scheme, the sink node aggregates $m = \sum_{k=1}^{n_C} m_k$ CS measurements $y_i, i = 1, \ldots, n$, however, the traffic load in each cluster c_k is reduced to m_k CS measurements.

4.2. Proposed CWCDA algorithm

The CWCDA scheme has been described in details in Algorithm 2. The network graph $\boldsymbol{G(V, E)}$, the number of clusters n_C, and the primary energy of the node, denoted by E_p (identical for all the nodes), are the inputs of this algorithm. We denote $E_i, i = 1, \ldots, n$, as the residual energy of each node. The outputs of the CWCDA algorithm are as follows:

Algorithm 2 The proposed CWCDA algorithm.

Inputs : $\boldsymbol{G(V, E)}$, n_C, E_p
Outputs : $\mathcal{T}_{i,k}, i = 1, \ldots, m_k$, $\mathcal{T}_k, k = 1, \ldots, n_C$, $\mathcal{B}_T$

```
Divide nodes into n_C clusters using K-means algorithm.
while all E_i > 0, i = 1, ..., n do
    for each cluster c_k, k = 1, ..., n_C do
        if first round then
            Assign nearest cluster node to center of the cluster as cluster head
        else
            Assign cluster node with the most remaining energy as cluster head
        end if
        Find R_{c_k} for a continuous graph of each cluster
        Create Distance_C and Adjacent_c relative to Range_C
        Distribute m_k collector nodes among clusters corresponding to number of their nodes
        Assign ⌈n_k/m_k⌉ candidate nodes for each collector node in cluster c_k
        Build collection Trees T_{i,k} in each cluster using Algorithm 1
        for each collector node r_i do
            Find the shortest path from r_i to corresponding cluster head
        end for
    end for
    for each cluster head c_k, k = 1, ..., n_C do
        Find shortest path to s_0
    end for
    for all nodes do
        calculate consumed E_i
    end for
end while
```

- **Collection tree:** We denote $\mathcal{T}_{i,k}, i = 1, \ldots, m_k$, as the *collection tree* corresponding to the ith collector node in cluster c_k. This tree is spread using the WCDA algorithm introduced in Section 3.3 until all the candidate nodes in cluster c_k are included.
- **Cluster head tree:** The *cluster head tree*, denoted by $\mathcal{T}_k, k = 1, \ldots, n_C$, corresponding to the kth cluster head, includes the cluster head as its root and all collector nodes.
- **Backbone tree:** The *backbone tree*, denoted by $\mathcal{B}_T$, consists of the sink node (considered as its root) which connects all cluster heads to the sink node.

To get more insight into how this algorithm works, we consider the scenario shown in Fig. 3 to describe the proposed CWCDA algorithm as follows:

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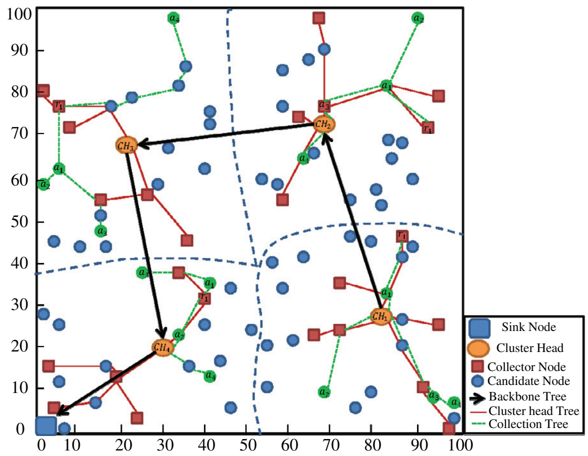

Fig. 3. A typical structure of the CWCDA algorithm in a multi-hop WSN.

- **Step 1: Initialization:** We divide all sensor nodes in the network into n_C clusters using K-means algorithm [34]. In each cluster c_k, $m_k = (n_k/n) \times m$, $k = 1, \ldots, n_C$, collector nodes are chosen randomly. We consider $\lceil n_k/m_k \rceil$ candidate nodes for each collector node in cluster c_k.
- **Step 2: Cluster Head election:** It is a well known fact that the cluster head election affects on the energy consumption in each clustering method [36]. For this purpose, in the first round of the CWCDA algorithm (as shown in Fig. 3), the midpoint of each cluster is identified, and then the nearest node to the selected midpoint is chosen as the Cluster Head (CH). This type of CH's election minimizes the intra-cluster energy consumption. In the next rounds, the node with a more residual energy is selected as the CH that balances the energy consumption over the whole network. In this case, the energy consumption is minimum within each cluster.
- **Step 3: Intra-cluster data aggregation:** This step employs the WCDA algorithm to form the collection trees for each cluster, in which data of candidate nodes are aggregated by collector nodes. Fig. 3 only presents one collection tree $\mathcal{T}_{1,k}$, shown with dash lines, for the first collector node r_1 in cluster c_k. Then, the collector nodes in each cluster c_k send their data to the corresponding CH using the shortest path tree, namely cluster head tree $\mathcal{T}_k$, $k = 1, \ldots, n_C$. To find the shortest path, the *dijkstra* algorithm [32] is used.
- **Step 4: Inter-cluster data aggregation:** In each round, the kth CH aggregates its own m_k received CS measurements y_k and then, all data of CHs are sent to the sink node through a backbone tree. To form the backbone tree as a shortest path tree between CHs, the proposed CWCDA algorithm makes a graph $\boldsymbol{G_{ch}} = (\boldsymbol{V_{ch}}, \boldsymbol{E_{ch}})$ in which $\boldsymbol{V_{ch}}$ is a set of the sink node and the CHs, while $\boldsymbol{E_{ch}}$ denotes the links between these nodes. In the graph formation, the algorithm calculates the maximum communication range, R_{min}, for a graph that contains the CHs and the sink node so that our graph is finally continuous. In each round, the kth CH collects m_k measured samples of its sensor nodes and forms $y_i = \sum_{j=1}^{n_k} \phi_{ij} x_j$, $i = 1, \ldots, m_k$. Then, the vector $\mathbf{x} = [\mathbf{x}_1^T, \mathbf{x}_2^T, \ldots, \mathbf{x}_{n_C}^T]^T$ of size $n = n_1 + n_2 + \cdots + n_{n_C}$ is formed where $\mathbf{x}_k \in \mathbb{R}^{n_k}$ denotes the data of n_k sensor nodes in kth cluster. When the sink node receives all $m \ll n$ CS measurements from the CHs, it can recover the original data of all sensor nodes. Finally, the CWCDA algorithm calculates the residual energy for all the nodes to choose the node with the highest residual energy as the CH in the next round.
- **Step 5: Terminate:** The algorithm is terminated when at least one E_i, $i = 1, \ldots, n$, is equal to zero.

5. Simulation results

In this section, we evaluate and compare the performances of the proposed WCDA and CWCDA algorithms in different scenarios with the existing conventional data aggregation methods such as Non-CS, Hybrid-CS [17] and MSTP [25] in a weighted WSN in terms of the energy consumption, the load balancing and the network's lifetime. For the scenarios under simulation, we investigate the effect of (*i*) location variation of the sink node, (*ii*) the number of CS measurements, and (*iii*) the number of sensor nodes, on the aforementioned performance metrics, and show the superiority of our algorithms compared with traditional data aggregation methods.

5.1. Simulation setup

We consider a WSN in which the nodes are randomly distributed with the uniform distribution inside a square area with the size 100×100 m^2. It is assumed that there exists a spatial correlation between the sensed data of sensor nodes. To apply this correlation on our simulations, we suppose that data of all sensor nodes have a sparse representation based on the Discrete Cosine Transform (DCT) basis. All simulations have been run in the MATLAB software. In our simulations, only the energy consumption of sending and receiving data over the network is computed, and we ignore the energy consumed by the data routing information. This assumption is used in many relevant literature (e.g., [25,28]). In addition, we set $E_{elec} = 50$ nJ/bit, $\epsilon_{amp} = 100$ $pJ/bit/m^2$ and the length of data packets is $L = 1024$ bits [30]. The primary energy of all nodes is set to $E_p = 2$ J. In addition, we compute the average of each performance metric over 10 runs of one algorithm with different measurement matrix $\mathbf{\Phi}$ and different collector nodes. We consider the *normalized reconstruction error* defined as $\frac{\|\mathbf{x}-\hat{\mathbf{x}}\|_2}{\|\mathbf{x}\|_2}$ in the CS signal recovery stage in which the vectors $\mathbf{x}$ and $\hat{\mathbf{x}}$ represent the original and the recovered signals, respectively. We evaluate the accuracy of our proposed methods using the real-world data collected by the LUCE WSN deployment at the EPFL [37] which focuses on the ambient temperature values.

5.2. Evaluation and comparison

First scenario: In this scenario, we set $n = 1000$ and $m = 100$ for the algorithms under simulation, and the number of clusters $n_C = 10$ for the CWCDA scheme. The validation of selection $n_C = 10$ will be provided numerically at the end of this section. In addition, the position of the sink node will

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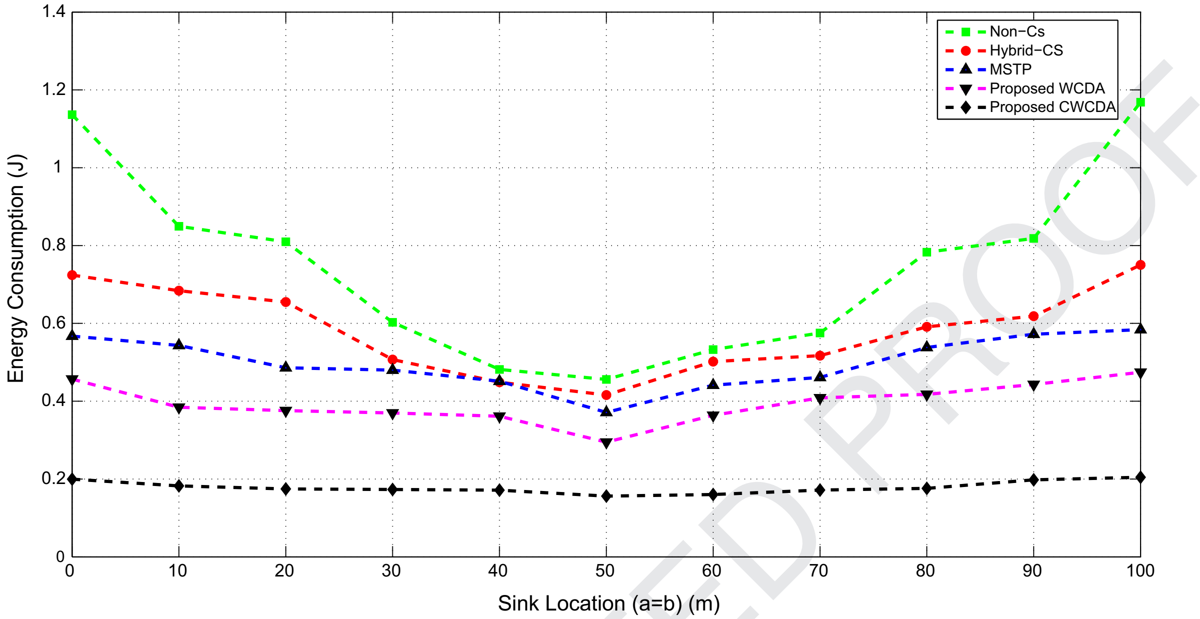

Fig. 4. Comparison of the energy consumption in Non-CS, Hybrid-CS, MSTP, WCDA and CWCDA data aggregation methods for $n = 1000$ when the sink node location varies on the main diameter ($a = b$).

Table 1
Comparison of load variance in Non-CS, Hybrid-CS, MSTP, WCDA and CWCDA data aggregation methods for $n = 1000$ when the sink node location varies on the main diameter ($a = b$ meter).

Algorithm	a = 0	a = 10	a = 20	a = 30	a = 40	**a = 50**	a = 60	a = 70	a = 80	a = 90	a = 100
Non-CS	4612.8	2494.6	2105.8	837.4	722.2	**613.5**	766.1	1174.1	1497.4	2919.2	4210.9
Hybrid-CS	663.6	592.7	569.2	443.2	425.3	**399.7**	418.7	464.7	549.0	647.5	727.3
MSTP	91.7	77.8	68.3	53.7	51.4	**48.4**	46.6	57.6	60.8	74.6	86.7
Proposed WCDA	75.1	66.0	64.6	49.4	46.8	**43.5**	43.5	57.3	59.8	73.1	81.1
Proposed CWCDA	38.5	30.7	19.9	17.9	15.4	**13.0**	13.3	16.1	18.2	36.8	47.8

be changed on the main diameter of the square area of the network to find the best place for this node in terms of the energy consumption. Fig. 4 compares the energy consumption of the proposed WCDA and CWCDA schemes with that of the traditional Non-CS, Hybrid-CS [17] and MSTP [25] methods versus the sink node location. Note that the natural variables $a, b \in [0, 100]$ represent the geographic coordinates of the sink node location on the main diameter, i.e., $a = b$ in Fig. 4. It is observed from Fig. 4 that the energy consumption of all traditional data aggregation methods, in particular the Non-CS scheme, strongly depends on the location of the sink node. In fact, the best position for the sink node to minimize the energy consumption in all schemes is the center of the network area. The main reason for this better performance is that the tree which connects the sensor nodes to the sink node is shortest in this point. The interesting result extracted from Fig. 4 is that the energy consumption of the proposed CWCDA scheme is almost robust against the location of the sink node. Furthermore, our algorithms exhibit a lower energy consumption in each location of the sink node when compared to other data aggregation methods. This can be justified for noting that in our WCDA algorithm, one specific sensor node does not need to adjust its power on the maximum value once it sends data to its nearest node. In fact, each sensor node sets its power level based on the Euclidean distance to the destination node. In addition, in the CWCDA algorithm, candidate nodes related to each collector node are selected among the nodes within one cluster. Therefore, the number of participated sensor nodes during each CS measurement is reduced. This leads to a more energy efficiency than other schemes.

Table 1 provides a fair comparison for the load variance $\mathcal{S}_n^2$ defined in (3) for the aforementioned data aggregation algorithms in different sink node locations $a = b$. As seen from Table 1, for all data aggregation methods, the minimum $\mathcal{S}_n^2$ is achieved when the sink node is located at the center of the network area, because the number of nodes in the neighborhood of the centered sink node is maximum. The results in Table 1 demonstrate that the WCDA, CWCDA and MSTP outperform the conventional Non-CS and Hybrid-CS methods from the load variance points of view. The worst case for load balancing belongs to the Non-CS method. In fact for the Non-CS scheme, the number of transmission packets in each round for the sensors is different, as the sensors near to the sink node send more packets than leaf nodes. This leads to a more energy consumption for the nodes in the vicinity of the sink node. In contrast, our CWCDA algorithm outperforms significantly the other schemes in terms of load

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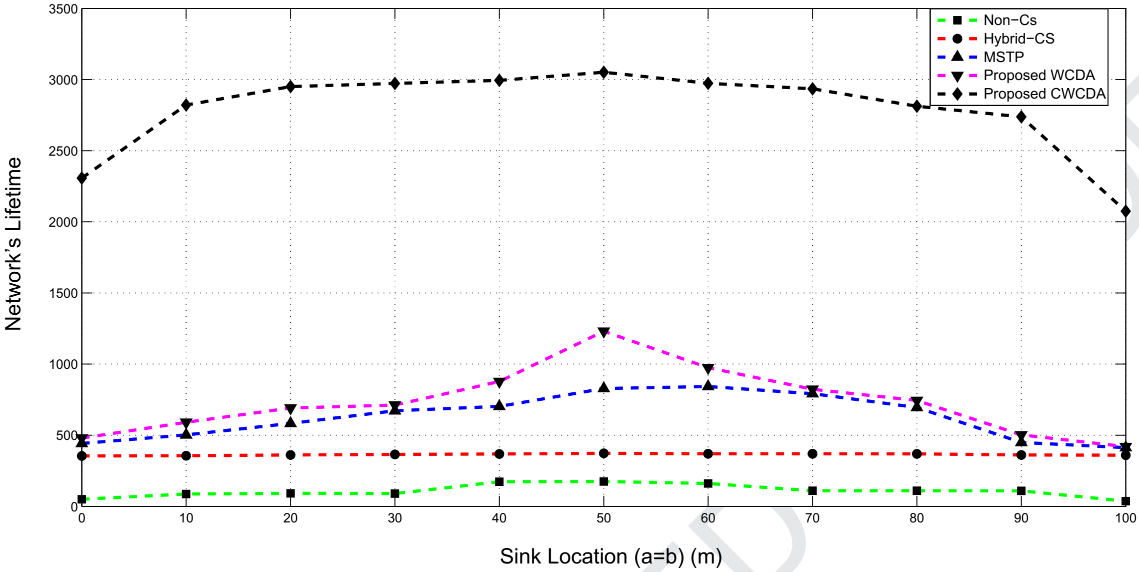

Fig. 5. Comparison of the network's lifetime in Non-CS, Hybrid-CS, MSTP, WCDA and CWCDA data aggregation methods for $n = 1000$ when the sink node location varies on the main diameter ($a = b$).

balancing. This superior performance comes from the fact that the distance of leaf nodes to the root of the collection tree is too short, thus, the collection tree corresponding to each collector node within a cluster experiences more enhanced balancing in the collection tree comparing to the case when the clustering method is not utilized.

To complete the evaluation of the first scenario, we compare in Fig. 5 the network's lifetime of the aforementioned algorithms in different sink node locations when the first node dies. As illustrated in Fig. 5, the maximum lifetime of the network for all data aggregation methods is obtained when the sink node is located again in the center of the network's area. This result comes exactly from the results in Fig. 4 and Table 1, where the energy consumption and the load variance are in the minimum values at this point. Similarly, the proposed WCDA and CWCDA schemes outperform the conventional Non-CS, Hybrid-CS and MSTP methods in terms of the network's lifetime. The interesting result from Fig. 5 is that the network's lifetime in the proposed CWCDA is significantly better than the proposed WCDA, due to the following reasons:

(*i*) Totally, the network's lifetime of cluster-based algorithms is more than that of non clustering methods [26].

(*ii*) In the CWCDA scheme, less sensor nodes are involved in the collection tree formation.

(*iii*) Of course, it should be noted that in a typical cluster-based algorithm, cluster heads consume more energy than other nodes that leads to a reduction in the lifetime of the network. However, we employ a heuristic cluster head election in the CWCDA scheme described in Section 4.2 to overcome the above problem in enhancing the network's lifetime.

Second scenario: In this scenario, we evaluate the effect of the number of CS measurements, $m \in [10, 250]$, on the network's performance, where we consider again a WSN with $n = 1000$ sensor nodes and the number of clusters, $n_C = 10$, for the CWCDA algorithm. We assume that the sink node is located at coordinate (0, 0). We follow the same performance metrics as in the first scenario to compare our proposed WCDA and CWCDA schemes with that of the conventional Non-CS, Hybrid-CS and MSTP methods. According to the results in Fig. 6, the minimum energy consumption of the networks in all schemes is achieved when parameter m is set at the minimum value, i.e., $m = 10$. This leads to a reduction in the number of collection trees and the number of packets transmitted to the sink node. On the other hand, as shown in Table 2 and based on CS theory, we know that reducing the CS measurement m increases the reconstruction error of signals in the network. Thus, there exists a compromise between the energy consumption and the data reconstruction error when m changes. With a similar arguments as in the first scenario, the best scheme in terms of the minimum energy consumption is the CWCDA algorithm for different values of m.

As seen from Table 3, an increase in the number of CS measurements m leads to an increase in the difference of the loads between the leaf nodes and the sensors around the sink node, hence, the load variance of all CS-based data aggregation methods will be increased. Accordingly, as well as the reasons mentioned in the first scenario, the WCDA, CWCDA and MSTP outperform the conventional Non-CS and Hybrid-CS schemes in terms of the load balancing for each value of m. On the other hand, for all data aggregation methods, by increasing the number of CS measurements, the lifetime of the network is reduced, because the number of collection trees and the number of packets transmitted by each node will be increased, as observed in Fig. 7.

Third scenario: In the last scenario, we evaluate the effect of changing the number of sensor nodes n on the performance of the proposed WCDA and CWCDA methods and compare their energy consumptions, load balancing and the network's lifetime with the aforementioned classical data aggregation methods. In this scenario, the sink node is located at coordinate (0, 0). For all values of n, the number of CS

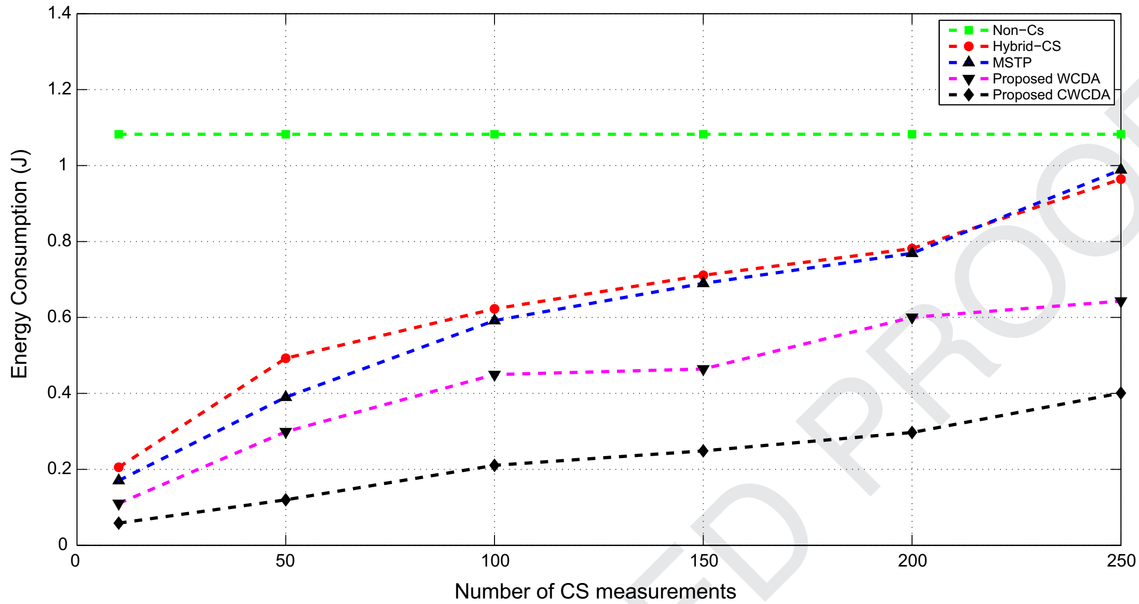

Fig. 6. Comparison of the energy consumption in Non-CS, Hybrid-CS, MSTP, WCDA and CWCDA data aggregation methods for $n = 1000$ with changing the number of CS measurements in the range [10,250].

Table 2
Comparison of data reconstruction error in WCDA and CWCDA methods for $n = 1000$ and different values of the number of CS measurements.

Data aggregation method	m = 10	m = 50	m = 100	m = 150	m = 200	m = 250
Proposed WCDA	0.29075	0.14145	0.06246	0.04766	0.04468	0.04216
Proposed CWCDA	0.29220	0.08815	0.07959	0.04851	0.04695	0.04415

Table 3
Comparison of load variance in Non-CS, Hybrid-CS, MSTP, WCDA and CWCDA data aggregation methods for $n = 1000$ and different values of the number of CS measurements.

Data aggregation method	m = 10	m = 50	m = 100	m = 150	m = 200	m = 250
Non-CS	3673	3673	3673	3673	3673	3673
Hybrid-CS	13.9	240.8	619.0	918.2	1456.1	1916.2
MSTP	1.8	32.5	91.2	220.5	317.4	454.6
Proposed WCDA	1.7	22.1	90.6	109.9	298.2	370.7
Proposed CWCDA	0.2	10.3	50.3	78.9	131.1	229.8

measurements is set to $m = n/10$. As previously mentioned, in the CWCDA algorithm, the total number of CS measurements increases linearly with the number of clusters n_C, therefore, we consider $n_C = m/10$. It is clearly predictable that with an increase in the number of sensor nodes n, the number of packets transmitted over the network is increased and as a result, the energy consumption and the load variance grow, however, the lifetime of the network will be reduced, as respectively observed from Fig. 8, Table 4 and Fig. 9. With the same arguments as in previous scenarios, our CWCDA scheme outperforms significantly other classical data aggregation methods in particular from the energy efficiency points of view.

Remark 1: In the final step of our simulation, we check the validation of selecting the number of cluster $n_C = 10$ in all previous simulations. Toward this goal, we run the proposed CWCDA scheme with different values of n_C, and set $n = 1000$ and $m = 100$, in order to evaluate the effect of n_c on the energy consumption as shown in Fig. 10. It is seen from Fig. 10 that the total energy consumption of the networks is a monotonically decreasing function of n_C, meaning that more clusters in the network results in more energy saving. However, it is shown in [35] that an increase in the number of clusters leads to an increase in the reconstruction error. Thus, we have a tradeoff between the energy consumption and the reconstruction error in terms of n_C. Since the reduction rate of the energy consumption in Fig. 10 is sufficiently low for $n_C \geq 10$, we set $n_C = 10$ in all simulations for the CWCDA scheme to guarantee an acceptable reconstruction error in our system model.

Remark 2: To complete our simulation results, we consider the following physical layer channel model and the practical energy efficiency in the physical layer which is widely utilized in many WSN literature (e.g., please see references [2,4,38]). Toward this goal, we consider the uncoded M-ary FSK modulation where M orthogonal carriers can be

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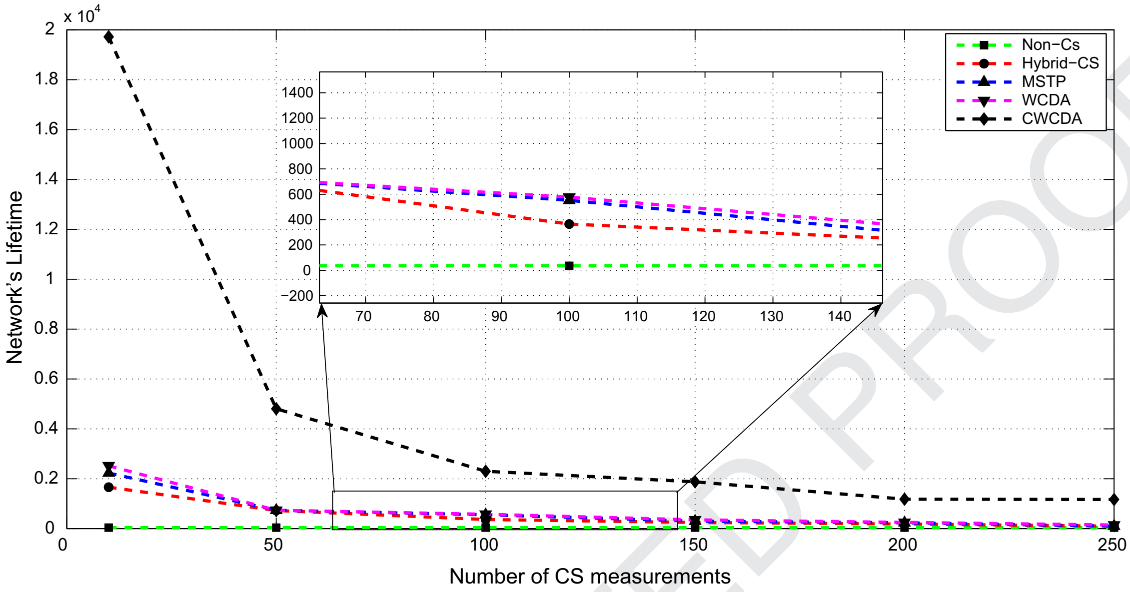

Fig. 7. Comparison of lifetime in Non-CS, Hybrid-CS, MSTP, WCDA and CWCDA data aggregation methods for $n = 1000$ with changing the number of CS measurements in the range [10,250]

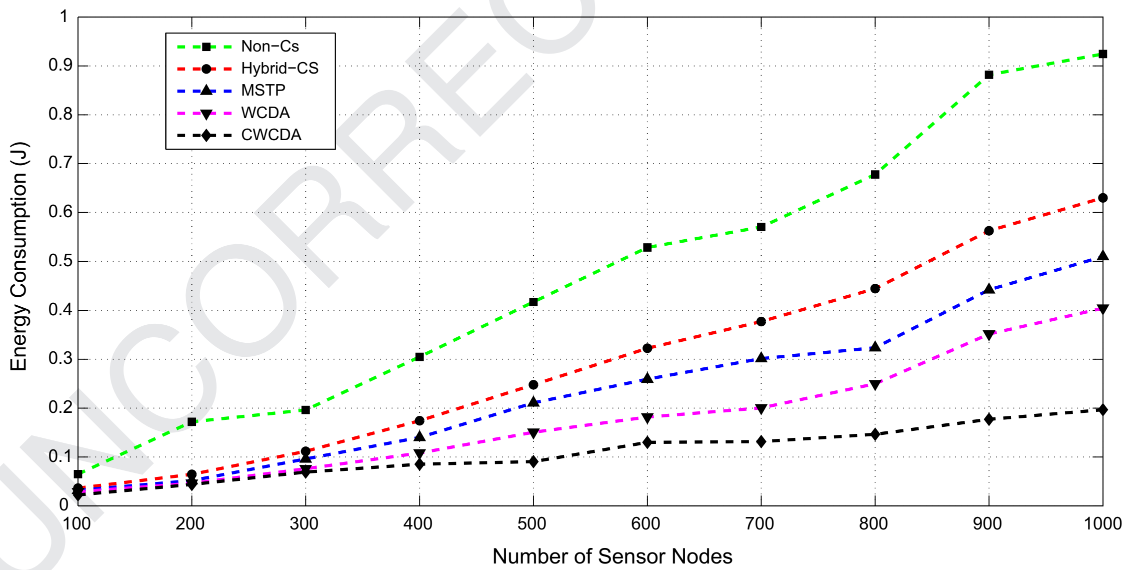

Fig. 8. Comparison of the energy consumption in Non-CS, Hybrid-CS, MSTP, WCDA and CWCDA data aggregation methods with changing the number of sensor node $n \in [100, 1000]$.

Table 4
Comparison of load variance in Non-CS, Hybrid-CS, MSTP, WCDA and CWCDA data aggregation methods with changing the number of sensor node.

Data aggregation method	n = 100	n = 200	n = 300	n = 400	n = 500	n = 600	n = 700	n = 800	n = 900	n = 1000
Non-CS	239.3	331.6	392.2	640.0	768.3	1412.8	1885.7	2127.7	3293.2	4131.3
Hybrid-CS	13.1	30.1	68.8	139.1	173.4	290.6	383.5	476.2	524.7	597.2
MSTP	12.8	25.3	32.0	37.8	49.8	68.5	70.3	79.2	89.6	98.2
Proposed WCDA	12.8	14.9	22.5	26.1	35.5	48.0	58.9	59.0	65.9	74.7
Proposed CWCDA	7.3	11.9	13.5	18.8	26.6	28.5	29.3	33.7	36.1	41.9

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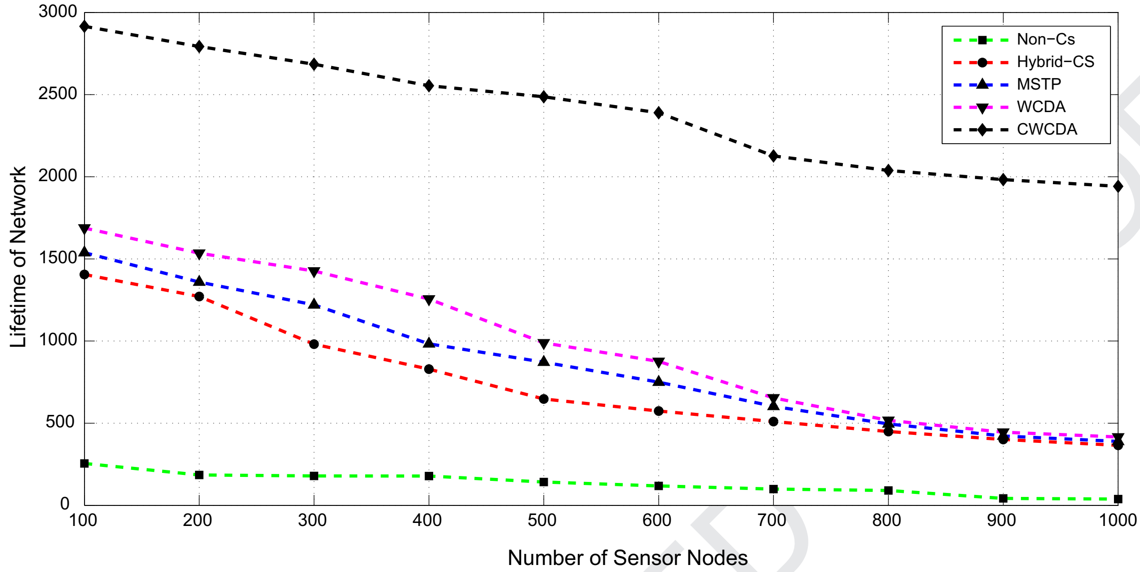

Fig. 9. Comparison of the network's lifetime in Non-CS, Hybrid-CS, MSTP, WCDA and CWCDA data aggregation methods with changing the number of sensor node $n \in [100, 1000]$.

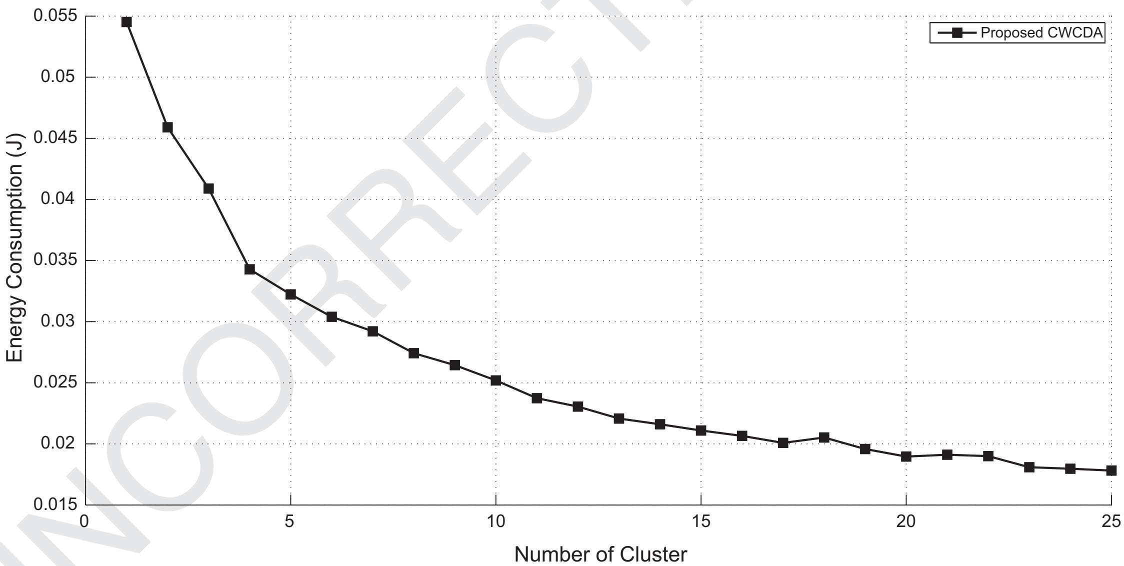

Fig. 10. Comparison of energy consumption in CWCDA algorithm with changing the number of cluster n_c.

mapped into $b \triangleq \log_2 M$ bits. It is shown in [39] that the transmit energy consumption per each symbol for an uncoded MFSK with non-coherent detector is obtained as

$$\mathcal{E}_t \triangleq [(1-(1-P_s)^{\frac{1}{M-1}})^{-1} - 2]\frac{\mathcal{L}_d N_0}{\Omega} \quad (9)$$

$$\overset{(a)}{=} \left[\left(1-\left(1-\frac{2(M-1)}{M}P_b\right)^{\frac{1}{M-1}}\right)^{-1} - 2\right]\frac{\mathcal{L}_d N_0}{\Omega}, \quad (10)$$

where (a) comes from the fact that the relationship between the average Symbol Error Rate (SER) P_s and the average Bit Error Rate (BER) P_b of MFSK is given by $P_s = \frac{2(M-1)}{M}P_b$. For the above equations and for a ηth power path-loss channel, the channel gain factor is given by $\mathcal{L}_d = M_l d^{\eta} \mathcal{L}_1$, where M_l is the gain margin which accounts for the effects of hardware process variations, background noise and $\mathcal{L}_1 \triangleq \frac{(4\pi)^2}{\mathcal{G}_t \mathcal{G}_r \lambda^2}$ is the gain factor at $d = 1$ meter which is specified by the transmitter and receiver antenna gains $\mathcal{G}_t$ and $\mathcal{G}_r$, and wavelength λ. In addition, we denote the fading channel coefficient corresponding to symbol i as h_i, where the amplitude $|h_i|$ is Rayleigh distributed with probability density function (pdf) $f_{|h_i|}(r) = \frac{2r}{\Omega} e^{-\frac{r^2}{\Omega}}, r \geq 0$, where $\Omega \triangleq \mathbb{E}[|h_i|^2]$.

According to introduced physical layer channel model, the effect of the number of CS measurements, $m \in [10, 250]$, on the network's performance is evaluated and the results are

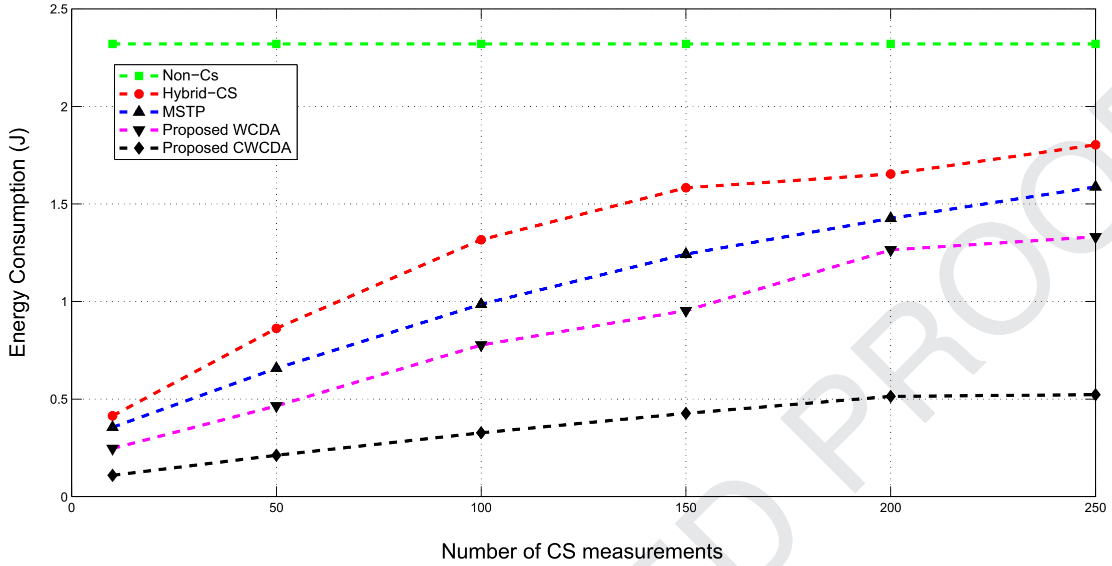

Fig. 11. Comparison of the energy consumption in Non-CS, Hybrid-CS, MSTP, WCDA and CWCDA data aggregation methods for $n = 1000$ with changing the number of CS measurements in the range [10,250] with taking the physical layer channel model into account.

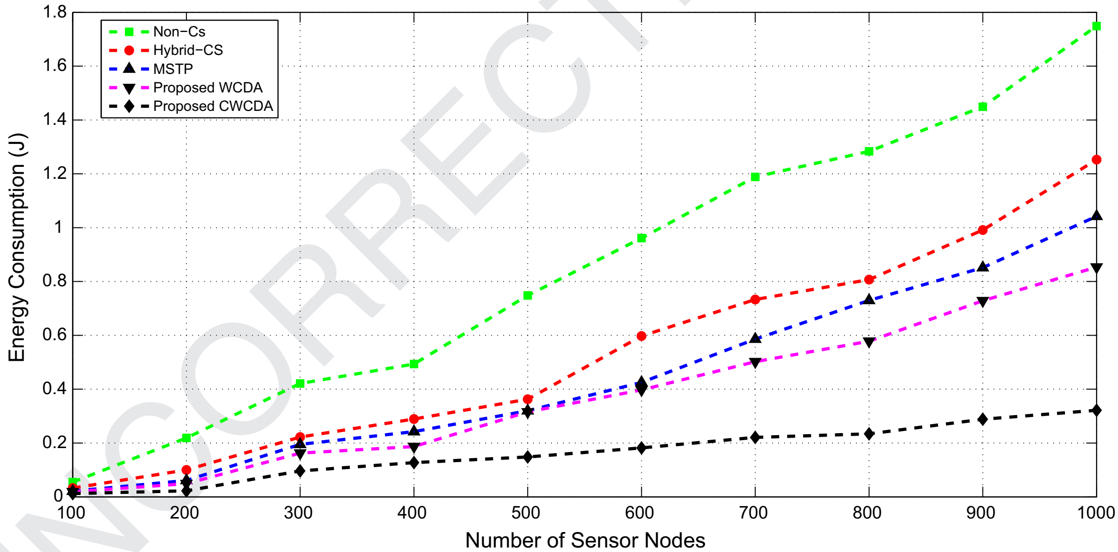

Fig. 12. Comparison of the energy consumption in Non-CS, Hybrid-CS, MSTP, WCDA and CWCDA data aggregation methods with changing the number of sensor node $n \in [100, 1000]$ with taking the physical layer channel model into account.

demonstrated in Fig. 11, where we consider again a WSN with $n = 1000$ sensor nodes and the number of clusters, $n_C = 10$, for the CWCDA algorithm. Like to previous scenarios, we assume that the sink node is located at coordinate (0, 0). Then, the proposed WCDA and CWCDA schemes are compared with the conventional Non-CS, Hybrid-CS and MSTP methods. As it can be seen from Fig. 11, with taking the physical layer channel model into account in the second scenario, the proposed schemes yet have the best performance in terms of the energy consumption for different values of m.

By considering the specifications and assumptions presented in third scenario and using the aforementioned physical layer channel model, the simulations have been repeated and the results have been shown in Fig. 12. As observed from Fig. 12, the proposed mehods, especially CWCDA, have lower energy consumption with compared to the conventional schemes.

6. Conclusion

In this paper, we used the compressive sampling and the power control ability in sensor nodes to propose a new energy efficient data aggregation scheme in a weighted WSN model, called “Weighted Compressive Data Aggregation (WCDA)”. It was demonstrated that the proposed WCDA algorithm uniformly selects collector nodes to form the collection tree in which each collector node aggregates a CS measurement from the corresponding candidate nodes, and then, each collector node sends the CS measurements to the sink node. We also extended the WCDA scheme to a new algorithm, namely "Cluster-based Weighted Compressive Data Aggregation (CWCDA)", to reduce more energy consumption based on an integration of the clustering method and the compressive sampling. Our work has focused on the improvement of the energy consumption, load balancing and the network's lifetime in different scenarios and has compared our proposed methods with three conventional schemes, Non-CS, Hybrid-CS and MSTP, which has demonstrated a superior efficiency of our proposed schemes. In particular, we derived numerical results for the aforementioned performance metrics in terms of the sink node locations, the number of CS measurements, and the number of sensor nodes. Numerical results have shown 20% energy saving for the WCDA algorithm keeping at the same time 10% lower load variance when compared to the MSTP algorithm in [25] when the sink node is located at the center of network's area. For this sensor node's location, the CWCDA algorithm performs 47% better than the WCDA scheme in terms of the energy consumption. In another scenario, when the number of CS measurements is 10 times the number of sensor nodes in the network, our simulation results showed that the WCDA scheme can reduce the energy consumption by about 24% when compared with the MSTP method. Meanwhile, the CWCDA algorithm can reduce the energy consumption up to 53% compared to the WCDA method. Overall, the CWCDA algorithm is attractive for using in large-scale WSNs already has the advantages of less energy consumption and load variance than classical CS-based data aggregation methods. However, the proposed CWCDA algorithm sacrifices 21% more data reconstruction error than the classical MSTP and WCDA schemes.

In this paper, we have selected randomly collector nodes in all proposed algorithms. A possible future extension of this work would be to find the optimal positions of collector nodes which minimize the energy consumption. In addition, this paper has focused on the spatial correlation properties of sensed data in real WSNs. A particularly nice extension of this work is to take into account both spatial and temporal correlations between sensors data in the proposed algorithms.

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