An Energy-Efficient Data Acquisition Technique for Hierarchical Cluster-Based Wireless Sensor Networks

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Abstract

The minimization of energy consumption related to data acquisition is of prime importance in energy constrained Wireless Sensor Networks (WSNs). The application of Compressive Sensing (CS) scheme can promote effective utilization of limited energy and radio resources of WSN, and reduce the wireless bandwidth needed for communication by decreasing the number of transmissions as well as the amount of data to be processed. This paper addresses the issue of energy-efficient data acquisition in WSN through the integration of CS and hierarchical routing method. The proposed technique divides the WSN into various clusters, and a set of Cluster-Heads (CH-set) is used to manage and control the activities within each cluster. The function of a CH-set member is to compress the acquired data from its respective cluster members (CMs) using the CS scheme. The results of simulation clearly demonstrate that the proposed CBHRP-CS technique facilitates energy-efficient data acquisition and is effective in improving the WSN lifetime over existing algorithms.

Keywords: Wireless Sensor Network (WSN), Clustering, Compressive Sensing (CS), Energy Efficiency, Data Acquisition, Hierarchical Routing.

1 Introduction

In Wireless Sensor Networks (WSNs), the sensor devices possess a very limited source of energy and hence it is required to conserve significant amount of energy for delivering durable operation of WSN. The major power hungry operations include data communication and multi-hop transmission of the captured data to a base station (BS). Therefore, it is essential to reduce the data communication and to have effective load distribution among nodes to conserve the overall WSN energy [1, 2]. Many researchers have contemplated the challenges of energy efficiency in WSN to enhance its lifetime through several techniques like sleep scheduling, data aggregation and topology control [3, 4, 5, 6, 7]. To make WSN durable and energy efficient, implementation of appropriate techniques for data routing and aggregation are necessary. The approaches of clustering and hierarchical routing can promote durability and energy efficiency through load balancing criteria and reliable data transmission in WSN [8, 9, 10].

The inherent characteristics of WSN with relatively large number of resource constrained sensor nodes make routing in WSN really challenging to meet the application requirements [9, 10, 11]. To reduce the energy consumption and to improve the network efficiency, routing methods developed for WSNs make use of various approaches such as in-network processing, data aggregation, data-centric methods etc. over different WSN topologies [12, 13, 14].

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The use of clustering techniques help in designing hierarchical energy efficient WSNs in order to achieve better load balancing, reliable data transfer and scalability [15, 16, 17, 18, 19]. Often, the data collected by the WSN nodes express high temporal-spatial correlation. The similarity in the data collected by the densely deployed WSN nodes is known as spatial correlation, which causes data redundancy and energy wastage [7, 20]. Moreover, some WSN deployment scenarios require high frequency data acquisition in order to ensure high data accuracy. As a result of high frequency of data acquisition, the sensed data in successive slots of time look highly similar, and is termed as temporal correlation. This also causes high data redundancy and increased energy consumption. Reducing such data redundancies before transmitting the data to the sink can help in improving the energy efficiency. The data aggregation techniques make use of the temporal-spatial correlation characteristics of the gathered data and thereby offer data minimization by removing redundancies. But, such schemes still endure some drawbacks such as information loss as they focus predominantly on forwarding a summary of the collected data to the BS. Even though various data acquisition techniques have been introduced and studied over the years, the data collection/aggregation schemes still need enhancement for improving the durability of resource constrained WSN [1]. To increase the energy efficiency and WSN lifetime, proper implementation of data aggregation and routing techniques are necessary [18, 19, 21].

The Compressive Sensing (CS) technique renders a new sampling strategy to reduce the size of data being transmitted and therefore minimize the energy utilization in WSNs [22, 8, 23, 24]. In a real-world WSN, the sensor data possess correlation properties and there exist incoherent sparsity of data sensed by the nodes in a known basis such as DCT or DWT (Discrete Cosine/Wavelet transform) [8]. The CS technique offers high quality signal reconstruction with reduced sampling rate (using a small number of linear measurements) for sparse signals [23]. Since the cluster-based approach of data gathering possess many advantages over tree-based or flat structure [9, 22, 24, 25], the CS-based data collection techniques in cluster based WSN were investigated comprehensively in the literature. The features of CS theory such as signal compression, robustness, computational asymmetry, and stability make it a good choice for WSNs operating in resource constrained environment. CS technique provides a concrete mathematical approach which wisely captures only M samples (which are highly appropriate for signal reconstruction) from N possible samples of a signal. When compared with other data compression techniques, implementation of CS strategy in WSN provides a promising enhancement because the resource constrained WSN nodes are not having enough capability to handle encoding of data compression techniques [22, 23, 24, 25, 26].

Motivated by this, a hierarchical cluster based routing protocol that makes use of the advantages of CS strategy for data collection in WSN is presented in this paper. This allows energy efficient acquisition of data in WSN through the integration of CS and hierarchical routing method, which provides an enhancement over existing cluster based hierarchical routing protocols in WSN. The proposed CBHRP-CS technique divides the WSN into various clusters, and a set of Cluster-Heads (CHs) called CH-set is used to manage and control the activities within each cluster. The function of a CH-set member is to compress the acquired data from its respective cluster members (CMs) using the CS scheme. Even though CH-set comprises of several virtual CHs, they work on rotation basis such that a single member of CH-set is active in one epoch. There are several iterations within each round. Each node joins as a member of CH-set once in each round of operation. All the members of CH-set share the same time slot for their frames transmission. The resultant data is then transmitted to the distant BS. The results of simulation show that the proposed approach allows energy-efficient data processing by performing efficient compression of data, and is effective in improving the network lifetime to a great extent.

1.1 Compressing Sensing

As stated by the Nyquist sampling theorem, the sampling frequency should at least be the double of the peak frequency of the signal being sampled. Conversely, the CS theory offers precise reconstruction of a sparse or sparsified signal at reduced sampling frequency, which can remarkably lower the energy drain of WSN [22, 23]. Hence, the CS scheme allows to eliminate the dependence between sampling frequency and the signal bandwidth.
Let signal $X \in R^N$ in the form of Eq. 1 depicts a compressible signal, using a transform matrix $\Psi \in R^{N \times N}$ and sparse cofficient matrix α of X.

$$X = \Psi\alpha, \tag{1}$$

Let signal X be expressed as a linear combination of $K \ll N$ vectors, where K denotes the count of nonzero coefficients in X. In many applications, the signals have only a few large coefficients and those coefficients can be approximated by K so that one can select the K largest coefficients and discard the remaining smallest coefficients.
Traditional compression techniques lack efficiency because they find all N coefficients and record all zero coefficients, even if $K \ll N$ [27]. The CS scheme performs acquisition and compression in one step and therefore a fewer count of coefficients are recorded and transmitted. As a result, CS helps to reduce energy utilization and computation cost. The CS provides M measurements ($K < M \ll N$) with sufficient information for accurate reconstruction of X.
The measurements of X can be denoted as $y = \Phi$ X, with $\Phi \in R^{M \times N}$ as the sampling matrix $(M \ll N)$. The measurements $y \in R^M$ can be stored, transmitted, and retrieved easily than compared to $X \in R^N$, since $M \ll N$. The measurements y is rewritten as follows:

$$y = \Phi\Psi\alpha. \tag{2}$$

such that $A = \Phi\Psi$ is termed as the sensing matrix. In WSNs, Φ is generally pre-designed, i.e., each node picks M elements locally of the random projection vectors, taking network address as the seed of a pseudorandom number generator.
In order to retrieve the original data precisely using the compressed sample, the Φ should satisfy RIP (Restricted Isometry Property). If $A = \Phi\Psi$ satisfies condition of RIP: $M \leq cK\log(N/K)$ s.t $c > 0$, it is possible to recover the vector α from y accurately, as the unique solution of Eq. 3 .

$$\hat{\alpha} = argmin_{\alpha} \|\alpha\|_1 \quad s.t. \quad y = \Phi\Psi\alpha. \tag{3}$$

Definition of RIP: If there exist δ_K (where $K = 1, 2, \ldots,$ integer values) of a matrix A which satisfies the property $(1-\delta_K)\|\alpha\|_2^2 < \|A\alpha\|_2^2 < (1+\delta_K)\|\alpha\|_2^2$ for all K-sparse vectors α such that $\|\alpha\|_0 = K$ (δ_K, isometry constant, not too close to 1); then A approximately maintains the Euclidean length of K-sparse signals α, and this implies the possibility to reconstruct α [24]. The X (original data) can be in sparse form on itself or can be converted to a sparse representation using appropriate transform such as Discrete Cosine/Wavelet Transform [28, 29].

The remainder of the paper is organized as follows: The Section 2 discusses the related research. In Section 3, we describe the proposed system model. In Section 4, we present the evaluation results of our CBHRP-CS protocol compared with CBHRP, WEEC and IMP-EEL protocols [17, 18, 19]. And finally, Section 5 concludes the paper.

2 Related Research

Over the past years, several routing protocols have been designed to improve the data acquisition efficiency of WSN [10, 15, 9]. Generally, most of such approaches adopted cluster based techniques to

improve energy efficiency and to achieve prolonged rounds of operation [13, 8, 4, 16, 19]. Clustering methods allows the CH to perform data aggregation to minimize energy utilization and role rotation approach is utilized to enhance the lifetime [30, 13, 17, 18]. Following the primitive LEACH protocol, several protocols evolved, together with the application of advanced routing techniques [31, 32]. The PEGASIS protocol and its variants [33] presented to be more efficient and robust when compared to LEACH. The work in [17] presented a cluster based protocol with the concept of using a set of CHs for managing the operations within each cluster, by dividing the WSN into numerous clusters, each of which is managed by a virtual head. The simulation results revealed that the method improved energy efficiency and network lifetime when compared to LEACH. Another extension of LEACH is presented in [18], which used the distance of the nodes from the BS as a factor for selecting the CHs through a weighting method. This ensures the selection of a desired number of CHs, however, it doesn't consider the residual energy of each node during the CH selection. [19] used a probabilistic approach in selecting suitable CHs promoting the efficiency and performance in terms of energy. The nodes which have highest residual energy will get more chances to become CH than others. The work in [15] integrated a new model of network structure with existing energy consumption model to choose optimal clusters by making use of distance variance and dual-CHs based energy balancing technique, whereas [13] provided a combination of static and dynamic clustering.

The past researches have revealed that significant conservation of energy in WSN can be attained by reducing traffic load and cost during communication. However, most of the protocols related to cluster based hierarchical WSN focused on choosing effective CHs in terms of energy or some other metrics to improve energy efficiency. The redundancy in data collection can cause significant energy wastage, as well. Considering this fact, adaptive sampling methods and data compression schemes were utilized to reduce the communication cost and consequently to improve the WSN lifetime [7, 34]. However, the traditional data compression schemes suffer from a restriction imposed by Nyquist-Shannon sampling theory, and in most cases the number of samples are still too high for resource constrained WSNs and require location identification of large coefficients [7, 34, 35]. To overcome these limitations, compressive sensing (CS) based schemes has been introduced [36, 37, 16, 34, 35, 38]. In the recent years, the effectiveness of CS strategy in data compression and its applicability in WSN is receiving widespread attention [39, 40, 41]. The features of the cluster structure such as traffic-load balancing and fault tolerance enable the CS-based clustering and data acquisition schemes to have competitive benefits over other approaches [42, 43, 44, 45]. Taking advantage of the CS technique, it is possible to bring remarkable reduction in the redundancy of temporally/spatially correlated data, which in turn can contribute significantly in improving the efficiency of WSN [30, 46, 36].

Various data acquisition schemes incorporating the CS technique and the cluster based hierarchical structure were developed over the past years [39, 40, 30, 43, 44, 45, 37, 34, 35, 38]. In [30], an efficient load-balanced cluster based (ERPLBC-CS) routing protocol using CS is presented. The simulation results indicate that the ERPLBC-CS scheme efficiently balances the energy consumption load, improve the stability period and the lifetime of the WSN. In [8], two schemes were used for data acquisition, raw method for intra- cluster and CS based method for inter-cluster. The method combined clustering with hybrid CS, and studied the relation between cluster size and transmissions count. A CS approach to resolve the energy hole problem in large scale WSN is presented in [40], to achieve load balancing and to prevent energy holes. The results indicate that the method improves transmission efficiency and provides an even distribution of load among nodes. [45] introduced a cluster based data aggregation technique using CS and adopted Treelet-based transformation for sparsification. It facilitates energy saving by taking advantage of the correlation structures and reduces communication overhead per reconstruction error for adopted data sets. A cluster-based data collection scheme combined with block-wise CS proposed in [43] studied the effect of optimal count of clusters for attaining energy efficiency. Block diagonal measurement matrix is used, and the CS performance is analyzed using various sparsifying bases. However,

block diagonal matrix may not be appropriate to well describe the relationship among sensor data since the values corresponding to different clusters may be correlated with each other and also the compression rate of each cluster is selected based on the number of cluster nodes and the sensed data distribution is not considered for selection. [44] proposed a weighted CS based data collection scheme by incorporating the benefits of clustering. Sparse random matrix is used as measurement matrix for achieving energy efficiency. The technique significantly reduced the number of nodes within a cluster that are involved in CS measurement. The unique energy control capability of nodes helped in constructing efficient routing trees, which provided better load balancing and enhanced the energy efficiency. In [46], energy efficient and high fidelity data collection approach using CS is presented, which uses the diffusion wavelets to find a sparse basis that characterizes the spatial (and temporal) correlations and investigate the minimum energy compressed data aggregation problem. The simulations on both real datasets and synthetic datasets showed performance improvement with significant energy saving. In [37], a reshuffling cluster based data acquisition using CS (RCCSDG) is proposed in which the CHs adopt a simple pre-processing on node data and reshuffle into ascending order, which can greatly improve the sparsity and effectively reduce the amount of transmitted data. The results show that RCCSDG is efficient in reducing the energy consumption and improve the WSN lifetime. [35] combines Kronecker compressed sensing (KCS) and cluster topology to exploit spatial and temporal correlations simultaneously and effectively balances the energy-performance trade-off. In [38], an energy consumption configuration model joint distribution compressive sensing and quantization compressive sensing is proposed for energy efficient data gathering. [34] uses sparse binary matrix as the measurement matrix, and based on the short-term stability of temperature data, studies the sequential data gathering problem in the temperature monitoring WSN. The clustering techniques that follows CS-strategy as mentioned above have made considerable effort in minimizing the energy consumption of the WSN. However, formulation of efficient strategy that can further reduce the communication and data acquisition/processing cost still needs significant enhancement and is an interesting topic that receives increased attention. We propose an energy efficient scheme of data acquisition for WSN through the integration of CS and hierarchical routing method which provides an enhancement over existing cluster based hierarchical routing in WSN. The benefits of both the CS and clustering are exploited to enhance the energy efficiency. Table 1 gives a comparison of existing related research on data acquisition concern in WSN.

Table 1: A comparison of existing related research on data acquisition in WSN

Technique	Ref	Focus	Advantages	Limitations
Cluster Based Hierarchical Routing Protocol	[17]	extension of LEACH, concept of headset based routing	reduced data transfer delay and improved energy efficiency, network lifetime	residual energy of node is not considered for CH selection
Improved Energy Efficient LEACH Protocol (IMP-EEL)	[19]	considered residual energy aspect during CH selection	network lifetime and stability, energy efficiency	CHs become exhausted and not helpful in large WSN scenario.
Weighted Energy Efficient Clustering (WEEC)	[18]	improvement of LEACH by considering the node location while cluster formation	minimize communication cost and improve network lifetime	residual energy of each node not considered in each round.
Efficient load-balanced cluster based (ERPLBC-CS) routing protocol using CS	[30]	Energy load balancing and prolong the stability period in WSNs	Reduces the energy consumption load, improve the stability period, network lifetime	Latency is not considered.
Transmission-efficient clustering method for WSNs using CS	[8]	an analytical model, hybrid CS method, studies the relationship between the cluster size and number of transmissions	the optimal size of clusters, reduced number of transmissions	chances for network coverage and connectivity issues, ignored the sparse random measurement utilization to reduce the packet transmissions.
Treelet-based clustered compressive data aggregation (T-CCDA)	[45]	energy saving by taking advantage of the correlation structures	reduces communication overhead per reconstruction error for adopted data sets	latency is not considered.

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Table 1 – *Continued from previous page*

Technique	Ref	Focus	Advantages	Limitations
Energy-efficient data collection in clustered WSNs using block-wise CS (CCS)	[43]	considered direct and multi-hop routing, studied the effect of optimal clusters and energy consumption under different sparsifying bases	energy efficiency, significant reduction in number of data transmissions	block diagonal matrix and compression rate decision based on cluster nodes count may not be convenient in some cases, hence it is desirable to consider the data distribution.
A CS approach to resolve the energy hole problem in large scale WSN (CIDPS)	[40]	to achieve load balancing and prevent energy holes	transmission efficiency and even distribution of load	latency is not considered.
Weighted compressive data aggregation in cluster-based WSN	[44]	power control ability in sensor nodes to form energy efficient routing trees, focus on load-balancing	energy efficiency, load balancing and network lifetime improvement	only random selector nodes are considered for the implementation.
Compressed Data Aggregation for energy efficient and high fidelity data collection	[46]	use of diffusion wavelets to find a sparse basis, investigation on minimum energy compressed data aggregation	simulations on both real, synthetic datasets showed performance improvement	complexity and traffic is larger.
Reshuffling cluster compressed sensing based data gathering (RCCSDG)	[37]	a simple preprocessing by CH on original data, reshuffling in ascending order, improve the sparsity, minimize the data transmission	efficient compression, reduced energy consumption	computational complexity and latency are not considered.
Energy efficient distributed compressed data gathering model (JSM-2 model)	[38]	constructed an energy consumption configuration model joint distribution CS and quantization CS	energy efficient data gathering	the assumptions seems to be a little strong in large scale WSN scenario where common sparsity property cannot be achieved as desired.
Spatiotemporal Data Gathering Based on CS	[35]	combines Kronecker compressed sensing (KCS) and cluster topology to exploit spatial and temporal correlations simultaneously	effectively balances the energy-performance trade-off	latency and lifetime are not considered
Compressive sensing-based sequential data gathering in WSNs	[34]	sparse binary matrix is used as measurement matrix, studies the sequential data gathering problem and short-term stability of temperature data	decreases total energy consumption	higher time complexity, other data types (or the data with great changes in a short time) are not considered.

3 Proposed CBHRP-CS model

Consider that N sensor nodes are distributed randomly within the observation field. Each node generates a data sample $x_j\,(j = 1,...,N)$ to be measured and the corresponding vector form $X = [x_1,...,x_N]$ is termed as the networked data and this needs to be transmitted to the BS.
Following are some assumptions which we use in the presented model.

- Distinct IDs are assigned to nodes to identify each node uniquely from the neighboring nodes.
- Each WSN node is static and is aware of its own location in terms of an (x,y) coordinate, using location services such as in [47].
- The BS is aware of the CIR of each connection between CH and any sensor node .
- All nodes are assumed to have same level of initial energy.

The proposed CBHRP-CS technique converts the WSN into a few real clusters. The CH selection is based on the residual energy of nodes. Every cluster includes a CH-set comprising of some virtual CHs, among which only a single CH will be active at a time. All the members of CH-set share the same time slot for frames transmission. Fig. 1 illustrates the working stages of the proposed CBHRP-CS protocol.

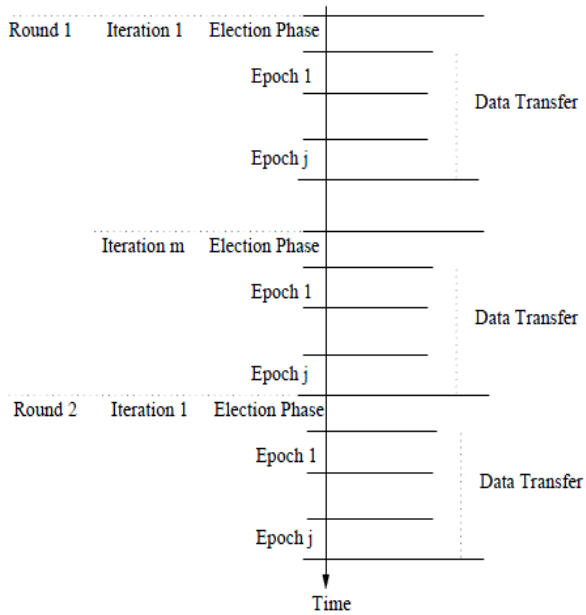

Figure 1: The working stages of the proposed CBHRP-CS protocol.

An operation round includes various iterations and in a round, a node act as a member of CH-set once in an epoch. Each iteration is further subdivided into two phases as follows: (i) Election Phase: The selection of CH is performed in this phase, (ii) Data Transfer phase: During this phase, the data transfer to the BS takes place. The first phase begins with the random election of a set of CHs. The selected CHs are then allowed to send broadcast advertisement messages via short range communication. If a node receives such an advertisement, it will acknowledge back to the CH. Depending on the acknowledgment messages (received signal strength), the CH further selects a set of nodes to act as associate CHs and adds them to the CH-set. Therefore every CH-set includes a CH and its chosen associates.

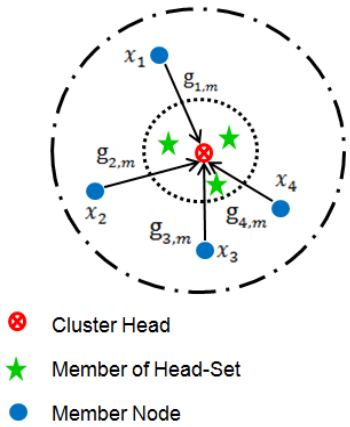

Figure 2: Transmission in clusters.

That means, in each election phase, a CH-set that includes a set of nodes is determined. The members of a CH-set are in charge of sending messages to the BS. The members of a CH-set become active one at a time and the remaining participants in CH-set stay in sleep or passive state. The responsibility of data transmission to the BS is distributed uniformly among all the participants in the CH-set.

Next comes the data transfer phase. During this phase, the active member of CH-set will receive data from its neighboring sensors and then applies CS strategy for data compression and delivers the resultant data to the BS. Fig. 2 illustrates the transmission within a cluster. Finally, the networked data will be reconstructed at the BS. Each phase of data transfer has several epochs. Members of CH-set takes the role of CH during epochs. As an iteration contains several epochs, when an iteration terminates, the CH-set members turn to non-candidate state and a new CH-set is elected for the next iteration. Ultimately, when a round ends, all the nodes turn to non-candidate state. At this phase, a new round begins and all the nodes take candidate state. Fig. 3 gives a detailed view of the proposed CBHRP-CS scheme.

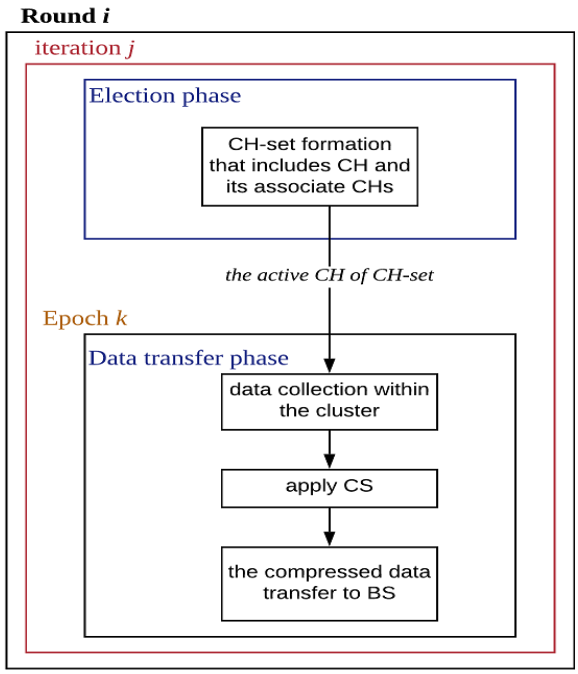

Figure 3: Scheme flow chart of the proposed CBHRP-CS protocol.

In our proposed approach, DCT matrix is used for sparsification and CIR (Channel Impulse Response) matrix [41] is employed as the sampling matrix.

3.1 DCT Basis

In order to sparsify X (the networked data), we use Discrete Cosine Transform (DCT) basis. DCT computes the set of transform coefficients (sparser than the original data) to replace the measurements set,

$$X = \Psi\alpha. \tag{4}$$

in which, $\alpha \in R^N$ denotes the transform coefficients (with K nonzero ($K \ll N$)) vector, and $\Psi \in R^{N\times N}$ the DCT basis.

3.2 CIR Basis

In each cluster, the current active member of the CH-set collects data from the CMs and uses CS to compress the collected data, and the compressed data is forwarded to the BS. The signal vector received at CH can be expressed using CIR matrix G as follows:

$$y = GX = G\Psi\alpha, \tag{5}$$

such that

$$G[m,n] = d_{m,n}^{-\beta} \left| h_{m,n} \right|, \tag{6}$$

The $G[m,n]$ denotes the CIR matrix component. The distance from n^{th} node to m^{th} CH is denoted as $d_{m,n}$ and β represents the propagation loss factor. $h_{m,n}$ corresponds to the Rayleigh fading coefficient modeled as zero-mean unit-variance complex Gaussian noise [41]. The n nodes send their samples to m CHs (See Fig. 4). Thereafter, the CHs independently transfer the measurements y to the distant BS. The BS takes y and reconstructs the original data X [48].

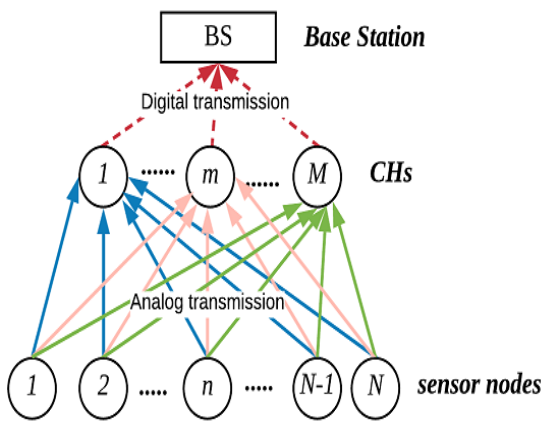

Figure 4: Basic CIR model

4 Evaluation

We provide and evaluate the results of simulation, in this section. The simulations are performed using MATLAB. We verify and compare the efficiency of the proposed CBHRP-CS technique in balancing and minimizing the energy utilization and its effect in prolonging the lifetime of WSN. The simulation parameters are as provided in Table 2. The performance of CBHRP-CS is compared with that of CBHRP, WEEC and IMP-EEL schemes.

Performance Metrics: The following are the performance metrics which we used for evaluating the performance of the proposed CBHRP-CS protocol.

(i) Energy Efficiency: The performance of the protocols are evaluated in terms of energy consumption by varying the clusters count and network diameter, and the node density.

(ii) Iteration time: The average time to finish an iteration is analyzed using CBHRP-CS and the performance is compared with CBHRP, WEEC and IMP-EEL schemes.

Table 2: Simulation Parameters

Parameters	Value
R	100 m
Initial Energy	0.5 J
K	60
N	1000
M	200
β	2
ε_{amp}	10 $pJ/(bit*m^2)$
E_{elec}	50 nJ/bit
ε_l	0.0013 $pJ/(bit*m^4)$

(iii) Count of frames transmitted per iteration: the count of frames transmitted per iteration is evaluated and compared with that of others.

(iv) Network Lifetime: the lifetime of the WSN using CBHRP-CS is evaluated and compared with that of other schemes.

4.1 Energy Efficiency

Since energy efficiency is one of the most important requirement in WSNs, we first discuss and compare the performance of the proposed protocol with the existing CBHRP, WEEC and IMP-EEL schemes. The performance of the protocols are evaluated in terms of energy consumption (1) for fixed number of frames, by varying the clusters count and network diameter, and (2) the node density.

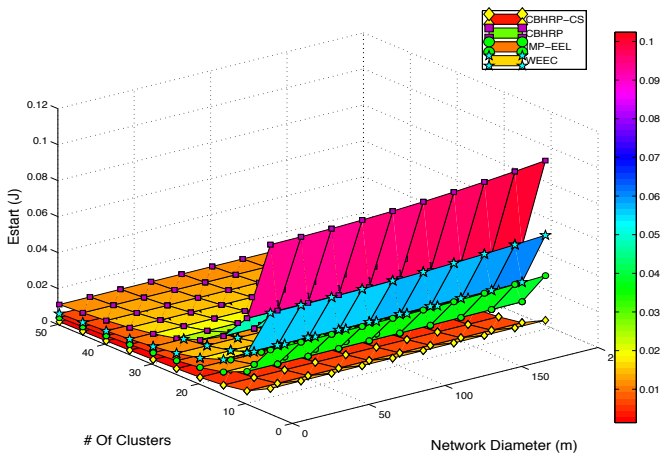

Figure 5: Energy consumption in terms of varying clusters count and network diameter.

a) Energy consumption with respect to the variation in the clusters count and network diameter: We evaluate the energy consumption with respect to the variation of cluster number and network diameter size, for fixed number of frames. Fig. 5 shows the difference in the energy consumption per

round for the proposed CBHRP-CS technique in comparison with WEEC, IMP-EEL and CBHRP protocols. The energy consumption of the proposed CBHRP-CS scheme is much lower than that of WEEC, IMP-EEL and CBHRP protocols. The use of CH-set instead of single CH and inclusion of CS strategy helped in improving the energy efficiency of our proposed CBHRP-CS scheme. From the figure, we can see the reduction in consumed energy when the cluster count is increased. For a network simulated with 1000 nodes, the optimal count of clusters lies within 20-60 range. However, when the cluster count is less or greater than the optimal range, it affects the energy utilization. When the count of clusters is less than the optimal range, the nodes need to transmit data to distant CHs; whereas, when the count of clusters go beyond the optimal range, it will result in increased transmissions to the distant BS. Also, with the increase in network diameter, the CHs should transmit data to the distant BS. Besides, when the network diameter decreases, the energy utilization also reduces and there will be more transmissions to the BS.

b) Energy Consumption for various node densities: We have further examined the performance of the network in terms of energy consumed under various node densities. Fig. 6 shows that CBHRP-CS consumes relatively less energy when compared to WEEC, IMP-EEL and CBHRP, under various node densities. The reason behind the energy efficiency of the proposed CBHRP-CS is that it guarantees effective and fast compression of data using CS strategy which is a major necessity for WSN with constrained resources. As a consequence, the energy consumption of the network is minimized compared to WEEC, IMP-EEL and CBHRP.

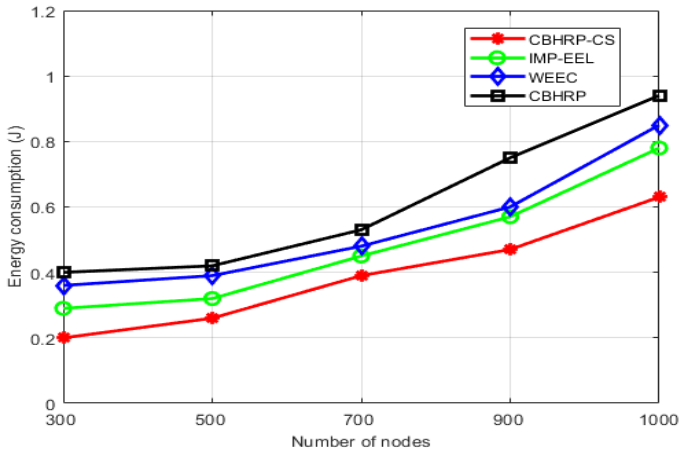

Figure 6: Energy Consumption for various node densities

4.2 Iteration time

In this section, the average time to accomplish one iteration such that every node becomes a member of the CH-set is analyzed using CBHRP-CS and the results are compared with that of CBHRP, WEEC and IMP-EEL protocols.

(i) Iteration time under various network diameter and CH-set size: Fig. 7 shows the estimated time for completing an iteration under various network diameter and CH-set size. The initial energy is fixed for all the cases. From the figure, it is clear that our proposed CBHRP-CS operates for long duration than other evaluated algorithms. The estimated duration for a single iteration of the

proposed scheme is more. The network will be alive for a longer time duration when the size of the CH-set is equal to 50% of the cluster size. The extension of the iteration time duration for CBHRP-CS as depicted in the figure results from the efficient compression the data using CS strategy and each node makes independent decision during CH election. Hence, CBHRP-CS is successful in extending the iteration time, and hence prolongs the network lifetime than other protocols. The iteration time is proportional to the network diameter and initial energy. However, it is more or less with respect to the size of the CH-set.

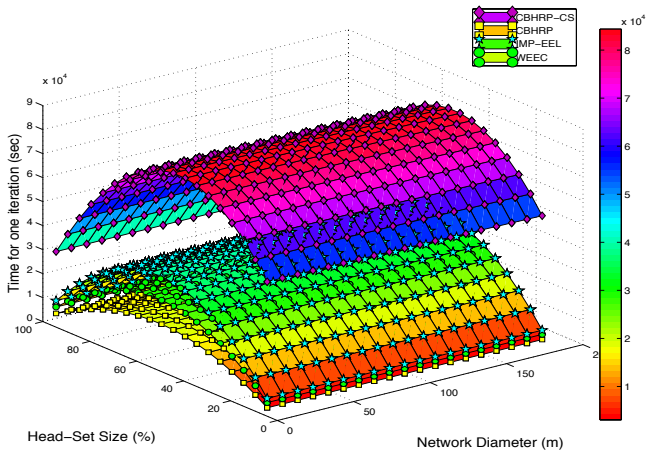

Figure 7: Time for iteration under various network diameter and CH-set size.

(ii) Iteration time under various number of clusters and CH-set size: Fig. 8 shows the estimated time for an iteration in terms of number of clusters and CH-set size. It is clear from the figure that for the same count of clusters, the iteration time increases with the increase in the CH-set size and for larger sized CH-sets, a single iteration can last longer. However, for increased clusters count, the iteration time is reduced. This indicates that the CH-set size and count of clusters have to be

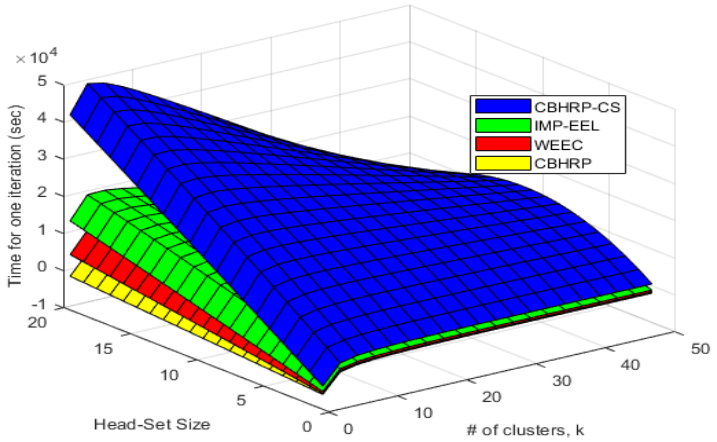

Figure 8: Time for iteration under various clusters count and CH-set size.

selected carefully for better extension of the WSN lifetime. The result shows that CBHRP-CS with the use of CS outperforms the other protocols in optimizing the energy consumption and consequently increases the time for a single iteration.

4.3 Count of frames transmitted

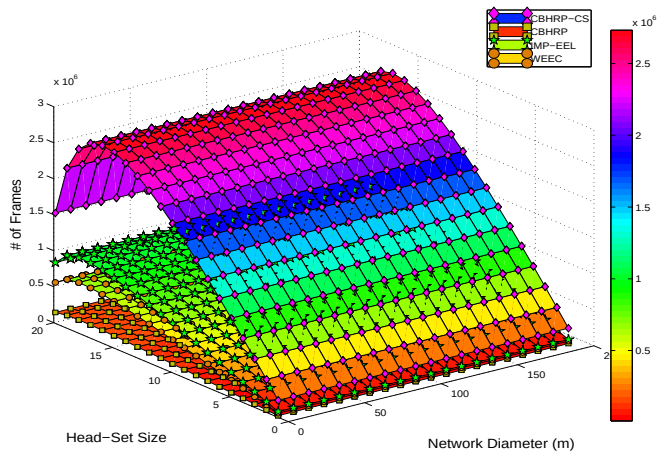

Figure 9: Count of frames transmitted per iteration.

Next, we evaluate the count of frames transmitted per iteration using CBHRP-CS and compare the results with CBHRP, WEEC and IMP-EEL protocols. Fig. 9 shows the transmitted count of frames under various CH-set size and network diameter. The increase in the CH-set size allows more count of frames to be transmitted, and therefore, an iteration can have more life, and this result is consistent with the findings from the Fig. 7. This implies that the increase in CH-set size can offer more CH nodes for cluster management and control. Therefore, the CH nodes can operate for longer time, and is able to transmit more frames of data when compared to the other algorithms.

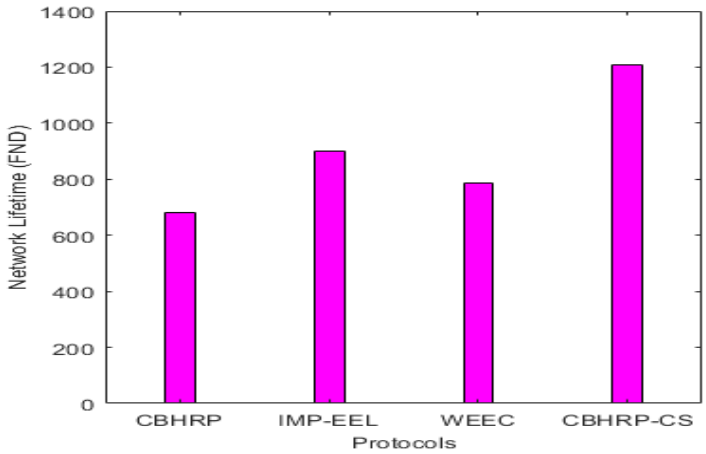

Figure 10: Network Lifetime

4.4 Network Lifetime

Finally, the lifetime of the WSN using CBHRP-CS is evaluated and compared with that of others. Fig. 10 shows the WSN lifetime in terms of rounds from the beginning of the network operation until the death of the first sensor node (FND), which is important for many critical applications in which the response from the WSN must be reliable. This gives an insight into the performance of the network in maintaining network stability from beginning round to the death of the first node. The figure shows that the proposed CBHRP-CS protocol enhances the lifetime of the WSN compared to the other protocols. CBHRP-CS maintained better network stability than the other three protocols using the combination of CS strategy with CH-set. This resulted in better energy efficiency and improved lifetime when compared to the other three evaluated protocols.

5 Conclusion

In this work, we proposed a CS enhancement over existing cluster based hierarchical routing protocols. CS measurements are obtained via the respective CH-set members within the clusters. For this, we have used CIR matrix as the sampling matrix and DCT as the sparsification basis. The simulation results clearly illustrate that our proposed CBHRP-CS protocol provides significant minimization in the energy consumption, improves the WSN lifetime and can allow more frames to be transmitted per iteration than compared to the other existing protocols.

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