Optimized Clustering Protocol for Balancing Energy in Wireless Sensor Networks

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***Abstract*:** While wireless sensor networks (WSNs) are increasingly equipped to handle more complex functions and in-network processing may require these battery powered sensors to judiciously use their constrained energy to prolong the effective network lifetime. Cluster-based Hierarchical Routing Protocol using compressive sensing (CS) theory (CBHRP-CS) divides the network into several clusters, each managed by a set of CHs called a header. Each member of the header compresses the collected data using CS. This paper proposes an optimized clustering protocol using CS (OCP-CS) to improve the performance of WSNs by exploiting compressibility. In OCP-CS, each cluster is managed by a cluster head (CH). CHs are selected based on node concentration and sensor residual energy, and performs data aggregation using CS to reduce the energy consumed in the process of data sampling and transmission. Simulations show that our proposed protocol is effective in prolonging the network lifetime and supporting scalable data aggregation than existing protocols.

***Keywords*:** Clustering algorithms, Compressive sensing, Energy efficiency, Node concentration, Wireless sensor networks**.**

1. Introduction

Advances in sensor and communication technology have focused interest on using WSNs, which are formed by a set of small untethered sensor devices that are deployed in an ad hoc fashion to cooperate on sensing a physical phenomenon, causing inferences, and transmitting the data. WSNs can be used for a wide variety of applications [8] dealing with monitoring (health environments, seismic, etc.), control (object detection and tracking), and surveillance (battlefield surveillance), connected cover, perimeter, and topology discovery [15, 16, 17, 18].

Energy consumption and energy-balancing are one of the primary research issues for WSNs. Since node's energy is limited and non-rechargeable, how to improve energy efficiency and balance the energy have become more and more important. As the sensors in the network have limited battery power, enhancing the lifetime of a network is the basic aim of designing an energy efficient routing protocol.

Routing in WSNs is very challenging due to the essential characteristics that distinguish WSNs from other wireless networks. It is highly desirable to find the method for energy efficient route discovery and relaying of data from each sensor node to base station (BS) so that lifetime of the network is maximized. In WSNs, the sensor nodes are often grouped into individual disjoint sets called a cluster, as clustering is used in WSN to provide network scalability, resource sharing and efficient use of constrained resources that gives network topology stability and energy saving attributes [24].

Clustering schemes offer reduced communication overheads, and efficient resource allocation, thus decreasing overall energy consumption and reducing the interferences among sensor nodes. The basic idea of clustered routing [28] is to use the information aggregation mechanism in the cluster head (CH) that reduces the amount of data transmission, thereby, reduces the energy dissipation in communication and in turn achieves the purpose of saving energy of the sensor nodes. In addition clustering facilitates load balancing and extends network lifetime. For example, if a CH's energy becomes depleted due to its tasks of intra-cluster communications, performing the aggregation function and inter-cluster communications, the CH may choose to resign its position; new clusters may be formed; and, other nodes may become CH to relieve the current CH of its duties. In this way, nodes in the network share the duties of being CH based on some parameter. Accordingly, clustering strives to maximize the lifetime of the network by balancing the duties of being CH.

CS is a new sampling theory which exploits compressibility of signals to reduce the samples required to reconstruct the original signal. Recently, CS [6, 7] provides a very different approach for data sampling and compression in WSNs [3, 11, 13, 20], remote sensing and medical imaging. The main idea of CS is that any unknown signal X having a sparse representation in one basis (sparsifying transform) can be recovered from a small number of projections onto a second basis (sampling matrix) which is incoherent with the first one. The combination of CS theory with WSNs shows a great potential to reduce energy consumption for sensors which is an important factor in WSNs [7, 27, 29]. It reduces global scale communication cost without introducing intensive computation or complicated transmission control. This results in extending the lifetime of the WSN.

In this paper, we propose an optimized clustering protocol using CS (OCP-CS) where, we assume that the network is randomly divided into several clusters; each managed by a CH called a group leader with the selection of a group leader member is based on residual energy and concentration degree of sensor nodes. Each member of the group leader compresses collected data using CS. Simulation results show that our proposed protocol can compress data efficiently, greatly reduce energy consumption and prolong the lifetime of the whole WSN to a great extent and balance load among CHs as compared to other protocols.

This paper is comprised of six sections, and is organized as follows. Related work is presented in the following section. The third section presents our problem. Section four introduces the details of proposed system model. Section five presents our simulation model and provides the comparative evaluation results of the proposed protocol through simulations. Conclusions are contained in the final section.

2. Related works

Recently, there has been a growing interest in WSNs. One of the major issues in WSN is developing an energy-efficient routing protocol. Routing in WSNs is a challenging task firstly because of the absence of global addressing schemes; secondly data source from multiple paths to single destination of BS, thirdly because of data redundancy and also because of energy and computation constraints of the network [5]. The conventional routing algorithms are not efficient when applied to WSNs. The performance of the existing routing algorithms for WSNs varies from application to application because of diverse demands of different applications. There is a strong need for development of routing techniques which work well across wide range of applications.

In [13], authors proposed (Low Energy Adaptive Clustering Hierarchy (LEACH) protocol, which is considered as the basic energy efficient hierarchical routing protocol. In the setup phase of LEACH, each node decides whether to become a CH for the current round, this decision is based on a predetermined fraction of nodes and the threshold *T(s)* as follows:

$$T(s) = \begin{cases} \frac{p_{opt}}{(1-p_{opt}\times(r \bmod (1/p_{opt})))} & if\ s \in G \\ 0 & otherwise \end{cases} \quad (1)$$

where $p_{opt}$is the predetermined percentage of CHs, r is the count of current round, and G is the set of sensor nodes that have not been CHs in the last $1/p_{opt}$ rounds. Using this threshold, each node will become a CH at some round within $1/p_{opt}$ rounds. After $1/p_{opt}$ rounds, all nodes are once again eligible to become CHs. LEACH does not consider the residual energy of each node, so the nodes that have relatively smaller energy remaining can be selected as CHs. This shortens the network lifetime. Many protocols have been derived from LEACH with some modifications and applying advance routing techniques.

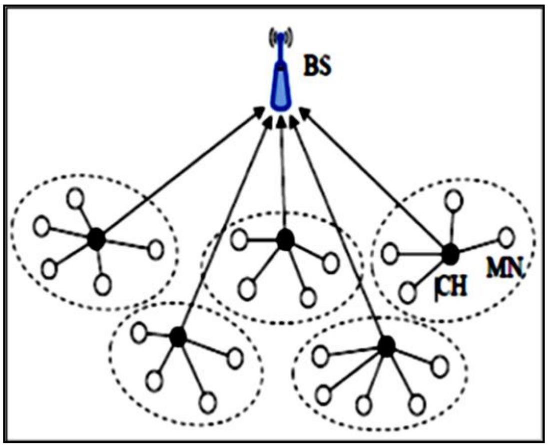

Figure1. General view of LEACH protocol.

A Weighted Energy Efficient Clustering algorithm for WSNs (WEEC) is proposed in [2], it is an improvement of LEACH. It takes into consideration the distance of the nodes to the BS as an important factor in CH selection phase and assigns a probability to each node which is analytically derived from the distance of the nodes to the BS. In [21], authors proposed Cluster-based Hierarchical Routing Protocol (CBHRP). CBHRP is an extension of LEACH [13]. It introduces a header for the control and management of clusters. It divides the network into a few real clusters that are managed by a virtual CH. In [23], authors proposed a technique named as Honey Bee Optimization (HBO) that aims to reduce the energy consumption by finding an optimal route with low cost. However, our proposed protocol (OCP-CS) uses group leader concept and CHs are selected on the basis of their residual energy and their concentration.

CS is a sampling theory, which gives a new solution for balancing the load of WSN. Based on the theory, as long as the sampled data is sparse under some basis, such as frequency domain, DFT domain, wavelet domain, it can be reconstructed through a small number of measurements with high precision [7, 11]. Using CS as the data acquisition approach in WSNs, it can significantly reduce the energy consumed in the process of sampling and transmission, and also lower the wireless bandwidth required for communication [29]. Under CS framework, any compressible signal $X \in \mathbb{R}^{N\times 1}$ can be represented in the form of:

$$X = \Psi\alpha \quad (2)$$

where $\Psi \in \mathbb{R}^{N\times N}$ is the transform matrix and α is the sparse representation of *X*. The signal X can be shown as a linear combination of K vectors with $K \ll N$, and K nonzero coefficients and $(N - K)$ zero coefficients in Equation (2). In many applications, signals have only a few large coefficients. These few large coefficients can be approximated by K. One would then select the K largest coefficients and discard $(N - K)$ smallest coefficients. Traditionally, one is required to acquire the full N-sample of signal X to compute the complete group of transform coefficients. Traditional compression techniques suffer from an important inherent inefficiency since they compute all N coefficients and records all zero coefficients, although $K \ll N$ [4]. CS can replace traditional sampling with new sampling scheme and reduce the number of measurements. CS combines the acquisition step and the compression step into one and can directly acquire signals without going through the intermediate steps. As a result, a small number of coefficients can be transmitted or stored rather than the full set of signal coefficients. Consequently, CS provides a scheme that reduces power consumption, data size and cost of the system.

Measurement of X is $Y=\Phi X$, where $\Phi \in \mathbb{R}^{M\times N}$ is a sampling matrix with far fewer rows than columns $(M \ll N)$. Measurement $Y \in \mathbb{R}^{M\times 1}$ is much easier than the original networked data $X \in \mathbb{R}^{N}$ to be stored, transmitted, and retrieved since $M \ll N$. Therefore, measurement can be expressed as,

$$Y = \Phi\Psi\alpha \quad (3)$$

If $A = \Phi\Psi$ satisfies restricted isometry property (RIP) [7] with condition $M \leq cK\log(N/K)$ such that c is a small constant with $c > 0$, the vector α can be accurately recovered from Y as the unique solution of:

$$\hat{\alpha} = arg\,min_{\alpha}\|\alpha\|_1 \quad s.t. \quad Y = \Phi\Psi\alpha \qquad (4)$$

The original networked data X may be sparse itself or can be sparsified with a suitable transform such as Discrete Cosine Transform or Discrete Wavelet Transform [20]. One example of the self-sparse X is a linear combination of just K basis vectors, with $K \ll N$, that is; only Ks are nonzero and $(N - K)s$ are zeros [14].

Usually, the networked data vector X is sparse with a proper transform in Equation (2). In WSNs, sampling matrix Φ is usually pre-designed, i.e., each sensor locally draws M elements of the random projection vectors by using its network address as the seed of a pseudorandom number generator. Based on CS theory [14] consider a sparse event detection scenario where the channel impulse response (CIR) matrix is used as a natural sampling matrix. In [10], authors proposed a basic global superposition model to obtain the measurements of sensor data, where sampling matrix is modelled as the channel impulse response (CIR) matrix while the sparsifying matrix is expressed as the distributed wavelet transform. In [26], authors proposed a JSM-2 model and a quantization configuration for data compressed collection for sensor network based on distribution compressive sensing theory. Then, they constructed energy consumption configuration model joint distribution compressive sensing and quantization compressive sensing. In this paper, we use CS to compress data efficiently and consider residual energy and nodes concentration in CH election to achieve a robust self-configured WSN that maximizes lifetime.

In [25], authors proposed an Energy-Efficient Cluster-based Dynamic Routes Adjustment approach (EECDRA) which aims to minimize the routes reconstruction cost of the sensor nodes while maintaining nearly optimal routes to the latest location of the mobile sinks. The network is divided into several equal clusters and CHs are selected within each cluster. However, in the proposed protocol, we discuss effective aggregation by using the CS and energy load is well distributed by dynamically created clusters and using dynamically elected CHs according to the residual energy and the nodes concentration.

In [19], authors proposed Energy Efficient Clustering and Data Aggregation Protocol for Heterogeneous WSNs (EECDA). It combines energy efficient cluster based routing and data aggregation for improving the performance in terms of lifetime and stability. In [22], authors proposed Improved and Balanced LEACH (IB-LEACH), a heterogeneous-energy protocol and examined the impact of heterogeneity of nodes, in terms of their energy in hierarchically clustered WSNs. In these WSNs, some high-energy nodes called NCG (Normal node/Cluster Head/ Gateway) become CHs to aggregate the data of their cluster members and transmit it to the chosen "Gateways" that requires the minimum communication energy to reduce the energy consumption of CH and decrease the probability of nodes failure. However, in the proposed protocol we discuss effectiveness of aggregation using CS and assume that CHs are randomly selected based on their residual energy and concentration degree.

In addition to the differences we mentioned before, all the above protocols do not consider efficient data compression with efficient selection of CHs. In this paper, we consider compression of data using CS and the selection of CHs is based on weights taking residual energy into account and concentration degree of sensor nodes. Simulation shows that the proposed protocol achieves much better performance as compared to CBHRP, IB-LEACH and EECDA protocols.

3. The Proposed optimized clustering protocol using CS (OCP-CS)

In this paper, we propose an optimized clustering protocol using CS (OCP-CS) where each sensor node independently elects itself as a CH based on its residual energy and concentration degree. Each CH compresses the data received from member nodes using CS and transfers it to the BS so that the energy dissipation of the whole network can be balanced. The proposed protocol efficiently improves data aggregation and therefore significantly reduces the energy consumed in the process of sampling and transmission and lower the wireless bandwidth required for communication. It improves load balancing among CHs which leads to increased system stability and improved communication between different nodes in the system.

4. System model

In clustering, CH selection criteria strongly influence the network behavior in terms of communication overhead, latency, and inter- and intra-cluster communication. In this paper, we propose an optimized clustering protocol (OCP-CS). We assume that the CH election is based on residual energy and node concentration and use CS for aggregating data.

Our model relies on the following key assumptions regarding to the field and the sensor nodes:

- N sensor nodes are uniformly dispersed within a square field of area $R \times R\,m^2$,
- All sensor nodes and the BS are stationary after deployment,
- Communication is based on single-hop approach,
- Networked data vector is sparse or highly compressible in Distributed Wavelet Transform (DWT) domain, i.e., it contains K largest coefficients. Setting the rest coefficients zero will not cause much information loss.

4.1 Architecture of OCS-CS

OCP-CS divides the network into a few real clusters. Each cluster has a group leader that consists of several virtual CHs; however, only one CH is active at one time. Iteration consists of two stages: an election phase and a data transfer phase.

At the beginning of the election phase, a set of CHs are selected according to the residual energy and concentration of sensor nodes. These CHs send a short range advertisement broadcast message. The sensor nodes receive the advertisements and choose their CHs based on the signal strength of the advertisement messages. Each sensor node sends an acknowledgment message to its CH. Moreover, in each iteration, the CHs choose a group of associate leaders based on election weights taking account of the residual energy and the concentration degree of sensor nodes and the signal strength of the acknowledgments.

A group leader consists of a CH and the associates. In the data transfer phase, the group leader member (CH) receives data from the neighboring nodes, aggregates the collected data using CS, aiming at improving the network lifetime and reducing the network energy consumption, and then CH transmits the aggregated results to the distant BS.

Finally, the BS decodes the networked data. Each data transfer phase consists of several rounds. Each member of the group leader becomes a CH once during a round. An epoch consists of several iterations. In one epoch, each sensor node becomes a member of the group leader for one time. All the group leader members share the same time slot to transmit their frames. The above communication stages are illustrated in Figure 2.

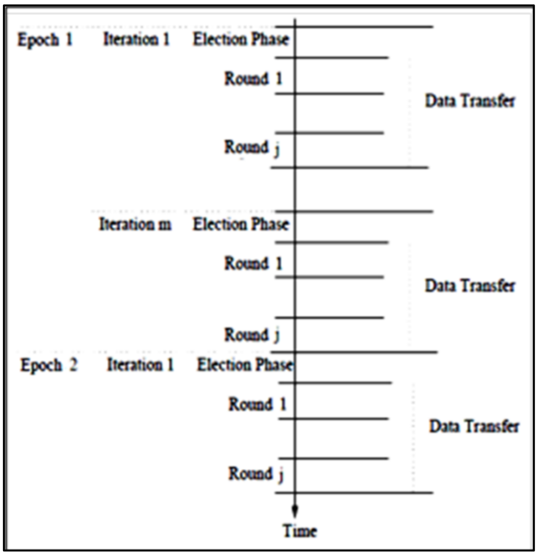

Figure 2. Communication stages in OCP-CS.

4.2 Radio communication model

We use the radio energy model proposed by [13]. According to the radio energy dissipation model illustrated in Figure 3, to achieve an acceptable Signal-to-Noise Ratio (SNR) in transmitting L-bit message over a distance d, the energy expended by the radio is given by:

$$E_{Tx}(L,d) = \begin{cases} L.E_{elec} + L.\epsilon_{fs}.d^2 & if\ d \leq d_0 \\ L.E_{elec} + L.\epsilon_{mp}.d^4 & if\ d > d_0 \end{cases} \quad (5)$$

where E_{elec} is the energy dissipated per bit to run the transmitter or the receiver circuit, ϵ_{fs} and ϵ_{mp} depend on the transmitter amplifier model used and d is the distance between the sender and the receiver. By equating the two expressions at $d = d_0$, we have $d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}}$. To receive an L-bit message the radio expends $E_{Rx} = L.E_{elec}$.

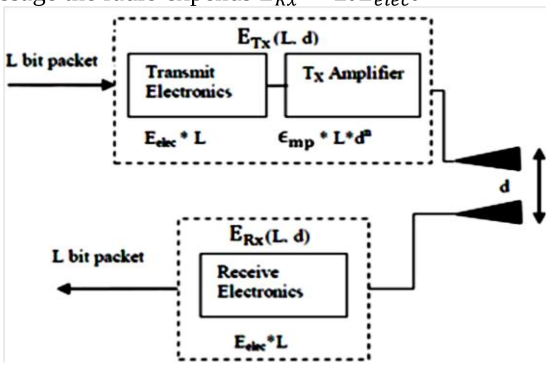

Figure 3. Radio energy dissipation model.

4.3 Optimal number of clusters

We assume that we have an area $A = R \times R$ square meters over which N nodes are uniformly distributed. For simplicity, we assume that the BS is located in the centre of the field, and the distance between any node to the BS or its CH is less than or equal to d_0. Thus, energy consumed by a CH is estimated as follows:

$$E_{CH} = \left(\frac{N}{C} - 1\right)Y.E_{elec} + \frac{N}{C}Y + Y.E_{elec} + Y\epsilon_{fs}d_{BS}^2 \quad (6)$$

where C is the number of clusters, Y is the aggregated data and d_{BS} is the average distance between CH and BS. The energy consumed by a non-CH node is given by:

$$E_{nonCH} = L.E_{elec} + L.\epsilon_{fs}d_{CH}^2 \quad (7)$$

where d_{CH} is the average distance between a cluster member and its CH. Using Euclidian metric, the area occupied by each cluster will be $A = \frac{R^2}{2\pi C}$ with node distribution $\rho(x,y)$:

$$d_{CH}^2 = \int\int (x^2 + y^2)\rho(x,y)\,dxdy$$
$$= \int\int r^2\,\rho(r,\theta) r dr d\theta \quad (8)$$

Assuming the area is a circle with $\eta = R/\sqrt{\pi C}$, $\rho(r,\theta)$is constant, and the density ρ is uniform and where $\rho = (1/(R^2/C))$, d_{CH}^2 can be simplified as follows:

$$d_{CH}^2 = \iint\int (x^2 + y^2)\rho(x,y)\,dxdy$$
$$= \rho \int_{\theta=0}^{2\pi}\int_{r=0}^{R/\sqrt{\pi C}} r^3 dr d\theta = \frac{R^2}{2\pi C} \quad (9)$$

The energy dissipated in a cluster per round is given by:

$$E_{cluster} \approx E_{CH} + \frac{N}{C}E_{nonCH} \quad (10)$$

The total energy dissipation in the network per round is the sum of the energy dissipation by all clusters, i.e.

$$E_{tot} = CE_{cluster} = Y\left(N(1 + E_{elec}) + C\epsilon_{fs}d_{BS}^2\right) + NL(E_{elec} + \epsilon_{fs}d_{CH}^2)) \quad (11)$$

By differentiating E_{tot} with respect to C and equating to zero, the optimal number of constructed clusters can be found:

$$C_{opt} = \sqrt{\frac{NL}{2\pi Y}}\frac{R}{d_{BS}} = \sqrt{\frac{NL}{2\pi Y}}\frac{2}{0.765} \quad (12)$$

where, the average distance from a CH to the BS d_{BS} is given by [1] as follows:

$$d_{BS} = \int \sqrt{x^2 + y^2} \frac{1}{A} dA = 0.765 \frac{R}{2} \quad (13)$$

If the distance of a significant percentage of nodes to the BS is greater than d_0, then following the same analysis as in [12] we obtain:

$$C_{opt} = \sqrt{\frac{NL}{2\pi Y}} \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \frac{R}{d_{BS}^2} \quad (14)$$

The optimal probability of a node to become a CH,p_{opt}, can be computed as follows:

$$p_{opt} = \frac{C_{opt}}{N} \quad (15)$$

The optimal construction of clusters is very important. [13] showed that if the clusters are not constructed in an optimal way, the total consumed energy of the sensor network per round is increased exponentially either when the number of constructed clusters is greater than the optimal number of clusters or especially when the number of constructed clusters is less than the optimal number of clusters. If the number of the constructed clusters is less than the optimal number of clusters, some nodes in the network have to transmit their data very far to reach the CH, causing the global energy in the system to increase. If the number of the constructed clusters is greater than the optimal number of clusters, the total routing traffics within each cluster will be reduced because of fewer members, however, more clusters will result in more one-hop transmissions from the CHs to the BS. The CHs will receive data from fewer members, reducing the local data aggregation being performed and increasing the communications among the CHs.

4.4 Cluster head election phase

An optimal probability of a node to become a CH is equivalent to the optimal construction of clusters. This clustering is optimal in the sense that energy consumption is well distributed over all sensors and the total energy consumption is minimal. Such optimal clustering highly depends on the energy model that we use.

Energy consumption of the CHs is relatively expensive, so the residual energy of sensor node is the main criteria for the election of CH. Moreover, data aggregation can save considerable energy when the source nodes forming one cluster are distributed in a relatively small region while the BS is far away from the source nodes, because sensor nodes only need much smaller energy for sending data to the CH than sending data directly to the BS when the BS is located at a remote distance. It is reasonable to infer that the closer source nodes within a cluster, lower are the energy to consume to send data.

Based on this deduction, an election weight taking account of the residual energy and the concentration degree of sensor nodes is introduced as OCP-CS for CH election.

Definition 1: Given a WSN of N sensor nodes ($i = 1, 2, \dots, N$), $D^r(i)$ is defined to be the concentration degree of node i, namely the number of sensor nodes that can sense during the r^{th} round. $W(i,r)$ is defined as the election weight of node i in r^{th} round,

$$W(i,r) = \omega \frac{E_i^r}{\bar{E}^r} + (1 - \omega) \frac{D^r(i)}{p_{opt}} \quad (16)$$

where $\omega = \frac{1}{1+\xi}$ is an adaptive factor to adjust the impact of residual energy and concentration degree on the election weight, $\xi = \frac{E_i^r}{\bar{E}^r}$ denotes the residual energy of node i in round r, E_i is the initial energy of node i and $\bar{E}^r$is the average residual energy of network in r^{th} round. With the reduction of residual energy, ω gradually increases to adapt to a decrease in the number of effective sensor nodes in WSN.

4.5 Setup phase

- *Step 1* During initialization, sensor nodes calculate their own concentration degree according to the Definition 1, and mark their own level as level 1.
- *Step 2* In the initialization phase of the network, the BS broadcasts $\bar{E}^r$ in "CH election" messages. When a node i receives the broadcast message, it compares its own residual energy E_i^r with $\bar{E}^r$. If $E_i^r \geq \bar{E}^r$, a node i calculates the election weight using its own $D^r(i)$ and E_i^r, and then send the weight and its ID to the BS for CH election in the "CH election" messages. Otherwise, a node i gives up as CH election, and chooses to join a cluster later.
- *Step 3* The BS marks its own level as level 1, chooses C_{opt} sensor nodes with maximum election weight as CHs. Sensor nodes that have been chosen to be the CHs by the BS, are marked themselves as CHs. After that, CHs broadcast to neighbor nodes to notify them that they have been elected as new CHs.
- *Step 4* When a node is elected as a CH, it broadcasts "re-join the cluster" messages to each regular node. After receiving the broadcast message, each regular node chooses its closest CH with the largest received signal strength and then informs the CH by sending a join cluster message. Furthermore, in each iteration, the CHs choose a set of associate leaders based on their election weight and the signal strength of the acknowledgments. A group leader consists of a CH and the associates. The group leader member is responsible for sending messages to the BS.
- *Step 5* The CH sets up a time-division multiple access (TDMA) schedule and transmits it to the nodes in the cluster. After the TDMA schedule is known by all nodes in the cluster, the set up phase is completed and the next phase begins.

4.6 Data transmission phase

Once the clusters are formed and the TDMA schedule is fixed, the data transmission phase can begin. We consider N sensors randomly located in a field, each generating a data sample x_j ($j = 1, \dots, N$) to be measured. The vector of data samples $X = [x_1, \dots, x_N]$ is called networked data [11], which is transmitted to the BS. We use DWT matrix as the sparsifying transform matrix and channel impulse response (CIR) matrix as the sampling matrix.

4.7 DWT basis

We assume that the sensed data is highly correlated in space domain. We use DWT to sparsify the networked data X and DWT is applied to the sampled data. DWT attempts to de-correlate the correlated data into uncorrelated coefficients using a group of wavelet basis functions. Once the BS knows the locations of all sensor nodes, DWT basis can be computed. DWT replaces the 2-D set of measurements with a set of transform coefficients that, for piecewise smooth fields, are sparser than the original data,

$$X = WS \tag{17}$$

where $S \in \mathbb{R}^N$ is the transform coefficient vector which contains $K(K \ll N)$ nonzeros, and W is the DWT basis.

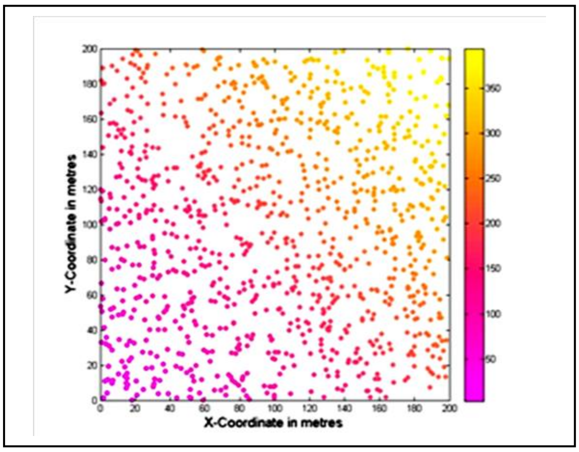

Figure 4. Network topology comprised of 1000 nodes.

Note: The locations of nodes are generated as random values drawn from the standard uniform distribution on the open interval (0, 200).

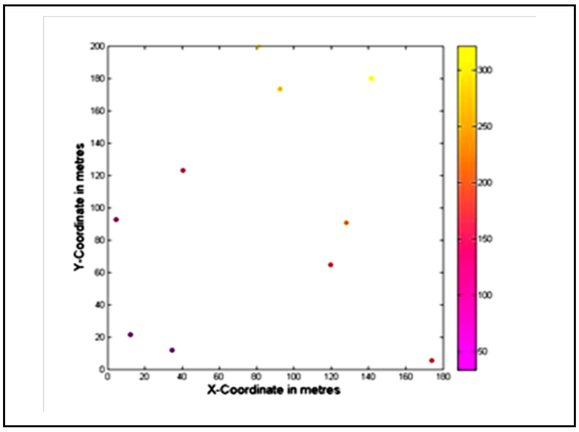

Figure 5. Sparsity of networked data in a DWT basis. The networked data can be presented with $K = 10$ nonzero coefficients after DWT transform.

4.8 CIR basis

At each cluster, a group leader member CH receives data from the neighboring nodes, aggregates the collected data using CS and transmits the aggregated results to the distant BS. The received signal vector at CH can be written as,

$$Y = GX = GWS \tag{18}$$

where G is the CIR matrix whose component can be written as,

$$G[m,n] = d_{m,n}^{-\gamma}|h_{m,n}| \tag{19}$$

where $d_{m,n}$ is the distance between the m^{th} CH and the n^{th} sensor node. γ is the propagation loss factor which is 2 for free space [9] and takes on other values for different media [14]. $h_{m,n}$ is the Rayleigh fading coefficient modeled as complex Gaussian noise with zero mean and unit variance.

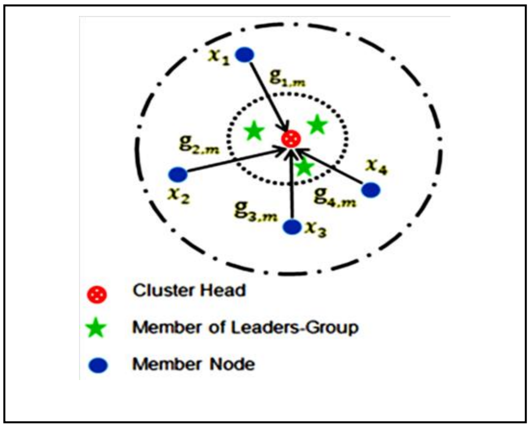

Figure 6. Transmission in clusters.

As shown in Figure 7 N sensor nodes transmit their samples to M CHs. Subsequently CHs transmit measurements Y to the BS independently. Finally, the BS decodes the networked data X from Y using the basis pursuit solver in Sparselab toolbox of Matlab [6].

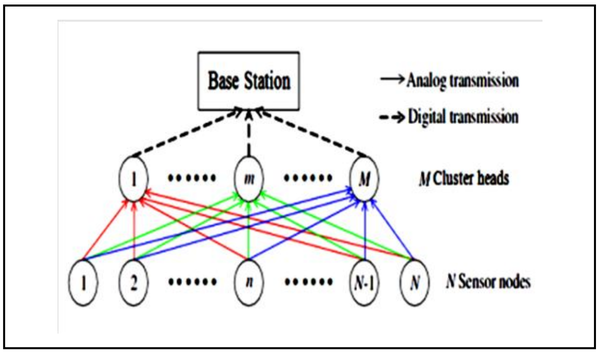

Figure 7. The basic CIR model.

5. Simulation results

In this section, analysis of the proposed OCP-CS protocol is carried out using MATLAB to evaluate the energy consumption and maximize the lifetime of the sensor network.

Table 1. Simulation parameters.

Description	Parameter	Value
No. of nodes	N	1000
Initial energy	E_0	0.5
Location of the BS	BS	(50,50)
Data packet size	L	4000 bits
Network area	$R \times R$	$200 \times 200\ m^2$
Transmit amplifier if $d_{BS} \le d_0$	ϵ_{fs}	$10\ pJ/(bit * m^2)$
Transmit amplifier if $d_{BS} \ge d_0$	ϵ_{mp}	$0.0013\ pJ/(bit * m^4)$
Threshold distance	d_0	87.7058 m
No. of nonzero Coefficients	K	10
No. of measurements	M	50
Propagation loss factor	γ	2

We describe our simulation environment and experimental results. The simulation parameters are summarized in Table 1.

5.1 Energy consumption

Since energy consumption is the most important issue in WSNs, we discuss the impact of using CS on energy consumption by comparing the performance of the proposed protocol with other existing protocols. Energy consumption for specific number of frames with respect to the variation of cluster number and network diameter size is also examined.
Figure 8 illustrates the difference of energy consumed per round for proposed, EECDA, IB-LEACH and CBHRP protocols. It shows that IB-LEACH achieves better performance compared with CBHRP, whereas the gateways take up the role to reduce the energy consumption of CH and decrease the probability of failed WSN. Also, EECDA performs better than IB-LEACH. The reason is EECDA selects path with a maximum sum of energy residual for data transmission in spite of paths with minimum energy. It is obvious that the energy consumption of the proposed protocol is much lower than that of CBHRP, IB-LEACH and EECDA. This is because OCP-CS uses an election weights residual energy and concentration degree of sensor nodes in electing CHs. Node having higher election weight has better chance to be a CH, therefore, the energy efficiency is enhanced. Besides, OCP-CS efficiently compresses the data and at the same time guarantees fast data compression which are important issues in WSNs due to the scare resources of sensor node. Consequent to this compression, the total network energy consumption is minimized as compared with CBHRP, IB-LEACH and EECDA.
Figure 8 shows that energy consumption is reduced when the number of clusters is increased and the network diameter decreases. For the simulated network of 1000 nodes, it is shown that the optimum range of clusters lies between 20 and 60. As the number of clusters increases and the network diameter decreases, the energy consumption also decreases. When the number of clusters is below the optimum range, for example 10, the sensor nodes have to send data to the distant CHs. On the other hand, when the number of clusters is greater than optimum range, there will be more transmissions to the distant BS. Moreover, when the network diameter increases, the CHs have to send data to the distant BS. Furthermore, when the network diameter decreases, the energy consumption also decreases and there will be more transmissions to the BS.

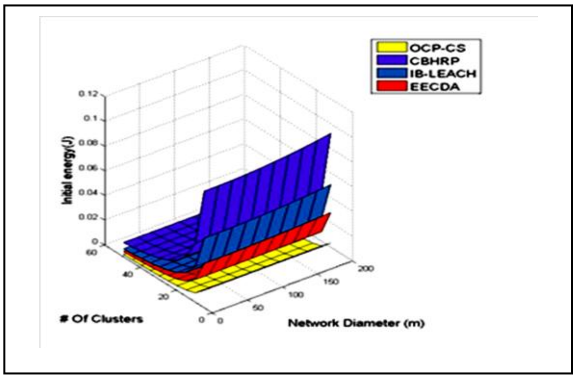

Figure 8. Energy consumption.

Figure 9 show that OCP-CS consumes lower energy as compared to CBHRP, IB-LEACH and EECDA. The reason is that all the sensor nodes in OCP-CS organize themselves into clusters with one node elected as a CH according to the residual energy and the concentration degree of sensor nodes leading to reducing the energy consumption of sensor nodes.

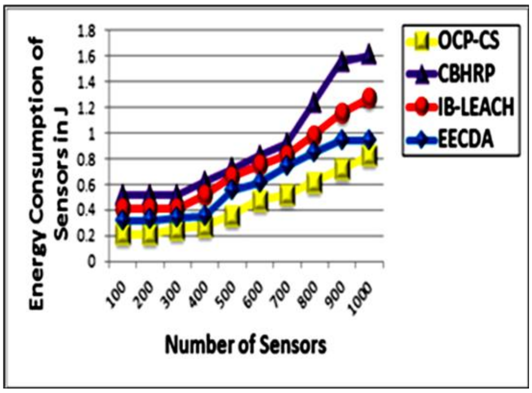

Figure 9. Energy consumption for every sensor node.

5.2 Iteration time

In WSNs, the most important metric is the total survival lifetime of the WSN. In this section, the average time to complete one iteration such that every node becomes a member of group leader is analyzed using OCP-CS and compared with existing protocols.
The estimated time for one iteration with respect to the network diameter considering the percentage of group leader size is shown in Figure 10. It is obvious that the estimated time for one iteration of the proposed protocol is more than that of EECDA, IB-LEACH and CBHRP. Whereas, in the proposed protocol the extension of the network service duration is because OCP-CS efficiently compresses data using CS and every sensor node independently elects itself as a CH based on its election weight. Therefore, OCP-CS would extend the estimated time for one iteration, and consequently the battery lifetime would be extended more than lifetime of other schemes. The iteration time is proportional to the initial energy and the network diameter obtained in this figure. The network will be alive for a longest period of time with initial energy when the group leader size is 50% of the cluster size. However, it is more or less with respect to the group leader size.

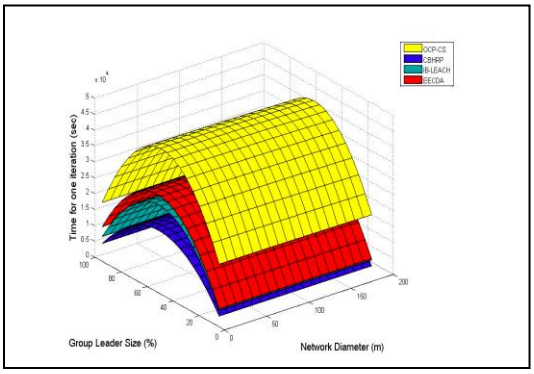

Figure 10. Time for iteration with respect to network diameter and group leader size.

Figure 11 shows a graph that illustrates the estimated time for one iteration with respect to the number of clusters and group leader size. The figure shows that for the same number of clusters, the time for iteration increases as the group leader size increases and one iteration can last longer for larger group leader sizes. However, for larger number of clusters, the time for iteration is reduced. This graph shows that the group leader size and the number of clusters should be carefully chosen to extend the network lifetime. The figure shows that OCP-CS outperforms EECDA, IB-LEACH and CBHRP protocols, the reason is using CS would optimize energy usage and this leads to prolonging the network lifetime.

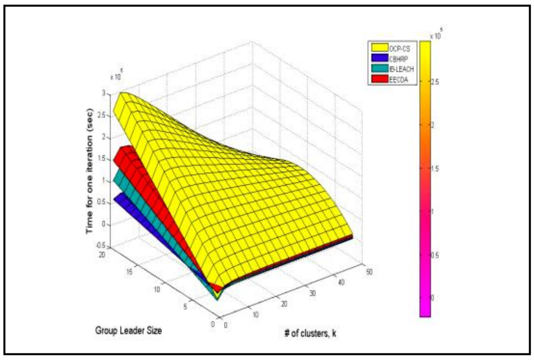

Figure 11. Time for iteration with respect to number of clusters and group leader size.

5.3 Number of frames

The number of frames transmitted in each iteration is evaluated using OCP-CS and compared with EECDA, IB-LEACH and CBHRP. Figure 12 shows the number of frames transmitted per iteration in the proposed, EECDA, IB-LEACH and CBHRP protocols. It is clear that the proposed protocol outperforms other existing protocols. It is also shown that when the group leader size increases, there are more control and management sensor nodes. As a result, the iteration can last for a longer time, which is also consistent with the results shown in Figure 10 and Figure 11. Consequently, the data collecting nodes can be used for a longer period of time. Our results show that the proposed protocol provides a more systematic approach of transmitting a larger number of data frames in contrast to EECDA, IB-LEACH and CBHRP.

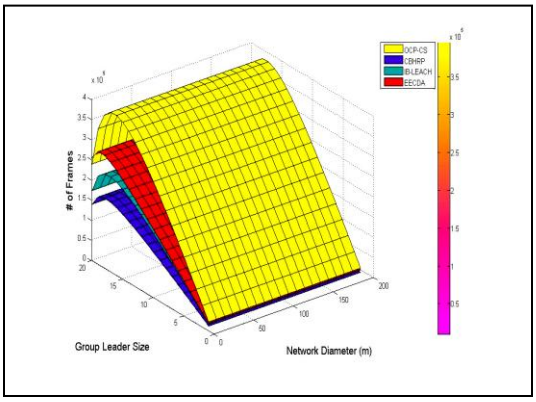

Figure 12. Number of frames transmitted per iteration.

5.4 Standard deviation of load

Standard deviation of the load is the variance in load which signifies that load is not uniformly distributed among the clusters. It gives a good evaluation of distribution on load per cluster. To test our system for different sensors densities, we measured standard deviation of load by increasing the number of sensors in the system from 500 to 5000 with uniform increments.

We measured standard deviations of load in the proposed, EECDA, IB-LEACH and CBHRP as shown in Figure 13. On average, the standard deviation of OCP-CS is 53.4% less than that of CBHRP, 35.8% less than that of IB-LEACH and 17.8% less than that of EECDA, indicating that OCP-CS shows more uniform performance than EECDA, IB-LEACH and CBHRP. Whereas, the rising values of EECDA, IB-LEACH and CBHRP protocols clearly indicate that the variance of load among different clusters increases, as more sensors are included in the system.

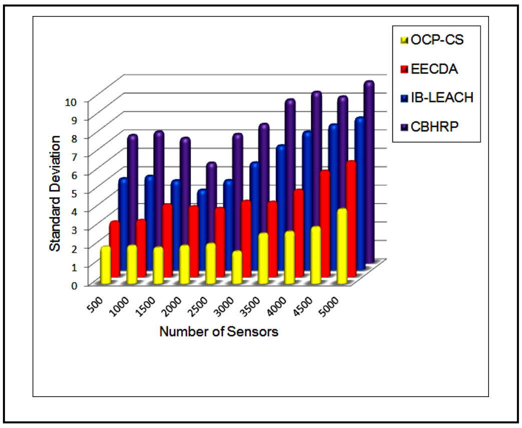

Figure 13. Standard deviations of load.

6. Conclusions

In this paper, we propose an optimized clustering protocol using compressive sensing to enhance the energy consumption, lifetime and throughput of the wireless networks. Compressive sensing measurements are obtained via cluster heads. Discrete Wavelet Transform (DWT) is used as the sparsifying matrix and channel impulse response (CIR) matrix is used as the sampling matrix. Using group leader concepts in a clustering algorithmic approach, nodes elect themselves as cluster heads based on their energy levels and concentration degree, retaining more uniformly distributed energy among sensor nodes. The simulation results show that our protocol decreases the energy consumption and therefore, prolongs the network lifetime and increases the number of frames transmitted per iteration as compared with EECDA, IB-LEACH and CBHRP protocols.

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