CHAPTER 5

ENHANCING ENERGY EFFICIENCY OF CLUSTER BASED MULTILEVEL HIERARCHICAL ROUTING USING COMPRESSED SENSING

5.1 INTRODUCTION

Sensor nodes are usually deployed in large or even huge number for continuous monitoring of a system or an area of interest. The neighboring sensor nodes may sense similar data on a specific phenomenon, because of the dense pattern of sensor deployment, which is referred to as spatial correlation. Since sensor nodes are run by battery power, it is critical to perform every operation in energy-efficient manner. For this purpose, it is desirable for a sensor node to remove the redundancy in the data received from its neighboring nodes before transmitting the final data to the BS.

Data redundancy is reduced by using an effective technique called Data aggregation which improves energy efficiency in WSNs. By using an aggregation process the redundancy in the data is minimized by combining the data received from different sources and also the energy consumption for transmitting the data is reduced. The data - centric nature of WSNs makes data aggregation as a crucial task as discussed by Krishnamachari et al (2002). Sometimes, however, users may be interested in knowing the attribute values at some specific locations. In this case, the locations of reporting sensor nodes, which can be geographical coordinates, should not be left out in performing data aggregation as quoted by Akyildiz et al (2002).

A major requirement for these battery-powered nodes is energy saving solutions. The energy consumption should be minimized to prolong the life time of network. Data aggregation plays a vital role in Wireless Sensor Networks since the aggregation schemes followed here involve in reducing the amount of power consumed during data transmission between the sensor nodes. The process of aggregating the data from multiple nodes to BS after eliminating the redundant transmission is known as Data aggregation and it is considered as an effectual technique for WSNs to save energy. By using proper data aggregation, the amount of data transmission load carried by a WSN may be reduced and hence it may improve its performance in every aspect.

A typical Wireless Sensor Network is the one which consists of a large number of wireless sensor nodes and the network data transmission are accomplished through multi-hop routing from individual sensor nodes to the data sink. The problem of efficiently transmitting or sharing information from and among a vast number of distributed nodes makes a great challenge to the energy and computation consumption of the sensor nodes. A compressive sensing theory can be used to resolve this problem. Compressed Sensing (also known as compressive sampling or CS) is a novel data compression technology is used to reduce global scale communication cost without introducing intensive computation or complicated transmission control in large-scale wireless sensor network. The lifetime of the sensor network will be extended by using compressed sensing.

Compressing sensor develops the inherent correlation in some input data set X to compress such data by means of quasi random matrices. The original data X can be reconstructed from its compressed version Y with high probability, by minimizing a distance metric over a solution space when the compression matrix and the original data X have certain properties.

To improve the performance of WSN, the CS has been envisioned as a useful technique. It can be used for signal processing, signal detection, channel estimation, etc. Single-hop aggregation and data distribution are mainly considered in recent aggregation works. In this chapter, for network data aggregation the application of a new decentralized compression technology known as compressed sensing is considered.

The applications of compressive sensing for data gathering have been studied in a few papers. Wang et al (2007) proposed that every sensor in the field computes and stores sparse random projections in a decentralized manner and sends its aggregates randomly within the network. In Lee et al (2009) CS for energy efficient data gathering in a multi-hop wireless sensor network was investigated. Luo et al (2009) applied compressive sensing theory for efficient data gathering in a large scale wireless sensor network. They showed that the proposed scheme can substantially save communication cost and increase network capacity.

The remaining of this chapter is organized as follows. In section 5.2 the basic CS concepts which are relevant to the problem have reviewed. Section 5.3 describes the Data Aggregation in Cluster based Hierarchical WSN based on CS for Wireless sensor network. Performance analysis of the Energy Efficient Clustering with multilevel hierarchical routing with CS based data aggregation in terms of energy consumption and the number of transmissions is discussed in section 5.4. Finally, the chapter is concluded in section 5.5.

5.2 COMPRESSED SENSING

Compressed Sensing is a newly developed signal processing technique, which promises to deliver a full recovery of signals from far fewer measurements than their original dimension, as long as the signals are sparse or compressible in some domain. The CS field has existed for at least four decades, but recently, researchers' interest in the field has exploded, especially in the areas of applied mathematics, computer science and electrical engineering, due to several important results obtained by Donoho (2006) and Candes et al (2006).

CS is a novel sensing paradigm that goes against the traditional understanding of data acquisition and can surpass the traditional limits of sampling theory. The sensory data traffic in WSNs is reduced without the need for adapting to the data correlation structure is suggested by the newly developed technique. The complication involved in the interaction between data routing and CS-based aggregation has postponed the development on this front until very recently. In this chapter, a new data aggregation technique derived from CS has promoted, and it is aimed at minimizing the total energy consumption of a WSN in collecting sensory data from the whole network.

In this section, first the basic theory of CS has briefly introduced, and then how the CS could be applied as an in-network data aggregation mechanism for WSNs has explained in detail.

5.2.1 Overview of Compressed Sensing

A sensing field usually exhibits high correlation between the measured data in WSN and it can be compressible in some transform domains. In many cases, the data are jointly processed which generated by different sensors while being forwarded towards the sink.

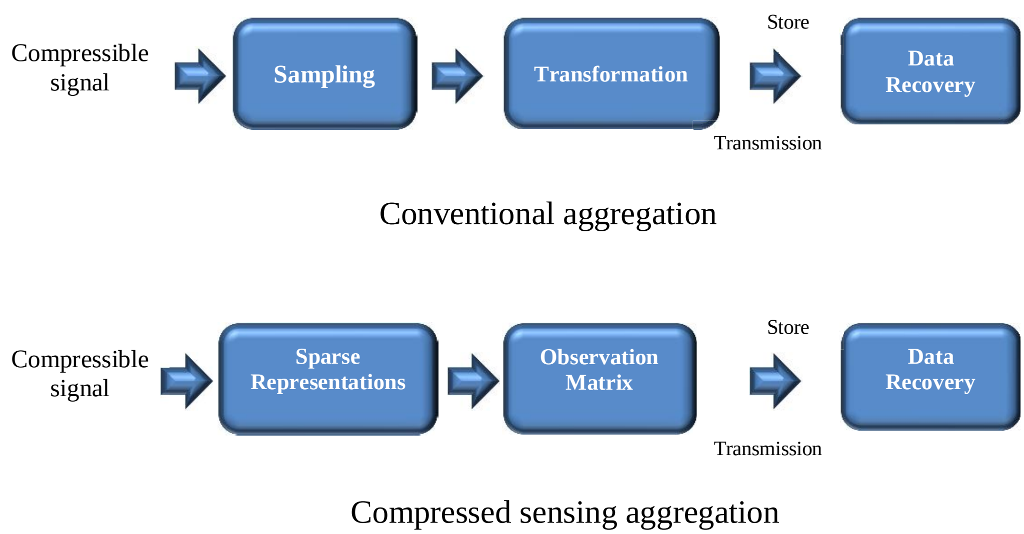

Figure 5.1 Conventional and Compressed Sensing method

When the signal is sparse and the projection matrix satisfies the Restricted Isometry Property (RIP), the CS can be explained as a signal projected linearly onto a lower dimensional space that can be used to reconstruct the original higher-dimensional signal with high probability. The work process is shown in Figure 5.1.

5.2.2 Compressed Sensing Basics

In many applications, including data network, sensor network, digital image and video camera, medical systems and analog-to-digital convertors a new theory of sampling called as Compressive Sensing is used as stated by Choi et al (2010). A potentially large reduction in the sampling and computation costs are achieved by CS for sensing data that have a sparse or compressible representation without relying on any specific prior knowledge or assumption on data as discussed by Donoho (2006). Without going through many complex signal processing steps, any sufficiently compressed data can be accurately recovered from a small number of measurements by using the compressed sensing theory. A direct method in which the compressed samples are acquired without going through the intermediate stages of conventional compression is provided by CS. The CS also provides several recovery routines in which the original signal can be regenerated perfectly from the compressed samples.

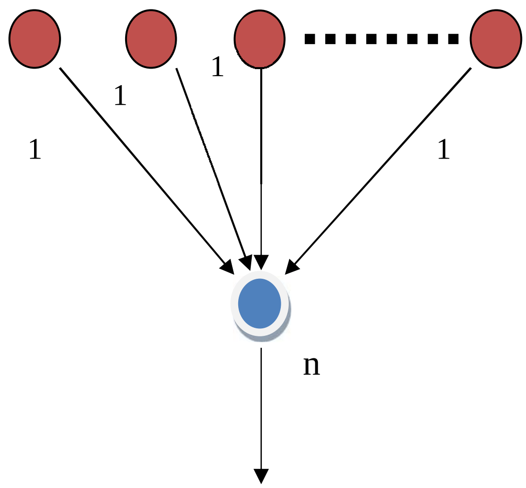

Figure 5.2 Non-aggregated data collection

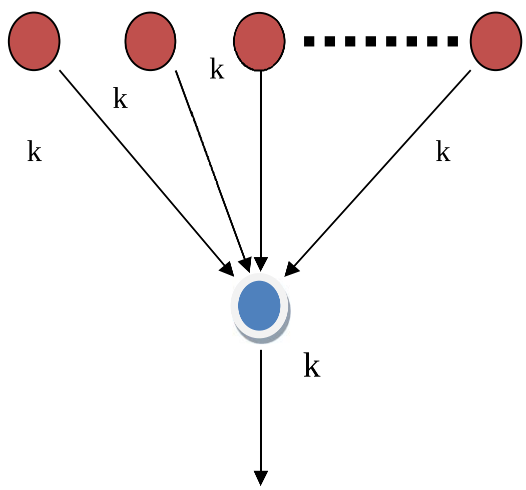

Figure 5.3 CS based data aggregation

As shown in Figure 5.2, let n-1 nodes are sending one sample to the n^{th} node, and then the outgoing link of that node will carry n samples. When CS based aggregation is directly applied as shown in Figure 5.3, it will carry only k samples which leading to avoid unnecessary higher traffic at the stage of transmissions.

All nodes are initialized with non-aggregation mode in a practical implementation by default. A node i wait to receive all the data which has to be send from all its downstream neighbors by given the publicly known threshold k. When the node i receives more than k -1 raw samples or any encoded samples, it will switch to the CS aggregation mode by creating a vector for every uncoded sample it receives. By using summation these vectors along with the already coded samples (if any) are combined into one vector. Finally, node i will send out exactly k encoded samples corresponding to the aggregated column vector.

Let x be the real-valued, finite-length, one-dimensional, discrete-time signal and it can be viewed as an $N \times 1$ column vector in R^N with elements x[n], n = 1, 2...n. Suppose a signal $x = [x_1, \ldots, x_n]^T$ has an k-sparse representation under a proper basis $\Psi = [\psi_1, \ldots, \psi_n]$, s.t. $x = \sum_{i=1}^{N} z_i \psi_i$ and m<<n. The theory of CS states that, under certain conditions, instead of directly collecting x, it is only need to collect m= O (k log n) measurements.

$$y = \Phi x \tag{5.1}$$

Where $\Phi = [\square_1, \ldots, \square_n]$ is a $k \times n$ "sensing" matrix whose row vectors are largely incoherent with Ψ. Consequently, x can be perfectly recovered from y w.h.p. by solving the convex optimization problem

$$min_{z \in R^N} \| z \|_{l1} \text{ s.t } y = \Phi \Psi z \tag{5.2}$$

And by letting $x = \Psi z$, with $\hat{w}$ being the optimal solution.

5.2.3 CS and its Application in Data Aggregation

When using conventional compression techniques in Wireless Sensor Network (WSN) there are two main problems are occurred. Firstly, the compression performance relies heavily on how the routes are organized. Compression and routing algorithms need to be jointly optimized in order to achieve the highest compression ratio. Secondly, efficiency of an in-network data compression scheme is also depends on the computational and communication overheads not solely determined by the compression ratio.

To solve these problems Compressive Sensing based data aggregation technique is used. The data are gathered at some intermediate node where the data size is reduced by applying compression technique without losing any information of complete data in CS technique. In Compressive data aggregation technique each node in the WSN should send exactly k packets irrespective of what it has received (i.e.) compared with traditional techniques, more load for the nodes which are far away from the sink and less load for the nodes that are close to the sink. The energy efficiency of WSN is improved by data compression and aggregation technique which minimize communication. The practical performance of CS coding depends on the sparsity of the signal, as well as the reconstruction algorithm. CS suits well for data collection in WSNs when networked data is generally quite sparse in nature.

5.3 DATA AGGREGATION IN CLUSTER BASED HIERARCHICAL WSN BASED ON CS

In WSNs, data generated by different sensors can be jointly processed while being forwarded toward the sink. The data from different sources or nodes are combined into a single entity by simplest type of in-network processing known as Data aggregation. In sensor networks, the data gathered by spatially close sensors are usually correlated, so the node information is compressible. The data redundancy is also eliminated by using CS technology.

In this method, sensor nodes are organized into clusters, and each cluster has a cluster head , represented by the solid square. Sensor nodes in each cluster transmit their original data to the CH without using CS. It is assumed that each CH knows the projection vectors (in measurement matrix Φ) of all nodes within its cluster. Thus, given the identifiers of the nodes in the network, the measurement matrix can be easily constructed at CHs or the sink locally.

WSN is modeled as a set of nodes, which consists of N nodes and a sink. Each node is associated with a geographical location. All the nodes send the sensory data to the sink with the same rate. The time is slotted and all the nodes are synchronized, and the network is operated in a conflict-free and scheduled manner and also assumes that all the nodes have the same transmit power and the same data-rate. For clustering, the Energy Efficient Clustering scheme is used; the cluster head collect data from cluster member and sent it to sink through multi level hierarchical routing.

5.3.1 Energy Efficient Clustering

As discussed in the previous chapter , the network is partitioned into a set of clusters using E2C technique in which each cluster has one cluster head. There are three phases in the E2C technique, Cluster head election phase, Cluster formation phase and Data transmission phase. In the cluster head election phase, well distributed cluster heads are elected with a little control overhead. The selected cluster head forms a group in the cluster formation phase.

Cluster Head (CH) Election

In the CH election phase, the network is partitioned into a set of CRs.In each CR, the nodes participate in CH election called CHN are found using a probability scale is assigned to each sensor. According to this value, each sensor decides on becoming a CHN. After CHNs is selected, each CHN in Cluster region CR_i transmits a “CH advertisement” packet and advertises its residual energy level within a neighborhood of radius $r_{i.}$ Eventually, the candidates with the highest residual energy among their neighboring CHNs become the CHs. Additionally, it is used d(CHN,BS) to break the tie of $E_{residual}$ during the comparisons.

Cluster Formation

After the CHs are elected, each CH transmits a “CH announcement” packet within an area of transmission radius r_i and informs other sensors of its availability as a CH. This CH-announcement range is a multiple of r_i selected to ensure that each CM receives at least one announcement packet and can associate to a CH. To ensure reception of announcement packets by other nodes, a straightforward method is used to send region-wide broadcasts. However, this potentially causes high transmission energy cost; a fine tuned value is required. Thus, a system parameter tuned to achieve high CH-association probability for non-CH nodes while avoiding an unnecessarily large transmission range.

Each CM nodes may collect announcement packets from multiple CHs and hence the ideal CH is selected based on the highest RSSI to associate. By sending a “CH Joining” request and upon reception of a subsequent “CH confirmation” all nodes are associated with CHs. At the end of the cluster formation phase, there may still be a few sensors that have not joined with any clusters as they may not have received any announcement packets. To recover from such cases, a sensor with no CH-association gradually increases its transmission range and seeks the closest CH to associate.

5.3.2 In-Network Data Aggregation based on CS

In large scale Wireless Sensor Network clustering is an efficient mechanism. After forming the cluster formation by using E2C technique, cluster heads will aggregate the data of slave nodes after Cluster formation phase was completed, and then it sent data to sink. Sensor nodes in each cluster transmit their original data to the CH without using CS. Assuming each CH knows the projection vectors (in measurement matrix Φ) of all nodes within its cluster. Thus, given the identifiers of the nodes in the network, the measurement matrix can be easily constructed at CHs or the sink locally. The measurement matrix Φ can be decomposed into sub-matrices, one for each cluster.

Let Φ^{Hi} be the sub-matrix of i^{th} cluster. For i^{th} cluster, let CH_i be the cluster head and data vector of the cluster is denoted by x^{Hi}. The projections of all data x^{Hi} which collected from the nodes in its cluster on the sub-matrix, which is $\Phi^{Hi}x^{Hi}$ is computed by the CH_i. By using CS technique the CH_i generates M projections from the data within its cluster. The value of M is determined by the number of nodes N and the sparsity level of the original data. Then it forwards the data to the sink in M rounds along a backbone tree that connects all CHs to the sink. Consider all the sensors nodes are divided into P clusters. All the cluster heads (i.e.) CH_1, CH_2, CH_3 ……CH_P are connected by multilevel hierarchical to the sink. Data vector x can be decomposed as $[x_{H1}\ x_{H2} \ldots\ldots\ x_{HP}]^T$, and matrix Φ can be written as $[\Phi^{H1}\ \Phi^{H2}\ \Phi^{H3} \ldots\ldots \Phi^{HP}]$.

$$y = \Phi x$$

$$= [x_{H1}\ x_{H2} \ldots\ldots\ x_{HP}]^T \begin{pmatrix} \Phi^{H1} \\ \Phi^{H2} \\ . \\ . \\ . \\ \Phi^{HP} \end{pmatrix} \tag{5.3}$$

The above equation shows that the projection of all data in the network on the measurement matrix Φ is the sum of the projections generated from the clusters. Thus the CH aggregate its own projection and also the projections received from its children CHs in the same round and forward it to the sink following the backbone tree. The original data for all sensor nodes can be recovered only if the sink receives all M rounds of projections from CHs.

5.3.3 Multilevel Hierarchical Data Transmission

When CS based aggregation method is used, the data is compressed by using the CS at the CHs. The data projections generated at each CH are forwarded to the sink through the intermediate CHs. The adjacent clusters CHs are known as neighboring CHs. The projection of each CH is forwarded to its neighboring CH via some intermediate CH nodes in each round of transmission.

After forming clusters, the route from the CH to the Base station is formed by Multi Level Hierarchical Routing as discussed in Chapter 4. In the Route Construction Phase, a Route Construction Packet is transmitted from BS to sink nodes to disseminate the packet throughout the network. During this dissemination process, the route request packets are exchanged between sink nodes to CHs or CH to CH. Based on this process route is created between CHs and sink nodes. In the proposed model, a level is assigned for each CH during the broadcast of RCP through the network. When a CH transmit a data packet to its next hop, it keeps the data packet for a pre-defined time and wait whether the data packet is successfully deliver to the next hop. If the CH receives a Failure packet within that pre-defined time, it recognizes that there is a broken path on that next-hop. Then the CH re-transmits the data packet to another next-hop according to its route cache and removes the Failure packet sender from its routing table as a next-hop.

5.3.4 Algorithm of Reconstruction

The sensors have spatial correlations in their readings when sensor networks are densely deployed. Let N sensor readings form a vector ($x = [x_1, x_2, \ldots, x_N]^T$), then d is a K-sparse signal in a particular domain. The correlation patterns among sensor readings are described by the matrix. It is utilized only in data recovery process, and is not required to be known to sensors. From equation 5.2 it is clear that through solving an L_1-minimization problem the base station is able to reconstruct the sensor readings.

$$min_{z \in R^N} \| z \|_{l1} \text{ s.t } y = \Phi\Psi z$$

There are lots of algorithms are used for CS reconstruction which includes both the LASSO (Least Absolute Shrinkage and Selection Operator) and LARS (Least Angle Regression) algorithms and the Orthogonal Matching Pursuit (OMP) algorithm as stated by Tropp & Gilbert (2007). For sparse recovery two distinct major approaches are there and each present different benefits and shortcomings. The first uses a linear optimization problem to recover the signal which is known as Basis Pursuit (BP). In this method the sparse vector θ can be accurately recovered from y using the reconstruction techniques, one of those is Orthogonal Matching Pursuit (OMP). It provides strong guarantees and which most potent is fast implementation and easy to realize, especially apply to energy limited WSN. The sink use OMP algorithm to rebuild $\hat{y}$ after it received the M values.

To solve the above L_1-minimization problem Orthogonal Matching Pursuit (OMP) algorithm can be used by the base station for Signal Recovery. It is necessary to determine which columns of α participate in the measurement vector y to identify the ideal signal x. The idea behind the algorithm is to pick columns in a greedy fashion. The base station chooses the column of α that is most strongly correlated with the remaining part of y at each iterations.

5.4 PERFORMANCE EVALUATION

The performance of the CS based data aggregation in cluster based hierarchical WSN has been analyzed in this section. To analyze the performance of the CS based data aggregation technique the network has been simulated in MATLAB, with statistical gathered data. The sensor nodes are randomly deployed in a region of size 100 m × 100 m when simulation is performed. For the analysis, the number of deployed sensor nodes are varies from 200 to 1000 in the increments of 200 nodes with base station at location (x=50, y=150) as shown in Table 5.1.

The same energy parameters and radio model are used to measure the energy consumption of sensor nodes as discussed in the chapter 3. To evaluate the performance of the CS based data aggregation in cluster based hierarchical WSN proposed there are two metrics are used: the number of transmissions which is required to collect data from sensors to the sink, and the energy consumption.

A sink node is located at outside of the sensor field. The measurement matrix Φ and the transform basis Ψ in CS could be selected as discussed in 5.3. There is no effect on the performance evaluation by using these parameters in this method.

Table 5.1 Parameters Used in the Simulation

Parameters	**Rating values**
Network size	100 m ×100 m
Number of sensors	200,400,600,800,1000
Compression Ratio	5, 10
Transmitter circuitry dissipation	50 nJ/bit
Data Aggregation Energy	5nJ/bit
Data packet size	512 bytes
ϵ_{fs}	10 pJ/bit/m^2
ϵ_{mp}	0.0013 pJ/bit/m^4
d_o	87 m

5.4.1 Number of Transmissions

The performance of the CS-based approach has been analyzed in terms of number of transmissions with and without CS transmission approach. The number of nodes N varies from 200 to 1000. Let the Compression Ratio CR = N/M. CR is set to 5 and 10, so that the projections are sufficient to recover the original data with satisfied accuracy. It is observed that the number of transmissions taken by the CS-based approach depends on the number of nodes N in the network and the number of random projections M needed for signal recovery as shown in Figure 5.4.

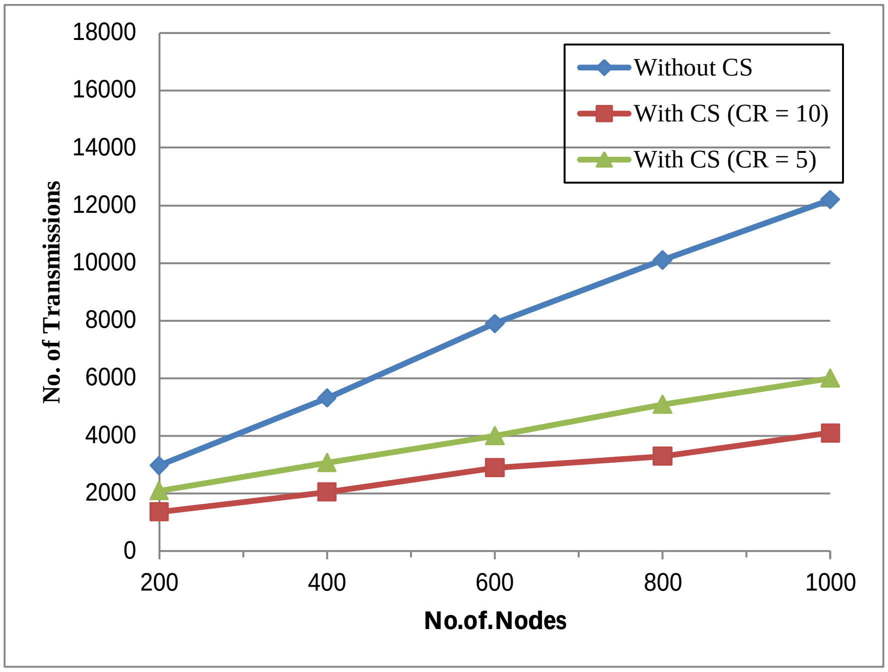

Figure 5.4 A comparison of the total number of transmissions between the CS-based approach and the traditional transmission approach in the network

Compared with the traditional transmission approach the CS-based approach may not be much energy efficient, when N becomes small. When N is high, the CS-based approach outperforms the traditional transmission approach, which requires less transmission to achieve a desired reconstruction quality.

5.4.2 Energy Consumption

The energy consumption also has been analyzed. Figure 5.5 shows that the CS based aggregation provides better performance compared with Non aggregation. The results are obtained from networks consisting of 1000 nodes, with aggregation factor k ranging from 100 to 400 as shown in Figure 5.5.

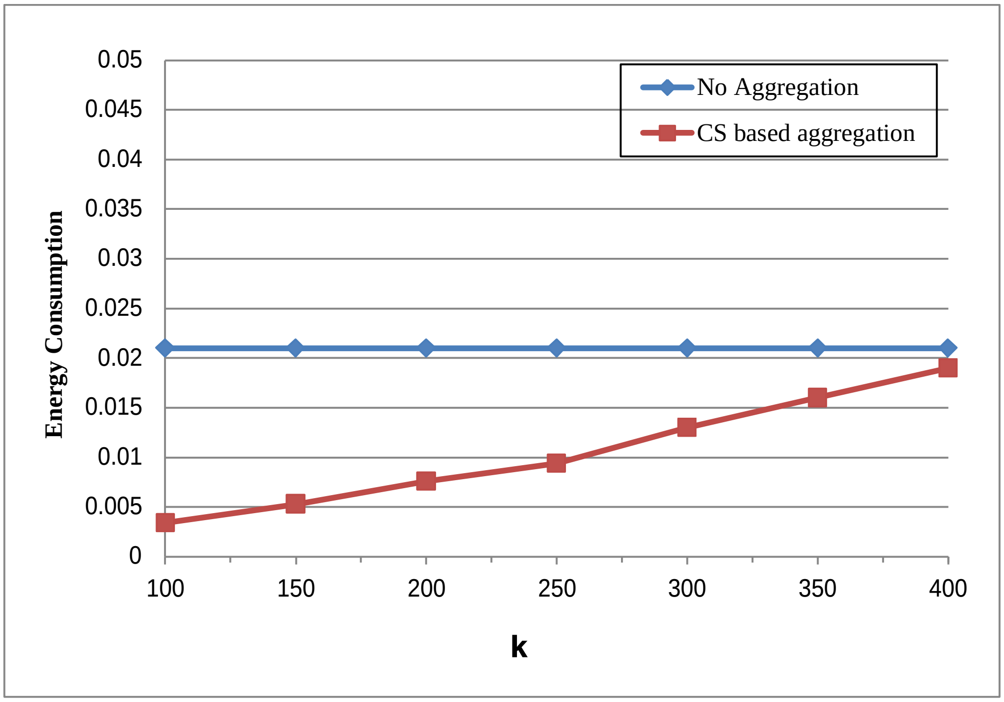

Figure 5.5 Comparing CS based aggregation against non-aggregation in 1000 node networks

It is observed that, CS based aggregation brings a remarkable energy reduction than non-aggregation technique. If k increases the energy saving will gradually reduced. In fact, CS aggregation is less energy efficient than non-aggregation unless k becomes unreasonably small (100). Evidently, compared with CS based aggregation Non aggregation always consumes several times more energy. Therefore, it is expected CS based aggregation to significantly outperform non-aggregation.

5.4.3 Average Energy Consumption

Figure 5.6 shows the average energy consumption per round for Energy Efficient Clustering with multi level hierarchical routing with and without CS based aggregation.

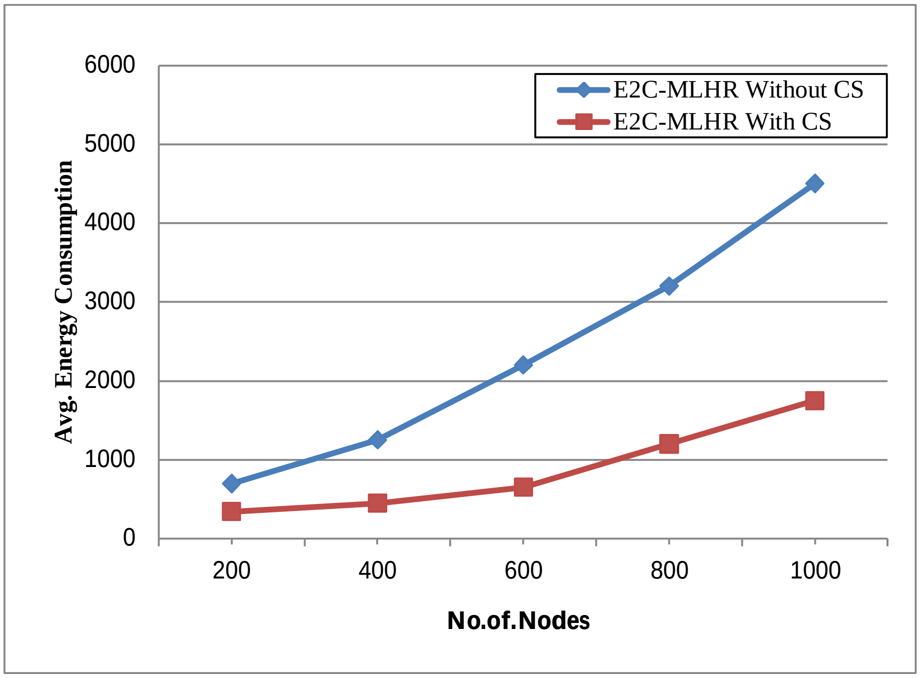

Figure 5.6 Average consumed energy per round as a function of number of sensor nodes

The average energy consumed by all the nodes in sending, receiving and forwarding operations known as Energy Consumption. The average energy consumption per round can be estimated as

$$E = \frac{\sum_{i=1}^{N} E_i(r)}{r}$$

Where N is the number of sensor nodes in the considered WSN, and r is the number of rounds.

In our simulation, the number of sensor nodes is varied from 200 to 1000 sensor nodes. It shows that, E2C-MLHR with CS based aggregation has less energy consumption compared with without CS based aggregation. When the original data are compressed by CS-based technique, each CH produces much smaller traffic volume which can be transmitted to the base station at a much lower transmission power and with a smaller time delay. Hence CS-based aggregation technique minimizes the overall energy consumption and therefore, extends the lifetime of the WSN and it is also shown by simulation results. Moreover, at the base station only the joint recovery is needed.

5.5 CONCLUSION

In this chapter, the energy efficiency aspect of applying Compressed Sensing used for data gathering from the perspective of in-network computation to collect the data in the cluster based Wireless Sensor Networks has been investigated. Energy Efficient Clustering with multilevel hierarchical routing and compressed aggregation has defined to minimizing the energy consumption. The performance of the Energy Efficient Clustering with multilevel hierarchical routing in terms of energy consumption and the number of transmissions with and without CS based data aggregation has analyzed. From the simulation results it is observed that the CS based data aggregation has improved the energy efficiency.