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An Energy Efficient Data Aggregation for Random Sensor Networks

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ABSTRACT

Energy-efficient computing is the thrust area of research in an energy-constrained Wireless Sensor Network (WSN). Comb Needle Model (CNM) exists in literature for energy efficient data aggregation in regular (grid-based) WSNs. Clustering concept is added to CNM to reduce the energy consumption further. Besides, basic CNM is extended for randomly deployed WSNs. In this paper, the extended CNM for random WSNs is augmented with clustering mechanism. When clustering is added to the Extended CNM, it will aggregate the data at Cluster Head and minimizes the number of data transmissions, and thereby extends the network life span. The CNM uses the push-pull data distribution approach. It may overload certain sensor nodes, and lead to hotspots, which causes excess amount of energy loss. We extend the CNM with clustering in random network to overcome these issues and perform energy efficient processing. This paper makes the simulation based comparative analysis of the Extended CNM with clustering with that of without clustering. The performance metrics considered are energy consumption, communication cost, delay, packet loss, packet delivery ratio, and throughput. It is empirically observed that the network life span is improved substantially.

Keywords: Wireless Sensor Network, Cluster based comb needle model, Communication cost, energy efficiency.

1 Introduction

Wireless Sensor Networks (WSNs) are widely deployed in recent era because they extend our ability to control and monitor physical environment from far away. They improve the accuracy of sensing by using distributed processing of large quantities of sensed information (e.g., high resolution images, seismic data, and acoustic data). When sensors are networked they can aggregate such data to provide the different views of the environment. Several difficulties need to overcome to deploy a good WSN. These difficulties may arise from the limited computation power, limited energy and communication resources available for the sensors in the WSN [1-3]. Figure 1 shows the wireless sensor network architecture for a military application [4].

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Energy: Sensor nodes have limited battery power, if they deployed in the sensing field their battery cannot be replenished, that is the reason, WSN require energy efficient protocols for computation and communication.

Computation: sensors are small devices they have limited computational ability, so they cannot run complex network protocols.

Communication: The sensed data should be communicated to sink otherwise it is useless. If all the sensor nodes try to send data to sink it consumes more power. So the data should be aggregated and only useful data should be communicated to sink. Hence we require efficient data aggregation techniques in WSN [5, 6].

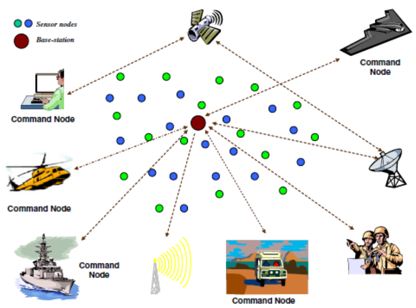

Figure1. Wireless Sensor Network Architecture for Military Applications [Taken from 4]

Many civilian and military applications have taken advantage of WSN. The advantage is its ability to perform operation in unattended harsh environments, where working of human beings is difficult and risky. In such cases sensor networks produce efficient results.

In large WSN hundreds or thousands of sensor nodes may involve to meet the civilian application requirements. To design and operate such large WSN would require scalable architecture and management strategies.

If we consider three key factors- Energy, computation and communication in a sensor node, designing energy-aware and efficient computing algorithms becomes an added advantage for WSN to extend the lifetime of sensors.

Clustering also plays important role in minimizing energy. So many clustering methods have been developed by research community to achieve the objective such as network scalability. Every cluster will be having a group of nodes with a group leader called cluster head (CH). Many clustering algorithms have been developed in literature for ad-hoc networks [7-11]. Recently, many number of cluster algorithms are specifically designed for WSNs [12-16]. The proposed clustering algorithms vary from one another in terms of network architecture, node deployment, network operation model, and the features of the CH nodes.

This paper proposes cluster based scheme for data aggregation mechanism by using Comb Needle Model (CNM), which is applied in random sensor networks.

In the Extended CNM for random networks [17], when an event occurs, all the sensor nodes present on the comb participate in transmitting the reply to the base station (See Figure 2). This may result in lot of communication cost and energy consumption, which depletes nodes energy and, it may lead to hotspot problem in the WSN. To overcome this issue clustering has been added for data gathering in extended CNM for random networks.

There are some assumptions in this research about the network and application as given below:

- Any time and any where an event may occur
- Any node may get query from its neighbor
- All nodes knows their location

Remaining paper organization is as follows: Related work is explained in Section 2. Section 3 elaborates the proposed method. The analytical evaluation of the proposed method is given in Section 4. Experimentation has been done using Network Simulator NS2, and the results obtained are presented in Section 5. Section 6 concludes the paper.

2 Existing Work on Data Aggregation in WSN

Data aggregation plays a vital role in the WSN for conserving energy [18]. Several characteristics associated with the aggregation have been discussed by researchers in literature. For example several energy efficient algorithms to perform data aggregation are studied [18]. To perform data aggregation scheduling algorithm for maximizing throughput and reducing delay were discussed in [19], and aggregation based routing protocol was demonstrated in [20].

Apart from data precision or data quality, delay, energy efficient algorithm also a significant performance outlook of data aggregation. The trade-off between energy efficiency and quality of data aggregation is first detected by Pharm et al. [21]. Afterwards, Zhu et al. [22] had analyzed the quality of service in the data aggregation of the wireless sensor networks for estimating the exact precision needed for completely specific task. Later on, Xu and Tang [23] had illustrated about the data precision gathered from various sensor nodes for improving network life span and minimizing the energy consumption. There are various similar papers, which aim to improve the data quality within the given life span or energy for the data aggregation [24].

Tang et al. [25] had proposed an energy-efficient protocol in the MAC layer for reducing the energy consumption in the nodes by altering the senders to detect the receiver’s wake up time. For achieving data transmission optimization with a static routing strategy, sensor nodes transfer the larger data to other nodes, which may consume the high energy at the earlier stage, it may create hotspots. To neglect the issues of the hotspots so many steps had been taken in the last decade. The previous methods are generally classified into two types: (i) Using the node-stage context for energy-aware data distribution strategy and (ii) exploiting the clustering methods for energy efficient management.

Hou et al. [26] had proposed a data protocol in wireless sensor networks. The protocol utilized adaptive network coding to minimize broadcast traffic for the function of codes updation in the wireless sensor networks. This protocol is further analyzed and developed by Shwe et al. [27], introduced an efficient neighbor discovery protocol to detect out all the nearby nodes for minimizing the power consumption in the wireless sensor networks. Later on, Lun et al. [28] have proposed a random linear network coding scheme that accomplishes the packet-stage capacity for both the unicast and multicast connections in wireless sensor networks.

Data classification, a prominent tool for data analysis, is widely used in variety of applications, such as, image processing, pattern recognition, market analysis, social behavior study, data mining, and so on. McQueen et al. [29] has proposed the k-means algorithm, one of the most fundamental and popular algorithm for unsupervised classification (data clustering). It employs the Euclidean distance, as a pattern similarity measure. The k-means algorithm is extended with additional heuristics to govern the process of splitting and/or merging of clusters, and is well known as ISODATA (Iterative Self-Organizing Data Analysis Technique) algorithm proposed by Ball et al [30]. ISODATA is used as a benchmark for all data clustering algorithms. Based on ISODATA, OBV Ramanaiah et al. [31] has proposed a distributed version (D-ISODATA). It clusters the voluminous distributed databases 'in place', without the need for uploading to a central location. It eliminates the demerits associated with the centralized clustering of voluminous database, such as, communication costs, storage requirements, and administrative complexity. D-ISODATA algorithm is adapted for mobile environment, which we call m-ISODATA *m* stands for mobile) [31]. Two schemes, named as discard partition and use recent history, are proposed to cope with the disconnection of MHs participating in the distributed clustering process. The proposed concept uses the basic ISODATA algorithm.

X. Liu [32] proposed Comb Needle Model to perform data aggregation based on push and pull strategies. Shanmukhi et al [33] had demonstrated Cluster based Comb Needle Model for grid networks. It has minimized communication cost and maximized the throughput. Shanmukhi et al [17] had applied the Comb-Needle Model in simple random network and achieved best results. Shanmukhi et al [34], carried out survey on data aggregation techniques. The survey of the data aggregation and energy consumption process had analyzed their mechanism and the drawbacks, our proposed method would be efficient than all these methods and overcome these drawbacks.

3 Proposed Concept

The CNM was proposed by X. Liu et al [32] for regular network (grid deployment) to perform data aggregation. Clustering has been added to CNM for regular network [33] to perform efficient data aggregation with energy efficiency. The basic CNM is extended to support the data aggregation in *randomly deployed* sensor networks [17] as shown in Figure 2.

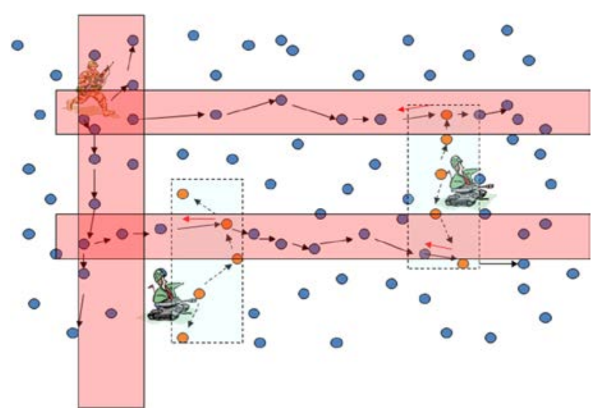

Figure 2. Basic Comb Needle Model in Random Network [Taken from 17]

Now in this work clustering is added to the extended CNM. The same is illustrated in Figure 3. See Table 1 for summarization of these works. When we add clustering to the Extended CNM, it helps to improve

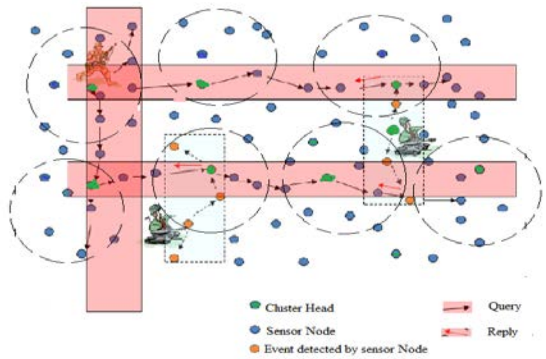

Figure 3. Proposed Cluster based Comb- Needle model with Cluster Heads

the data aggregation and decreases the energy consumption and improves the lifespan of network.

Table 1.Summarization of Our Works

Deployment Method	Basic CNM	Cluster-based CNM
Regular Network (Grid Deployment)	Combs, Needles, Haystacks: Balancing Push and Pull for Discovery in Large-Scale Sensor Networks [32]	Cluster-based Comb-Needle Model for Energy-efficient Data Aggregation in Wireless Sensor Networks [33]. *(Our Published Work)*
Randomly deployed Network	Extended Comb Needle Model For Energy Efficient Data Aggregation In Random Wireless Sensor Networks [17] *(Our Published Work)*	Now Proposed work is explained in this paper

3.1 Network Model

ASSUMPTIONS:

The following are the assumptions in the network model used for simulation as well as analysis:

(1) Wireless sensor network consists of *N* stationary and location-aware (using GPS or some other localization method) sensor nodes deployed randomly in the square field region of size *m* X *n*.
(2) Base station is in top left corner. (Multiple base stations may be available in network, each soldier is considered as base station)
(3) All the sensor nodes have the equal transmission power.
(4) All communication links are assumed to be symmetric.
(5) There are no transmission errors.
(6) Sensor node turns as an aggregator, if the size of the data is bigger than the certain limit.
(7) Clustering is done using ISODATA [31] scheme.

3.2 Applying ISODATA Clustering Algorithm

Many variants of k-means algorithm are available in literature. One such variant is the well-known ISODATA (Iterative Self-Organizing Data Analysis Technique) algorithm [30]. The variation employed is, splitting and merging of the resulting clusters of the k-means algorithm. In other words, ISODATA algorithm is based on the k-means algorithm with additional heuristics that govern the splitting and/or merging of clusters. Using these heuristics, it is possible to obtain the optimal partition starting from any arbitrary initial partitions, provided proper threshold values are specified. Splitting is done if a cluster has variance exceeding a threshold value, while merging is performed when the distance between a pair of cluster centroids is less than another threshold value. ISODATA is used as a benchmark for all unsupervised classification algorithms.

The application of ISODATA clustering in the proposed concept is as follows:

All the sensor nodes are initialized in 2D plane in random network, and then ISODATA algorithm is applied. How ISODATA algorithm works in our proposed concept is as follows: ISODATA has assigned initial cluster vector and it will take the sensor nodes positions into consideration to make them into clusters. The next step classifies each node to the closest cluster. Further new cluster mean vectors are calculated based on all sensor nodes in one cluster. The above two steps are repeated until the variation between the iteration is small. The variation is computed by the change in mean cluster vector iteratively. Clusters are merged if the number of sensor nodes in a cluster is less than a certain threshold value, or if the centroids of any two clusters are closer than a certain threshold. Clusters are split further into two different clusters if the cluster standard deviation exceeds another predefined value.

ISODATA ALGORITHM:

Input: N_C: Initial number of clusters, M: Final (desired) number of clusters, CT: Convergence threshold,
K: No of clusters required
Output: *M* number of clusters along with their centroids.

begin
1. Select N_C (< *M*) initial cluster centroids either arbitrarily or using some criterion;
2. *while* (stopping criteria not satisfied)
   2.1. **repeat** /* k-means Algorithm */
   Assign each pattern to the closest cluster centroid;
   Re-compute the cluster centroids using the current memberships.;
   until (clustering converges) /* Convergence rate < CT */
   2.2. Choose the clusters eligible for split and/or merge;
   2.3. Update the number of clusters N_C ;
   2.4. Determine the current centroids.

End

4 Analytical Evaluation

4.1 Analysis Of Comb Needle Model

It is considered that any node in the random networks can produce any event.

The following important performance metrics are determined as:

f_q = Query frequency

f_e = Event frequency

$f_d = \frac{f_e}{n^2}$ events occurs frequency in the sensor node

However, in our proposed mechanism, overall communication cost may be based on the broadcast or unicast, which utilized in the random networks. Here, we assume unicast for the analysis in the Extended Comb Needle Model. The cost of the developing the single comb needle for the length l is $l-1$.

We consider that frequency of Query f_q, The frequency of data event f_e is termed as ${f_e}/{f_q}$, which means that number of events produced for per query in a comb needle is $l-1(f_e/f_q)$. As $C_l = l-1$, then it would be modified and given as event produced for needle:

$$= C_l(f_e/f_q)$$

Complete Comb Needle Model analysis is given in our previous work [33].

4.2 Cluster Based Comb Needle Model for Random Networks

We consider the random network with *N* nodes located in plane at (x, y), where sensor node range is specified as 0<=*x*; *y*<*n*. The deployment area starts at (x, y) and the boundary is given as (x_n, y_m). Here, it is assumed that sensor nodes are uniformly distributed in the network.

We apply ISODATA [30] algorithm on randomly deployed sensor network, it will divide the sensor field into clusters called *i*. On top of the cluster region a CNM is applied.

The mathematical analysis for the proposed concept is as follows:

When a query is generated then the comb structure is formed in the network as shown in Figure 6. Let's assume that query node is located at (x, y). If the query is sent through the vertical direction from (x, y) to (x, y_m) and (x,0). Then the query is distributed at the horizontal lines from nodes (*x*,*y*+*s*),(*x*,*y*+*2s*) to (x_n,*y*+*s*), (x_n,*y*+*2s*). In this mechanism, *s* is used as combing degree or inter spike spacing. The resulting routing structure looks like a comb.

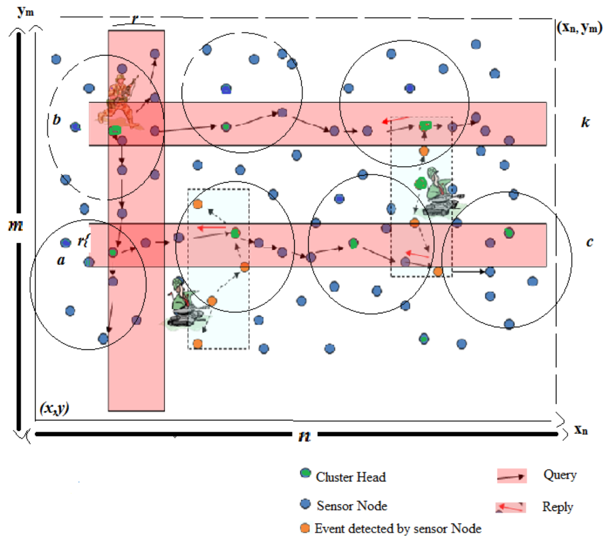

Figure 4. Definition of Comb base and spike for Extended Comb Needle Model

Let us assume that theoretical analysis of the random networks is given below:

$$(x,y+s) = a \tag{1}$$
$$(x,y+2s) = b \tag{2}$$
$$(x_n,y+s) = c \tag{3}$$
$$(x_n,y+2s) = k \tag{4}$$

From the equation (1) to (3) and (2) to (4) where the horizontal lines are formed, (x, y) to $(x,0)$ and (x,y) to (x,y_m) vertical lines are formed. While estimating the distance from the plane s.

$$s = (y_m-y_0)/3 \tag{5}$$

For illustrating the query response in horizontal direction $(x,y+s)$ and $(x,y+2s)$ are points generated for the horizontal response. Thus the push based query performance is operated while it is performing in the horizontal direction in the Figure 4. The comb structure has been developed. Then we need to specify the range of the comb needle model in the random network by using the following criteria, where r represents the range of the comb base and spike.

When the range is established for the random networks, it is demonstrated in the following equations

$$\text{Vertical range: } (x+r, y) \text{ to } (x+r, y_m)$$

Based on equation (1) and (3) horizontal range for spike *a* to *c* is

$$(a+\frac{r}{2}, a-\frac{r}{2}) \text{ to } (c+\frac{r}{2}, c-\frac{r}{2}) \tag{6}$$

Based on equation (2) and (4) horizontal range for spike *b* to *k* is

$$(b+\frac{r}{2}, b-\frac{r}{2}) \text{ to } (d+\frac{r}{2}, d-\frac{r}{2}) \tag{7}$$

The sensor nodes would pass the query depending on the Euclidean distance, which is used to consider the shortest path. The Euclidean distance is represented in the following equation:

$$\xi_{dist} = ((p,q)(u,v) = \sqrt{(p-u)^2 + (q-v)^2} \quad (8)$$

For example, consider the scenario as shown in Figure 5. e, f, and g are neighboring nodes on the spike. As per Euclidian Distance link is established in between *e* and *f*.

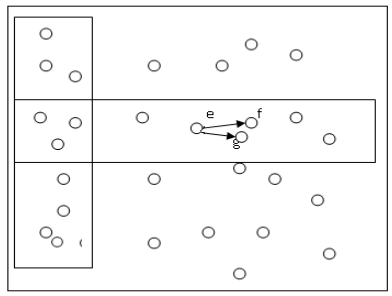

Figure 5. Establishing communication link in between neighbors

4.3 Analysis of Communication Cost

For analyzing the communication cost in both Grid (Regular) and random networks, the following scenario is considered:

Comb is assumed to be at the extreme left and needle at the extreme right. See Figure 6.

Case 1: Grid Network:
Number of hops for event notification = n hops as shown in Figure 7.

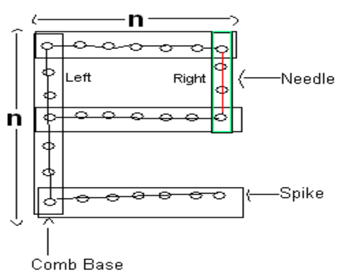

Figure 6. Comb and Needle in Grid Network

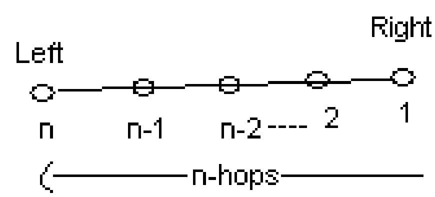

Figure 7. Communication using n hops in Grid Case

Case 2: Random Network:

Communication overhead depends on the way the nodes take their position at the time of random deployment as shown in Figure 2.

Best Case:

Nodes between two ends, Left and Right, take position as shown in Figure 7.

Number of hops required for event notification = n;

Increase in hops compared to Case1 (Grid network) = 0.

Worst Case:

In the worst case nodes take their position as shown in Figure 8

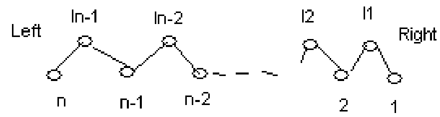

Figure 8. Communication in Random Network

Number of hops required for Event Notification = n+(n-1); (9)

Increase in hops compared to Regular deployment = (n-1); (10)

To calculate the Number of hops required for Event Notification in the average case, we consider the results of both the best and worst cases.

Therefore Increase in Number of hops for Event Notification in average case = 0+(n-1)/2

= (n-1)/2 (11)

This means that the communication overhead increases by 50% in case of random deployment.

When compared to regular deployment (Grid networks).

As per the reference [32] for CNM based grid networks Communication Cost Coptimal is

$$\text{Coptimal} = O(\sqrt{n}) \tag{12}$$

When clustering is implemented in CNM based grid network [33]

$$\text{Coptimal}=O(\sqrt{n}/Nc) \tag{13}$$

Since *Nc* is number of clusters

When CNM based random network is considered the Coptimal is *O (n)* (14)

When clustering is implemented in CNM based random network the Coptimal is as follows

$$Coptimal=O(n/Nc) \tag{15}$$

5 Experimental Analysis

Experiment is conducted with the following simulation parameters given in Table 2. The performance of the Extended CNM with clustering is compared with Extended CNM without clustering.

5.1 Simulation Parameters

Simulation of the WSN with 50 nodes deployed randomly in an area of 20x10 square units is carried out using NS2. It is assumed that the wireless sensor nodes are distributed uniformly and independently. The MAC protocol is used is IEEE 802.11, number of nodes are 50 to 70. The radio propagation model is two ray ground reflection model.

NS2 has implemented three different propagation models (PM) to simulate the wireless channel: they are Free space model, Two-ray ground model and Shadowing model. Generally the propagation models are used to compute the received power. PM determines the attenuation between transmitter and receiver and computes received signal strength, when a packet is received. In Free space model, it assumes ideal propagation conditions and a single line-of-sight path between the transmitter and receiver. In two-ray ground reflection model, it considers both the ground reflection path and a direct path. In this model, both transmitter and receiver node are assumed to be in line-of-sight path. This model is more accurate in case of long distance line-of- sight path. Both the Free-space model and the two-ray model expect the received power as a deterministic function of the distance between the receiver and transmitter. The shadowing model will do deterministic path loss that predicts the received power from the distance between the receiver and transmitter nodes. The detailed information about NS2 propagation models can be found in the NS2 manual [35].

Table 2. Salient simulation parameters

Parameter	Value
Mac protocol	802.11
Number of nodes	50 to 70
Node deployment	Random
Radio propagation model	Two ray ground
Radio transmission range	200 m

5.2 Performance Metrics

The following metrics are used for evaluating the performance of proposed concept, which are defined as follows [17]:

a) Packet Delivery Ratio (PDR): It is determined as the ratio of overall packets received to the overall packets sent.

b) Throughput: It is determined as rate of successful message delivered over a communication channel in the random networks.

c) Average Delay: It means time difference between packets sent and packets received.

d) Energy consumption: It is determined as the average energy consumed on idle sleep, data processing, sensing, and data transmission.

e) Communication cost: It is determined as the number of packets transmitted and received for query and event notification.

5.3 Results And Discussion

The performance metrics are utilized to validate the proposed Cluster based CNM in random networks. The obtained results are demonstrated in [Figures 9 to 18]. From the obtained simulation results, it is clear that Cluster Based CNM in random network is significantly better than Extended CNM in simple random network.

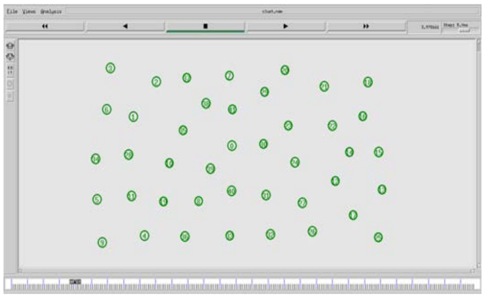

Figure 9. Simple Random Network

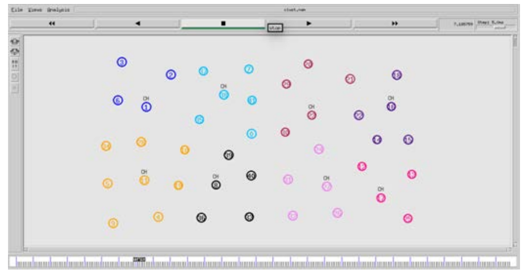

Figure 10. Clusters in Random Network

Figure 11. Cluster based Comb Needle Model (when query generated)

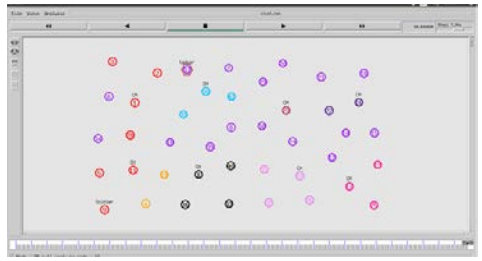

Figure 12. Cluster based Comb Needle Model With Needle (when Event found)

Figure 9 represents the network topology of the random network. The cluster network topology of the Cluster based CNM in the random network is demonstrated in Figure 10. Whereas Figure 11 shows the Comb structure in which base station sends the query in vertical fashion called comb base and horizontal spikes are formed for query forwarding in order to process information efficiently with minimum energy consumption. The result of query is shown in Figure 12 (i.e., when query received by node it sends event information to Cluster Head, Cluster Head aggregates data and sends back to soldier via the same path that is called Needle).

Hence, the simulation results are compared between the Cluster based CNM and Extended CNM in the random network. It is well understood from the obtained results graph that Cluster based CNM got higher performance than Extended CNM.

The performance analyzed in terms of communication cost, energy consumption, packet delivery ratio, packet loss, delay and throughput. They are represented in [Figures 13 to 18].

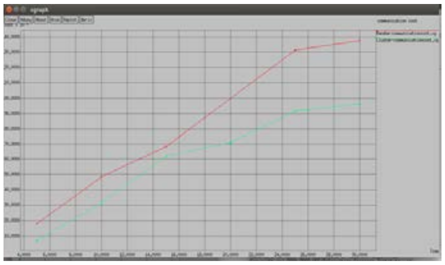

Figure 13. Communication Cost
***Red line indicates Extended CNM in random network. *Green line indicates Cluster based CNM**

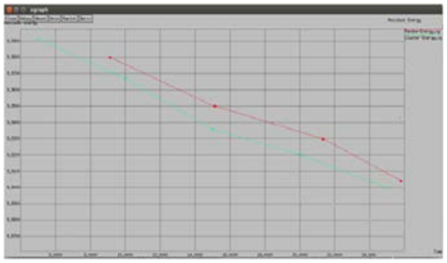

Figure 14. Energy Consumption
***Red line indicates Extended CNM in random network. *Green line indicates Cluster based CNM**

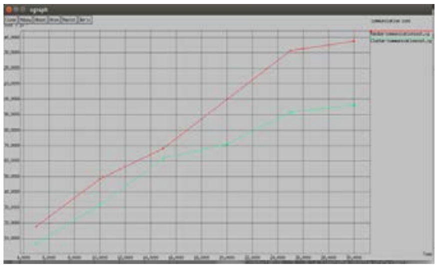

Figure 15. Packet Delivery Ratio
***Red line indicates Extended CNM in random network. *Green line indicates Cluster based CNM**

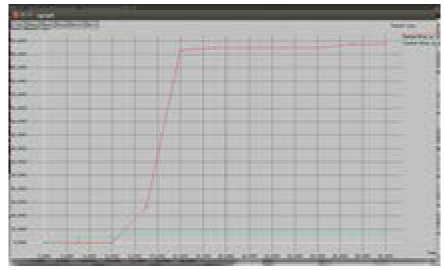

Figure 16. Packet Loss
***Red line indicates Extended CNM in random network. *Green line indicates Cluster based CNM**

The graphs [Figures19 to 21] shows that efficiency of Cluster based Comb Needle Model in random networks and Extended Comb Needle Model in random networks

- Communication cost in Cluster based Comb Needle Model for Random Network is 30 % and in Extended Comb Needle Model for Random Networks is 58%. So 28% Communication Cost is decreased in our proposed model.

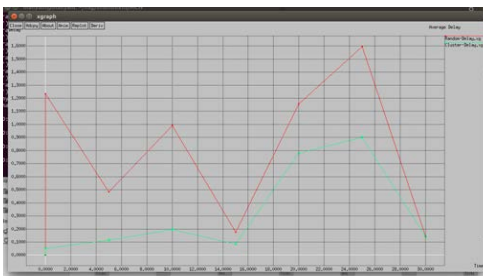

Figure 17. Delay
***Red line indicates Extended CNM in random network. *Green line indicates Cluster based CNM**

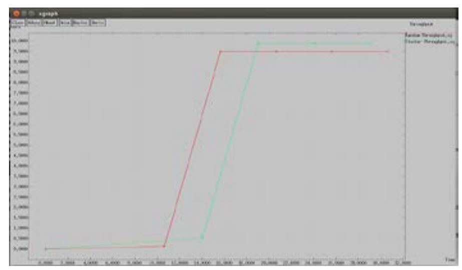

Figure 18. Throughput
***Red line indicates Extended CNM in random network. *Green line indicates Cluster based CNM**

Average Energy Consumption in Cluster based Comb Needle Model for Random Network is 25 % and in Extended Comb Needle Model for Random Network is 41%. So 16 % energy is saved in our proposed model.

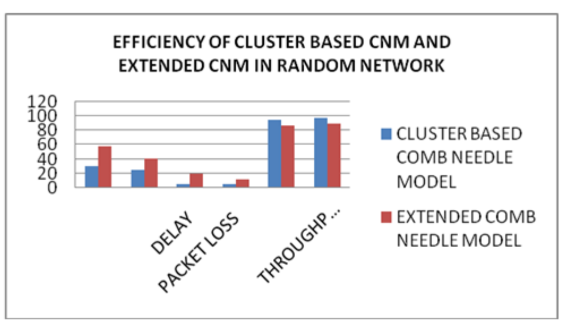

Figure 19. Efficiency of Cluster based CNM and Extended CNM in Simple Random Network

Delay in Cluster based Comb Needle Model for Random Network is 5 % and in Extended Comb Needle Model for Random Network is 20%. So 15% delay is reduced in our proposed model.

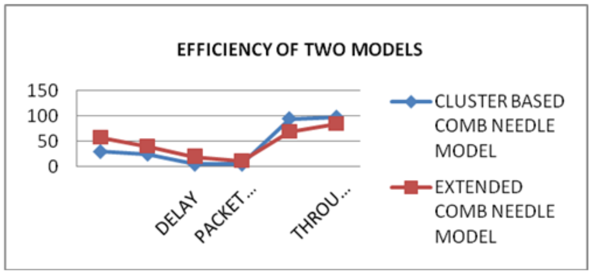

Figure 20. Efficiency of Two models

- Packet Loss is 5% in Cluster based Comb Needle Model for Random Network where as 12% in Extended Comb Needle Model for Random Network. So 7% is reduced in our proposed model.

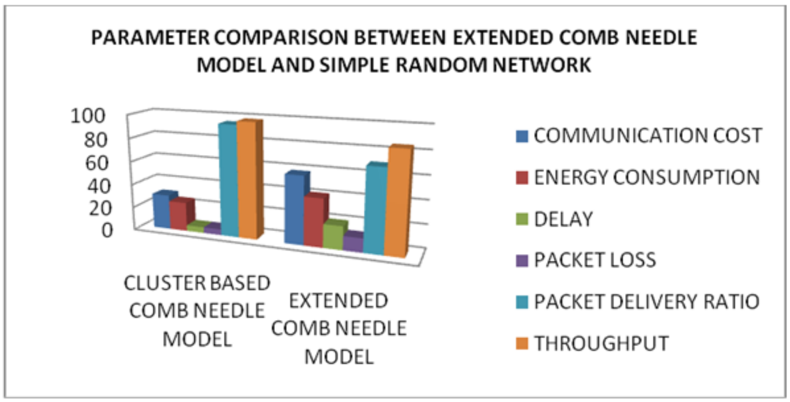

Figure 21. Parameter comparison between Cluster based CNM and Extended CNM in Simple Random Network

- Packet Delivery Ratio is 95% in Cluster based Comb Needle Model and 87% in Extended Comb Needle Model for Random Network. 8% is improved in our proposed model.
- Throughput is 98% in Cluster based Comb Needle Model and 90% in Extended Comb Needle Model for Random Network. 8% is improved in our proposed model.

6 Conclusion

At present, Wireless Sensor Networks have attracted much attention. An increasing list of military and civilian applications can employ WSN for increased effectiveness; especially in remote areas. For example Border protection, combat field surveillance and disaster management etc. These applications require good architecture and energy efficient data gathering and aggregation mechanism. We designed the Cluster based Comb Needle Model for Random WSN, by using two things clustering algorithm and comb needle model. All together it is Cluster based Comb Needle Model for Random sensor network. We analyzed the performance by using different parameters. They are Packet Delivery Ratio, Delay, throughput, Packet loss, Communication Cost, and Energy Consumption. Then we compared the proposed model with the Extended Comb Needle Model for random network. We observed that the Cluster based Comb Needle Model in Random networks is providing better results when we compare with a Extended Comb Needle Model in Simple Random Networks. It is well suited for military applications. Further our proposed model can be enhanced by applying compression techniques.

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