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Energy Efficient Clustering and Localization in Wireless Sensor Networks

Neha Verma, Rakhi Rani

***Abstract*— Energy of the sensor nodes is valuable and scarce in Wireless sensor Networks(WSN) therefore it is vital to reduce energy consumption in order to improve lifetime of WSN. An excellent way to do so is to divide sensor network into groups of cluster and sink node, where cluster head acts as leader of the cluster. For WSNs with a large number of such sensors, it is very important to use a method which automatically arranges the sensors in clusters such that minimum energy is used to communicate information from all nodes to the respective Base station. We also observed that it is accompanied by a phenomenon of spatial dependence of continuous process, in which data bare a certain spatial correlation. Generally, the degree of the correlation in the data increases with the decrease with the separation between sensor nodes. We propose in-network compression and optimum clustering way of sensor optimization to be implemented together for large WSNs.**

***Index Terms*— Energy Efficient; Routing technique; Optimum Clustering; Sensor Networks; Spatial Correlation; localization; Data aggregation.**

I. INTRODUCTION

A wireless network consisting of spatially distributed mobile and random devices using sensors to monitor physical or environmental natural phenomenon like vibration, motion, temperature, pressure, sound or pollutants at worldwide locations. Such a network was originally developed as military applications for battlefield surveillance. However, WSNs are now used in many civilian and engineering application areas, such as in healthcare, habitat monitoring, home applications, automation and in traffic control.

It has hundreds to thousands of low-power sensor nodes that perform multifunctions with limited computational and sensing capabilities. In order to take advantage of these WSNs, we need to consider certain constraints associated with them. Specially, minimizing energy consumption, which is a key requirement in the designing of efficient network and algorithms. As sensor nodes are equipped with small and limited power capacity batteries, thus it is essential that the network is energy efficient so that we can maximize the lifespan of the network[6, 7].

Since a large number of low-power nodes have to be networked together, conventional techniques like direct transmissions from a specified node to a particular base station have to be avoided. Clustering and generating a sink node can be of use here but as the no. of hops from a cluster to other increases, the energy efficiency of network decreases. On the other hand, utilizing multihop routing schemes will result in an equally undesirable effect. Thus a novel approach of combining compression and routing is required at both clustering and in-cluster environment.

II. PROBLEM FORMULATION

The objective behind this work is to suggest solution to major problems of energy efficient coding for data aggregation in cluster-based WSNs with a special focus on optimizing compression and the total amount of data transferred in whole network is minimized such that it estimates the number of clusters needed to efficiently utilize data correlation of sensors[4].

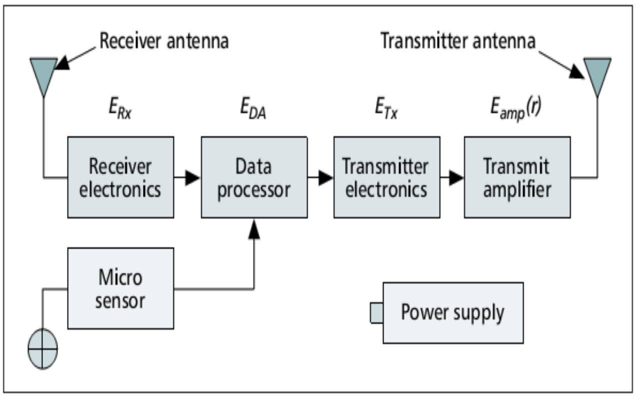

Fig. 1: Hierarchical WSN that is considered apt of saving Energy.

To do so, we must improve the energy allotment and limit its expense in sensor network. This way we can maximize the sensor node lifetime and in totality it will make the wireless sensor network more fault tolerant as well. We must note that once deployed, the capacity of batteries is not expected improve much in the future[9]. Thus in this research, we explore energy consumption and various trade-offs associated with lossless data aggregation. The techniques used will extend the lifetime of sensor network along with reducing size of data due to correlation. Reducing data size, less bandwidth is required for sending and receiving data thus the communication is made more efficient in more than one way.

Thus our areas of interest are to:

- Use data compression techniques as compressed data use low energy at transmission and receiver end.
- Work towards self localization of sensor node so that efficient routing paths can be defined with accuracy.
- Out of all the possible paths, find the shortest distance to destination.
- Calculate the minimum hop or cost of method to find optimum path.

- Compare the effect of using the energy efficient routing w.r.t to a general clustering method.
- Calculate the effect of size of cluster and spatial on cost of setting up a WSN.

III. RELATED WORK

Consider a WSN having many sensor nodes sensing a common data independently and sending their sensed readings to a base station for information extraction and further processing. As these readings will be highly correlated, thus we can say highly redundant data will appear in the readings. Thus we can conclude that sending this redundant information to base station can be avoided if the sensor nodes can compare data with each other before sending them forward. Although, in many cases it is difficult to attain; but in the cases that sensors can communicate, this communication among nodes will consume lot of energy, which is not contributing to any useful flow of information. This is the most critical issue in a design and implementation of efficient WSNs[5].

Consider X to be a discrete random variable taking values in the set X = {1,2,...,M}.

The probability of such a long typical sequence is, therefore,

$$P_T = P_X(1)^{nP_X(1)} \;....\; P_X(M)^{nP_X(M)}$$
$$= \exp[\, nP_X(1) \log P_X(1)] \,....\, \exp[\, nP_X(M) \log P_X(M)]$$
$$= \exp\,[-nH(X)]$$

Where, $H(X) = -\sum_1^M P_X(i) \log P_X(i)$

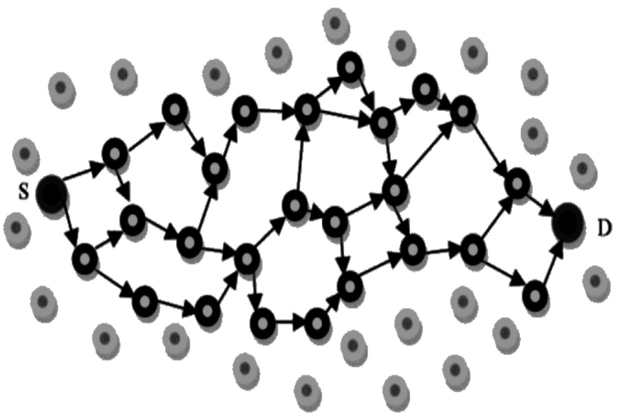

Fig. 2: Concept of correlated sources and finding optimum rate R.

Under an assumption of correlation between information sources, a DSC framework can be taken in which any no. of information sources can be compressed and aggregated in a distributed way, has been demonstrated by X.

In the case of two random sources X1 and X2 that are correlated, intuitively each of the sources can code their data at a rate greater or equal to their respective entropies R1= H(X1), R2 = H(X2) respectively. If they are able to communicate, then they could coordinate their coding and use together a total rate R is equal to the joint entropy, R1+ R2 =H(X1,X2).

This can be done, for instance, by using conditional entropy, that is, R1 = H(X1) and R2 = H(X2|X1), since X1 can be made available at node 2 through explicit communication. Slepian and Wolf showed that two correlated sources can be coded with a total rate H(X1,X2) even if they are not able to communicate with each other. Fig. 2 shows the correlated rate region for the case of multiple sources and destination nodes.

This result shown in Fig. 3 can be generalized to the N-dimensional case. Consider a network consisting of N sensor nodes uniformly distributed in a region of interest, where each node i produces reading Xi and all the readings constitute a set of jointly ergodic sources.
For example, consider a simple case of two sensor nodes producing readings X1 and X2 . Their individual rates is subject to R1 ≥ H (X1 | X2) and R2 ≥ H (X2 | X1).
Thus R1 + R2 ≥ H (X1 , X2) (1)

According to chain theory[10], under the above constraints, it is always possible to find a rate allocation for the two nodes, which makes the total rate (bits) of two nodes equal to their joint entropy, e.g.,

$$R = R1 + R2 = H(X1) + H(X2 \mid X1) \quad (2)$$

In general, for an arbitrary ordering of N nodes (e.g., in the ascending or descending order of nodes' ID numbers), there exists a rate allocation (vector) {Ri},
Where i = 1,2…….N such that the number of generated bits from all nodes can achieve the value of their joint entropy, e.g., $Ri = \sum_{i=1}^{N} H(X1, X2 \ldots\ldots, XN)$
(3)
Where R1 = H (X1)

$$\therefore\ Ri = H(Xi \mid Xi-1, Xi-2, \ldots, X1),\ 2 \le i \le N \quad (4)$$

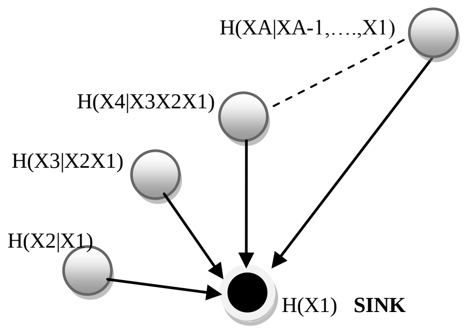

Fig. 3: Slepian–Wolf Method for compression within a cluster

Therefore, a cluster made out of various nodes A can be encoded with entropy of H (X1,X2, ….., X|A|) bits using correlation method of Slepian-Wolf coding without communicating with each other and thus we can say that there always exists an optimal allocation rate to attain a maximum compression efficiency that affects the performance of system all in good way as shown in Fig. 4.

Now coming to intra-network collection of this compressed data. The data collected by each sensor is transferred by sensor nodes into groups, so that sensors communicate information only to their heads and then these cluster-heads forward the compressed data to the information collecting center, may save

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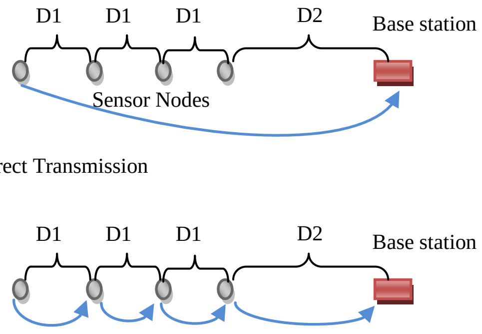
energy.



(a) Direct Transmission

(b) Energy saving Multi-hop Transmission

Fig. 4: Two methods of data routing from sensor nodes to base station.

For this it is important to select an alternative to direct transmission. Experiments shows that multihopping is guaranteed to give better results that direct transmission which is logical enough looking at fig. 4. In the case of total energy required to reach base station being E and each sensor node having maximum energy limited to E, Fig. 4.(a) requires the first node to expend all the energy to route its data to base station. But, Fig.4.(b) shows a method that shares the workload with neighboring sensors. Thus (b) method of minimum transmission energy must be used.

IV. PROPOSED METHOD

In our research, we propose a randomized, distributed clustering algorithm that organizes the sensors in a WSN in form of energy efficient clusters. We then elaborate this algorithm to design a hierarchy of such clusterheads and prove that the energy consumption decrease in comparison to existing hierarchy clustering methods. Stochastic geometry results are obtained and later used to derive solutions for parameters that minimize the total energy spent in implementing our algorithm in the network.

Criteria of designing large-scale sensor network:

- Energy-efficient (particularly in wireless communication can acquire notably higher energy than computation cost[1])
- Robust (to environmental effects, nodal and link related failures).
- Scalable (these networks might involve thousands of nodes)

Our particular interest lies is in the approach of path reinforcement that a node in cluster may make a local decision (based on anticipated traffic characteristics) to draw data from one or more neighbours based on distance w.r.t some other neighbours.

A. *Algorithm:*

Let us say that each sensor in the network becomes a clusterhead 'CH' with probability 'P' and announces its existence to the sensors within its transmission range, thus we call these CHs as the volunteer-CH. This information is broadcasted to all the sensors that are not more than 'k' hops far from the its CH. Any sensor node that gets such announcement message and is not a clusterhead itself can be a part of this newly generated cluster. On the other side, in a scenario where a node which is neither a clusterhead nor has joined any cluster becomes a clusterhead; we call such clusterheads, as the forced-CH. As we have limited the no. of broadcasting messages that can be send to k hops, thus if a sensor doesn't receives a CH advertisement within 't' time duration (here t is the time required for information to reach the CH from a sensor node k-hops away) it can interpret that it is not within the range of any volunteer-CH and hence it by default becomes a forced-CH.

B. *Optimal parameters for the algorithm:*

To shortlist the optimal parameters for the algorithm explained above, we shall make the following assumptions:

- The sensor nodes in the WSN are distributed as per a homogeneous spatial Poisson process of intensity 'λ' in a 2D space.
- All nodes transmit at the same energy and hence will have the same transmission range.
- Data transmission between two sensor nodes in range is not within each other's radio range is forwarded by other sensors.
- A distance of 'd' units between any sensor node and its clusterhead 'CH' is taken as 'd/ r' hops.
- Each node uses single unit of energy to transmit and/or receive one unit of data.
- A routing infrastructure is also in picture; hence, when a sensors communicates data with each other, only those sensor nodes that are on the routing path gets to forward their data.
- The communication environment we have considered as testbed is error- and contention-free; hence, there is no need for sensors to retransmit any information.

The basic motive of finding and implementing the optimal parameter values is to define a method for the energy used to communicate data to the information collecting and processing base station. Later we find the rate and values at which these parameters would minimize the required energy.

C. *Calculating the optimal probability of becoming a clusterhead:*

As per above made assumptions, the sensors are distributed according a homogeneous spatial Poisson process and hence, the number of sensor nodes in a square area of side a^2 is a Poisson random variable, N with mean 'λA', where 'A= $4a^2$'. Now, Let us take the assumption that for a considered realization of the process there are 'n' sensors in this area. Assume that the processing unit is located at the center of the square, for making calculations easier[13,14].

If, probability of becoming a clusterhead is taken as "P', then on average, 'np' sensors can become clusterheads. Let D_i be a random variable which denotes the length of segment from a sensor located at $(x_i, y_i), i = 1,2,\ldots n$ to the processing unit. With keeping generality, we assume that the processing unit is also at the center of the square made.

Then,

$$E[D_i|N = n] = \int_A^{\infty} \sqrt{x_i^2 + y_i^2}\left(\frac{1}{4a^2}\right) dA = 0.765a \qquad (5)$$

Let, 'C' is taken to be the total energy consumed in transmission by the system. Then,

$$E[C|N=n] = E[C_2|N=n] + E[C_3|N=n] = \frac{np}{r}\frac{(1-p)}{2p^{1.5}\sqrt{\lambda}} + \frac{0.765nap}{r} \quad (6)$$

Eliminating the conditioning on N and simplifications yields a equation that has 3 roots, out of which 2 are imaginary. The 2nd derivative of eq. (6) is positive for the real root of it and hence it shows that the energy spent is minimized. The only real root of it is given by:

$$p = \left[\frac{1}{3c} + \frac{\sqrt[3]{2}}{3c\left(2+27c^2+3\sqrt{3c}\sqrt{27c^2+4}\right)^{\frac{1}{3}}} + \frac{\left(2+27c^2+3\sqrt{3c}\sqrt{27c^2+4}\right)^{\frac{1}{3}}}{3c}\frac{1}{\sqrt[3]{2}}\right]^2$$

Where $c = 3.06a\sqrt{\lambda}$.

V. SIMULATION RESULTS AND ANALYSIS

In our simulation, we have considered a network with 'N' sensor nodes randomly distributed over an area of 100m×100m sensing region and our the data sink, which is node i=1, is located at the left-bottom corner of the sensing region. The simulation results obtained are based on the various experiments and each experiment uses a new randomly-generated network.

A. Correlation and Compression ratio:

For correlation structure, we assumed that the observations at $X_1, X_2, \ldots\ldots, X_N$ of N sensor nodes are modeled as an N-D random vector $X = [X_1, X_2 \ldots.., X_N]^T$, Which has a multivariate-normal-distribution with mean zero and covariance matrix 'K' ,i.e., the density of X is given by function:

$$f(X)=\exp((-1/2).X^T.K^{-1}.X)/(\sqrt{2\pi}).|K|^{1/2} \quad (7)$$

And the differential entropy of ($X_1, X_2 \ldots.., X_N$) is

$$H(X_1,X_2\ldots..,X_N)= (1/2)\log[(2\pi e)^N.\det(K)]\text{bits} \quad (8)$$

Notation	Meaning	Value
N	Cluster size (1D)	50, 60, 70, 80, 90 or 100
S	Number of sensor node in a cluster	40, 50, 100
K	Covariance matrix	Depends on 2D input matrix
Q	Correlation parameter	Between 0.01 to 0.003
n	pathloss exponent	2.2

Table 1: Simulation parameters for homogeneous network

The network size or the total no. of sensor nodes N is taken as a set of 5 increasing values {80, 90, 100, 110, 120}. The parameter 'θ' in the covariance model which is set of {0.01, 0.009,……………, 0.003 } where 'θ = 0.01' indicates low correlation and 'θ = 0.003' indicates high correlation.
The optimal number of cluster depends on the number of sensors in the entire sensor network and the degree of correlation.

It can be expressed as : $K_{opt} = \frac{N}{S_{opt}}$ (9)

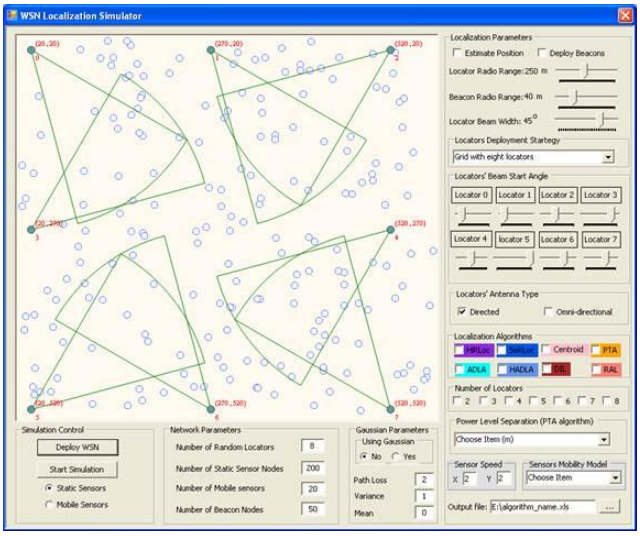


Fig. 5: Analytical curves for number of cluster k and correlation parameter Q

Fig. 5 shows how different number of clusters and cluster size perform across a range of correlation levels and sensor network sizes . As expected low correlation levels require small cluster sizes while high correlation levels require larger cluster sizes. Also the number of clusters is relative to sensor network size. In other words, the larger the sensor network (N) the more clusters are required to apply optimal data aggregation[19].

B. Simple localization:

Localization is one the most important task of the future WSNs. There are lots of algorithm for localization and tracking of a mobile node in the network which can categorized into following groups:

1. Distance based localization: which assumes that the distances between the nodes of the WSN are measured.
2. Angle based localization: which assumes the mobile nodes can measure the angles to the anchor nodes with respect to some origin.
3. Received signal strength: In this type, it is assumed that the mobile can only measure the signal power from the base stations at its location [21].
4. Hybrid

Here, we consider only the distance based localization of a single target. There are N anchor nodes in the system and one mobile node, we use the measured distances and we find the location of the mobile through multilateration.

Setting Parameters:
N = 4 (number of anchors)
M = 1 (number of mobile nodes)
noisePow = 20;

The estimated error in Fig. 6. shows that the accuracy of distance measurement is 90 % for instance the inaccuracy of a 1m measured distance is around 0.1 meter. Thus Implementing simple localization concept for self optimization of sensor node is achieved.

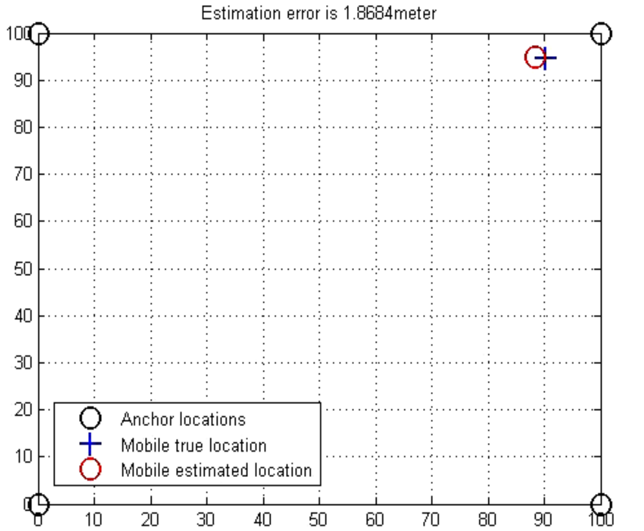


Fig. 6: Implementing 4 anchor, 1 mobile user, localization to find detection error.

C. Generating a compression deployed WSN:

Intially we are using depth first search algorithm (DFS) to first create a clusterhead for each set of node and then choosing a sink node.

Creating Clusterhead: firstly an DFS function was tested for 15 neighbours and maximum limit for neighbour-hood was defined. Here 'N' are the neighbours found by sample clusterhead.

Creating a broadcast Network originating from Sink Node: For this we use DFS function created for clusterhead and test for condition 'If the Euclidean distance b/w 2 nodes < the transmission range, a link exist between them.

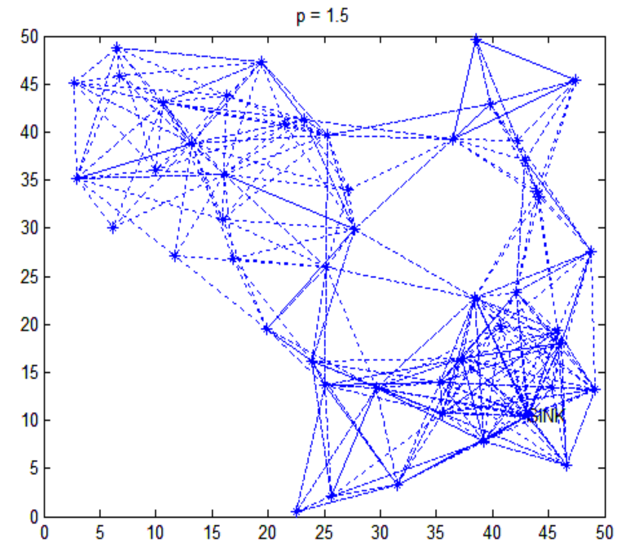


Fig. 7: Created a broadcast network of 50 nodes using gossip Algorithm.

Fig. 7. Uses DFS method that results in saving 13 transmissions. DFS method explains a probabilistic broadcast simulated here. In probabilistic broadcast, each node re-transmits a data packet according to certain probability. The transmission of message will start from a sink node and an array stores the boolean value of visited nodes.In the end 'saved transmission' (no. of 'CHs' found to be connected to sink node) is calculated.

D. Implementing Dijkstra's Algorithm for Single-Source Shortest Path:

The function method of Dijkstra's algorithm is applied with a variety of changes in our approach. For example, it is sometimes required to present solutions which are mathematically as well as practically optimal. To obtain a hierarchical list of less-optimal solutions, we firstly calculate the most optimal solution. A unique response that appears in the optimal solution is removed from the graph and then we calculate the next optimum solution to this new graph. This process of suppressing next edge of the original solution is in turn a method to calculate shortest-path. The other solutions are then arranged and presented after most optimal solution.

In our program we have used it for two purposes:
• To find the shortest distance b/w origin(sink) and destination.
• To find min. numbers of hops required to reach the destination node (i.e. total cost).

This implementation method can be taken from the perspective of linear programming as shown in Fig. 8: there we see simple linear program for calculating shortest paths and their dual linear programing solutions are feasible only if they make a consistent heuristic dual (roughly speaking , as the sign conventions differ from place to place in the reference). This dual/consistent heuristic defines a non-negative cost reduction and thus our algorithm is essentially running Dijkstra's method to reduce costs and therefore the energy.

The parameters used in programs are:

- Number of nodes =50.
- Sink node is at i=1.
- Destination node is 15.
- The maximum permisiable distance (range) for hoping(transmission) is 20.

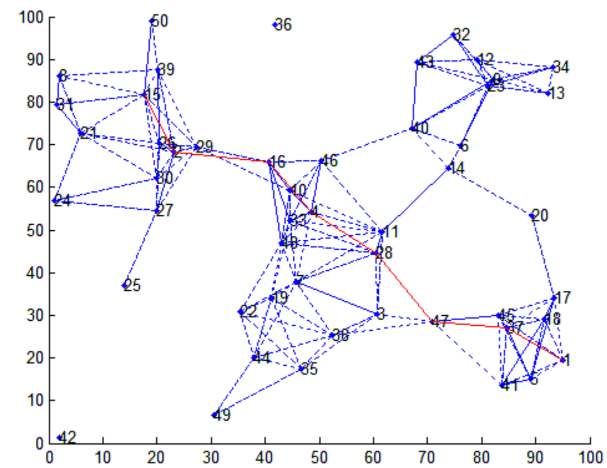


Fig. 8: Implementation of Dijkstra's Algorithm to find shortest path.

Results obtained:
>> path = 1 37 47 28 4 16 2 15
>> totalCost = 7
Thus we can optimized the number of sensor nodes used to reach the required node. Likewise if a sensor node knows its

position (self localization) and if it is well informed about its neighbours an optimal path between sink node (clusterhead) and receiving station can be established.

E. Effect of optimum allocation on RSSI signal:

We now investigate the performance of optimal intra-cluster rate allocation with respect to the intra-cluster communication cost of a cluster of different network size. Fig. 10 shows effect on the optimal rate allocation and rate without using this distributed source coding scheme, respectively. The optimal rate allocation scheme first arranges nodes in cluster A in ascending order of their distance to the cluster head, thus the rate assigned to the node i can be expressed by $Ri = \sum_{i=1}^{N} \sum_{j=1}^{N} H(Xi \mid \{Xj \mid d(j,1) \leq d(i,1), j \in A\})$

Intra-cluster communication cost with the optimal rate allocation $= \sum_{i=1}^{|A|} Ri . d(i,1)$

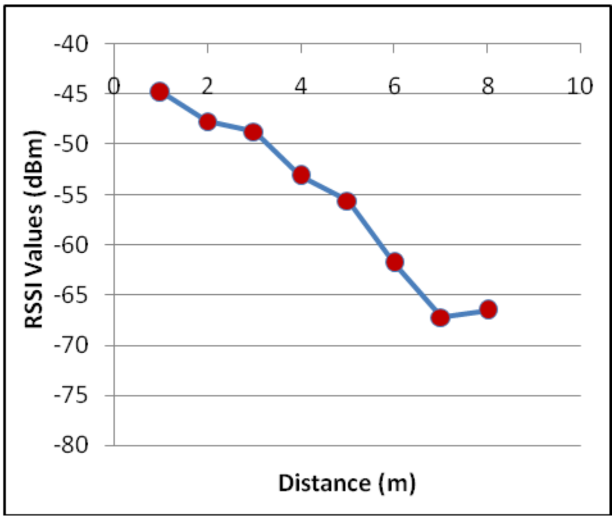


Fig. 10: The average values of RSSI obtained vs. distance

We use parameter θ = 0.006 to model moderate spatial correlation. The result shown is an intra-cluster communication cost of a cluster with different network sizes. As expected, the optimal intra-cluster rate allocation results in less communication cost compared with rate without using this distributed source coding scheme because former scheme jointly considers rate assignments and transmission distances between the cluster members and the cluster head.

VI. CONCLUSION

Overall we interpret that if we compress data using in-network compression method, data distribution will reduced with increasing no. of clusters. Also if optimum sensor node localization is implied, the expense of energy at each node will also be minimzed due to removal of ideal and inactive nodes. Completing these processes, we have optimized the no. of sensor nodes used to reach the destination node from sink node. Practically speking, if a 'alive' flag is assigned to each node (by default set to value 1) that keeps track if it is part of shortest distance route to a particular node. If not, the sensor is put to OFF (alive set to 0) mode until it is found to be useful for some other shortest path route. This can only be done if a sensor node attains self localization(knows its position) and if it is well informed about its neighbours as well. An optimal path between sink node (clusterhead) and receiving station can thus be established.

The simulation results demonstrate that the clustered Distributed Source Coding can significantly reduce the total amount of data in the whole network while the transmission cost within cluster can be remarkably reduced by performing the optimal intra-cluster rate allocation. We also interpret that if we compress the data using slepian wolf coding the data distribution will reduced with increasing N.

We have proposed a novel distributed algorithm for organizing sensors into a hierarchy of clusters with an motive of minimizing the total energy expense in the system to communicate the only relevent information gathered by sensor nodes to the data-processing unit (Base station). We have found that the optimum values of parameters for our algorithm that minimize the energy spent in the algorithm has a time complexity of $O(k_1 + k_2 + \ldots + k_h)$ which has visibily significant improvement over the various O(n) clustering algorithms available and thus this fact makes our new algorithm more suitable for networks of large number of nodes. Therefore an energy efficient method to optimize the no. of sensor nodes those will remain active in a cluster and in turn in a network is presented.

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Neha Verma Received M.Tech. degree in 2015 from YMCA university of science and technology in the field of Electronics and Communication Engineering. Worked in the field of Industrial automation for almost four years, Prior the same she received her B. E degree in electronics and communications engineering from Manav Rachna college of Engineer in year 2009. Her key interest lies in research work in wireless sensor networks, its energy optimization and Node optimization. Her other field of interest includes Antenna designing and studying recent advancements in the field of wireless communications.

Rakhi Rani has done her B.Tech in Electronics & Communication Engineering from Ch. Devi Lal Memorial Govt. Engg. College, India in year 2013 and later completed her M.Tech in the same field from YMCA University of Science & Technology, India in year 2015. Currently she is independently working on research fields like wireless networks and antenna designing. Her other interest lies in studying various wireless network deployment methods and to compare them so find new and energy efficient methods.