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Adaptive Clustering in Wireless Sensor Networks

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Abstract

Recently, wireless sensor networks (WSNs) have gained increasing attention from researchers due to their wide range of applications. Main aim of deploying WSNs based applications is to make real time decision. As WSNs are highly resource constraint, it is difficult to make computation on huge volume of sensed data. Clustering has always been a basic method to organize large number of objects into suitable groups. Clustering in WSNs helps in network scalability, conserve the communication bandwidth, and increase the networks life time. In addition to these advantages, clustering is now an active area of research in WSNs. Most of the existing clustering techniques in literature are based on network topology or distribution of the sensor nodes. In this paper, we propose an adaptive clustering protocol that exploits spatial and temporal correlation among the sensor based upon sensed data.

Keywords*: Clustering; Data Mining; WSNs; Scalability; Adaptive clustering; spatial correlation; temporal correlation*

1. Introduction

Wireless sensor networks (WSNs) have many applications ranging from environmental monitoring, healthcare applications, habitat monitoring, and avalanche prediction to virtual fencing, agriculture, structure monitoring [1-5]. The main reason of deploying the WSNs is to collect the suitable data desired in particular application. One of the advantages of WSNs is their ability to operate unattended in harsh environments in which contemporary human-in-the-loop monitoring schemes are risky, inefficient and sometimes infeasible. Therefore, sensors are expected to be deployed randomly in the area of interest by a relatively uncontrolled means, *e.g.* dropped by a helicopter, and to collectively form a network in an ad-hoc manner. As sensor networks are deployed in finite boundaries, the collected data may exhibit temporal and spatial correlation. By exploiting these correlations, we can save several resources in terms of bandwidth consumption, energy, *etc.* In general, by forming a cluster of nodes whose readings are spatially correlated, there are chances to reduce the cost of coverage and reporting a group sensor reading [6]. Consequently, dealing with the large volume of data produced by WSNs possess a challenge, as the communication consumes a significant amount of energy in a WSN, minimizing it is another major challenge.

Data mining is the computational process of discovering patterns in large data sets by using supervised or un-supervised methods. In un-supervised methods, there is no identified target variable as such. Instead, the data mining algorithm searches for patterns and structure among all the variables. In supervised methods, there is a pre-specified target variable with algorithm. The given algorithm helps to decide which values of the target variable are associated with which values of the predictor variables.

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In this paper, we exploit temporal and spatial relations among the sensor nodes and propose a Temporal Spatially Correlation based Adaptive Clustering (TSCAC) for WSNs. In proposed approach, we are exploiting temporal correlation locally and spatial correlation globally to form clusters. To form clusters, we initially collect data values at grid level and process these values to find frequent patterns. These frequent patterns are further processed at sink to identify the spatial relationship between patterns from neighboring grids to form the clusters.

The rest of the paper is organized as follows. Section 2 discusses about related work. Section 3 describes the various assumptions regarding system model. Proposed adaptive algorithm for clustering is discussed in Section 4. In Section 5, we have given performance evaluation of our proposed algorithm. Section 6 gives the conclusion.

2. Related Work

Clustering is done to form logical groups of similar nodes and it saves unnecessary energy wasted in direct data transmission to the base station. Many clustering algorithms have also been proposed in the past in various contexts. In k-mean clustering algorithm [7], authors proposed two types of clustering: Centralized k-mean clustering and Distributed k-mean clustering. These algorithms use Euclidian distances and energies for choosing cluster head. This information is obtained by every node by exchanging messages among themselves.

The Weighted Clustering Algorithm (WCA) elects a node as a cluster head based on the number of neighbors, transmission power, battery-life and mobility rate of the node [8]. In Distributed WSN Data Stream Mining based on Fuzzy Clustering [9], authors proposed Subtractive Fuzzy C-Means Algorithm (SUBFCM) clustering approach of given data streams. Chen *et al.* proposed an algorithm in which first core points are detected [10]. Core points are the points which always present or exist in a cluster. On the basis of these core-points, other points or nodes are covered or linked to form the clusters. Core points are always chosen to be cluster head. This algorithm effectively works on spatio-temporal correlation of data streams. Yeo *et al.*, propose modified TDMA scheme to form the clusters in senor networks [11].

3. System Model

In this work, we assume that set of homogeneous sensor nodes are randomly deployed in the square field to continuously monitor the phenomenon under inspection [12],[13]. All nodes have same sensing and communication range R. The location of the sensors and the base station are set and known apriori. It is assumed that localization process is carried out just after the deployment, so all sensor nodes have the knowledge of their location. Due to several environmental conditions, battery recharge is not possible. Therefore, energy efficient, energy-aware sensor network protocols are required for enhancing network lifetime. All nodes have similar capabilities and equal significance. Each sensor produces some information as it monitors its surrounding area. We suppose that initially the whole network is divided into a number of square grids [14].

Generalized energy consumption model is based on first order energy consumption. This generalized model is used for energy consumption calculation for the sensor nodes within the sensing area [15]. The energy consumption of a sensor node for transmitting k bits of data over a distance d can be expressed as Equation (1) and (2) [16], [17]:

$$E_{Tx}(k,d) = E_{elect-Tx}(k) + E_{amp-Tx}(k,d) \tag{1}$$

$$E_{Tx}(k,d) = \begin{cases} k * E_{elect} + k * \epsilon_{fs} * d^2, & d < d_0 \\ k * E_{elect} + k * \epsilon_{mp} * d^4, & d \geq d_0 \end{cases} \quad (2)$$

$E_{elect-Tx}$ is transmission electronics energy; which is energy consumed by the sensor node for modulation, coding, spreading schemes, filtering operations, *etc.* $E_{amp-Tx}(k, d)$ is the power amplifier stage energy consumption of sensor node to transmit k bits of data over a distance of d meter with acceptable signal to noise ratio (SNR). k is the number of bits transmitted over a distance d (distance between transmitter and receiver). E_{elect} (nJ/bit) is energy dissipation per bit to run transmitter and receiver electronic circuitry. ε_{fs} (pJ/(bit-m^{-2})) is energy coefficient of power amplifier stage of sensor node for free space energy dissipation model, when transmission distance is less than threshold *i.e.* $d < d_0$. ε_{mp} (pJ/(bit-m^{-4})) is energy coefficient of power amplifier stage of sensor node for multipath energy dissipation model, when transmission distance is greater than threshold *i.e.* $d \geq d_0$. The energy consumption of sensor node to receiver k bits of data is given by Equation (3):

$$E_{Rx} = k * E_{elect} \quad (3)$$

Table 1. Notation Used

Notation	Meaning
NR	Maximum number of items in an itemset
k-itemset	An itemset with k items/sensors
F_k	The set of frequent k-itemsets (with minimum support)
f_i, f_j	Any of the frequent (k-1) itemsets within F_{k-1}
$f_i[m]$	m^{th} item in itemset f_i
f_k	A new frequent k-itemset obtained by combining a frequent (k-1) itemset with one item
v_{avg}	Average value of the pattern
δ	Threshold difference between sensor values
v_i	Data value of the s_i sensor node
EL	Empty list (initially ϕ)
C_i	i^{th} Cluster (initially ϕ)
CV_{avg}	Average data value of the cluster
RD(i, j)	Relative distance between sensor nodes s_i and s_j
RD(CH, i)	Relative distance between CH and sensor node s_i
R	Communication range of sensor nodes
T_r	Re-clustering time interval

4. Proposed Work

In this section, we propose an adaptive clustering protocol for wireless sensor networks. Proposed protocol is based on spatial and temporal correlation among the sensor nodes. Initially whole sensor field is divided in to virtual grids. Each grid is of size $l \times l$ as shown in Figure 1. The grid side l is a vital factor for effective cluster formation. For reliable communication, it is to ensure that any two nodes in adjacent grids are within the communication range, R, of each other.

In worst case scenario, the grid side l should be such that the maximum distance between two nodes placed at the corners of two diagonally adjacent grids must be less than or equal to R. Therefore, to ensure one hop communication among the nodes between adjacent grids, *d* (diagonal distance as shown in Figure 1) given by

$\sqrt{(2l)^2 + (2l)^2} = 2\sqrt{2}\,l$ must be less than or equal to maximum transmission range (R), *i.e.* $2\sqrt{2}\,l \leq$ R. Hence, $l \leq {R}/{2\sqrt{2}}$. If l is set to ${R}/{2\sqrt{2}}$, all sensors in adjacent grid can communicate to one another in one hop.

Every grid has Grid Id $G_{x,y}$. For a node s_i with coordinates (x_i, y_i), the grid id is computed as follows: $G_{x,y} = \left(\left\lfloor \frac{x_i}{l} \right\rfloor, \left\lfloor \frac{y_i}{l} \right\rfloor\right)$, where $\lfloor b \rfloor$ is the largest integer less than equal to b. After splitting the sensor field into equal sized grids, one cluster head will be selected in each grid. Each cluster head is responsible for determining sensor reading patterns among the nodes and these patterns are used during temporal correlation. In addition to this, each cluster head is also responsible for data routing and data aggregation. Each cluster head can communicate directly or through another cluster head to the sink depending upon its distance from the sink.

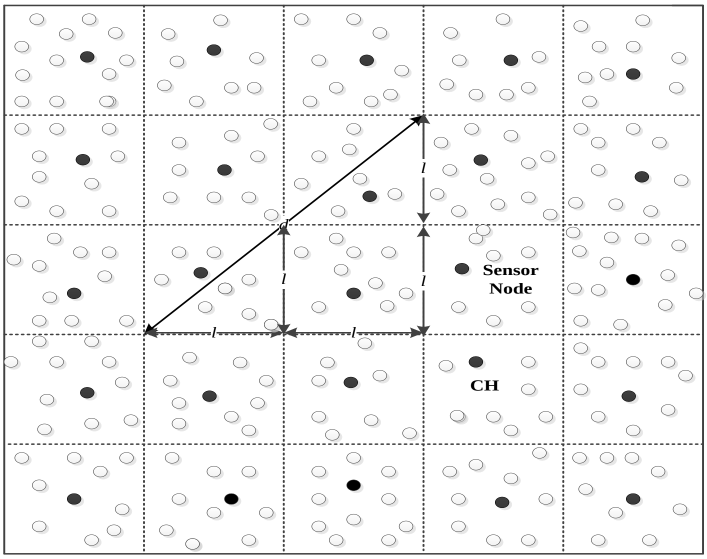

Figure 1. Formation of Virtual Grids in a WSN

To exploit spatial correlation, initially we divide the given sensor field into virtual grid like clusters as shown in Figure 1. Thereafter, data mining techniques are applied to exploit the temporal correlation among sensors based upon their sensed values over a time interval. The initial selection of cluster head (CH) within a grid/cluster is based upon the choice of a node that is located nearest to the centroid of the grid. The centroid (x_c, y_c) inside a grid with Grid ID $G_{x,y}$ is given as $x_c = \left(\frac{G_x + G_{x-1}}{2}\right) * l$, $y_c = \left(\frac{G_y + G_{y-1}}{2}\right) * l$. Each node s_i with coordinates (x, y) calculate its distance d_i from the centroid (x_c, y_c) as $d_i = \sqrt{(x_c - x)^2 + (y_c - y)^2}$. We use the concept of back-off timer to select a CH. For a node s_i, the back off timer t_i is set as $t_i = d_i * B_t$ where B_t is a random number whose value is in the range (0.9, 1). B_t is used to resolve the tie for nodes having same value of d_i. Each node s_i sets its back-off time t_i and decreases it with increase of time. A node whose back-off timer decreases zero, elects itself as CH and broadcasts the CH declaration message to the members of the cluster. Further the proposed adaptive clustering technique exploits temporal correlation among the sensor nodes.

4.1. Finding Frequent Itemsets

In this section, we propose an algorithm to find frequent itemsets from central database (CD) based upon temporal correlation. The algorithm accepts CD, minimum support and threshold difference (δ) as inputs. In the first step, CD is analyzed to find the frequent 1-itemsets. This is done by calculating the support of each data item and comparing it to the minimum support. As a result, every data item that has minimum support forms one frequent 1-itemset. The second step is to find all the frequent 2, 3, …, k itemsets. Each itemset is paired with other if and only if they are reported at the same time interval and the difference between their sensed values is less than δ. This process is repeated, until it is not possible to find new itemset or number of items in an itemset exceeds the predefined limit in NR (maximum number of items in an itemset). At the end, algorithm returns all the frequent itemsets generated in that iteration. Algorithm 1 illustrates the steps to generate frequent itemsets.

4.2. Correlation Based Cluster Formation

This section describes adaptive cluster formation based upon frequent itemsets generated using Algorithm 1. To do this we exploit the spatial and temporal correlation among the sensor nodes. The algorithm accepts frequent itemsets, location coordinates of sensor nodes and communication range R as inputs. This is done by processing each element of the frequent itemset. Any two elements of the frequent itemset may be member of the same cluster if they belong to same grid or adjacent grid. After processing all the itemsets there might be some nodes which are left alone. Such nodes form an empty list EL. To accommodate nodes of the EL, we increase δ from 1 of 1.5 and nodes will be part of the cluster C_i whose relative distance with that node is less than R. Algorithm 2 illustrates steps of proposed correlation based cluster formation.

5. Simulation Results

In this section, we evaluate the performance of proposed algorithm TSCAC through simulating using MATLAB. We first define simulation parameters and performance metrics used. We then see the effect of various factors like transmission range, number of nodes and network size on performance metrics to measure the effectiveness of proposed algorithm. Simulation results are compared with grid based scheme GBS [18], where grid type clustering is used based upon spatial correlation among the nodes. This approach does not consider temporal correlation. In this approach head rotation takes place after every round and all the nodes participate in cluster head re-election.

Algorithm 1: Finding Frequent Item Sets

F_1 = {frequent 1-itemset}
$v_{avg} = v_i$ // initialize v_{avg} to v_i
k =2
while $F_{k-1} \neq \phi \wedge k \leq NR$ **do**
    $F_k = \phi$
    for each itemset $f_i \in F_{k-1}$ **do**
        for each itemset $f_j \in F_{k-1}$
            if $f_i[1] = f_j[1] \wedge f_i[2] = f_j[2] \wedge \ldots \wedge f_i[k-2] = f_j[k-2] \wedge f_i[k-1] < f_j[k-1] \wedge (v_{avg} - v_i) \leq \delta$ **then**
            $f = \{f_i\} \cup \{f_j[k-1]\}$
            $F_k = F_k \cup \{f\}$
            $v_{avg} = (v_{avg} + v_i)/2$
            for each (k-1)-subsets $s \in f$ **do**

```
13                if s ∉ F_{k-1} then
14                F_k = F_k – {f}; break
15        for each itemset f_i ∈ F_k do
16            if support (f_i) < minimum support then
17            F_k = F_k - {f_i}
18    k = k+1
19    return ∪_k F_k
```

Algorithm 2: Cluster Formation

```
1   for(i = 1; i ≤ k; i++)
2   if f_k[i] is already processed then
3      i = i+1
4      else  C_i = C_i ∪ {f_k[i]}
5        C_i.x = x_i
6        C_i.y = y_i
7        CV_avg = v_i
8        for(j=i+1; j≤k; j++)
9          if f_k[j] is already processed then j = j+1
10            else if f_k[i] & f_k[j] belong to same Grid then
11                C_i = C_i ∪ {f_k[j]}
12                C_i.x = (C_i.x + x_j)/2
13                C_i.y = (C_i.y + y_j)/2
14                CV_avg = (CV_avg + v_j)/2
15                mark f_k[j] as processed break
16              else if f_k[j] ∈ (G_{x,y+1}|| G_{x,y-1} ||G_{x+1,y} ||G_{x-1,y} ) && RD(f_k[i], f_k[j])≤ R then
17                Repeat step 11-15
18              else EL = EL ∪ {f_k[j]}
19  for each x_i ∈ EL
20        for each C_i cluster in C list
21            Find the cluster whose (CV_avg – v_i) ≤ 1.5×δ
22            if RD (C_j, x_i) ≤ R then
23            Repeat step 11-15
```

Effect of Transmission Range on Network Lifetime

We define network lifetime as the time until a fraction of sensor nodes run out of energy. We use two measures for network lifetime *i.e.* FND (first Node Die) *i.e.* the number of rounds since initial deployment when first node dies, and HND (Half of Nodes Die) *i.e.* the number of rounds since initial deployment to the time when 50% of the nodes die. Figure 2 shows the results of network lifetime as a function of transmission range of sensor node. Figure 2(a) gives the variation of network lifetime calculated in terms of FND and Figure 2(b) indicates the variation of network lifetime obtained in terms of HND.

To see the effect of transmission range on the network lifetime, the number of nodes and the network size are kept fixed at its default values. Simulation results have been compared with GBS. From the Figures 2(a) and 2(b), it is observed that when the transmission range of node is small, the WSN is divided into large number of smaller grids because the grid size is directly related to the transmission range of sensor node. Therefore, the average number of hops for the sensed data to reach the sink increases which results in more consumption of energy. As a result of which the number of rounds for the FND and HND are less.

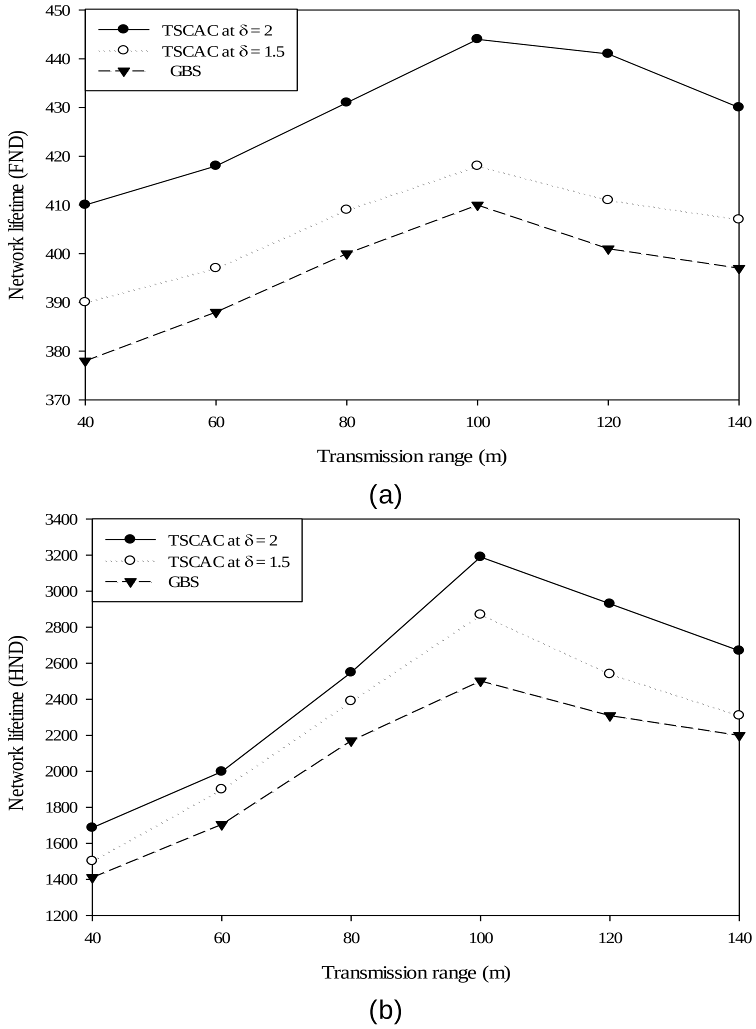

Figure 2. Effect of Transmission Range on (a) FND and (b) HND

With the increase in transmission range, the grid size increases that decreases average number of hops for the sensed data to reach the sink. Because of this the energy consumption decreases and the number of rounds for the first node to die and half the nodes to die increase. At this stage, an optimal transmission range is achieved.

If the range continues to increase, the data communications are subject to d^4 attenuation and the energy consumption associated with transmission increases super linearly with the radio range, so the total energy consumption grows exponentially with node separation which results in the decrease in network lifetime. From the simulation, it has been observed that the transmission range of node should be between 100 m to 140 m in order to optimize the network lifetime. Results of TSCAC are better than GBS because in GBS cluster heads are elected after every round so the frequency of head rotation is quite high. Moreover, in GBS all the nodes participate in cluster head re-election process irrespective of their current residual energy, whereas in TSCAC only current CH is responsible to elect the new cluster head, thus TSCAC gives better results than GBS approach.

It can be observed that TSCAC at $\delta = 2$ performs better than TSCAC at $\delta = 1.5$. This is due to fact that when δ increases from 1.5 to 2, there will be more sensor nodes, which are part of the same cluster. This results into lower average load on a sensor node.

Effect of Transmission Range on Network Latency

Figure 3 shows the result of network latency as a function of transmission range of sensor nodes. From the graph, it has been observed that when the transmission range of sensor node is small, the numbers of hops for the data transmission from sensor node to the cluster head and from cluster head to sink are more and therefore the time taken by the data to reach the sink is more. With the increase in transmission range, the number of hops decreases which results in decrease in the data transmission time and network latency. With the further increase in transmission range, sensor node will be able to reach the cluster head or to the sink in almost one hop distance and hence results in constant data transmission time which makes the network latency to appear constant after a transmission range of around 100 m. TSCAC at $\delta = 2$ and TSCAC at $\delta = 1.5$ results are better than GBS approach.

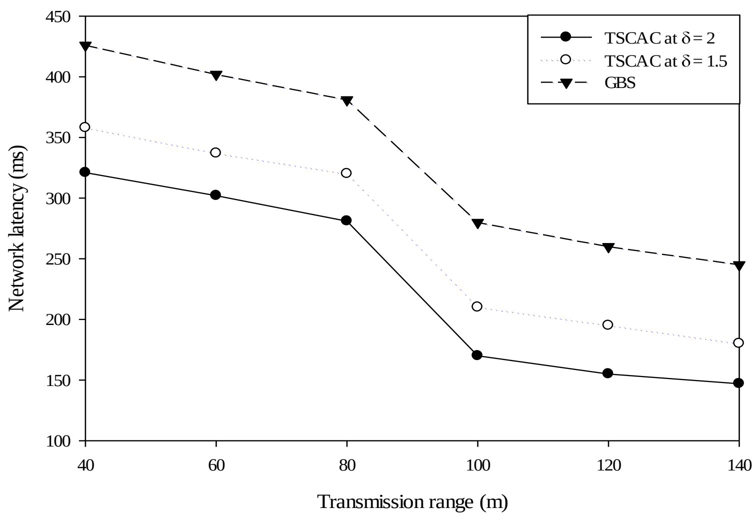

Figure 3. Effect of Transmission Range on Network Latency

Effect of Transmission Range on Energy Consumption

From Figure 4, it is observed that when the transmission range of node is small, data transmission follows the Friis free-space model. Although signal attenuation is not significant, but the number of grids which is a function of transmission range are more which further increases the average number of hops required for the transfer of data to the sink. Therefore, when the transmission range is less, the energy consumption is more. With the increase in transmission range, some data communications are subject to d^4 attenuation, but with the increase in transmission range the grid size increases and the average number of hops for the transfer of data to sink decreases and also more redundant nodes can be put to sleep mode in larger clusters. Therefore, energy consumption decreases with increase in transmission range. At this stage, an optimal transmission range is achieved. If the range continues to increase further, the energy consumption associated with transmission increases super linearly with the radio range, so the total energy consumption grows exponentially with node separation which results in the decrease in network lifetime. From the simulation, it has been observed that the transmission range of node should be about 100 m in order to optimize the network lifetime. Results of TSCAC at δ = 2 and TSCAC at δ = 1.5 are better than GBS because in GBS, frequency of head rotation is quite high and all the nodes participate in cluster head re-election, thus leading to poor energy utilization and lower network life.

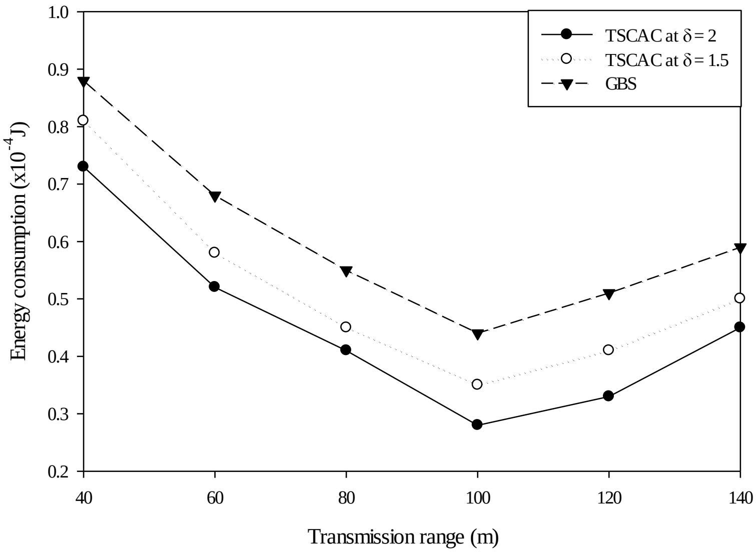

Figure 4. Effect of Transmission Range on Energy Consumption

Effect of Transmission Range on Percentage of Nodes Acting as Cluster Head

Figure 5 shows the plot of transmission range versus percentage of nodes acting as cluster head. As the transmission range increases the size of cluster increases. This results into less number of clusters. Hence with the increase in transmission range percentage of nodes acting as cluster head decreases. TSCAC at δ = 2 and TSCAC at δ = 1.5 are better than GBS because TSCAC exploits temporal as well as spatial correlation.

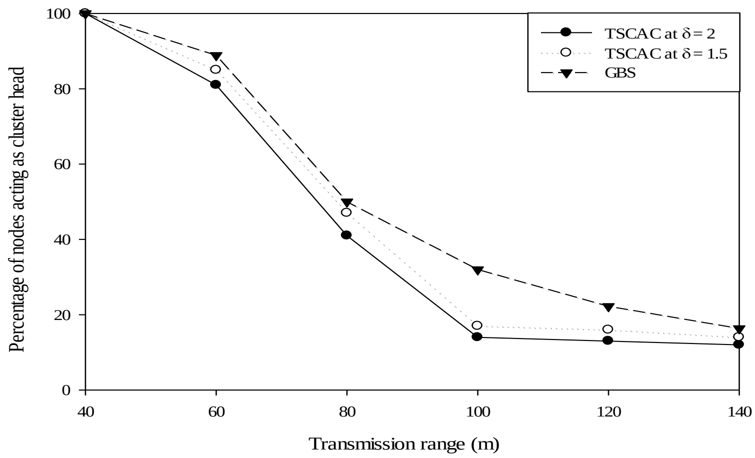

Figure 5. Effect of Transmission Range on Percentage of Nodes Acting as Cluster Head

As transmission range increase from 40 to 140, the number of grids decreases hence the number of clusters as well as cluster heads. However, in case of TSCAC, after grid formation, temporal and spatially cohesive clusters are formed which results into less number of clusters as well as cluster heads.

Effect of Transmission Range on Percentage of Single Node Clusters

From 6, it is observed that when the transmission range of node is small, the percentage of single node cluster is high. As transmission range increases, the percentage of single node cluster decreases because the size of clusters increases, which leads to more number of sensor nodes in a single cluster. In case of TSCAC, clusters are temporally and spatially correlated, which leads to less number of single node clusters as compared to GBS. Moreover, TSCAC at $\delta = 2$ performs better than TSCAC at $\delta = 1.5$ because TSCAC at $\delta = 2$ possess more temporal and spatial cohesiveness.

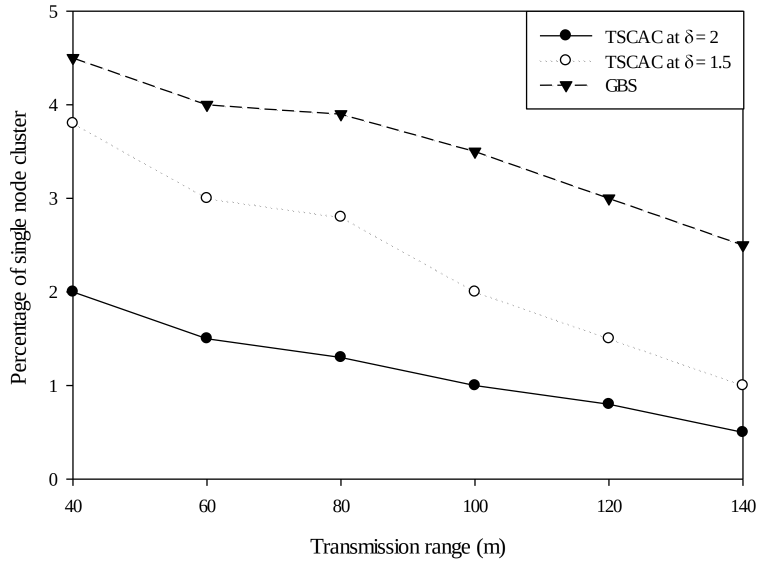

Figure 6. Effect of Transmission Range on Percentage of Single Node Cluster

6. Conclusion

In this paper, an adaptive clustering algorithm for wireless sensor networks has been proposed. The proposed clustering algorithm ensures the formation of uniform clusters within square sensing field size. Temporal and spatial correlations among data values are exploited to form the clusters. To demonstrate the effectiveness of proposed protocol, simulation is performed and results show that proposed protocol performs better than existing protocol.

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