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Top-K with diversity-M data retrieval in wireless sensor networks

Kiran Kumar Puram

TOP-K WITH DIVERSITY-M DATA RETRIEVAL IN WIRELESS SENSOR NETWORKS

by

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A THESIS

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ABSTRACT

Wireless Sensor Network is a network of a few to several thousand sensors deployed over an area to sense data and report that data back to the base station. There are many applications of wireless sensor networks including environment monitoring, wildlife tracking, troop tracking etc. The deployed sensors have many constraints like limited battery, limited memory and very little processing capacity. These constraints show direct effect on the network life time.

In many applications of Wireless Sensor Networks, such as monitoring chemical leak, the user is not interested in all the data points from the entire region, but may want only top-k values. Moreover, a user may also be interested in getting top-k with diversity-m, Top (k,m), that is, top-k data should come from m different sub-regions (i.e., clusters). In this thesis, thus, we have considered the problem of continuous top-k query with diversity-m, i.e. we want to find the k highest values from at least m different clusters over a period of time in a wireless sensor network. In this context, we introduce an energy efficient scheme called Top (k,m). Our scheme is to utilize the Gaussian's probability function in estimating the probability of a sensor node value being in the final top-k set. Based on the probability, the node decides whether to forward data values to the base station or not. Moreover, we also make sure that top-k data items are coming from at least m-clusters, which is very helpful in monitoring applications. We have examined the performance of our scheme with respect to EXTOK and Grid approaches in terms of communication, energy usage and network life time.

ACKNOWLEDGEMENTS

I would like to express my gratitude to all those who have helped me with this research. First, I would like to thank my advisor Dr. Sanjay Kumar Madria who gave me the opportunity to work on this research topic. I am grateful to him for the advice and guidance he gave me throughout my Master’s program. Secondly, I would like to thank Dr. Sriram Chellappan and Dr. Maciej Jan Zawodniok for being part of my thesis committee and taking time to review this work.

A special thanks to all my friends for understanding and standing by me during my tough times. Finally, I would like to dedicate this work to my parents and my brother for their emotional support and unconditional love and sacrifices.

TABLE OF CONTENTS

Page

LIST OF ILLUSTRATIONS

Page

LIST OF TABLES

Page

1. INTRODUCTION

Wireless sensor networks are mainly used for habitat monitor, environment monitoring, and battlefield surveillance and to control a forest fire. These types of networks consist of a base station and huge number of sensor nodes deployed over a large area. The base station is the central unit of the network, which has high energy and is responsible for collecting and storing the data values generated by the sensor nodes. The deployed sensor nodes sense data values periodically and send them to the base station when queried. These queried results are then forwarded to the respective users who need them.

Wireless sensor networks are low in resources; they have constraints like slow processing speed, limited memory space and low bandwidth. Another major drawback of wireless sensor networks is the energy limitation. The sensor nodes are battery powered, equipped with two AA size batteries which cannot be replaced every time they are dead. The main reason these batteries cannot be replaced is because these sensor nodes are deployed in dense forest or under water or hard to reach areas.

There are several applications where top-k is very useful, for example, tracking chemical leak in a region. In addition, a user may be interested in monitoring top-k with diversity m so that all the values are not drawn from say the same cluster. The final top-k results produced by the network are based on the nodes that reply; some nodes may be dead. The most accurate top-k is when all the nodes reply.

1.1 ENERGY EFFCIENT TOP (K,M) - MOTIVATION

There is always a need to reduce the energy consumption in wireless sensor networks in finding top-k. Therefore, our main objective is to reduce the number of messages exchanged between the sensor nodes and the base station in finding top-k with diversity m. A sensor node consumes good amount of energy for sending or receiving a message (energy required to establish a connection between the nodes plus actual energy required to transfer the data packet). This energy is almost 100 times to that of computational energy within each sensor. Thus, we would reduce the unnecessary updates from being forwarded to the base station, i.e. we try to restrict the propagation of values that do not contribute to the final top-k with diversity-m set. By reducing the energy required for communication, we would like to increase the network life time; the time starting from the deployment of sensors to the time when the first sensor node in the network goes down.

1.2 ORGANIZATION OF THESIS

The rest of the thesis is organized as follows. Section 2 reviews the related work on top-k query processing in wireless sensor networks. Section 3 introduces our proposed approach, Top (k,m), and discusses how we can reduce the number of messages exchanged between sensor nodes and the base station to increase the network life time and followed by a detailed illustration of our approach. Section 4 contains the experimental results for the simulation of the proposed scheme and other schemes which are used for comparison and finally, Section 5 concludes the thesis.

2. LITRATURE REVIEW

2.1 TINY AGGRAGATION SERVICE (TAG)

Retrieving top-k data items in wireless sensor networks has been extensively studied in the literature. One of the first approaches that talk about top-K in WSN is TAG approach given by Madden et al [1]. In TAG approach, a logical tree topology is used for data aggregation. All the values sensed by sensors are forwarded to the base station. As the data flows up this tree, it is aggregated according to the aggregation function. The major drawback of this approach is that it incurs unnecessary updates in the network and is not energy efficient.

2.2 FILTER BASED MONITORING APPROACH (FILA)

Minji Wu et al [2] proposed a novel filter-based monitoring approach called FILA. The basic idea of this scheme was to install a filter at each sensor node and suppress unnecessary updates. The sensor nodes will update its readings only when the reading passes the filter. The base station will then probe the other sensor to send its current reading to evaluate the final top-K. This scheme has two drawbacks, the first one is the efficiency of this scheme depends on the filter settings. If the filter range is small, then there will be too many updates and also the filter ranges may overlap with one another. Second, this scheme has to do a lot of probing to determine the final top-K.

2.3 EXACT TOP-K IN WSN (EXTOK)

Malhotra et al [3] et al proposed an energy efficient scheme called EXact TOp-K or simply EXTOK. EXTOK is a continuous data retrieval scheme, where previously contributed top-K nodes or Triggering nodes have to send their update to the base station which will generate a threshold and broadcast it to all non-top-K nodes or filtering nodes. The filtering nodes, when encounter values greater than the received threshold, send an update to the base station. The base station will then calculate the final top-K. The major drawback of this approach is in the generation of threshold values. If a threshold value generated is too small, then there will be a lot of updates, which is almost equal to normal data collection.

2.4 DATA AWARE PRIORITY ALGORITHM (PRIM)

Yeo et al [4] have proposed a data-aware approach called PRIM to monitor top-K queries in wireless sensor networks. The basic idea of this scheme is to collect readings sequentially with highest readings being collected first. A data-aware priority algorithm is proposed which allocates a particular timeslot to each sensor to transmit its data to the base station. When the base station receives enough values to determine the final top-k, it sends a broadcast message to all the sensor nodes to stop transmitting any more data packets. This scheme has two disadvantages. First, the sensed data of sensor nodes far away from the base station may be ignored as the time during which it arrives at the base station. Second, the broadcast message consumes at lot of energy.

2.5 AN EFFICIENT DATA STORAGE SCHEME (GRID)

Liao et al [5] have proposed an energy efficient storage method to process top-k queries. The sensor network is divided into a number of GRIDs and there is a grid head present at the center of each grid. Each grid is assigned a definite sub-range and the grid head stores only those sensed data. The base station will query the grid head which is responsible for storing the highest values. If the grid head has ‘k’ values, then it will update it to the base station. If the grid head does not have ‘k’ values, then it will forward the request and the values it has to the next grid head. The next grid head is now responsible to handle the query. The same procedure is repeated until top-K values are obtained. This scheme has two major drawbacks. First, in worst case scenario, a lowest value sensed by a node has to be sent to a grid head present far away from the base station, though it does not participate in the top-k. Second, if all the sensed values fall into a particular sub-range then the grid head will not have enough storage memory.

There are also many other schemes [6], [7], [8], [9], [10] in the literature which deal with monitoring top-k queries in wireless sensor networks. Each scheme has its own advantages and dis-advantages.

3. TOP(K,M): TOP-K DATA ITEMS WITH DIVERSITY M

3.1 NODE DEPLOYMENT AND CLUSTERING

We consider a network of S nodes, S= {s_i: i=1, 2…N} where s_i is the ith node deployed randomly in a given area. We use LEACH clustering algorithm [10] with an exception that every cluster head(CH) is accesable by its parent cluster head in one-hop and divide the entire network into 'C' hierarchical clusters. The network deployment and clustering can be seen in the below Figure 3.1.

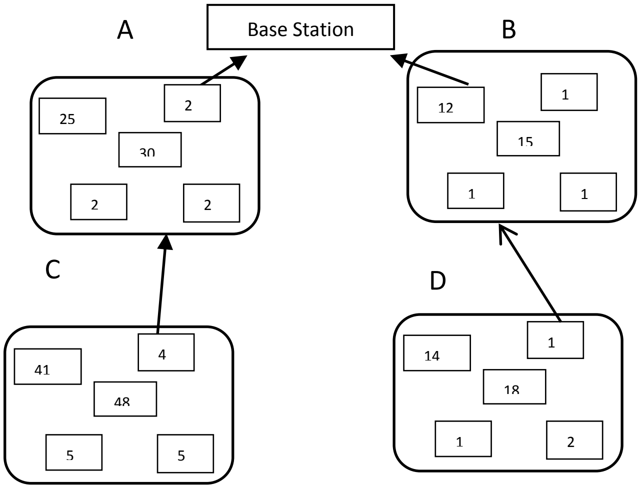


Figure 3.1 A wireless sensor network divided into 4 clusters.

In a given time interval or round, a sensor node senses one value v (s_i), where s_i is the sensor id. The problem we address in this thesis is to find the k-highest/lowest data values with diversity-m, $D_{k,m}$= {v ((s_i)$_{p,j}$) : p=1, 2…k & j=1, 2..m}, i.e. we try to find the k-highest/lowest values in the network from at least m-different clusters where m≤C.

3.2 INITIALIZATION PHASE

Once the node deployment and clustering is done, our process enters initialization phase. In this phase, all the sensor nodes (including the cluster heads) in the network sense data values over a period of ‘n’ rounds. The number of round should be large enough to satisfy the Gaussian's probability distribution function requirements. According to Gaussian’s pdf the minimum number of values should not be less than 30. Here, while considering the value of ‘n’, the memory constraint of the sensor node should also be taken into consideration. Increasing the ‘n’ value will increase the network life time by certain rounds. During these ‘n’ rounds, our scheme will not send any updates to the base station. Once the readings are obtained, each sensor nodes calculate the mean and standard deviation from the collected readings. The nodes will use their respective means and standard deviations along with Gaussian's probability distribution function properties (according to Gaussian’s probability function, if the values fall under normal distribution, then there is a 97% probability of the future values to fall around ±3 standard deviation around the mean) and generate an approximation range called high approximation range. These ranges will be used in the later stages of the scheme. Now, each node will send its mean, standard deviation, high approximation range and the most recent sensed values to the cluster head in which it is present. The algorithm at each node executes in the initial 30 rounds in presented in Table 3.1. The calculation of means, standard deviation and high approximation ranges in done every ‘n’ round from here on.

Table 3.1 Algorithm for sensor nodes to compute mean, standard deviation and H.A.R.

Algorithm for Sensor Nodes in initialization Phase

Input: Given N nodes in a network and n rounds of sensed data $\{a_1, a_2 \ldots a_n\}$.

Output: Send S_M, S_{SD} , H.A.R and $S_{id}[n]$ to the cluster head CH.

Variables Used: N:Total nodes, n:Initial rounds for determining range, S_{id}:Sensor Id, S_M: Mean of Sensor Values, S_{SD}: Standard deviation of Sensor Values, H.A.R: High approximation range.

```
--------------------------------------------------------------------------------
for id= 1 to N
{
for i= 1 to n (n≥30)
$S_{id}[i] = \{a_1, a_2 \ldots a_n\}$
Calculate Mean $S_M = \frac{a_1+a_2+\ldots+a_n}{n}$ ,
Standard Deviation $S_{SD} = \sqrt{\frac{1}{n}\sum_1^n (a_i - S_M)^2}$
Generate H.A.R (high approximation ranges) based on Gaussian's pdf for each element in R.
H.A.R = $\{S_M - 3\ S_{SD}, S_M + 3\ S_{SD}\}$
}
```

Now the cluster head will add its own reading to the received values, arrange them in decreasing order and will send the top-k data set from all the available readings (its own reading and the recent values sent by cluster nodes) to the hierarchal above cluster. Along with the top-k readings, the cluster head will also send the highest mean and standard deviation.

The intermediate clusters in the hierarchal path can act as aggregating or non-aggregating clusters. A non-aggregating cluster is the one which does not look into the diversity part. On the other hand an aggregating cluster is the one which looks into the diversity part, i.e. if a cluster head gets values from at least 'm' different clusters then it acts as a aggregating cluster and looks into the diversity part. Table 3.2 shows the algorithm for both non-aggregating and aggregating cluster head.

Table 3.2 Algorithm for non-aggregating and aggregating cluster head.

Algorithm for non-aggregating Cluster Heads

Input: Receive R_{CHi} = {top-k values, highest S_M, S_{SD}} from all cluster heads below it.

Output: Send 'Top-K set' to the cluster above it.

Variables Used: R_{CHi}:Readings from Cluster head i, R_{CH}:Its own readings, v_1:First value from R, DS:Diversity Set, m:User specified diversity, CH:Cluster Head, k:User specified top-k.

```
• CH = Non-Aggregating Cluster
Add $R_{CH}$ = {top-k values, highest $S_M$, $S_{SD}$} its own readings.

$R = R_{CHi} \cup R_{CH}$

• CH = Aggregating Cluster
Add $R_{CH}$ = {top-k values, highest $S_M$, $S_{SD}$} its own readings.

$R = R_{CHi} \cup R_{CH} = \{v_1, v_2, \ldots\ldots v_t\}$

Diversity

Insert $v_1$ from R to set DS

While (DS.size < m)

Insert $v_i$ ($i \geq 2$) from R to set DS such that $CH(v_i) \neq CH(v_j)\ \forall v_j \in DS$

Top-K

$k^1 = k - m$

$R^1$ = Set containing top $k^1$ elements from set (R – DS)

Top-K set = $R^1 \cup DS$
```

The concept of aggregating and non-aggregating cluster heads in explained using the Figure 3.2. In this figure we have a networks of 25 nodes divided into 5 clusters. If we consider a top-4 query with diversity-3, the intermediate cluster, say CH2 is just a non- aggregating cluster, it will simply receive the values from clusters below it, add its own reading to the received readings and forward it to the cluster above it (refer Table 3.3).

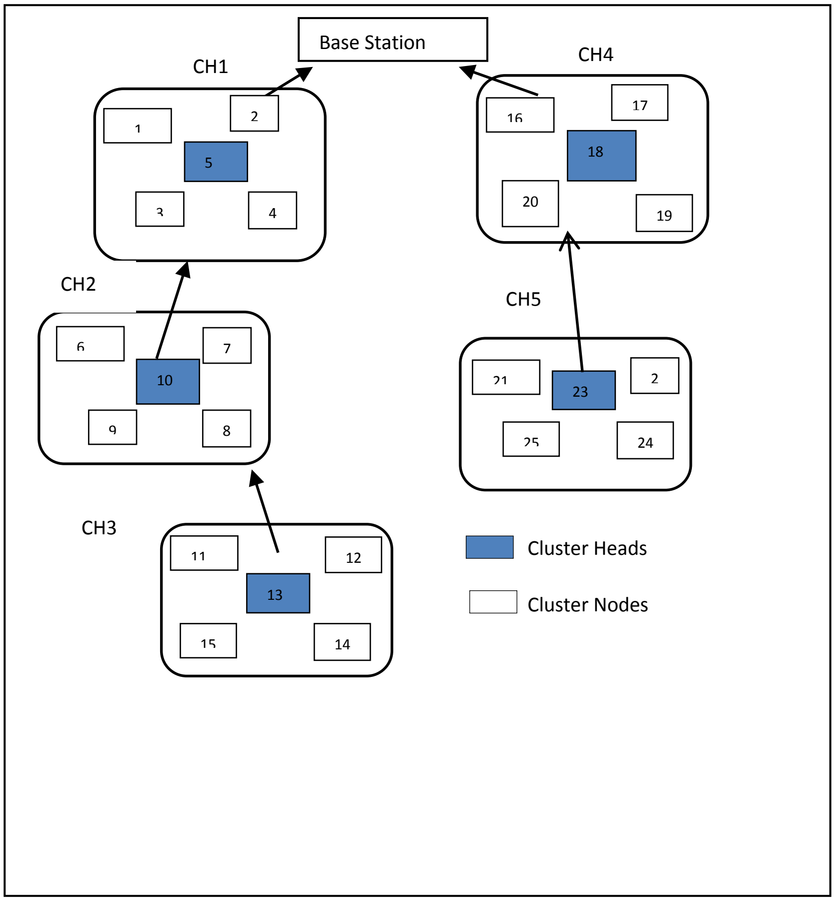


Figure 3.2 A wireless sensor network consists of 25 nodes divided into 5 different clusters

.

Table 3.3 An example of non-aggregating cluster head.

Received: {CH3:: top-4 {11, 13, 14, 15}, Highest Mean:30, Standard Deviation: 1.5}

Own Reading: {CH2:: top-4 {6, 7, 9, 10}, Highest Mean:26.4, Standard Deviation: 2.3}

Send: **{**{CH3:: top-4 {11,13,14,15}, Highest Mean:30, Standard Deviation: 1.5} +

{CH2:: top-4 {6,7,9,10}, Highest Mean:26.4, Standard Deviation: 2.3}**}**

If the intermediate cluster, say CH1 is an aggregating cluster, it will receive the values from clusters below it, adds its own reading to the received readings and compute the top-k in such a way that the top-k will at least come from 'm' different clusters (refer Table 3.4).

Table 3.4 An example of a aggregator cluster head.

Received: **{**{CH3:: top-4 {11,13,14,15}, Highest Mean:30, Standard Deviation: 1.5} +

{CH2:: top-4 {6,7,9,10}, Highest Mean:26.4, Standard Deviation: 2.3}**}**

Own Reading: {CH1:: top-4 {1,2,4,5} , Highest Mean:24.4 , Standard Deviation: 2.7}

Send: **{**{CH1:: top-4 {1,2,11,6} , Highest Mean:30 , Standard Deviation: 1.5}

Once the base station receives values from all the clusters, it will decide on the final top-k set and also it uses the means and standard deviations sent by the cluster heads to compute an approximation range know as low approximation range. These ranges will be used in later stages for verification of top-k set. The base station will also broadcast the final top-k nodes. The algorithm is presented in Table 3.5.

Table 3.5 Algorithm for the base station

Algorithm for Base Station

Input: Receive ‘top-k’ data sets from all CH_i

Output: Broadcast final top-k values and the sensor id’s.
Variables Used: k:User specified top-k, L.A.R:Low approximation range.

SELECT first “k” values from the all the received sets and forward to the respective users.

Compute Low Approximation Ranges (L.A.R)

L.A.R= {Highest Mean – 3S.D, Highest Mean + 3S.D}

3.3 VERIFICATION PHASE

In the second phase, the nodes who previously contributed to the final top-k, and the non-top-k nodes who encounter a value exceeding the local or high approximation range have to send their values to the cluster head. Here, we are limiting the number of messages exchanged between nodes and the base station to a very large extent. Therefore, by decreasing the number of messages, we decrease the energy spent for communication and thereby, we can say that this is the first step towards increasing the network life time. The algorithm for top-k nodes and non-top-k nodes in explained in Table 3.6.

Table 3.6 Algorithm for sensor nodes to compute and decide on whether to send present value to the Cluster Head or not.

Algorithm for Nodes in Verification Phase

Variable Used: S_{id}: Sensor Id, pV: Present Value, CH: Cluster Head, k:top-k, H.A.R:High approximation range.

```
----------------------------------------------------------------------

top-k Nodes

Generate $S_{id}$.presentValue ($S_{id}$.pV)

send $S_{id}$.pV to C.H

non-top-k Nodes

Generate $S_{id}$.presentValue ($S_{id}$.pV)

Check if  $S_{id}$.pV exceeds H.A.R

send $S_{id}$.pV to C.H

else

ignore $S_{id}$.pV
```

Once the cluster head receives values from top-k and non-top-k nodes, it will check if the lowest received value overlaps with H.A.R of other nodes which did not send their value. If there is any such node who's H.A.R is overlapped, the cluster head will probe that particular node to send its recent value. Once the node sends its value, the cluster head will compute the present top-k and send it to its parent cluster. This process will repeat until all the values reach the base station.

Once the base station receives reading from all its previous contributed top-k nodes and non-top-k nodes (who encounter a value exceeding the approximation range), it will start the validation phase.

3.4 VALIDATION PHASE

In this phase, after receiving values from the top-k nodes and non-top-k nodes (who encounter a value exceeding the approximation range), the base station will take the lowest value from all the received values as threshold “T”. This threshold is used to check whether it overlaps with any low approximation range of clusters which did not participate in the verification phase. If no such overlapping is found, the base station will compute the final top-k and broadcast it. If it finds any such overlapping of threshold and L.A.R’s, then it will probe only that particular non-top-k cluster to send its recent values if their recent values is greater than threshold T sent by base station. The algorithm for base station is explained in Table 3.7.

Once the non-top-k cluster sends its values, the base station will decide on the final top-k. While this entire processing is going on, the clusters which already participated in verification phase will enter sleep mode i.e. they do not receive any messages from the base station until the next round has started.

There is one special case in which the base station will omit a top-k value sent by the non-top-k cluster node. This case arises when the non-top-k node senses a value greater than the threshold value and sends it to the base station. The base station cannot include this value in the final top-k as the diversity constraint is already fulfilled. This special case in explained in Section 3.6.

Table 3.7 Algorithm for the base station to validate the final top-k.

Algorithm for Validation Phase

Base Station

Input: Receive values from both top-k and non-top-k nodes

Output: Send top-k to respective users and broadcast the final top-k values and the sensor id’s.

Variables Used: T: Threshold, L.A.R:Low approximantion range, k: user specified top-k.

```
--------------------------------------------------------------------------------
Compute Threshold (T) = Lowest of all received values.
Check if ‘T’ overlaps any L.A.R
then probe non-top-k clusters to send values if greater that ‘T’
Receive all such values.
Compute final top-k
else
decide on final top-k without any probing.
```

This step will terminate the current round and after a certain amount of time the next round will be started and this process will be continued until the first node in the network dies.

3.5 CORRECTNESS OF TOP (k,m)

The correctness of our scheme can be proved round-by-round. Let us consider a sensor network ‘S’ containing ‘N’ nodes be divided into ‘C’ clusters with each cluster having its own cluster head (CH) and data is retrieved in continuous rounds and let ‘r’ be the round number.

Theorem: In any round ‘r’, the base station will receive a minimum of ‘k’ values to decide the final top-k set with diversity-m.

Proof: In the first round (r=1).

Every sensor node in the cluster will send its most recent value to the cluster head. The cluster head will select top-k values from the received set and forward it to the base station. These values are routed to the base station via intermediate cluster heads. Every intermediate cluster head CH_i will receive c*k values from its children clusters heads, where ‘c’ is the number of children cluster heads CH_i has. Here, intermediate cluster heads can be non-aggregating cluster heads or aggregating cluster heads.

Case 1: Intermediate cluster head is a non-aggregating cluster head.

Let CH_{nA} be a non-aggregating cluster head. The cluster head CH_{nA} will receive c*k values from children cluster heads and add its own top-k values to the received set. Now, as the cluster head CH_{nA} does not look into diversity part, it will just forward (c+1) * k values to the cluster head above it.

Case 2: Intermediate cluster head is an aggregating cluster head.

Let CH_A be an aggregating cluster head. The cluster head CH_A will receive c*k values, adds its own k values to the received set. The total number of values CH_A has is equal to k + c*k or simply (c+1)*k. Now CH_A will select top-k values from the available (c+1)*k values such that they come from ‘m’ different clusters. Therefore, an aggregating cluster head (CH_A) forwards only top-k values with diversity-m.

From both the above cases, it is clear that the base station will receive a minimum of k values (only top-k values from aggregating cluster heads or a mixture of top-k values from aggregating cluster heads and (c+1)*k values from non-aggregating cluster heads) to decide the final top-k.

In consecutive rounds (r>1).

According to our scheme, in consecutive rounds the previously contributed top-k nodes and non-top-k nodes (who encounter a value exceeding their approximation range) have to send an update. Once the base station receives these values, it will verify and decide on final top-k.

Case 1: Only previous top-k nodes send an update.

In this case, the base station receives exactly ‘k’ values from previous top-k nodes. The base station will now select the lowest received value as threshold and broadcast it to non-top-k clusters to verify and decide the final top-k. If any non-top-k clusters encounter a value exceeding threshold, it will send an update to the base station. Here, the base station will have ‘k’ values from the previously contributed top-k nodes and ‘k$^{’}$ values from non-top-k clusters (if no non-top-k clusters encounter a value exceeding threshold, then ‘k$^{’}$ can be zero). This proves that base station will have at least ‘k’ values to decide the final top-k.

Case 2: Both previous top-k nodes and non-top-k nodes send an update.

In this case, the base station receives exactly ‘k’ values from the previous top-k nodes and say ‘k$^{’}$ values from non-top-k nodes. The base station will now select the lowest received value as the threshold and broadcast it to non-top-k clusters which did not send an update. If any non-top-k cluster encounters a value exceeding threshold, it will send an update to the base station. In this case, the base station will have ‘k’ values from previously contributed top-k nodes, ‘k’ values from non-top-k nodes (values that were received initially and values received during verification). This proves that the base station will have at least ‘k’ values to decide the final top-k.

3.6 TOP (k,m) ILLUSTRATION WITH EXAMPLE

Consider a network of 25 nodes, divided into 5 clusters (Figure 3.3). The base station has issued a query to retrieve top-4 data items with diversity 3. In the initialization phase, each node will sense and stores around 30 values (in this example the n value used for Gaussian’s pdf is taken as 30). Once the 30 values are sensed, the sensor nodes will calculate the mean, standard deviation and high approximation ranges of the values. The mean, standard deviation, H.A.R and the most recent value will be sent to the cluster head.

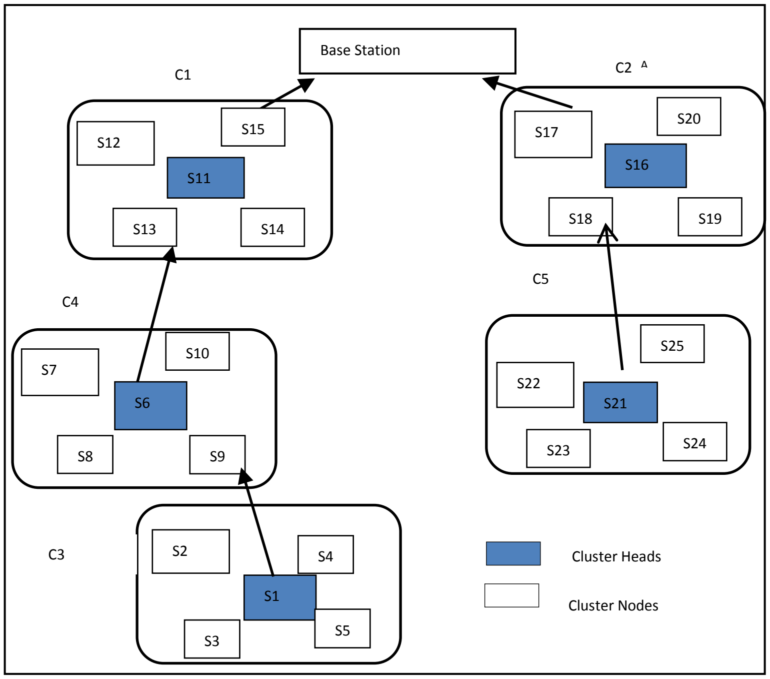
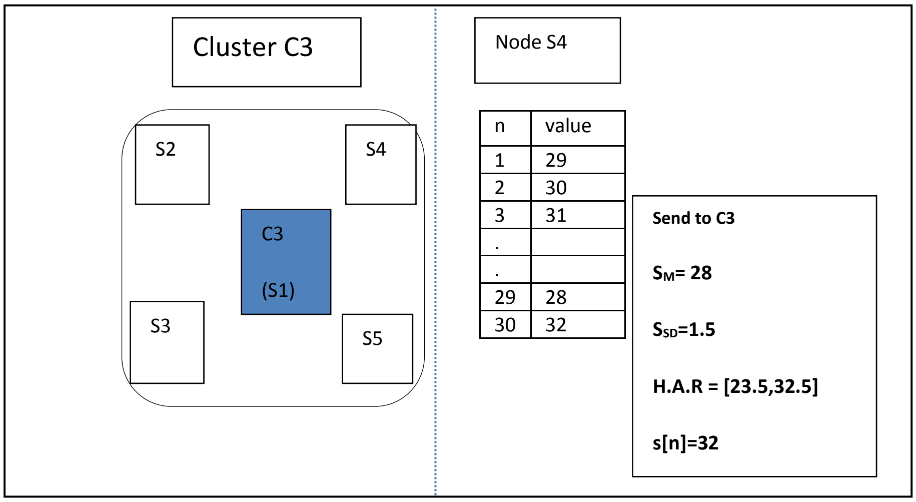


Figure 3.3 A wireless sensor network consists of 25 nodes divided into 5 different clusters.

For example in Figure 3.4, Cluster C3 is a part of the entire network shown in Figure 3.3. This cluster contains 5 node(S1,S2,S3,S4 and S5). Here, the sensor nodes S4 belonging to cluster C3, senses 30 values (29, 30, 31….28, 32) in the initialization phase or the first phase of our scheme (during this period our scheme will not send any updates to the base station), then using these values it calculates mean (M) = 28, standard deviation (SD) = 1.5, H.A.R = [M-3SD,M+3SD] = [23.5,32.5] and the most recent value s[30] = 32. These values are stored in the sensor node memory for next 30 rounds. This process is repeated for all other nodes in the cluster as well as all other nodes in the network. Now the node S4, sends these values (Mean, Standard Deviation, Range and the most recent sensed value) to the cluster head C3.



n	value
1	29
2	30
3	31
.	
.	
29	28
30	32

Send to C3

S_M= 28

S_{SD}=1.5

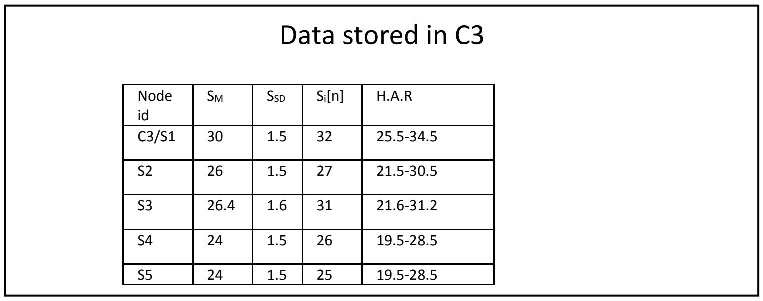
H.A.R = [23.5,32.5]

s[n]=32

Figure 3.4 A sensor node S4, senses 30 values, calculates mean, standard deviation, H.A.R and sends it to cluster head C3.

Once the cluster head receives all the means, standard deviations, H.A.R and recent values from all its cluster nodes, it adds its own reading to the list and stores them in a table. This can be seen in Table 3.8.

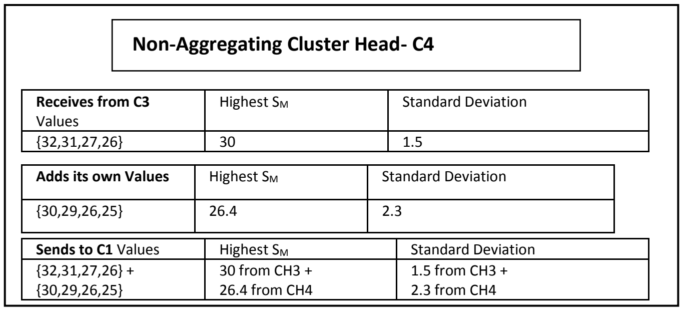
Table 3.8 Cluster head C3 calculating H.A.R's.



Data stored in C3

Node id	S_M	S_{SD}	$S_i[n]$	H.A.R
C3/S1	30	1.5	32	25.5-34.5
S2	26	1.5	27	21.5-30.5
S3	26.4	1.6	31	21.6-31.2
S4	24	1.5	26	19.5-28.5
S5	24	1.5	25	19.5-28.5

Now the cluster head C3 computes top-4 values (32, 31, 27, 26) from the sorted list. It sends the top-4 values, their respective Id's, highest value from all the means (mean = 30 in this example), its respective standard deviation (standard deviation = 1.5) and its H.A.R's it to the cluster above it. In the example we considered, cluster head C3 sends it values to cluster head C4. Here, C4 is a non-aggregating cluster head (as it receives values from only one cluster and it cannot look into the diversity part as the user specified m is 3). It receives values from C3, adds its own values and forwards it to the cluster C1 which is above it. This is shown in Figure 3.5.



Non-Aggregating Cluster Head- C4

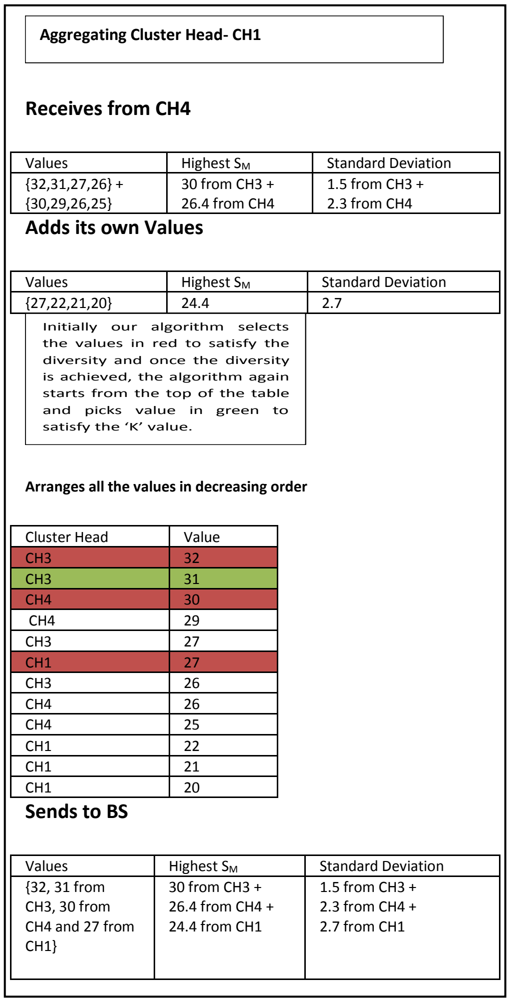
Receives from C3 Values	Highest S_M	Standard Deviation
{32,31,27,26}	30	1.5

Adds its own Values	Highest S_M	Standard Deviation
{30,29,26,25}	26.4	2.3

Sends to C1 Values	Highest S_M	Standard Deviation
{32,31,27,26} + {30,29,26,25}	30 from CH3 + 26.4 from CH4	1.5 from CH3 + 2.3 from CH4

Figure 3.5 Cluster head C4 receiving values from C3, adding its values and then forwarding them to C1.

The cluster head C1 is an aggregating cluster (as it receives values from 2 different clusters and it can look into the diversity part). It receives values from C4, adds its own values to the list and then sorts then in decreasing order. Our algorithm works in such a way that it will select ‘m’ values coming from ‘m’ different clusters. These values are selected to satisfy the diversity constraint which is m=3 in this example. After selecting the ‘m’ values, our algorithm will again start from the top of the sorted table and select the first ‘k-m’ values. In Figure 3.6, the cluster head C1 receives eight values from C4, adds its values to the list and sort them in decreasing order. Now it will select values ‘32’ from C3, ‘30’ from C4 and ‘27’ from C1 to satisfy the diversity constraint m=3. Later it will loop back and select the value ‘30’ from C3 (k-m values have to be selected, here k=4 and m=3. Therefore, 1 value has to be selected).



Aggregating Cluster Head- CH1

Receives from CH4

Values	Highest S_M	Standard Deviation
{32,31,27,26} + {30,29,26,25}	30 from CH3 + 26.4 from CH4	1.5 from CH3 + 2.3 from CH4

Adds its own Values

Values	Highest S_M	Standard Deviation
{27,22,21,20}	24.4	2.7

Initially our algorithm selects the values in red to satisfy the diversity and once the diversity is achieved, the algorithm again starts from the top of the table and picks value in green to satisfy the ‘K’ value.

Arranges all the values in decreasing order

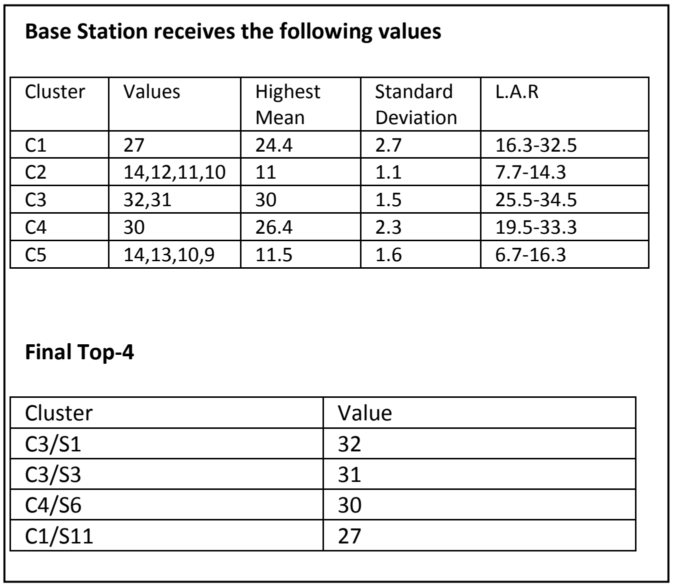
Cluster Head	Value
CH3	32
CH3	31
CH4	30
CH4	29
CH3	27
CH1	27
CH3	26
CH4	26
CH4	25
CH1	22
CH1	21
CH1	20

Sends to BS

Values	Highest S_M	Standard Deviation
{32, 31 from CH3, 30 from CH4 and 27 from CH1}	30 from CH3 + 26.4 from CH4 + 24.4 from CH1	1.5 from CH3 + 2.3 from CH4 + 2.7 from CH1

Figure 3.6 Cluster head C1 receiving values from C4, adding its values and then looks into diversity.

On the other hand, the base station will receive values from all the cluster heads (both aggregated and non-aggregated). These values are sorted in decreasing order and the first ‘k’ values are sent to the desired user. The means and standard deviations received are used to compute low approximation ranges (L.A.R) as shown in Figure 3.7.



Base Station receives the following values

Cluster	Values	Highest Mean	Standard Deviation	L.A.R
C1	27	24.4	2.7	16.3-32.5
C2	14,12,11,10	11	1.1	7.7-14.3
C3	32,31	30	1.5	25.5-34.5
C4	30	26.4	2.3	19.5-33.3
C5	14,13,10,9	11.5	1.6	6.7-16.3

Final Top-4

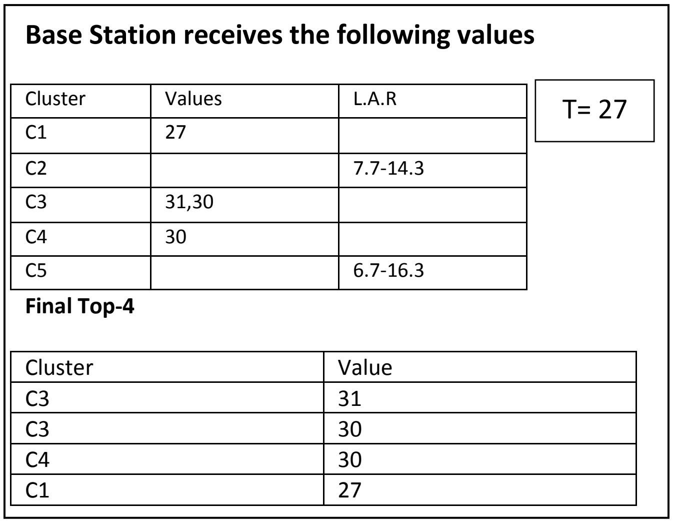
Cluster	Value
C3/S1	32
C3/S3	31
C4/S6	30
C1/S11	27

Figure 3.7 Base station computing the final Top-4 and the low approximation ranges.

In the later stage or the verification phase, all the previously contributed top-4 nodes and the non-top-4 nodes who encounter a value exceeding their H.A.R have to send their data values. In our example, node S1, S3, S6 and S11 have to send their values. For instance if the value of node S1 changes from 32 to 30 and all other values remain same, then before sending the value to the base station, the cluster head C3 has to check with the H.A.R’s of all the cluster nodes. In our case, the node S2 H.A.R overlaps with the S1 present value. Therefore cluster head C3 has to probe the node S2 to send it value. Once S2 sends its value, the cluster head C3 or simply the node s1 will compare the values and send the highest of two to the cluster above it. This process is continued for C4 and C1 as the previous top-4 values came from these clusters.

The base station after receiving the values from the all the previously contributed top-4 nodes and non-top-4 nodes (if any node senses value exceeding H.A.R), it will start the verification phase. First it will take the least value from the received values as the Threshold (T). Later this T value is checked with the L.A.R's of non-contributing clusters. If any overlapping is found, the base station will probe that particular cluster to send its recent values which are greater that the threshold value T. If no such value is sensed, the base station will simply compute the final top-4 from the received values. If any value greater that threshold T is sensed, then it is sent to the base station and base station will then compute the final top-4.

In our example (see Figure 3.8), the threshold value T will be 27 (least of all received values) and as the threshold T does not overlap with any non-contributing clusters (C2 and C5), the base station can directly compute the final top-4 set.



Base Station receives the following values

Cluster	Values	L.A.R
C1	27	
C2		7.7-14.3
C3	31,30	
C4	30	
C5		6.7-16.3

T= 27

Final Top-4

Cluster	Value
C3	31
C3	30
C4	30
C1	27

Figure 3.8 Base station computing threshold value T, checking for overlapping with L.A.R of non-contributing clusters and then computing the final Top-4.

Special Case: Let us consider the same example as discussed above, but here the values sent by previous top-k nodes of C3 are different. The new values sent by C3 are 31 and 15 and rest is same. In this case, the threshold T will be equal to 15. As this threshold overlaps with the low approximation range of cluster head C5, this cluster head C5 is probed to send its value if it is greater than generated threshold. Let us assume C5 encounters a value 16. As this value is greater than the threshold (T=15), it is updated to the base station. Here, the base station will omit this value from the final top-k list, because the base station already has top-3 values (31 from C3, 30 from C4 and 27 from C1) coming from 3 different clusters. This has satisfied the diversity constraint m=3. Therefore, it cannot include a new value coming from a different cluster. It will select value 15 coming from C3 instead of 16 from C5. This is the case where our scheme produces an approximate top-k instead of exact top-k. This case will be ruled out if we switch off the diversity part in our scheme.

4. EXPERIMENTS AND RESULTS

In order to evaluate our scheme, we have performed simulations using Matlab. For our experiments we have considered the Intel Berkeley Research lab data [11], where they have deployed a network for 54 nodes and collected temperature readings every 31 seconds. The arrangement of sensor nodes can be found in the Figure 4.1.

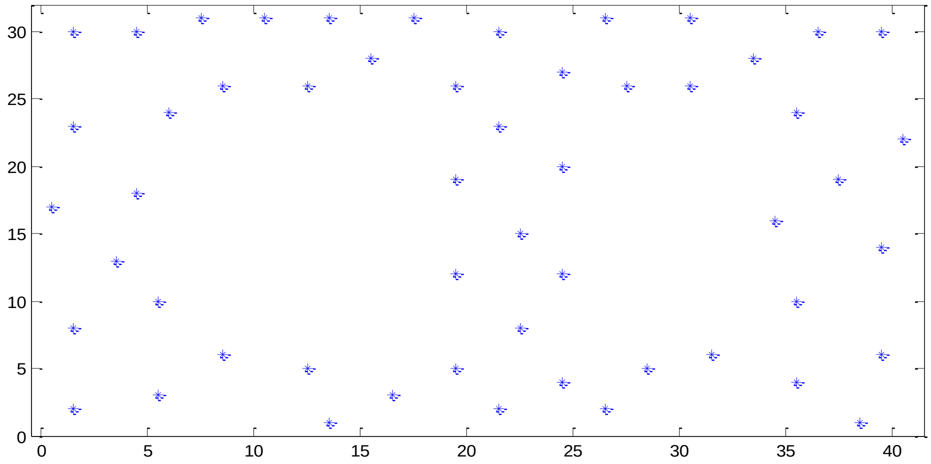


Figure 4.1 The node locations of sensors inside Intel Lab

Once we had the node locations, we have used the LEACH algorithm with an exception for clustering. The exception we had was the children cluster heads have to be within one-hop distance from its parent cluster. The clustering of nodes into different clusters can be seen in Figure 4.2.

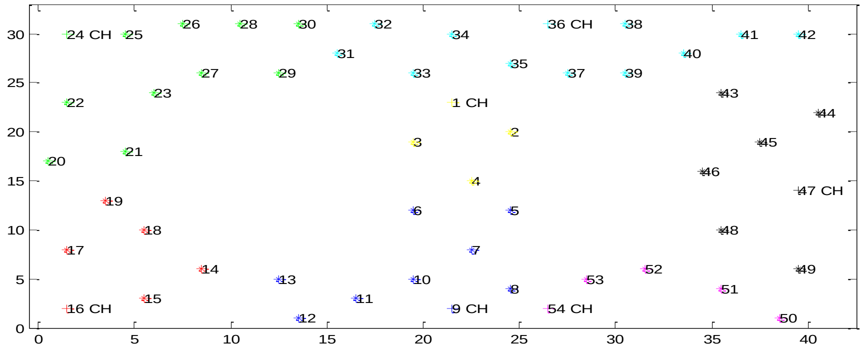


Figure 4.2 Clustering of sensor nodes

Our initial experiments were performed to evaluate the performance of our scheme with respect to EXTOK [3] and GRID [5] schemes. The parameters used in our experiments are ‘n’ which specifies the initial number of round where the sensor nodes have to just sense values, store them and compute Mean, Standard Deviation, High Approximation ranges. Until ‘n’ rounds are completed our scheme will not send any updates to the base station. For our experiments ‘n’ value is initialized to 30. Other parameters used include ‘k’ which is used to specify the number of top values required, ‘m’ which is used to specify the diversity required. In all the experiments, used for comparisons with other schemes, the value of ‘m’ were set to 0 i.e. we have tested our scheme without any diversity constraint. All the experiments were performed to evaluate Average Messages per Round, Average Energy per Round and to determine the total number of rounds for each scheme given a constant initial energy. The comparison of our scheme to EXTOK and GRID scheme yielded the following results presented in Table 4.1, 4.2 and 4.3.

Table 4.1 Comparison of Average messages/round, average energy/ round and total number of round for a given constant energy E = 50000mJ.

E = 50000mJ			
	Avg Messages/Round	Avg Energy/Round	Total Rounds
GRID			
k =5	55.2	108.93	459
k =10	55.2	110.61	452
k = 15	55.2	112.35	445
EXTOK			
k =5	42.45	92.59	540
k=10	46.60	93.10	537
k=15	62.60	99.60	502
OUR SCHEME			
k =5	23.89	67.47	741
k =10	25.74	70.72	707
k =15	27.64	73.96	676

Table 4.2 Percentage improvement in our scheme compared to GRID scheme.

PERCENTAGE IMPROVEMENT IN NETWORK LIFE TIME	
k =5	61.43%
k=10	56.41%
k =15	51.91%

Table 4.3 Percentage improvement in our scheme compared to EXTOK scheme.

PERCENTAGE IMPROVEMENT IN NETWORK LIFE TIME	
K =5	37.22%
K=10	31.65%
K =15	27.06%

Graphical representation of the above data can be seen in the Figures 4.3, 4.4, 4.5 and 4.6. In Figure 4.3, the ‘k’ value was set to 5, i.e. each scheme will result in top-5 values. Similarly in Figure 4.4, ‘k’ value was set to 10 and in Figure 4.5, ‘k’ value was set to 15. Each of the experiment was done by taking an initial energy (E) of 50000mJ. Whenever the energy goes below 0, the network will be collapsed, that means the first node in the network has died. If a node in the network dies, the yielded results are not 100% accurate. This can also be termed as network life time. In Figure 4.3, the network life time of GRID scheme is 459 rounds, the network life time of EXTOK scheme is 540 rounds and network life time of our scheme is 741 rounds. This implies that our scheme network life time has increased by 61.43% when compared to GRID scheme and has increased by 37.22% when compared to EXTOK scheme.

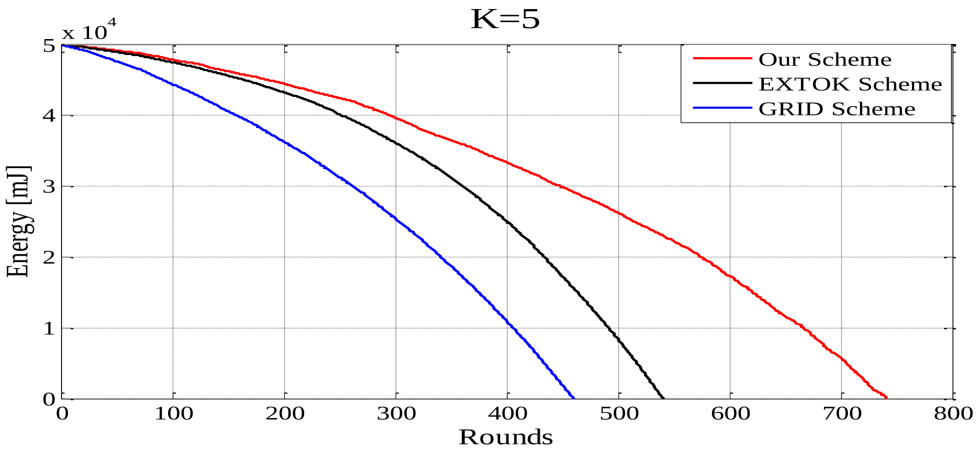


Figure 4.3 Energy Consumption Vs Rounds for K=5 and initial E = 50000mJ.

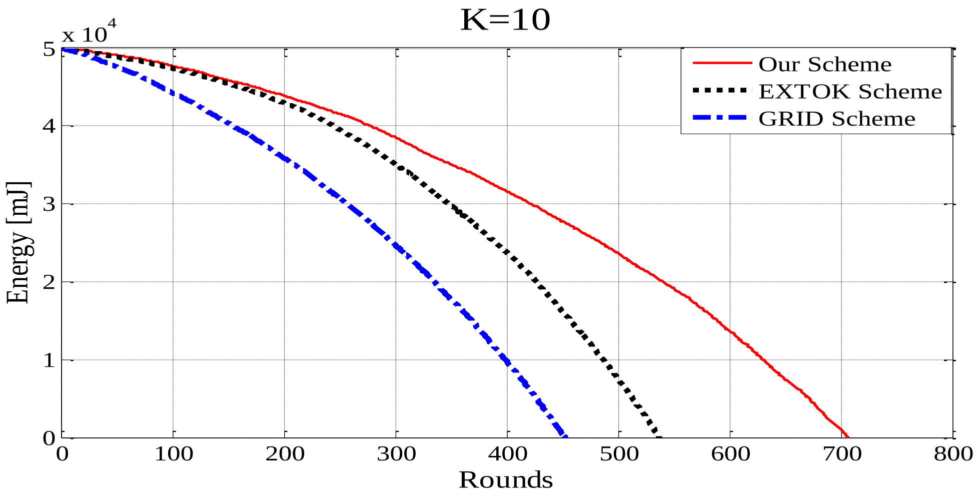


Figure 4.4 Energy Consumption Vs Rounds for K=10 and initial E = 50000mJ.

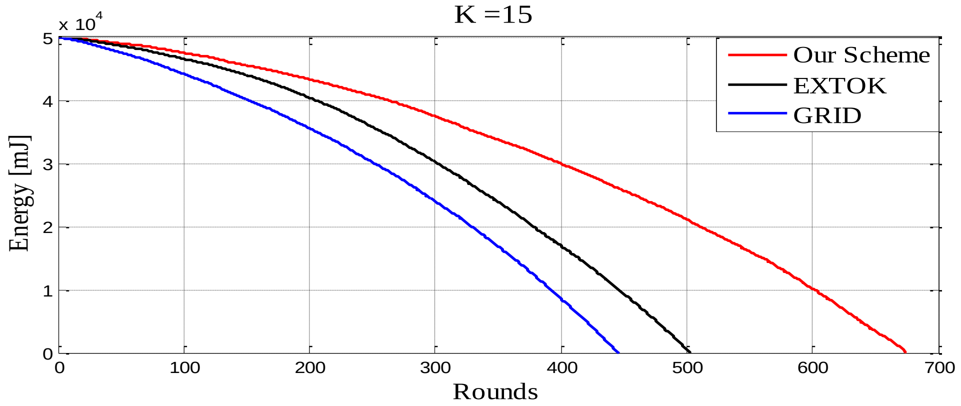


Figure 4.5 Energy Consumption Vs Rounds for K=15 and initial E = 50000mJ.

In Figure 4.6, the bar graph represents the total number of rounds for each scheme for different ‘K’ values [5, 10, 15], and a constant initial energy (E) = 50000mJ.

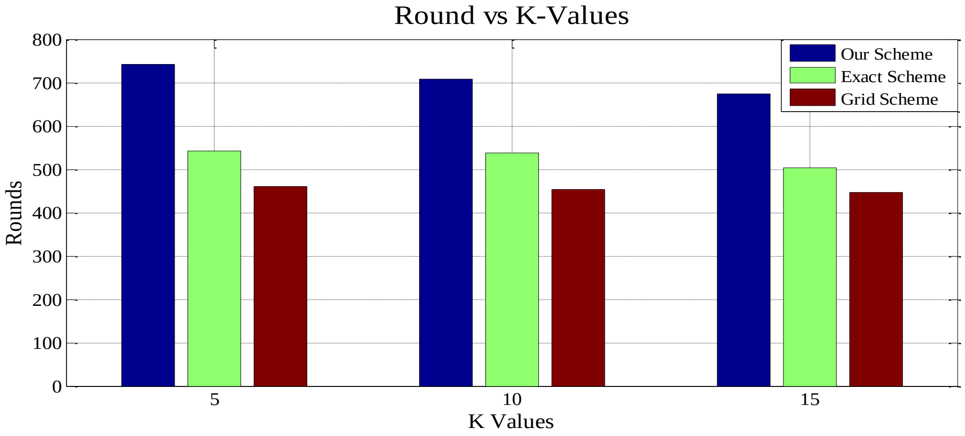


Figure 4.6 Total number of rounds for each scheme using different ‘K’ values and same initial energy E = 50000mJ.

The Figure 4.7 represents the average number of messages exchanged for every 25 rounds when the ‘k’ is 5 and ‘n’ is 30. In the Figure 4.7, the average number of messages from round 50 to round 150 is more in our scheme that is because of the error values in the Intel data set. In the Intel data set we considered for our experiments, there were a few values missing, which were replaced by a default value much higher than the regular values. These error values showed effect on our scheme performance as they were changing the approximation ranges drastically. The Figure 4.8 represents the same average messages for every 25 rounds but after replacing the error values with its previously sensed value in the Intel data set.

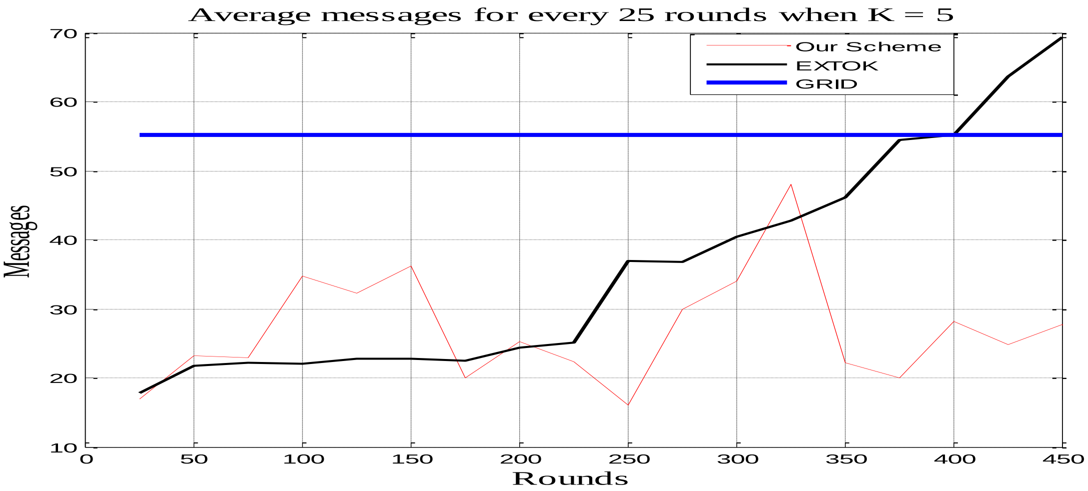


Figure 4.7 Average number of messages for every 25 rounds when ‘K’ = 5, ‘n’=30 and error in data set.

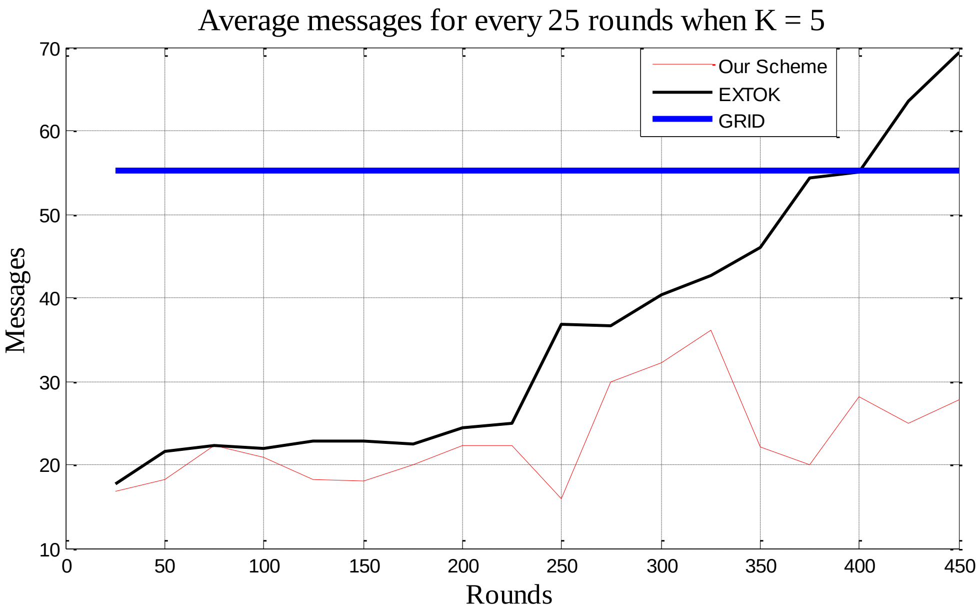


Figure 4.8 Average number of messages for every 25 rounds when ‘K’=5, ‘n’=30 and without any error in data set.

The Figure 4.9 represents the average number of messages exchanged for every 50 rounds when the 'K' is 5 and 'n' is 50. In the Figure 4.9, the average number of messages from round 100 to round 150 is more in our scheme. This is because of the error values in the Intel data set which has been already explained. The Figure 4.10 represents the same average messages for every 50 rounds but after replacing the error values in the Intel data set.

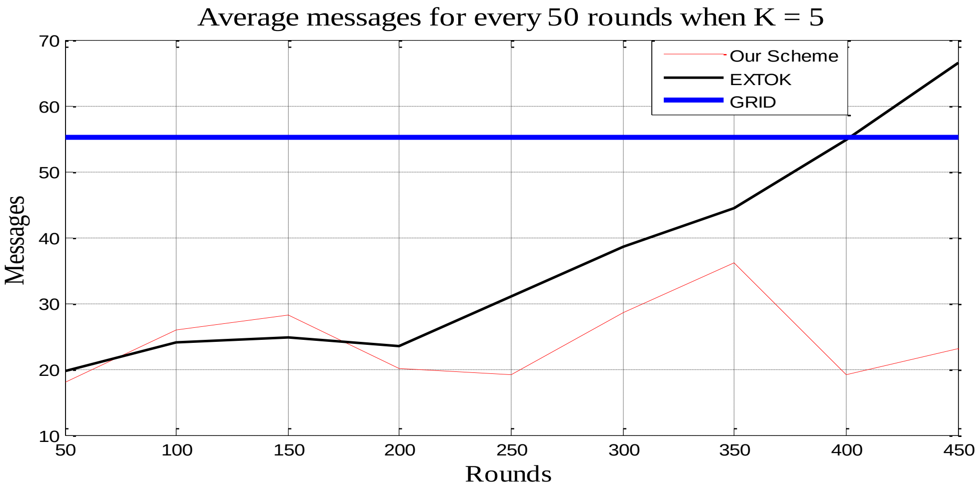


Figure 4.9 Average number of messages for every 50 rounds when 'k' = 5, 'n'=50 and error in data set.

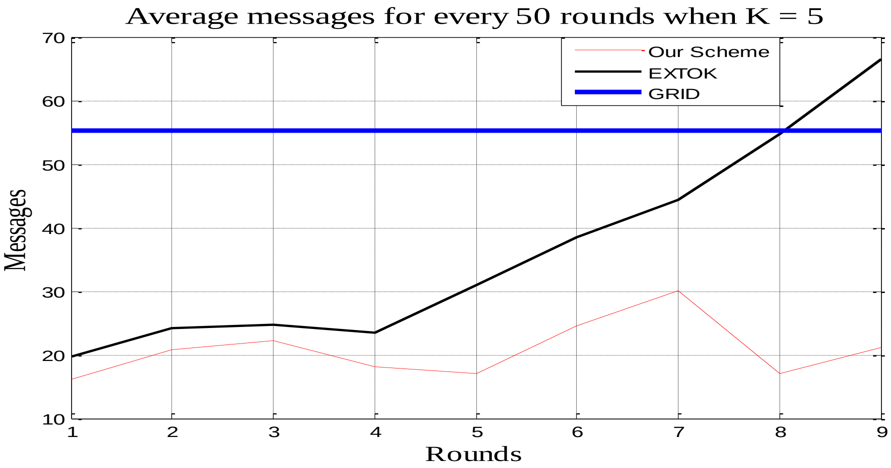


Figure 4.10 Average number of messages for every 50 rounds when 'k'=5, 'n'=50 and without any error in data set.

Our second set of experiments were performed to evaluate the performance of our scheme with respect to different ‘k’ values. This set of experiments was also performed to check the diversity part of our scheme. In these experiments only the ‘k’ value was changed i.e. ‘k’ was initially 5 and then 10 and later 15. We have fixed the ‘m’ value to 4. We have not changed the ‘m’ value as the change of ‘m’ value will not have much effect on the energy required for communication i.e. for any given ‘m’ value the number of messages exchanged between the nodes will be same, the changing ‘m’ value will just have very minute impact on the processing energy, which is almost negligible. For our experiments ‘n’ value is initialized to 30. All the experiments were performed to evaluate Average Messages per Round, Average Energy per Round and to determine the total number of rounds for each scheme given a constant initial energy (E=50000mJ). The comparison of our scheme for different ‘k’ values is shown in Table 4.4.

Table 4.4 Comparison within our scheme for different ‘K’ Values

E = 50000mJ			
	Avg Messages/Round	Avg Energy/Round	Total Rounds for given E
OUR SCHEME			
K =5	25.29	48.73	1026
K =10	23.28	47.43	1054
K =15	21.27	46.21	1082

Graphical representation of the above data can be seen in the Figure 4.11. In the Figure 4.11, the ‘k’ values are being varied, ‘k’ = [5, 10, 15]. Each of the experiment was done by taking an initial energy (E) of 50000mJ. Whenever the energy goes below 0, the network will collapse, that means the first node in the network has died. If a node in the network dies, the yielded results are not 100% accurate.

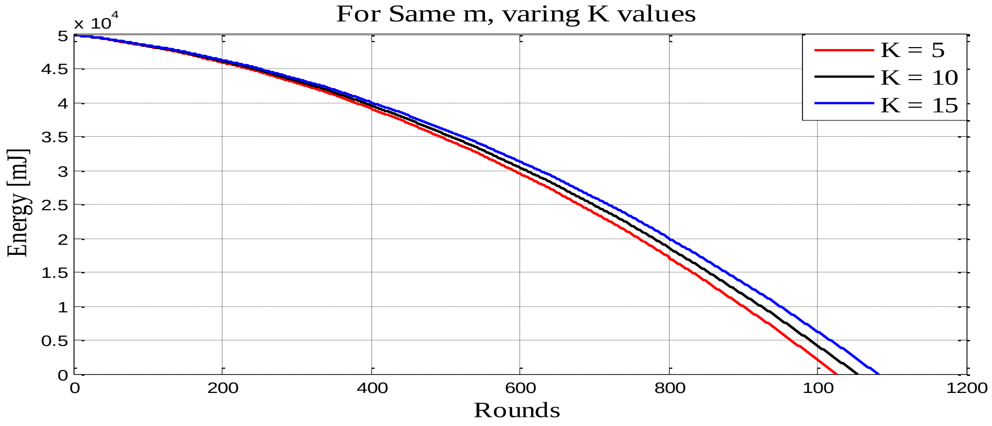


Figure 4.11 Comparison for different ‘k’ values within our scheme.

5. CONCLUSIONS

In this thesis, we have proposed an energy efficient scheme called Top (k,m) for processing top-K queries with diversity m in wireless sensor network. By using the Gaussian’s properties to estimate the probabilities of a nodes contribution to the final top-k, we could limit the number of message exchanged between nodes and the base station. By doing so, we have not only decreased the messages exchanged per round, but also increased the network life time which was our primary goal. This has been experimentally shown by comparing our results with EXTOK scheme and GRID scheme by using different performance parameters. Thereby, we conclude that our scheme is efficient enough for processing top-k queries in wireless sensor networks with better network life time.

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