

# A CLUSTER BASED APPROACH TOWARD SENSOR LOCALIZATION AND K-COVERAGE PROBLEMS

**Zhanyang Zhang**

Computer Science Department

College of Staten Island / City University of New York

2800 Victory Boulevard, Staten Island, NY 10314, USA

[zhangz@mail.csi.cuny.edu](mailto:zhangz@mail.csi.cuny.edu)

## ABSTRACT

In this paper we present a cluster based approach to using a sensor's sensibility and laser signal to address both sensor node localization and K-coverage problems. After sensors were randomly deployed, a virtual grid was mapped over the deployment area. Location guided laser beams are projected to the centers of grid cells to trigger sensors within one hop of communication range to form sensor clusters in the virtual grid. Therefore, all clusters are aware of their locations within the precision of location guided laser beams. We assume there are redundant sensors in each cluster. Thus the cluster members can operate alternatively (duty-cycle) in active or sleep modes under the coordination of the cluster head to conserve energy while providing sufficient and robust coverage in the presence of both node power depletions and unexpected failures. We introduce two distributed algorithms to form sensor clusters and to manage cluster members in duty cycles while maintaining the required K-coverage. Simulation and analysis results show that our algorithms scales well with overhead cost as a linear function of sensor population in terms of energy consumption..

**Keywords:** Sensor localization, location guided laser, cluster and K-coverage.

## 1 INTRODUCTION

Wireless sensor networks (WSN) extend our capability to explore, monitor and control the physical world. A wireless sensor has limited data processing, storage and communication capabilities, and most critically, limited energy resources. In many WSN applications, large quantities of sensors are randomly deployed over a region to perform a variety of monitoring and control tasks. The problem of determining a sensor's physical location is a challenging one and the sensor's location information is extremely critical for many applications. For example, location information is necessary to assess the coverage requirements that generally are known as the K-coverage problem. Given the limitations of these sensors, it is not feasible to equip each sensor with a GPS receiver.

This has motivated many researchers to seek GPS-less solution for locating sensors. In particular, the authors in [1, 2, and 3] designed distributed algorithms that yield sensor node locations without addressing the K-coverage problems. In addition, their algorithms require the existence of anchor-nodes (sensor nodes with known locations) and time synchronization of the whole network. Wang et al. [4] addresses the connected K-coverage problem with a localized heuristic algorithm for the problem,

but their heuristic does not provide a guaranteed solution. In [5], the authors investigate linear programming techniques to optimally place a set of sensors on a sensor field (three dimensional grids) for a complete coverage of the field. In many applications, such precision deployment of sensor nodes is not feasible. Our approach to sensor location problem does not assume the existence of anchor nodes and time synchronization. We provide an integrated solution to both sensor localization and the K-coverage problems.

In addition, due to the short battery life that powers individual sensors, the lifetime of sensor networks are severely restricted. Significant research has been done to improve energy efficiency both at the individual sensor level and the sensor network as a whole [6, 7]. By observing societies formed by certain natural species, such as an ant colony, we learn that a colony can sustain its functions and life for a long period of time despite the fact that each individual ant has a limited lifespan. This is achieved through member collaborations and reproduction. Inspired by such observations, our research addresses the K-coverage problem while maximizing the lifetime of sensor networks and supporting robust WSN operations through self-organized sensors. Most existing energy efficient techniques at the individual sensor level are

orthogonal to our work. Therefore they can be applied within our model to further enhance WSN energy efficiency.

The key components of our model are a cluster formation/localization algorithm and a cluster maintenance algorithm. We developed a signal stimulation model (SSM) that uses location guided laser beams to trigger sensors within one hop of communication range to form geographically bound sensor clusters. Based on the SSM model, we proposed a sensor cluster localization algorithm (SCLA) that can form a cluster and elect a cluster head based on their responses to the stimulation signal projected at the center of a grid cell. Once the cluster is formed, all the cluster members are aware of their locations. They can provide required K-coverage as long as the number of members is greater than or equal to K.

In reality, sensor failures happen randomly due to hardware/software malfunction or power depletion. We proposed a sensor cluster maintenance algorithm (SCMA) that can prolong WSN lifetime by maintaining the smallest subset of cluster members in active mode necessary to perform required tasks while permitting the remaining cluster members to enter sleep mode in order to conserve energy. The sensors in sleep mode turn off their communication and sensing functions while sleeping. Periodically they awaken and may replace one or more active nodes which are deceased (either because they have depleted their power or failed prematurely) or when their energy levels fall below a minimum threshold. Unlike an ant colony which can maintain its population through reproduction, we assume that a WSN does not have sensor replacement capability. To achieve the simultaneous goals of energy conservation and providing K-coverage with fault tolerance operations, it is obvious that SCMA requires a sensor population with sufficient density and redundancy. Our approach is particularly suitable to open-space environment monitoring WSN applications which are subject to long network operation time and harsh operating conditions with a high degree of random node failures.

The rest of the paper is organized as follows. In section 2, we describe the SSM mode as the basic operational model for solving both sensor localization and K-coverage problems. The SCLA algorithm and its performance analysis are also presented in section 2. In section 3, we present the SCMA algorithm and discuss the behaviors of different cluster components. State transition diagrams are used to demonstrate the interactions between different cluster components. A set of definitions and theorems are presented in section 4 to prove that the above proposed algorithms satisfy the K-coverage requirements during the life of WSN operations. In section 5, we show the results of our simulation study to validate the algorithms and

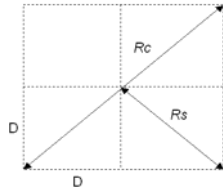
performance analysis. Finally, we conclude this paper in section 6.

## 2 THE CLUSTER MODEL AND CLUSTER FORMATION ALGORITHM

We introduce the SSM model (SSM) as a basic model that defines the parameters and constraints within which a WSN application is deployed and operated. The SSM model is defined by the following set of assumptions.

1. Sensors – Each sensor has sensing, data storage, data processing and wireless communication capability that is equivalent to a MICA Mote developed at UC Berkeley [8, 9]. Each sensor covers a communication cell and a sensing cell defined by radius  $R_c$  and  $R_s$  respectively. All of the sensors are non-mobile and they can sense optical signals (delivered by laser beams).
2. Sensor network – A sensor network consists of a set of homogeneous sensors. Sensors can communicate with each other via wireless channels in single or multiple hops, thus they form an ad-hoc network. There are one or more base stations located outside the sensor region but near the border of the sensor network with wired or long range wireless communication links to the Internet for collecting data or disseminating queries and control commands to the sensor network.
3. Deployed region – Sensors are deployed over an open-space area. A virtual grid marks this area. Each cell in the grid is a  $D$ -by- $D$  square.
4. There is a lightweight location guided laser designator system that can project a laser beam to a given location  $(x, y)$  with acceptable accuracy, such as the system produced by Northrop Grumman which has target range up to 19 kilometers with accuracy of 5 meters [10]. Obviously, this assumption requires a line-of-path for laser beams to reach the sensors at ground level. However for many open space environment monitoring applications, this is not a major problem.
5. To ensure the coverage and connectivity of a sensor network, the model requires that  $D$ ,  $R_c$  and  $R_s$  satisfy the following constraints:
  - To ensure that a sensor anywhere in a cell can cover the cell, it must satisfy the condition,  $R_s^2 \geq 2D^2$ . In our model we assume  $R_s^2 = 2D^2$ .
  - To ensure a sensor anywhere in a cell can communicate with a sensor anywhere in a neighboring cell, it must satisfy the condition,  $R_c \geq 2R_s$ . In our model, we assume  $R_c = 2R_s$ .

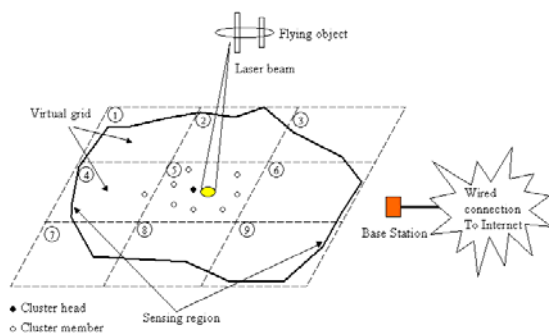
Figure 1 below shows the parameters that define a virtual grid with 4 neighboring cells.



**Figure 1:** Parameters of a virtual grid

Every point in the region can be represented by a pair of  $(x, y)$  coordinator values. A sensor has three possible states, U (unknown), H (cluster head) and M (cluster member). Initially all sensor states are set to U. During the post-deployment phase, an object flies over the deployed region and projects a laser beam to the center of a grid cell  $(X_c, Y_c)$ . The sensors nearby will sense the signal. The sensor readings are stronger if they are closer to the projected laser beam. The sensor with the strongest reading is identified as the cluster head (state=H). All sensors that have a reading greater than  $\lambda$  ( $\lambda$ -cut) and are one hop away from the cluster head become members of the cluster (state=M). Ideally,  $\lambda$  should maximize the possibility of including a sensor in the cluster if it is within the cell, and minimize the possibility of including a sensor in the cluster if it is outside the cell. An optimal value of  $\lambda$  can be obtained through experimentation and simulation. Since an accurate light energy propagation model is extremely difficult to obtain and light wave is a form of electromagnetic wave, we believe it is a reasonable assumption that the light signal decay model should be similar to the attenuation of radio waves between antenna and wireless nodes close to the ground for our study and simulation. Radio engineers typically use a model that attenuates the power of a signal as  $1/r^2$  at short distances (where  $r$  is the distance between the nodes), and as  $1/r^4$  at longer distances [11]. In our model the size of the virtual grid is small and thus we assume the light signal attenuation follows the short distance model.

Figure 2 shows the cluster formed in grid cell 5. The black dot indicates the sensor node is a cluster head in the cluster.



**Figure 2:** Sensor cluster localization and formation

In this paper, we assume that a laser beam is projected to one cell at a time with a cluster forming time interval,  $T$ , for each cell.  $T$  should be just long enough to allow the sensors in a cell to form a cluster, but not so long as to cause unnecessary delay for the operations between cells. In general,  $T$  is a function of sensor density -  $n$  (the number of sensor nodes in a cell), radio propagation delay  $\tau$  and IEEE 802.11 MAC layer back off delay  $\beta$  in its CMA/CA protocol with  $p$  as a probability of package collision in the form of:

$$T = n^2 \beta p + n \tau + c \tag{1}$$

Where  $c$  is a constant for initial delay from sensing the light signal to transmitting the data.

With this assumption, a sensor node can only belong to one cluster, since once it joins a cluster it will not respond to the laser signals projected to other cells. This works even for the sensors located on the border of grid cells.

Based on the model described above, we present the SCLA algorithm with the following steps:

1. Let  $t_0$  be the time when the laser beam is projected to a cell and let  $T$  be the time interval for cluster formation. Let  $t = t_0$  when starting the algorithm.
2. While  $t > t_0$  and  $t < (t_0 + T)$  repeat step 3 and 4.
3. For each sensor with unknown status that has detected the signal, if the sensor reading is greater than  $\lambda$ , then it will broadcast a message with the sensor id and sensor reading (SID, Value) to its neighbors within one hop of communication. Otherwise it keeps silent.
4. When receiving a message, a sensor with unknown status acts according to the following rules:
  - Rule1 - If the reading value of the received message is greater than its own reading and its own reading is greater than  $\lambda$ , then it will set the state = M (a cluster member) and reset its local memory.
  - Rule2 - If the reading value of received message is less than its own reading and its own reading is greater than  $\lambda$ , then save the message (SID, Value) in its local memory.
5. For a sensor that still has unknown status, if its own reading is greater than  $\lambda$  it will set the state=H (a cluster head).
6. The cluster head sends the cluster membership information (SID, Value) pairs, which were saved at step 4, to the closest base station.
7. Project laser beam to the next cell and repeat the above steps 1 to 6 until all the cells are visited.

Our analysis shows the SCLA algorithm performs and scales well when sensor network size increases in terms of both the number of cells in a grid and the total number of sensors in a cell. Let  $L$  be the largest number of communication hops from a cluster head to the closest base station. Let  $M$  be the total number of cells in the grid. Let  $N$  be the total number of sensors deployed. Let  $n(i)$  be the number of sensors in cell( $i$ ). The cost of SCLA algorithm in terms of the number of messages transmitted is given as:

$$Cost(L, M, N) \leq \sum_{i=1}^M n(i) + M * L \quad (2)$$

where  $\sum_{i=1}^M n(i) = N$

If we assume sensors are uniformly distributed, then we have:

$$Cost(L, M, N) \leq M*(N/M) + M*L = N + M*L \quad (3)$$

Formula (3) is equivalent to the notation,  $O(N)$ , when  $M$  and  $L$  are significantly smaller than  $N$ , which is true in most high-density sensor networks. These results show that it is feasible to deploy large amount redundant sensor nodes in order to compensate for high rates of sensor failure with limited overhead cost.

### 3 SENSOR CLUSTER MAINTENANCE ALGORITHM

The SCMA algorithm consists of three components, namely, cluster member component, cluster head component, and base station component. These components work together to achieve the following functions:

1. Coordinating a subset of cluster members as active nodes that perform required tasks while tagging the remaining cluster members as sleep nodes to conserve energy.
2. Replacing the nodes that failed unexpectedly or whose energy level falls below a certain threshold to guarantee required coverage.
3. Warning the network operators if the required coverage is going to be compromised.

After the cluster is formed according to the SCLA algorithm, all cluster members are in active mode ( $m=A$ ) by default. A member listens to the initialization message, (I, sensor\_list), from the cluster head. A member turns into sleep mode ( $m=S$ ) unless its SID is on the sensor\_list in the initialization message. We use finite state automata to precisely describe the behavior of each component in a simple canonical form. Particularly we employ a special type of finite state automata, called Mealey machine, which is formally defined by Hopcroft and Ullman [12] as below:

Let finite state automata,  $F = (Q, \Sigma, \Delta, \delta, \gamma, q_0)$  where:

- $q_0$  is the initial state ( $q_0 \in Q$ ),
- $\Sigma$  is a set of inputs,
- $Q$  is a set of states,
- $\Delta$  is a set of outputs,
- $\delta$  is a state transition function:  $Q \times \Sigma \rightarrow Q$ ,
- $\gamma$  is an output function:  $Q \times \Sigma \rightarrow \Delta$ .

To help understand the state transition diagrams, we list all the message definitions in the table below.

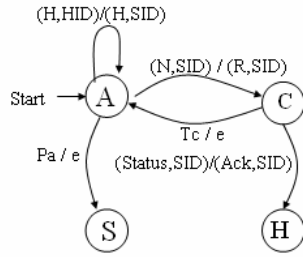
**Tab. 1** message definitions for SCMA algorithm

Message	From	To	Description
(A, SID)	Head	Member	Activate a member (SID)
(Ack, SID)	Member	Head	Acknowledgement: a member (SID) is activated
(Ack, SID)	Member	Base	Acknowledgement: a member (SID) is a new head
(E, HID)	Head	Base	Emergency message to the base station
(H, HID)	Head	All members	Broadcast "hello" message
(H, SID)	Member	Head	Reply to "hello" message by a member (SID)
(I, Sensor_list)	Head	All members	Broadcast initial active sensor list
(N, SID)	Base	Member	Appoint a member (SID) to be the new head
(R, SID)	Member	Base	A member requests the cluster status
(Status, HID)	Head	Base	Send cluster status to the base station
(Status, SID)	Base	Member	Send cluster status to a member (SID)
(W, HID)	Head	All members	Broadcast "wakeup" message
(W, SID)	Member	Head	Reply to "wakeup" message by a member (SID)
Tx / e	Time trigger – while in state x for time interval $T_x$ , then return to previous state		
Pa / e	Event trigger – power level below a.		

#### 3.1 The Cluster Member Component

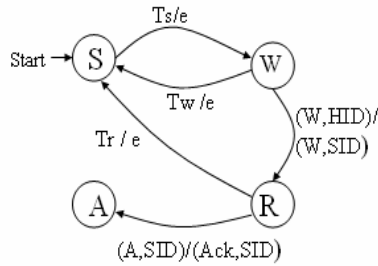
We use two state transition diagrams, one represents cluster members in active mode and the other represents cluster members in sleep mode. Figure 3 defines the behavior of an active member node within the SCMA algorithm and how it can change to sleep mode or become a cluster head when a cluster head has failed. For example, when an active member receives a "Hello" message from the cluster head (H, HID), it replies with message (H, SID) and goes back to the same state. An arrow indicates such a transition with a text label on top in

the form of (input message) / (output message). The same notation applies to all the state transition diagrams in this section.



**Figure 3:** State transition diagram for active members

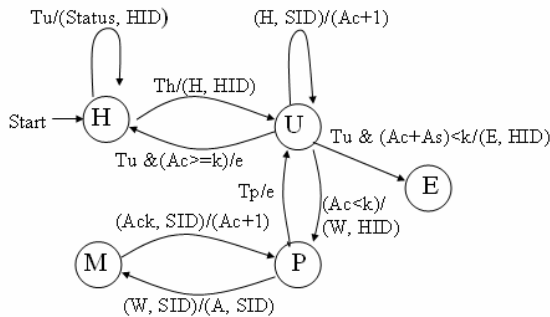
Figure 4 describes the behavior of a sleep member node and how it can change to active mode.



**Figure 4:** State transition diagram for sleep members

### 3.2 The Cluster Head Component

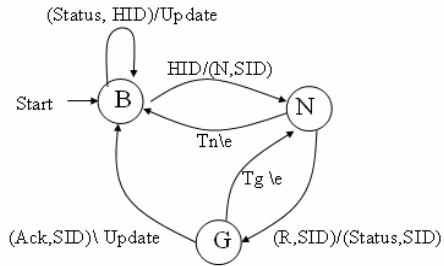
The cluster head component coordinates members between active and sleep modes. It updates cluster status and synchronizes the cluster status with the base station. It uses an active node counter ( $A_c$ ) and sleep nodes counter ( $A_s$ ) to track active members and sleep members. The Figure 5 below describes how a cluster head works. The cluster head issues an emergency message, (E, HID) to base station if the required coverage is going to be compromised within this cluster.



**Figure 5:** State transition diagram for cluster heads

### 3.3 The Base Station Component

In the SCMA algorithm, the function of a base station component is to oversee the status of clusters and the condition of networks. Figure 6 shows how it works.



**Figure 6:** State transition diagram for base stations

## 4 K-COVERAGE THEOREMS

We introduce the following definitions and theorems to formally prove that the proposed SCLA and SCMA algorithms together can solve the K-coverage problem.

**Definition 1:** *K-coverage problem:* a WSN application is required to guarantee that for any given points in the deployed region, there are at least  $K$  sensors whose sensing range can cover the points.

**Definition 2:** *The membership degree of a cluster is the number of sensors in a cluster including the header.*

**Theorem 1:** *For a cluster( $i$ ) formed at a cell( $i$ ) in according to the SCLA algorithm, if the membership degree of the cluster( $i$ ) is no less than  $K$  during the lifetime of operation, then the area within the cell( $i$ ) is  $K$ -covered.*

**Proof:** Based on the assumption 5.1 in the model definition section, a sensor located anywhere within a cell can cover any points in the cell including the border of the cell. If the  $cluster(i)$  has no less than  $K$  member sensors during the lifetime of the operation. Then, by definition 1 & 2, any points within the  $cell(i)$  are covered by no less than  $K$  sensors during the lifetime of the operation. Therefore  $cell(i)$  is  $K$ -covered.

**Theorem 2:** *Given a deployed region  $R$  which is enclosed in a virtual grid  $G$ , if there is one cluster formed in each cell with membership degree no less than  $K$  during the lifetime of the operation, then the deployed region  $R$  is  $K$ -covered.*

**Proof:** By theorem 1, every cell in  $G$  is  $K$ -covered and the virtual grid  $G$  encloses the entire region  $R$ , therefore the deployed region  $R$  is  $K$ -covered.

Based on Theorem 2, it becomes obvious that SCMA algorithm can satisfy a WSN application  $K$ -coverage requirement as long as it can maintain at least  $K$  active member sensors in the cluster at each cell during the life of WSN operations.

## 5 SIMULATION AND DATA ANALYSIS

In order to validate the model and algorithms presented in this paper and to gain insights into how the algorithm works, we conducted simulation studies using the NS2 simulator with Monarch Extensions to ns [13, 14] for SCLA algorithm. We extended our simulation for SCMA algorithm with C++ modules to study the energy conservation and the impact on WSN lifetimes. Our simulations are implemented with two scenarios. The first scenario involves simulating a single cell grid with different sensor densities (number of sensors in the grid).

The focus of this simulation is to study the performance and scalability of our model against sensor density. In the second scenario, we take the same measurements from a multi-cell grid simulation with considerations of both sensor density and the size of the deployment area in terms of the number of cells. The purpose of this simulation study is to understand the performance and scalability of our model in a multi-cell grid.

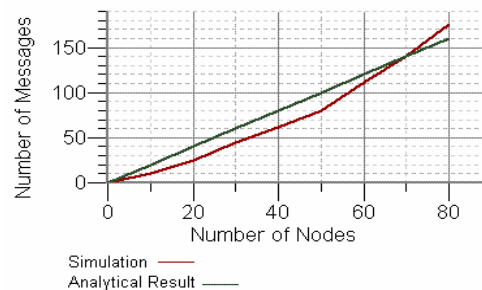
We set the cell dimension to 10 meters for all the simulations presented in this paper. Our simulation tests indicate that the outcomes are not as sensitive to the cell dimension as they are to sensor density. We let the number of sensor nodes vary from 10 to 80 in increments of 10. In our simulation model, we set the propagation delay between two nodes as 10 ms ( $\tau = 10\text{ms}$ ). We use multicast in UDP

protocol to simulate sensor node broadcast in one hop distance. We set  $p$  as the probability for a node to receive the broadcast message successfully ( $p$  in the range 0 to 1).

The message package size is set to 128 bytes and the bandwidth between two nodes is set to 2mbs. To simulate IEEE 802.11 MAC layer CMA/CA protocol, we introduce a back-off time delay, a random number between 50 and 100ms, which is assigned to a node when it detects that a channel is busy. The node will back-off for a delay interval before it tries to broadcast again.

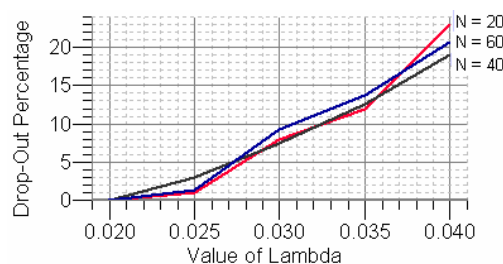
The simulation results capture two key measurements, the number of messages being transmitted and the time interval for cluster formation in the grid. All of the simulation results presented below are the average of five simulation runs.

Figure 7 shows the number of messages being transmitted in a single cell grid. It compares the analytical result with simulation results. It indicates that the cost of message transmissions is close to a linear function of  $n$ , the number of sensor nodes in the cell.



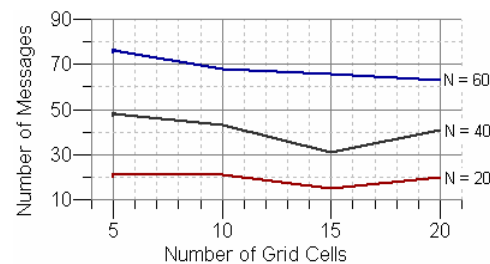
**Figure 7:** Messages transmitted in single cells

To better understand cluster membership distributions and study the impact of  $\lambda$  values on member selections, we used a single grid cell of 10 meters by 10 meter with  $\lambda$  values in the range [0.02, 0.04]. The simulation result in Figure 8 shows the percentage of sensors that are dropped from the cluster for the cell as the value of  $\lambda$  changes. It shows the higher  $\lambda$  value leads to more sensor nodes being excluded from the cluster.



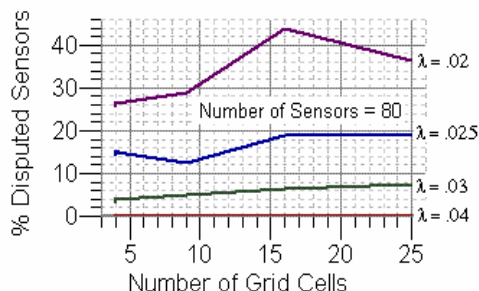
**Figure 8:** Membership distribution over  $\lambda$  values

The simulation results below are for a multi-cell grid scenario with the same key measurement as we presented for a single cell grid. Figure 9 shows that with a fix number of sensor nodes, the number of messages being transmitted actually drops as we expected as the cost function defined in Formula (3). Because there are fewer collisions as sensor density decreases. This simulation result indicates that the number of messages being sent is more sensitive to the density in each cell than the number of cells in a grid.



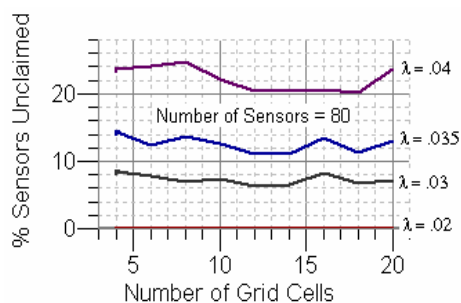
**Figure 9:** Performance and scalability in multi-cells

Figure 10 presents an interesting measurement, the percentage of sensors wrongly claimed by clusters. It is closely correlated with the  $\gamma$  values. The ratio of disputed sensors drops or stays at the same level after the number cells reach 16 due to the decrease in sensor density.



**Figure 10:** Number of disputed sensors with  $\lambda$  values

Figure 11 shows the percentage of sensors that are unclaimed in a multi-cell grid with 80 sensors total. This is more likely happens to sensors at the cell borders and is sensitive to  $\lambda$  values.



**Figure 11:** Percentage of unclaimed sensors

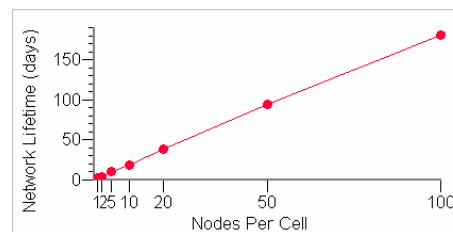
Our simulation study of the SCMA algorithm is designed to understand the relationships between the network lifetime, sensor node density and the overhead cost with K-coverage constraints. The WSN lifetime is defined as the time interval that a WSN network can sustain its operations and services with respect to K-coverage requirement. In other words, the service quality, such as sensing and communication coverage requirements, cannot be compromised during the lifetime of WSN operations.

Given the parameters defined in the SSM model, the communication coverage of a WSN can be reduced to the sensing coverage (assumption 5). The sensor network lifetime is defined by the shortest cluster lifetime. If a cluster is unable to provide the required coverage in one cell then the whole network is considered compromised. In the notation of SCMA(K), the degree of sensing coverage (K-coverage requirement) is defined as an input

parameter. It is obvious that different WSN applications may require different K-coverage.

In our initial simulation, we baseline our study in unit degree coverage with  $K=1$ . We assume sensors are uniformly distributed over grid cells during deployment for simulation study purposes. We use the sensor node power consumption characteristics published by Crossbow [15] for our energy consumption computations.

Figure 12 shows a cluster lifetime vs. the number of nodes in a cluster, which has a linear growth in terms of sensor population. But we expect this linear growth at lower slopes as K-coverage increases (more active nodes required). It also incurs overhead costs for the cluster head to probe active nodes with “hello” messages. Further simulation can be done to study this impact and how to control the head node’s probing cycle to balance the trade-off of required coverage and overhead costs. Given the cell size in our simulation (10 m by 10 m), 100 nodes per cell is far beyond the most population density of WSN applications.

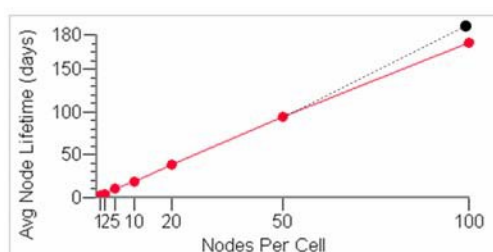


**Figure 12:** Network lifetime over number of nodes in a cluster

It is interesting to observe the relationship between the average node lifespan and node density. If we let an active node cycle into sleep mode when its power level falls below a certain threshold, it might increase the average member node lifetime as node density increases, since the workload is more evenly distributed among a larger node population. But the simulation result in Figure 13 shows the average node lifetime is slightly below linear growth in term of node density. Particularly, as the node density goes beyond 50 nodes. This result is not in total agreement with our theoretical analysis on SCMA. We contribute this discrepancy to the additional overhead cost of switching an active node to sleep node on a volunteer basis when the active node’s power level is below a certain threshold.

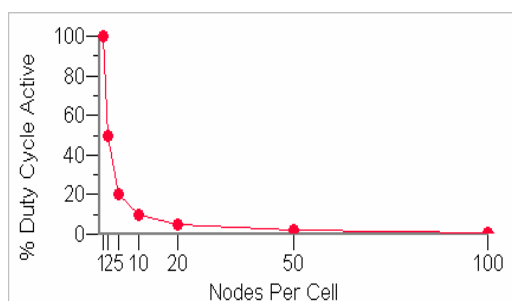
We are aware of that the average lifetime of a cluster head is expected to be shorter than member nodes, since the head node assumes more duties than members. We could introduce the same logic to the SCMA algorithm by permitting a head node to sleep when its power level falls below a certain threshold. We might expect a greater overhead cost in doing so. Currently we are conducting more extensive

simulation studies to understand this issue better.



**Figure 13:** Average node lifetime vs. node density

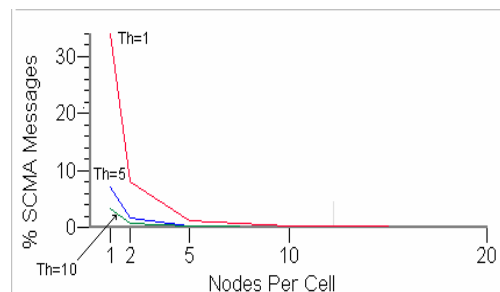
Figure 14 shows that as the percentage of active duty cycle (the percentage of active time over total node lifetime) is decreased as the node density increases with  $K=1$  coverage. We expect this percentage to follow the same trend but at less decline rate percentage as the  $K$  value increases, since more nodes must stay active.



**Figure 14:** Percentage of active duty time vs. number of nodes in a cluster

Based on the simulation results shown in Fig. 13, we expect the cluster head probing cycle ( $T_h$  – the time interval before sending next “hello” message) of “hello” messages will impact the overhead cost of the SCMA algorithm. As interval  $T_h$  increases, the overhead cost of SCMA will decrease. We conducted simulation tests under three  $T_h$  values.

The simulation results shown in Figure 15 validate our expectations. It shows the overhead cost as the percentage of SCMA message transmitted over the total potential bandwidth capacity of a sensor cluster. For three different  $T_h$  values, we can see the impact of  $T_h$  remains significant only before the node population reaches a “critical mass” where nodes/cell = 5 for  $K = 1$  coverage. As the node population increases beyond the critical mass, the total message capacity of the cluster grows at a much faster than the overhead cost. This result tells us that SCMA scales well as node population increases measured by the percentage of overhead cost. This result also suggests that it is most cost-effective to increase the  $T_h$  value for the clusters with a smaller population (less than 5 sensor nodes per cell).



**Figure 15:** Percentage of SCMA message vs. node density per cell

## 6 CONSLUCSION

In this paper we propose a unique solution to address both sensor localization and  $K$ -coverage problems that can conserve energy while supporting robust WSN operations. Simulation results show that both of our distributed algorithms, SCLA and SCMA, perform and scale well with overheads in linear proportions to the deployed sensor population in a variety of deployment densities. SCMA can guarantee the  $K$ -coverage requirements of WSN applications over their network lifetimes and it can warn network operators should coverage requirements be compromised.

The work reported in this paper leads to several interesting topics for future research. We plan to investigate the possibility of using this model for differential  $K$ -coverage problems [16] where different cells may require different  $K$ -coverage within the same WSN application. We are conducting more extensive simulation studies on two issues. One investigates the overhead impact and the worthiness of having a head node fall back to sleep if its energy level falls below a certain threshold. The other studies the impact of having  $K$ -coverage values as a function of time and location. We expect these studies will help us to refine our model and to achieve even greater energy efficiency. We are aware that we did not take into consideration the energy consumed by sensors for providing normal operational tasks. Our analysis and simulation results only explore the overhead portion of energy consumed by SCLA and SCMA without regard to the application. The energy credited to WSN normal operational tasks are highly application dependent, therefore it is out of the scope of this paper.



## 7 REFERENCES

- [1] L. Doherty et al., "Convex Position Estimation in Wireless Sensor Networks," IEEE INFOCOM, Alaska, April 2001.
- [2] N. Bulusu et al., "GPS-less Low-Cost Outdoor localization for Very Small Devices," IEEE Personal Communications, October 2000.
- [3] A. Savvides et al., "Dynamic Fine-Grained Localization in Ad-Hoc Networks of Sensors." ACM SIGMOBILE, Rome, Italy. July 2001.
- [4] X. Wang, G. Xing, Y. Zhang, C. Lu, R. Pless, and C. Gill, "Integrated coverage and connectivity configuration in wireless sensor networks," in *Proceedings of the ACM SenSys*, 2003.
- [5] K. Charkrabarty, S. Iyengar, H. Qi, and E. Cho, "Grid coverage for surveillance and target location in distributed sensor networks," *IEEE Transaction on Computers*, 2002.
- [6] I.F. Akyildiz et al. "A Survey on Sensor Networks." IEEE Communications Magazine, August 2002, pp. 102-114.
- [7] C. Jone, et al. "A Survey of Energy Efficient Network Protocols for Wireless networks", Journal of Wireless Networks, Kluwer Academic Publishers, 2001, Vol. 7, pp. 343-358.
- [8] "MICA Wireless Measurement System", <http://www.xbow.com/Products/>
- [9] "University of Berkeley Mote", <http://webs.cs.berkeley.edu/>
- [10] Northrop Grumman, "Lightweight Laser Designator Rangefinder Data Sheet", <http://www.dsd.es.northropgrumman.com/DSD-Brochures/laser/LLDR.pdf>
- [11] J. Broch, et al. "A Performance Comparison of Multi-Hop Wireless Ad Hoc Network Routing Protocols." The 4th Annual ACM/IEEE International Conference on Mobile Computing and Networking, October, 1998, Dallas, Texas.
- [12] Hopcroft J. and Ullman J., "Introduction to Automata Theory, Language, and Computation." Addison Wesley publishing company, 1979.
- [13] "The Network Simulator ns-2: Documentation", <http://www.isi.edu/nsnam/ns/ns-documentation.html>.
- [14] "Monarch Extensions to ns", <http://www.monarch.cs.cmu.edu/>
- [15] "MICA2 AA Battery Pack Service Life Test" [http://www.xbow.com/Support/Support\\_pdf\\_files/MICA2\\_BatteryLifeTest.pdf](http://www.xbow.com/Support/Support_pdf_files/MICA2_BatteryLifeTest.pdf)
- [16] X. Du and F. Lin, "Maintaining Differentiated Coverage in Heterogeneous Sensor Networks." EURASIP Journal on Wireless Communications and Networking, Vol. 4, 2005, pp 565-572.

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