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TECHNICAL PAPER

An Energy-efficient Clusterhead Assignment Scheme for Hierarchical Wireless Sensor Networks

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Abstract We study the problem of assigning clusterheads in a hierarchical Wireless Sensor Network (WSN). That is, for a given hierarchical WSN, how many clusterhead nodes we should assign, and how to geographically allocate these clusterheads. Since an assignment scheme optimizing all factors is impossible, we will focus on the crucial issue of energy efficiency of the WSN. Because it is mostly true that the nodes of WSN are powered by batteries, power saving is an especially important consideration in WSN architecture design. We will propose a hierarchical WSN architecture toward the end of saving energy of both sensor nodes and clusterheads. Using analytical result, experiments are conducted in which realistic scenarios are simulated.

Keywords Energy efficiency · Hierarchical structures · Network architecture · Wireless networks · Wireless Sensor Networks

1 Introduction

A Wireless Sensor Network (WSN) is composed of a large number of sensor nodes, and a few (at least one) "central" node(s). The sensors are embedded into various physical environments mainly for the collection of physical world data. The data are transmitted to, or gathered by, the central nodes for aggregation, analysis, and processing. The central nodes also play the role of manager of the WSN. The communication among nodes is all via wireless means. Therefore all nodes are equipped with radio transceivers/receivers. WSNs have very promising prospect in many applications, such as environment monitoring, traffic monitoring, target tracking, and fire detection.

Different models of WSN have been proposed. However some basic characteristics can be observed that are common in most proposed models.

- They are all composed of a large number of sensor nodes, and a small number of (in some models just one) master nodes (central nodes);
- All sensor nodes are relatively low cost, perform relatively limited computational operation. Their main job in the whole system is to collect raw data, and render it to the master nodes, with or without some primitive preprocessing;
- The master nodes collect the data from all sensors, and analyze/process them. They are much more powerful, costlier processors than ordinary sensors. The master nodes are also the managers of the network.

A WSN can have either just one master node or a group of master nodes, depending on the network's scale of geographical coverage and/or cost effectiveness consideration. In a single-master WSN, the master node (also called base station) collects and processes data from all sensors. It is also the sole manager of the entire network system. In a multi-master WSN, the tasks of data collection, aggregation, processing, and network management are distributed among a group of nodes working collaboratively. The organization of these master nodes is one of the essential issues in the design of WSN architecture.

Many WSN clustering schemes have been proposed, citing advantages on various metrics such as convergence rate, cluster stability, cluster overlapping, location-awareness, support for node mobility, and most importantly, prolonged

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lifetime of the network [1, 7–9, 11, 12, 14, 16]. In a cluster-based, hierarchical structure, there is a group of sensor nodes functioning as clusterheads (CHs) to collect data from their neighboring nodes. The data traffic can be greatly reduced by applying data aggregation at clusterheads. Cluster members have low energy consumption, as they transmit sensor data to a nearby node. The CHs form a second layer of network. The selection of CHs depends on factors such as topology of the WSN, the applications, and the optimization objectives. One invariable target is to keep the battery-operated WSN's working life as long as possible.

In [12], a cluster-based, hierarchical model for WSN, named COSMOS, was proposed. COSMOS takes up a hierarchical network architecture comprising of a large number of low power, low cost sensors. The sensors are organized into spatial clusters. For each sensor cluster, there is a *clusterhead*. Sensors within a cluster communicate in a time synchronized manner, using single hop communication. The clusterheads form a mesh-like topology and communicate asynchronously. Algorithms basic to sensor networks, such as sorting and summing, are addressed using COSMOS as the underlying architecture.

As a matter of fact, the topologies of many distributed systems are more or less hierarchical. If distributed functions are performed in such a way as to reflect the underlying hierarchical topology, the algorithm design can be greatly simplified. A hierarchical architecture may also help improve scalability of the distributed functions, or even the scalability of the network itself. The hierarchical approach has been used in solving many different problems of distributed nature, such as distributed monitoring, resource scheduling, and network routing, either to effectively coordinate the local control activities or to enhance the overall system performance [2–6, 13].

In this paper, we study the problem of adequately assigning clusterheads (master nodes) in a hierarchical WSN. That is, for a given WSN, how many clusterhead nodes the WSN should have, and where they should be positioned. There are numerous factors affecting the assignment of clusterheads. A solution optimizing all performance metrics, such as time, memory space, and energy consumption, is impossible to obtain. A solution to the optimization problem is both application and network topology dependent. In this work, we will focus on the important issue of energy efficiency of the WSN. A widely accepted convention of WSN is that nodes are running on batteries. Therefore power saving is an especially important goal in architecture design. We will propose a hierarchical WSN architecture toward the end of saving energy of both sensor nodes and clusterheads.

The rest of this paper is organized as follows. In Sect. 2, we describe the WSN model we will be working on. In Sect. 3, we will present the clusterhead assignment scheme minimizing energy consumption. The assignment scheme is based on the analysis of the WSN model, which abstracts the energy characteristics of the sensor nodes, especially multiple power states. In Sect. 4, we use the obtained scheme as a guide to assign clusterheads for a more irregular hierarchical WSN. We will present simulation results to demonstrate the gain in energy saving. Section 5 gives concluding remarks and discusses directions the work of this paper can be extended.

2 The Sensor Network Model

A wireless sensor network resembles a conventional parallel and distributed systems in many ways. However, several unique characteristics standout to call for redefinition, or modification, of the network model. Those characteristics include energy efficiency consideration, communication reliability, and global awareness of individual nodes, among others. Because of the wide diversity of sensor applications, it is hard to capture all characteristics in a single model.

In this paper, we will adopt, with slight modification, the WSN model called COSMOS (standing for Cluster-based heterOgeneouS MOdel for Sensor networks), proposed by Singh and Prasanna [12]. A WSN model aiming at large size and scalability, COSMOS features a cluster-based, hierarchical network architecture. It comprises of a large number of low power, low cost sensors, presumably distributed in a large physical environment. The distribution of sensors is close to uniform. That is, in each unit area there is a sensor with high likelihood. Sensors are organized into equal-sized, square-shaped clusters according to their spatial proximity. For each sensor cluster, there is a clusterhead, which is costlier, more powerful in computational capability and radio transmission range. The clusterheads of the whole WSN form a mesh-like topology. The sensors' main job is to collect first-hand, raw data, with or without some initial processing. The clusterheads perform more intensive, more complex tasks. It is at the clusterheads that the data of the sensor network get processed in a collaborative manner. Figure 1 illustrates the basic structure of the hierarchical WSN.

In Fig. 1, the sensors (represented by black squares) are almost evenly distributed in a two-dimensional terrain. Each unit area (or cell) contains one sensor with a high probability. There may be a few unit areas that have no sensors. A group of near-by sensors are organized into square-shaped clusters. At the center unit area of a cluster is stationed a clusterhead (represented by a bigger, black circle). For the purpose of energy saving, an ordinary sensor's communication capability is presumably very

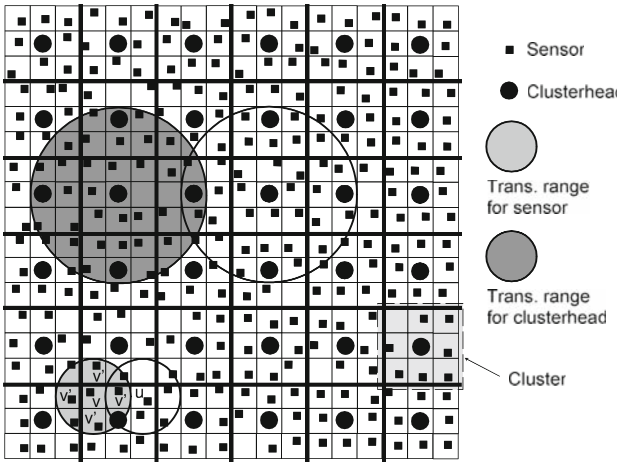


Fig. 1 A clustered, hierarchical wireless sensor network

limited, consuming as low as possible power in radio transmission. We assume it can only communicate directly with its four immediate neighboring sensors. For example in Fig. 1, sensor v can only guarantee reliable transmission to the four v' sensors. To communicate to sensor u, the message has to be relayed by one v' sensor.

On the other hand, a clusterhead is equipped with more powerful transceiver that can communicate with any node within the cluster. However, again for the purpose of energy saving, we do not assume a limitless, super powerful clusterhead that can send/receive radio messages to all sensors/clusterheads in the system. Beyond all nodes in its own cluster, the transmission range of a clusterhead is such that it can only guarantee reliable communication with the clusterheads of its four neighboring clusters. See Fig. 1.

For the communication mechanism, since a sensor has very limited radio range, if it wants to "actively" send message/data to its clusterhead, it can only do so by relaying through intermediate sensors (routing scheme in this context is another issue, which will not be addressed in this work). Most of the time the sensor data are "passively" picked up by its clusterhead. For analysis purpose, we quantify the energy dissipated by one round of sensor transmission to a simplified, normalized unit. Refer to the example in Fig. 1 again: If sensor v wants to send one unit of data to sensor u, 2 units of energy will be consumed—1 for transmission from v to v', 1 from v' to u. The clusterhead, we assume, can support multiple power states to transmit to sensors/clusterheads of different distances. We also assume that the clusterhead fetches a unit of data in one unit time.

We demonstrate the communication model in Fig. 2. In Fig. 2a, the darkest node represents the clusterhead for the central cluster, drawn in grey (for clear viewing, ordinary sensors are not drawn). In this particular example, a clusterhead is equipped with three different transmission power states, represented by the three circles in Fig. 2a. The largest transmission power allows a clusterhead to transmit to the four clusterheads of its neighboring clusters. The number in a cell stands for the clusterhead's power state level needed to reach that cell. Note that a rather strict standard is adopted here to guarantee reliable transmission: In the grey cluster, the four corner cells are not covered by a state-1 transmission because the circle does not completely cover the cell area. They will be properly covered by a state-2 transmission, incurring more power. The grey nodes in Fig. 2a are all clusterheads, of which four will be reached by the central clusterhead with a one-hop, state-3 transmission. Figure 2b summarizes the cells covered by the central clusterhead with various power states.

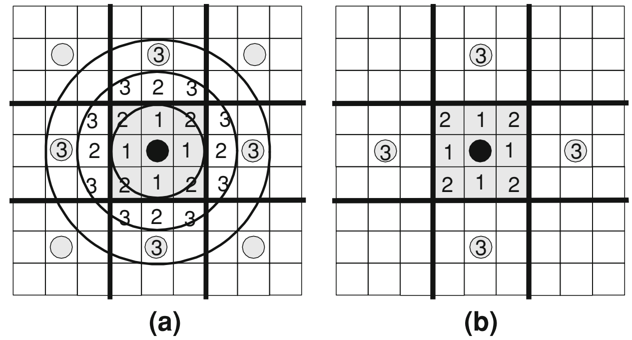


Fig. 2 (**a**) The center clusterhead uses different power states to transmit to sensors/clusterheads of different distances. (**b**) Cells the center clusterhead will transmit to with different power states

It is worth pointing out that the communication model we use for the analysis is a simplified abstraction of the behavior of real WSNs. When a more accurate model incorporating all realistic variables is beyond analysis, a simplified one has strong relevance because the analytical results, in spite of the fact that the model does not consider many realistic variables, provide an estimate or trend of what could happen in reality. The results from a simplified model can then be used as a guideline of the simulation design. The proposed scheme based on analysis can serve as a starting point of simulation.

3 A Power-efficient Clusterhead Assignment Scheme

A "super" cluster that contains all sensors would be desirable. However it is not feasible as the size of WSN grows larger. Considerations such as energy limitation, cost, and scalability make a single-centered WSN not only unfavorable, but also difficult to implement. The proposal of hierarchical organization of WSN [10, 12, 15] is to distribute the computational and managerial tasks to a group of clusterheads. The approach will reduce the communication traffic in network, and will allow the deployment of less powerful, lower priced processors to do the WSN's computational and managerial jobs in a collaborative manner. One basic question in constructing a hierarchical WSN is how to cluster the sensor network, or equivalently, how many clusterheads are to be used and where to position them.

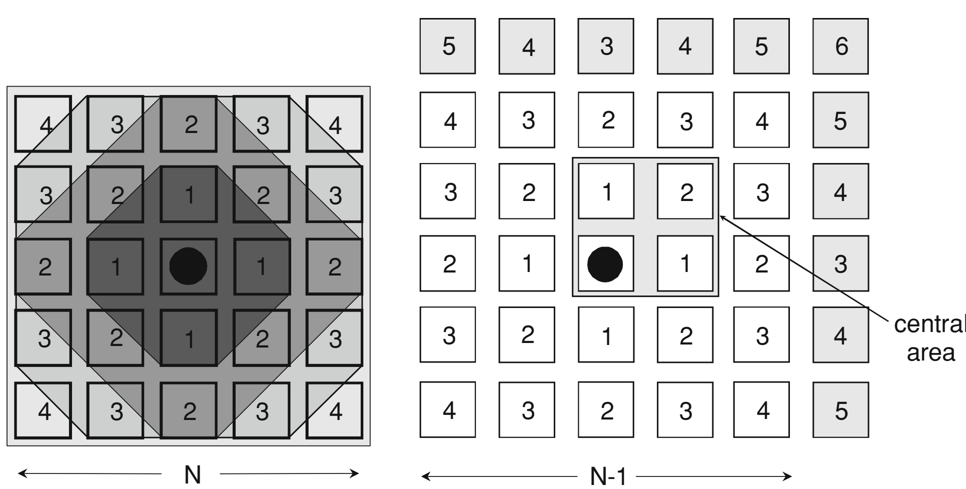
Due to the diversified nature of WSN's data processing tasks and concerns like cost effectiveness and system robustness, it is impossible even to define a comprehensively "optimal" architecture, let alone achieve it. An optimal, or asymptotically optimization is practical only in terms of narrowed optimization target. In this work, we will consider such a narrowly defined optimization target, i.e., we are trying to find a clusterhead assignment so that the WSN's overall battery power dissipation is minimized. The scenario we use to justify our assignment scheme is an operation that presumably requires most amount of energy: The central processor of the WSN needs to process data collected from all sensor nodes. We assume that the nature of the application allows "partial preprocessing" of data before they reach the central processor. There are many such data in both computational and managerial tasks. For instance, the aggregatable sensor data is of such nature. Another example is to get the sum of certain value from all sensors: It is not necessary for the central processor of the WSN to collect all addends before it performs the addition—partial sums can be obtained by clusterheads, and sent to the central processor. That will prevent the central processor from collecting all data from afar, reducing the energy use. It is in this context that we propose an optimal scheme for clustering the WSN.

The target is to find a hierarchical clustering, so that the data collection/processing task by the center station dissipates the minimum amount of energy overall. To formulate problems quantitatively for analysis, we assume a simple model for calculating battery consumption. It should be pointed out that the model is a normalized abstraction from vastly variable real scenarios. Refer to Fig. 2b again. Firstly, we use the battery state level to represent needed power to transmit to a cell. This representation is characteristic of the reality: The farther the sensor, the more power the clusterhead needs for transmission. Secondly, we assume each transmission round will collect data from one sensor. That is a simplification of real situations where multi-channel transmission/reception may be supported. However the results obtained from the single-channel model can be applied to multi-channel models with minor adaptation. With the above assumption, in Fig. 2b, if the center clusterhead wants to collect one round of data from its own cluster, a total of $1 \times 4 + 2 \times 4 = 12$ units of power will be consumed.

As has been stated, we will compare the power-saving gain of the proposed clustering scheme against the "one-cluster, one-center" approach. The one-center approach's power consumption can be illustrated in Fig. 3.

Suppose the WSN's square terrain contains N^2 cells, with dimensions $N \times N$. If the whole WSN has just one central station, it should be positioned at the central cell. In Fig. 3a, where N is odd, a real central cell exists as illustrated. The numbers in other cells are the power states needed to reach them from the center. The four shaded polygonal areas, from dark to light, indicate the properly covered cells by each power states. We point out again that power state is assigned to each cell in a very conservative manner: It is guaranteed that a cell will reliably receive the signal from the center station with the given power state.

In Fig. 3b, where N is even, there is no true central cell. Any one of the four nodes in the central "area" can be picked as the center station. Without loss of generality, we choose the lower-left cell to host the center station, as shown in Fig. 3b. With the cell for center station chosen,



(a) N odd: N = 5 **(b)** N even: N =6

Fig. 3 (**a**) A 5 × 5 terrain. At center is the central station (*dark circle*). Numbers in cells represent power states consumed communicating with them. (**b**) A 6 × 6 terrain. The dark circle at the "central area" is the central station the transmission power states to all cluster cells can be assigned following the same pattern as in Fig. 3a. We will give separate treatment for odd- and even-dimensioned terrains when calculating power consumption of one-center WSNs.

3.1 N is Odd

Refer to Fig. 4. Under our assumed communication model, the total power consumption for one round of (center station to all sensors) transmission is just the sum of all state numbers in the cluster.

Let $C_o(N)$ denote the total consumed power, where subscript "o" stands for odd. We have

$$C_o(N) = \underbrace{\overbrace{1\cdot1\cdot4}^{\text{cells of state 1}} + \overbrace{2\cdot2\cdot4}^{\text{cells of state 2}} + \overbrace{3\cdot3\cdot4}^{\text{cells of state 3}} + \cdots + \overbrace{((N-1)/2)\cdot((N-1)/2)\cdot4}^{\text{cells of state }(N-1)/2}}_{\text{all white cells in Fig. 4}}$$
$$+ \underbrace{\overbrace{(N-1)\cdot1\cdot4}^{\text{cells of state }N-1} + \overbrace{(N-2)\cdot2\cdot4}^{\text{cells of state }N-2} + \overbrace{(N-3)\cdot3\cdot4}^{\text{cells of state }N-3} + \cdots + \overbrace{(N-(N-1)/2)\cdot((N-1)/2)\cdot4}^{\text{cells of state }N-(N-1)/2}}_{\text{all grey cells in Fig. 4}}$$
$$= 4\sum_{i=1}^{\frac{N-1}{2}} i^2 + 4\sum_{i=1}^{\frac{N-1}{2}} (N-i)i$$
$$= 4N\sum_{i=1}^{\frac{N-1}{2}} i$$
$$= \frac{N^3-N}{2}$$

3.2 N is Even

Refer to Fig. 3b. When N is even, there is no true central cell. The lower-left one in the central area is chosen as the center station. The total cost, denoted as $C_e(N)$ ("e" for even), is $C_o(N-1)$ plus the cost of grey nodes.

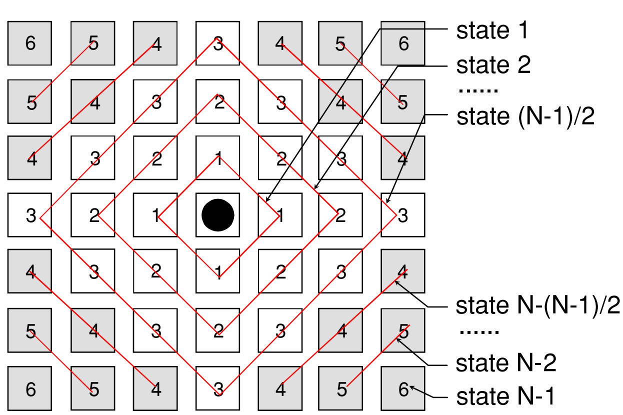


Fig. 4 Power calculation for odd dimensioned terrain

$$C_e(N) = \underbrace{\frac{(N-1)^3-(N-1)}{2}}_{C_o(N-1)} + \underbrace{2\cdot(N/2) + 4\sum_{i=\frac{N}{2}+1}^{N-1} i + 1\cdot N}_{\text{grey cells in Fig. 3b}}$$
$$= \frac{N^3}{2}$$

To summarize the preceding discussion, the total power cost $C(N)$ for an $N \times N$ terrain using one central station is

$$C(N) = \begin{cases} \frac{N^3-N}{2}, & N \text{ odd} \\ \frac{N^3}{2}, & N \text{ even} \end{cases} \quad (1)$$

(1) gives the total energy dissipation for the scenario that the one-station WSN wants to do one round of transmission with every sensor in the network. Using the same scenario, in the rest of this section we will derive an energy-efficient clusterhead assignment scheme for the hierarchical WSN.

In a hierarchical WSN design, the whole square terrain is divided into a set of smaller, square-shaped clusters. There is still a center station for the whole WSN, located at the center of the mesh composed of all clusterheads. The data collection of central station is performed in two phases. In the first phase, all clusterheads collect data from sensors in their own clusters. The data is aggregated and/or preliminarily processed in clusterheads. In the second phase, the WSN's center station collects data from all clusterheads. Figure 5 illustrates the structure of hierarchical WSN.

In Fig. 5, each square-shaped cluster consists of $x \times x$ cells. The whole WSN is divided into $(\frac{N}{x})^2$ clusters. Each cluster has a clusterhead located at the center. The $(\frac{N}{x})^2$ clusterheads form a mesh, and at the center of the mesh is the WSN's center station. But what is x, the size of the clusters? The choice of this size can affect many aspects of the WSN. However, as stated earlier, we will narrow our target and figure out an appropriate cluster size x

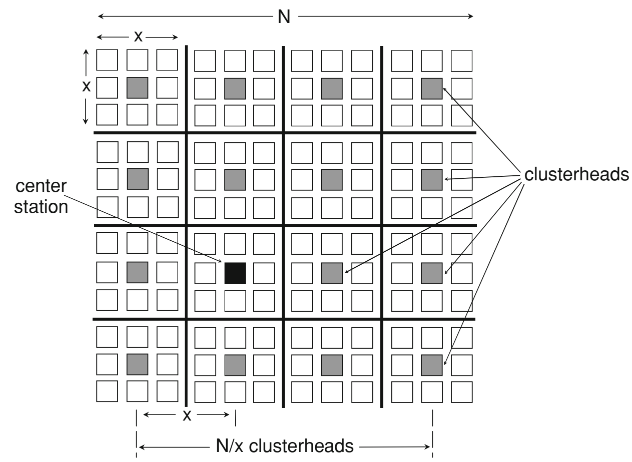


Fig. 5 The hierarchical WSN. The $N \times N$-cell terrain is divided into $(\frac{N}{x})^2$ $x \times x$ -cell clusters. The grey nodes are clusterheads, the darkest node is the center station of the WSN

favoring minimizing the power consumption incurred by communication.

Refer to Fig. 5 again. Suppose a cluster is of dimension $x \times x$, so that x divides N. Then by Eq. 1, the power consumption for a round of in-cluster communication is:

$$C(x) = \begin{cases} \frac{x^3 - x}{2}, & x \text{ odd} \\ \frac{x^3}{2}, & x \text{ even} \end{cases}$$

Since there are $(\frac{N}{x})^2$ clusters, the total power in *phase one* for all clusters is given by:

$$C_{\mathrm{I}}(N,x) = \begin{cases} \frac{1}{2}(x^3 - x) \cdot (\frac{N}{x})^2, & x \text{ odd} \\ \frac{1}{2}(x^3) \cdot (\frac{N}{x})^2, & x \text{ even} \end{cases} \quad (2)$$

As for the clusterheads, note that the $(\frac{N}{x})^2$ clusterheads form a squared mesh by themselves (the darker nodes in Fig. 5). So choosing the central or near-central cell among them as the center station (the darkest node in Fig. 5) will give the minimum power cost. However, the power state needed for transmission from center to the nearest clusterheads is x instead of 1; the transmission power from center to the second nearest clusterheads is $2x$, etc. Applying Eq. 1 again, the power for the mesh of clusterheads in *phase two* is given as follows:

$$C_{\mathrm{II}}(N,x) = \begin{cases} \frac{1}{2}\left((\frac{N}{x})^3 - \frac{N}{x}\right) \cdot x, & \frac{N}{x} \text{ odd} \\ \frac{1}{2}(\frac{N}{x})^3 \cdot x, & \frac{N}{x} \text{ even} \end{cases} \quad (3)$$

Combining (2) and (3), we arrive at the expression for total power consumption for the whole WSN system for one round of data collection/aggregation:

$$C_{\mathrm{total}}(N,x) = C_{\mathrm{I}}(N,x) + C(N,x)$$
$$= \begin{cases} \frac{1}{2}(x^3 - x) \cdot \left(\frac{N}{x}\right)^2 + \frac{1}{2}\left(\left(\frac{N}{x}\right)^3 - \frac{N}{x}\right) \cdot x = \frac{N^2x^3 - Nx^2 - N^2x + N^3}{2x^2}, & x \text{ odd}, \frac{N}{x} \text{ odd} \\ \frac{1}{2}(x^3 - x) \cdot \left(\frac{N}{x}\right)^2 + \frac{1}{2}\left(\frac{N}{x}\right)^3 \cdot x = \frac{N^2x^3 - N^2x + N^3}{2x^2}, & x \text{ odd}, \frac{N}{x} \text{ even} \\ \frac{1}{2}(x^3) \cdot \left(\frac{N}{x}\right)^2 + \frac{1}{2}\left(\left(\frac{N}{x}\right)^3 - \frac{N}{x}\right) \cdot x = \frac{N^2x^3 - Nx^2 + N^3}{2x^2}, & x \text{ even}, \frac{N}{x} \text{ odd} \\ \frac{1}{2}(x^3) \cdot \left(\frac{N}{x}\right)^2 + \frac{1}{2}\left(\frac{N}{x}\right)^3 \cdot x = \frac{N^2x^3 + N^3}{2x^2}, & x \text{ even}, \frac{N}{x} \text{ even} \end{cases}$$

There exists an optimal x to make the value of $C_{\mathrm{total}}(N, x)$ minimum. To obtain the optimal x, just take the derivative of $C_{\mathrm{total}}(N, x)$ with respect to x, denoted $C_{\mathrm{total}}(N,x)'_x$, and solve $C_{\mathrm{total}}(N,x)'_x = 0$ for x.

$$C_{\mathrm{total}}(N,x)_x = \begin{cases} \left(\frac{N^2x^3 - Nx^2 - N^2x + N^3}{2x^2}\right)'_x = \frac{N^2}{2} + \frac{N^2}{2x^2} - \frac{N^3}{x^3}, & x \text{ odd}, \frac{N}{x} \text{ odd} \\ \left(\frac{N^2x^3 - N^2x + N^3}{2x^2}\right)'_x = \frac{N^2}{2} + \frac{N^2}{2x^2} - \frac{N^3}{x^3}, & x \text{ odd}, \frac{N}{x} \text{ even} \\ \left(\frac{N^2x^3 - Nx^2 + N^3}{2x^2}\right)'_x = \frac{N^2}{2} - \frac{N^3}{x^3}, & x \text{ even}, \frac{N}{x} \text{ odd} \\ \left(\frac{N^2x^3 + N^3}{2x^2}\right)'_x = \frac{N^2}{2} - \frac{N^3}{x^3}, & x \text{ even}, \frac{N}{x} \text{ even} \end{cases}$$

Solving $\frac{N^2}{2} + \frac{N^2}{2x^2} - \frac{N^3}{x^3} = 0$ and $\frac{N^2}{2} - \frac{N^3}{x^3} = 0$, respectively, for x, and only taking the real root, we have

$$x = \begin{cases} \frac{\sqrt[3]{27N + 3\sqrt[2]{3} + 81N^2}}{3} - \frac{1}{\sqrt[3]{27N + 3\sqrt[2]{3} + 81N^2}}, & x \text{ odd} \\ \sqrt[3]{2N}, & x \text{ even} \end{cases}$$

The difference between $\sqrt[3]{2N}$ and $\left(\frac{\sqrt[3]{27N+3\sqrt[2]{3}+81N^2}}{3} - \frac{1}{\sqrt[3]{27N+3\sqrt[2]{3}+81N^2}}\right)$ is vanishingly small. So for all practical purposes, we can just use an integer close to $\sqrt[3]{2N}$ for the size of cluster to achieve the minimum total cost. We have the following proposition for the optimal cluster size in an $N \times N$-cell WSN.

Proposition 1 *In a hierarchical $N \times N$-cell WSN, if the clusters are of dimension $x \times x$, so that*

1. *x is as close to $\sqrt[3]{2N}$ as possible*
2. *x divides N*

then the system's total power consumption for one round of data collection/aggregation is minimum.

Figure 6 illustrates the level-1 cost (i.e., power incurred by all intra-cluster transmission), level-2 cost (i.e., power incurred by transmission among clusterheads), and the total power cost, as function of cluster size x. The example WSN size is $N = 72$. $\sqrt[3]{2N} = \sqrt[3]{144} \approx 5.24$. Then by Proposition 1, $x = 6$ will be chosen as the optimal cluster size. The total cost is 20,736, which is minimum.

The saving of power gained by this hierarchical scheme is quite substantial. The ratio of minimal hierarchical power cost versus non-hierarchical cost is (assuming even N, even x) given by

$$\frac{\left.\frac{N^2x^3+N^3}{2x^2}\right|_{x=\sqrt[3]{2N}}}{\left(\frac{N^3}{2}\right)} = \frac{3}{2}\sqrt[3]{\frac{2}{N^2}}$$

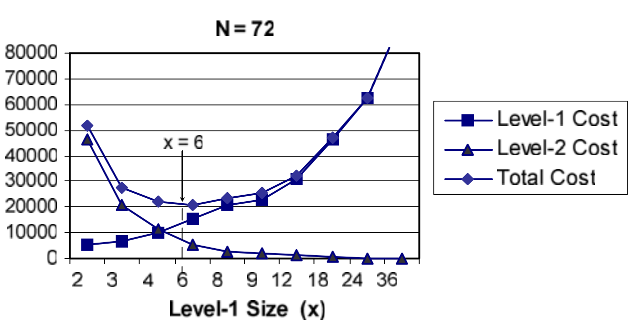


Fig. 6 Intra-cluster (Level-1), clusterheads (Level-2), and total costs as function of cluster size x. The original WSN size is $N = 72$. It can be seen that there exists a minimum total cost

which is ever decreasing as N grows. Figure 7 shows a comparison between minimum hierarchical cost and non-hierarchical cost. When $N = 10$, the min-hierarchical-cost/non-hierarchical-cost ratio is about 40%; when $N = 100$, less than 9%; when $N = 200$, less than 6%.

4 Experiments with the Hierarchical Scheme

Experimental simulation is an effective means to evaluate the competence of hierarchical schemes. Especially in the case of irregularly connected networks, it is the only instrument to definitely quantify the improvement brought by a specific hierarchy method. In the preceding section, we have proposed an energy-efficient clustering scheme for Wireless Sensor Networks. Analytically, the clustering scheme substantially saves the WSN's overall power consumption. However, for tractability, the preceding section dealt with hierarchical configuration of WSN only in ideal context . In this section, we will extend the theoretical result by performing experimental measurements. To show practical relevance of the proposed clustering, we will use the theoretical result as a guide to simulate hierarchical WSNs in more realistic settings.

In simulating the real-world WSNs, we do not assume that all cells in the terrain have a sensor; and we do not assume that in one round of data collection/aggregation, the clusterheads access each sensor exactly once. Figure 8 illustrates the simulation results.

In Fig. 8, the table on the left shows the costs for the ideal, "neat" scenario situation. That is, every cell in the $N \times N$ terrain has one sensor in it. The data in the table represent the power cost for one round of data collection by

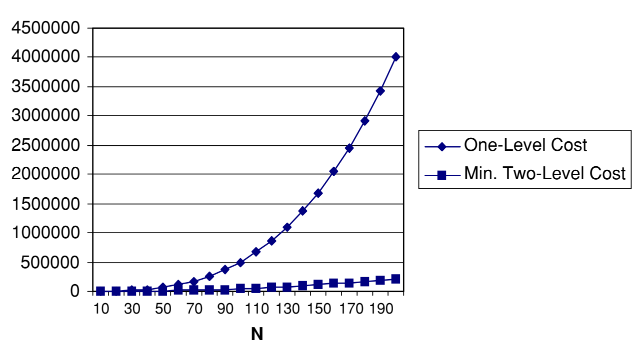


Fig. 7 Comparison of minimum hierarchical cost and non-hierarchical cost

Fig. 8 Non-hierarchical power cost versus minimum hierarchical cost

N	All Cells Have Sensors			Not All Cells Have Sensors		
	1-Level Cost	2-Level Cost	2-L Cost/1-L Ocst Ratio	1-Level Cost	2-Level Cost	2-L Cost/1-L Ocst Ratio
4	32	24	75.00%	15.90	12.29	77.31%
6	108	60	55.56%	53.50	29.40	54.96%
8	256	128	50.00%	129.55	65.43	50.51%
9	360	144	40.00%	177.05	72.37	40.87%
10	500	220	44.00%	243.23	109.78	45.13%
12	864	288	33.33%	426.57	141.36	33.14%
14	1372	532	38.78%	691.63	257.84	37.28%
15	1680	480	28.57%	824.38	237.59	28.82%
16	2048	640	31.25%	1015.03	321.50	31.67%
18	2916	756	25.93%	1493.31	394.01	26.38%
20	4000	1040	26.00%	1958.85	501.89	25.62%
21	4620	1092	23.64%	2332.10	547.72	23.49%
22	5324	1804	33.88%	2642.48	896.47	33.93%
24	6912	1584	22.92%	3420.16	799.59	23.38%
25	7800	1800	23.08%	3904.59	905.88	23.20%
26	8788	2860	32.54%	4387.45	1436.39	32.74%
27	9828	2052	20.88%	4929.19	1034.29	20.98%
28	10976	2240	20.41%	5486.56	1107.12	20.18%
30	13500	2700	20.00%	6722.50	1330.36	19.79%
32	16384	3072	18.75%	8166.13	1548.09	18.96%
33	17952	3432	19.12%	8968.02	1725.19	19.24%
34	19652	6052	30.80%	9722.38	2997.31	30.83%
35	21420	3780	17.65%	10717.66	1892.69	17.66%
36	23328	4032	17.28%	11654.96	2025.46	17.38%
38	27436	8284	30.19%	13777.50	4156.79	30.17%
39	29640	5304	17.89%	14811.24	2662.11	17.97%
40	32000	5200	16.25%	15948.14	2589.67	16.24%
42	37044	6468	17.46%	18571.23	3244.45	17.47%
44	42592	6512	15.29%	21276.15	3258.71	15.32%
45	45540	6660	14.62%	22827.62	3317.99	14.53%
46	48668	14260	29.30%	24188.19	7048.50	29.14%
48	55296	8064	14.58%	27746.51	4027.94	14.52%
49	58800	9408	16.00%	29401.25	4700.11	15.99%
50	62500	8500	13.60%	31280.33	4243.16	13.56%
51	66300	10812	16.31%	33017.20	5392.84	16.33%
52	70304	9776	13.91%	35105.59	4909.37	13.98%
54	78732	10908	13.85%	39408.60	5472.26	13.89%
55	83160	10560	12.70%	41604.14	5310.67	12.76%
56	87808	11760	13.39%	43879.45	5868.09	13.37%
57	92568	14592	15.76%	46386.85	7317.64	15.78%
58	97556	27724	28.42%	48788.75	13850.07	28.39%
60	108000	12960	12.00%	54196.25	6512.18	12.02%
62	119164	33604	28.20%	59353.96	16685.02	28.11%
63	124992	16128	12.90%	62438.83	8068.81	12.92%
64	131072	16384	12.50%	65609.34	8195.86	12.49%

center station from all sensors. “1-Level Cost” is the cost without clustering, whereas “2-Level Cost” represents the power cost with clustering. Making cluster size an integer in the neighborhood of $\sqrt[3]{2N}$ that divides N, the power cost is minimum.

The table on the right side of Fig. 8 is the simulation result for more realistic situations. Here we assume that a cell does not always have a sensor in it; or if there is a sensor, it is not always accessed in every round of data collection. Combining these two scenarios, each cell is assigned an independent probability of having a sensor. The power cost associated with each cell is now the original cost times the assigned probability. See Fig. 9 for an example. With this setting, we use cluster size $\sqrt[3]{2N}$, derived under ideal assumptions, for clustering the terrain. We want to see what cost reduction the clustering will bring about under this setting. The result can be viewed as the expected saving in power when adopting the 2-level clustering. The right table of Fig. 8 shows the average result for 100 simulations.

Figure 10 shows the comparison of costs and ratios for ideal and more realistic scenarios, respectively. The cost chart (the left one in Fig. 10) plots non-hierarchical (1-level) and hierarchical (2-level) costs for both situations. In hierarchical clustering, cluster size $\sqrt[3]{2N}$ is used for both ideal and realistic settings. It can be observed that costs for

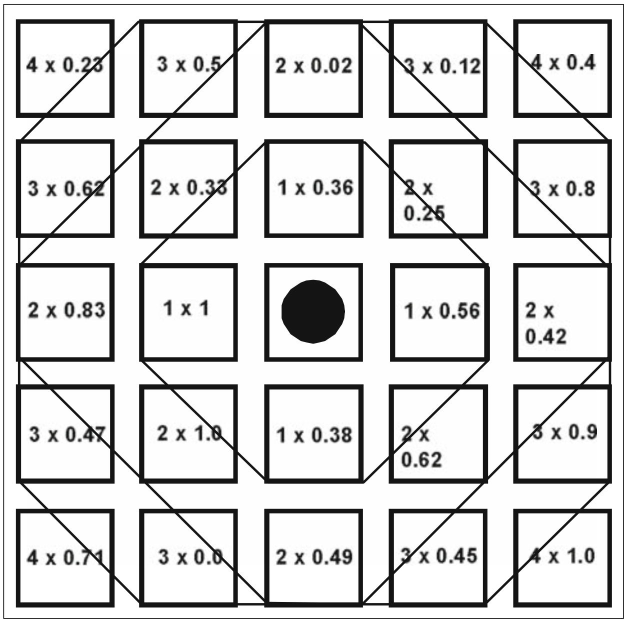


Fig. 9 Each cell has a probability of having a sensor. It represents the scenarios that (1) not all cells have a sensor in it; or (2) a sensor may not be accessed in every round of data collection/aggregation

the two settings follow the same pattern in terms of 1-level/2-level relationship. The ratio chart (the right one in Fig. 10) plots the ratios of 2-level-cost/1-level-cost for both ideal and realistic settings. We can see that reduction rates for the two scenarios are almost identical. What these experimental findings tell us is that the optimal cluster size $\sqrt[3]{2N}$, although derived from ideal setting, also works well for realistic situations.

Note that both cost and ratio charts in Fig. 10 show some "spikes" out of the normal decreasing pattern. These spikes in 2-level cost (and therefore in 2-level/1-level ratio) are caused by those terrain sizes (N) that can not produce an ideal cluster size, i.e., an integer number somewhere near $\sqrt[3]{2N}$ that divides N. When $\sqrt[3]{2N}$ does not evenly divide N, for some N the closest integer to $\sqrt[3]{2N}$ that can divide it is quite "far away" from $\sqrt[3]{2N}$ on either side. If that is the case, the total power cost could go up (only at that particular point, though) against the otherwise decreasing trend as N increases. However, the corresponding 2-level cost is still minimum for the given N.

We have simulated other possible scenarios using the $\sqrt[3]{2N}$ cluster size. We envision a situation in which some cells of the square-shaped terrain will never have sensors in them. This can cover the cases where the sensors' distribution does not constitute a nearly-square area (see Fig. 11).

Two results are presented in Fig. 12. In the left chart of Fig. 12, the simulated scenario is that 90% randomly selected cells have sensors with various probabilities, while the remaining 10% cells never have sensors. The power reduction (i.e., the ratio of 2-level-cost/1-level-cost) under this assumption and the ideal situation are compared in the chart. We see again that the reduction rates for the two scenarios are almost identical. (There are two curves in the chart, which are almost completely overlapping using the current scale. The slight difference between the two would be more visible with a larger scale.) Similar comparisons are done for cell-occupying percentages 80, 70%, etc., and all show the same pattern. The right chart of Fig. 12 shows the reduction rate comparison for cell-occupying percentage 50%.

5 Concluding Remarks

Power-efficiency is a very crucial issue in the design of wireless networked systems. We have studied the problem of assigning clusterheads in a hierarchical WSN toward the

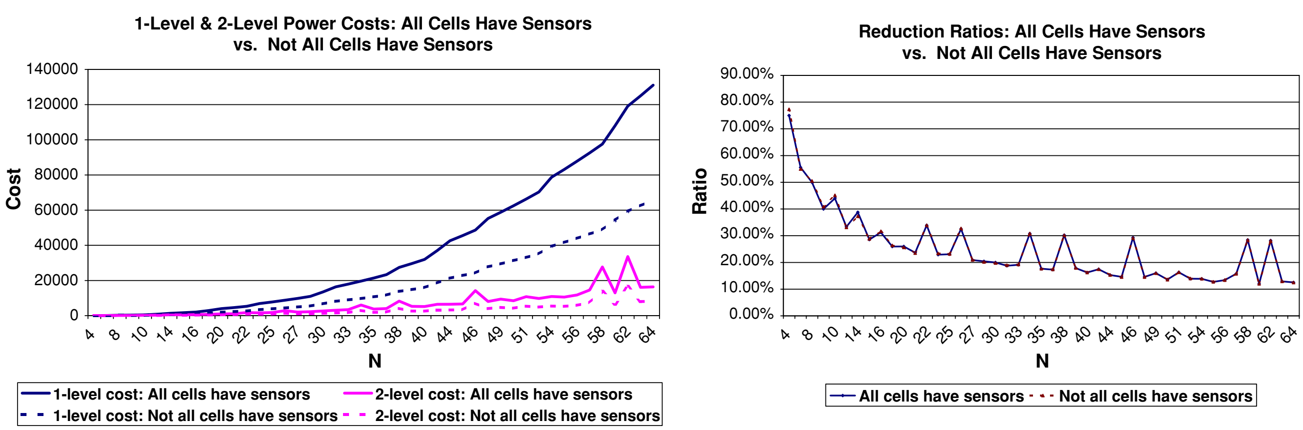


Fig. 10 Comparison of minimum hierarchical cost and non-hierarchical cost under ideal and realistic settings; and comparison of reduction rates for the two settings

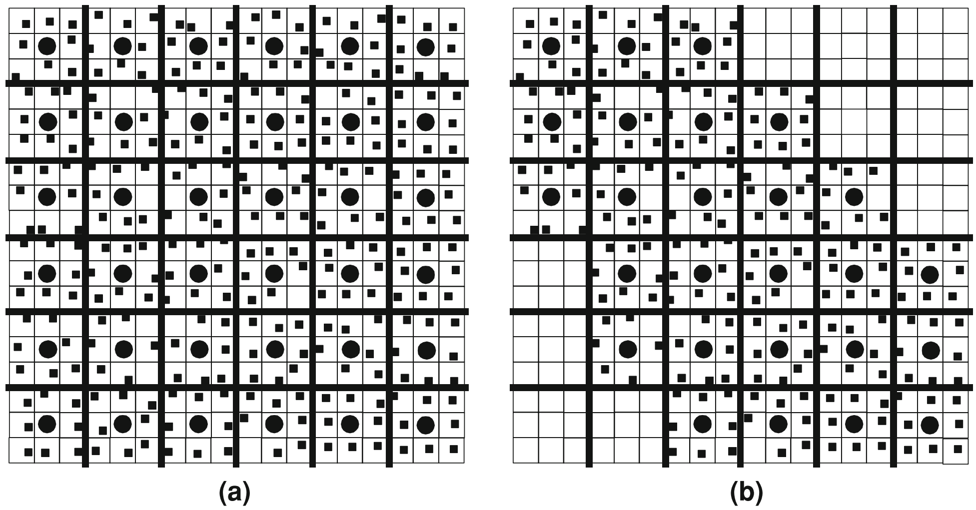


Fig. 11 (**a**) A square terrain. (**b**) A non-square terrain

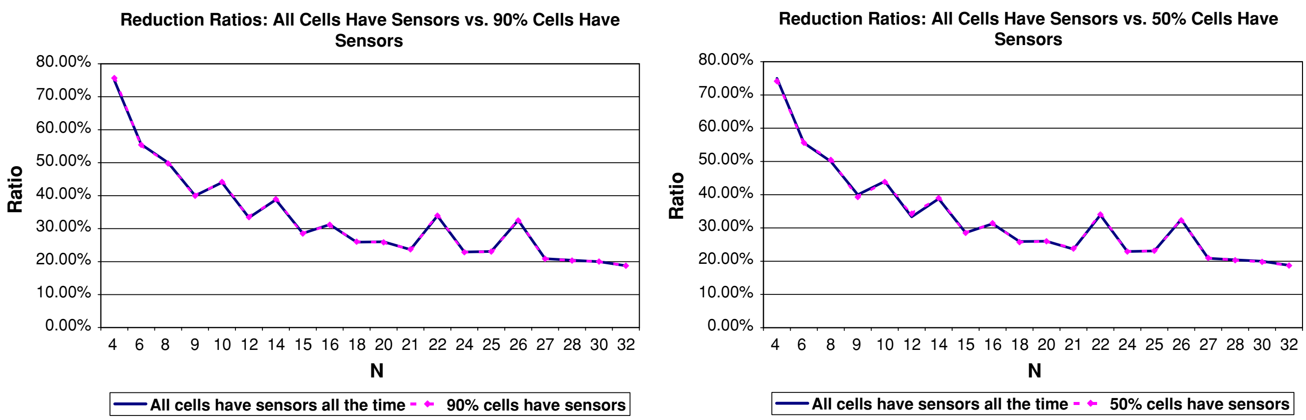


Fig. 12 Simulation of non-square terrains

end of minimizing the power consumed for transmission. Using the COSMOS hierarchical WSN model [12], we derived an analytically optimal clustering scheme, in the sense that the resulting 2-level WSN consumes minimal power. With the analytically optimal cluster size, we conducted simulation experiments for more realistic situations. The simulation results showed power reduction rate similar to the ideal situation, based on which the cluster size was determined.

Power conservation is a problem that has been extensively addressed in research of wireless networks. There exist many open problems regarding this issue. We can see some obvious directions to which the work of this paper can be immediately extended. For example, in our work, when the analytical cluster size was derived, we assumed a rather simple communication model, not only for tractability reason, but also for the lack of a statistical model that better reflects the realistic transmission activities. Finding an appropriate communication model that's more realistic as well as facilitating tractability would greatly increase the practical relevance of the hierarchical schemes.

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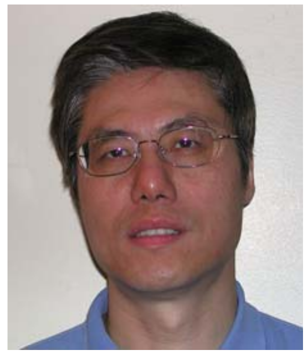
Author Biography



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