On the Planning of Wireless Sensor Networks: Energy-Efficient Clustering under the Joint Routing and Coverage Constraint

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Abstract—Minimizing energy dissipation and maximizing network lifetime are important issues in the design of applications and protocols for sensor networks. Energy-efficient sensor state planning consists in finding an optimal assignment of states to sensors in order to maximize network lifetime. For example, in area surveillance applications, only an optimal subset of sensors that fully covers the monitored area can be switched on while the other sensors are turned off. In this paper, we address the optimal planning of sensors' states in cluster-based sensor networks. Typically, any sensor can be turned on, turned off, or promoted cluster head, and a different power consumption level is associated with each of these states. We seek an energy-optimal topology that maximizes network lifetime while ensuring simultaneously full area coverage and sensor connectivity to cluster heads, which are constrained to form a spanning tree used as a routing topology. First, we formulate this problem as an Integer Linear Programming model that we prove NP-Complete. Then, we implement a Tabu search heuristic to tackle the exponentially increasing computation time of the exact resolution. Experimental results show that the proposed heuristic provides near-optimal network lifetime values within low computation times, which is, in practice, suitable for large-sized sensor networks.

Index Terms—Wireless sensor networks (WSNs), coverage, clustering, routing, network lifetime, energy efficiency, optimization, mathematical programming, Tabu search heuristic.

1 Introduction

Wireless sensor networks (WSNs) consist of a large number of limited capability (power and processing) MicroElectroMechanical Systems (MEMS) capable of measuring and reporting physical variables related to their environment. In surveillance applications, sensors are deployed in a certain field to detect and report events like presence, movement, or intrusion in the monitored area [1]. As depicted in Fig. 1, data collected by sensors are transmitted to a special node equipped with higher energy and processing capabilities called "processing node" (PN) or *"sink"* [1]. The PN collects, filters, and compiles data sent by sensors in order to extract useful information. Due to their energy constraints, wireless sensors usually have a limited transmission range, making multihop data routing toward the PN more energy efficient than direct transmission (one hop). Energy conservation in WSN is critical and has been addressed by substantial research [2], [3]. Generally, energy conservation is dealt with on five different levels [1], [2]:

1. efficient scheduling of sensor states to alternate between sleep and active modes;
2. energy-efficient routing, clustering, and data aggregation;
3. efficient control of transmission power to ensure an optimal trade-off between energy consumption and connectivity;
4. data compression (source coding) to reduce the amount of uselessly transmitted data;
5. efficient channel access and packet retransmission protocols on the Data Link Layer.

The scope of this paper includes both the first and the second levels. We address the global problem of maximizing network lifetime under the joint clustering, routing, and coverage constraint. We consider a sensor network that is deployed in a certain area A to monitor some given events. When the network is dense, sensing ranges of neighbor sensors usually overlap. This means that when an event occurs at a point P of A, it will be detected and reported by all the sensors whose sensing range encompasses P. This redundant transmission results in useless energy consumption. To save network energy and increase its lifetime, we propose to switch on only a subset of sensors that covers A while all other sensors are turned off. Fig. 2 depicts an example of full-covering sensor set. On the other hand, clustering has been proven energy efficient in WSN [4], [5], [6]. In cluster-based WSN, sensors are organized in clusters each having one sensor promoted as CH. All non-CH nodes transmit their data to their CH, which routes it to the remote PN. Clustering can provide for substantial energy saving [4], [5], [6], [7] since only CH sensors are involved in routing and relaying data. Moreover, clustering alleviates bandwidth, enables its reuse, and can, thus, increase system capacity [8]. Besides, the fact that only the CH is transmitting information out of the cluster helps avoid collisions between the sensors inside the cluster and helps avoid the

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Manuscript received 26 June 2008; revised 20 Nov. 2008; accepted 9 Dec. 2008; published online 6 Jan. 2009.
For information on obtaining reprints of this article, please send e-mail to: tmc@computer.org, and reference IEEECS Log Number TMC-2008-06-0251.
Digital Object Identifier no. 10.1109/TMC.2009.16.

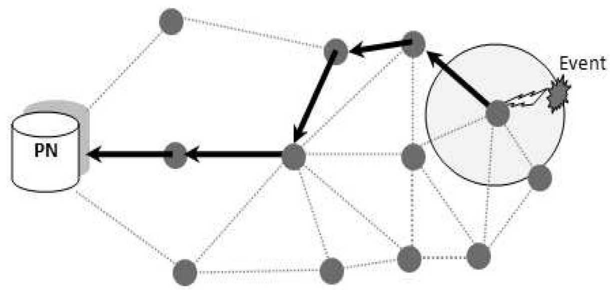

Fig. 1. Multihop routing of collected data.

uncovered hole problem [9]. However, since CHs consume more energy in aggregating and routing data, it is important to have an energy-efficient mechanism for CHs' election and rotation [8], [10]. In flat networks, sensors route data to the PN through their peer sensors using one of the many routing protocols proposed in the literature [4]. In contrast, in clustered networks, CHs transmit aggregated data to the PN, either directly (one hop) [10] or in multihop [11]. For the sake of minimizing energy consumption, both optimal number and optimal placement of CHs have to be sought.

In a cluster-based monitoring sensor network, any energy-efficient sensor scheduling mechanism has to guarantee a certain area coverage rate. Besides, the connectivity of every sensor to a CH has to be ensured at any time. Furthermore, for data to be routed from any CH to the PN, all CHs have to belong to a single connected graph. Hence, for sensors' states allocation to be optimal, coverage, connectivity of sensors to CHs, and routing have to be taken into account within the same global planning process. When coverage and connectivity are dealt with separately, the obtained configuration may not be optimal. For example, an optimal covering subset of sensors can fail to guarantee network connectivity because some nodes are switched off or the optimally designated CHs may belong to the set of switched-off sensors.

Many papers addressed separately energy-efficient routing [4], clustering [5], [6], and area coverage [2], [12], [13], [14]. Many other works [15], [16] addressed the integrated problem of maintaining area coverage and network connectivity but only on flat networks and did not take advantage of the potential energy saving and ease of manageability of cluster-based networks [1], [6], [7]. To the best of our knowledge, the problem of maximizing sensor network lifetime under the integrated constraint of clustering, coverage, and routing has not been addressed within the same global optimization process. In this paper, we address the optimal planning of cluster-based WSN under the joint routing and coverage constraint. In our architecture, any sensor can be active, switched off, or upraised as CH, and only CHs can route data. We seek an optimal allocation of states to sensors, which maximizes network lifetime, while ensuring simultaneously full area coverage, connectivity of every sensor to a CH, and connectivity of the overlay network composed of CHs.

This paper is organized as follows: In the next section, we present some related work. In Section 3, we outline our problem and enumerate our assumptions. In Section 4, we mathematically formulate our problem as an Integer Linear Programming (ILP) model. In Section 5, we present our resolution method based on a Tabu search algorithm. In Section 6, we discuss our simulation results. Finally, Section 7 concludes this paper and points out some future directions.

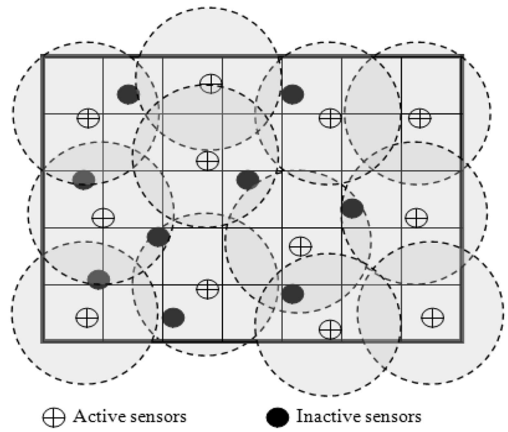

Fig. 2. A full-covering sensor set.

2 Related Work

The problem of maintaining both area coverage and network connectivity under energy constraint in WSN has been extensively addressed in the literature and many protocols were proposed to alternate sensor states between active and sleep in order to maximize network lifetime. For example, Xing et al. [15] provide a geometric analysis of the relationship between coverage and connectivity, and propose the Coverage Configuration Protocol (CCP) that dynamically configures the network to guarantee different degrees of coverage depending on the application requirements. In CCP, every node decides its state (*Active* or *Sleep*) based on the coverage degree of the intersection points of its sensing circle with those of its neighbors. When coupled with any connectivity maintenance protocol, CCP offers connectivity and K-coverage. Lu et al. [17] present Scalable Coverage Maintenance (SCOM), a localized coverage maintenance algorithm where sensors use the same redundancy eligibility rule as in [15] to decide whether to turn on or turn off. SCOM implements, for each sensor, a back-off timer proportional to its residual energy. The back-off timer allows sensors with lower residual energies to decide about their states before sensors with more energy, making them more likely to turn off than the other sensors, if they find themselves redundant. Chamam and Pierre [18] propose a centralized heuristic which dynamically calculates a near-optimal subset of sensors that guarantees a predefined coverage rate while ensuring network connectivity when the transmission range is greater than or equal to twice the sensing range. Yan et al. [16] propose to schedule sensors' activities (*Active/Sleep*) so that every point in a grid-monitored area is covered at any time. Neighbor sensors exchange a random reference time T_{ref} within cyclic rounds of constant duration T and decide to be active for a certain time duration within T. The round period T is equally shared among all the neighbor sensors that cover a common grid. Even though the proposed schedule balances consumed energy over neighbor nodes, it does not take into account the residual energy of sensors when calculating the activation time period of every node, which makes nodes with less residual energy more prone to expiration. However, all the works cited above do not address cluster-based architectures. Cluster formation is typically based on the energy reserve of sensors and sensors proximity to the cluster head [5], [6]. Energy-efficient cluster-based routing algorithms for WSN have been widely addressed in literature [4]. For instance, Low-Energy Adaptive Clustering Hierarchy (LEACH) [10], one of the most popular hierarchical routing algorithms for WSN, proposes to form clusters of sensor nodes based on the received signal strength and use local cluster heads as routers to the sink. This saves energy since the transmissions will only be operated by cluster heads rather than all sensor nodes. Even though LEACH is completely distributed, it uses single-hop communication between cluster heads and the sink, which is energy consuming and not applicable to networks deployed in large regions. Power-Efficient GAthering in Sensor Information Systems (PEGASIS) [19] and its variant Hierarchical-PEGASIS are two improvements of LEACH. Rather than forming multiple clusters, PEGASIS forms chains of sensor nodes so that each node transmits to and receives from a neighbor and only one node is selected from that chain to transmit to the PN. But still, communication between the elected CH and the PN is made in one hop, which is not suitable for large networks. Energy-efficient sensor state scheduling mechanisms in cluster-based WSN also raised much interest in the research community. For example, Yao and Giannakis [8] proposed a scheduling algorithm for the one-level-clustered WSN, where sensors have different data sequence lengths to transmit within a period of time T. The authors propose an Inverse-Log algorithm that finds, for every sensor, a set of optimal time allocations that minimizes the dissipated energy of the whole network over the period T. However, all sensors are activated during the time period T and no coverage constraint is considered. Besides temporal scheduling, other publications propose a spatial scheduling scheme based on the selective activation of sensors to maximize network lifetime [2], [20], [21]. Tian and Georganas [21] propose a localized algorithm that finds an optimal subset of sensors ensuring full area coverage or, if not possible, the least uncovered points. If the whole range covered by a sensor is covered by a subset of its neighbors, then the sensor decides to turn off. A random back-off time ensures that two nodes do not make the decision to turn off at the same time. When implemented over LEACH [10], the protocol proposed in [21] shows some energy saving. However, this protocol is not optimal because of the uncontrolled coverage redundancy due to the random aspect of switch on/off of sensors. In [20], sensors' sensing ranges follow a certain distribution derived from the channel characteristics and the log-normal path loss. An event occurring outside a certain range is still detected with a corresponding probability. The cumulative detection probabilities are shown to increase the mean area coverage which obviously decreases the number of sensors activated within the covering subset, thus reducing the consumed energy. However, the proposed algorithm is not optimal because it only takes into account each sensor's range and not its residual energy making nodes with very little residual energies prone to expiration. Hwang et al. [9] propose a cluster-based coverage-preserved node scheduling scheme. This mechanism assumes a dense network and assigns states (*Active, Sleep, Cluster head)* to sensors in a distributed and self-organized manner. The algorithm starts by dividing sensors into clusters and defines, for each cluster, a number of sponsor sensor sets that may be turned on simultaneously. Only one among the computed sponsor sets is elected to be turned on until it completely runs out of energy. Even though Hwang et al. [9] provide an efficient coverage and clustering mechanism, they assume that sensed data are routed to the sink in one hop, which may be energy intensive for the relay nodes.

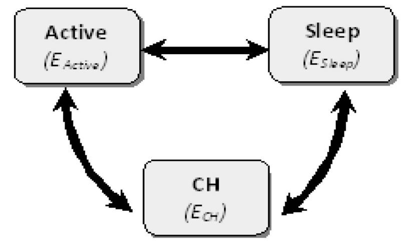

Fig. 3. Sensor states.

3 Problem Statement and Assumptions

In this paper, we consider a WSN deployed in an area A to monitor certain critical activities or events. As shown in [3], for the case of Rockwell's WINS seismic sensors, a sensor's radio can be in one of the following four activity modes, characterized by their respective power consumptions: *Transmit* (0.38-0.7 W), *Receive* (0.36 W), *Idle* (0.34 W), and *Sleep* (0.03 W). We note that when sensors are transmitting, receiving, or idle, they have roughly the same energy consumption and can then be associated to a same state, *Active*, in which the sensor's radio is switched on.

Moreover, in this paper, we consider a cluster-based topology in which CHs route the data they receive from the non-CH sensors of their cluster to the PN through an overlay network solely composed of CHs. CH election and cluster formation are very important issues that deeply affect network lifetime of WSN and different approaches exist to implement these stages. For example, it is possible to use a fixed distribution of the sensor nodes and CHs, or use a dynamic algorithm for CH election. If CHs were chosen a priori and fixed throughout the system lifetime, they would quickly exhaust all their energy making them no longer operational. In this work, we propose to dynamically designate the set of CHs according to their residual energies, their distance to their neighboring non-CH active nodes, and their position within the graph formed by CHs. As depicted in Fig. 3, we will consider, without loss of generality, that each sensor can be in one of the three states: *Sleep*, *Active,* and *Cluster Head (CH)* having, respectively, power consumptions E_{Sleep}, E_{Active}, and E_{CH} per time unit, where $E_{Sleep} \ll E_{Active} < E_{CH}$.

To control energy dissipation of the sensors that perform data relaying, we restrict the routing task to CHs. For this, there must exist a route from any CH to the PN. The most straightforward solution for that is to have a connected graph linking all the CHs. In our problem modeling, we propose that any admissible configuration must exhibit a spanning tree connecting all CHs, as shown in Fig. 4. This

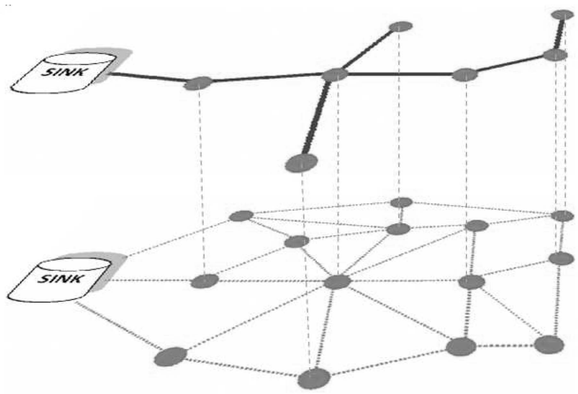

Fig. 4. Overlay network composed of the selected cluster heads.

makes the overlay network formed by the CHs sufficient to route data from any sensor toward the PN. The spanning tree construction is explained in the next section.

On the other hand, we assume that all sensors have the same sensing range R_s and that their detection model follows a binary probability function, also called *Disk model* [2], [15], in which an $Active$ sensor i detects any event that occurs within its sensing range R_s with the same probability $P_d = 1$, whatever the distance from the event is. And any event occurring outside R_s is not detected by i. Let us note that this binary probability sensing model is a simplified representation of a sensor's detection probability and it does not necessarily reflect the received signal loss model on a real wireless channel. In fact, on a real wireless channel, because of signal fading and interference, events occurring far away from a sensor are less likely to be detected than events occurring close to it. In other words, an event occurring outside a sensor's range is still detected with a certain probability which decreases when the distance to the sensor increases. Many papers in the literature addressed probabilistic coverage in wireless sensor networks [20], [22] and proposed coverage protocols based on this model. However, to simplify the representation of the sensing model, substantial work in the literature [2], [15], [23] make the assumption of disk model. In this paper, we also make this simplifying assumption but we will show later that our optimization model and our proposed heuristic can be easily adapted to handle probabilistic coverage.

Definition 1. *A set of sensors S_c is a covering set of area A if and only if $\forall$ point $P \in A$, $\exists\, i \in S_c$ such as i covers P.*

In critical surveillance applications, it is important to guarantee that the monitored area is fully covered by sensors at every instant of the network lifetime. Hence, in our problem, the optimal network configuration must

- contain a full-covering set of active sensors;
- contain a set of CHs so that every sensor is connected to a CH;
- ensure that all CHs belong to a spanning tree over which data will be routed toward the PN.

Our objective is to find the network-lifetime-optimal allocation of sensors' states (*Active, Sleep, CH)* that meets these three conditions. Before modeling our problem, we make the following assumptions:

1. Each sensor has a unique ID, known to the PN and to the sensor itself.
2. The position of each sensor is fixed and known to the PN. The location information can be obtained either through a Global Positioning System (GPS), as assumed in [2] (but this technique is still expensive due to the high cost of placing a GPS on each sensor), or using one of the many GPS-free localization techniques proposed in the literature [24], [25], [26]. However, in this paper, we do not specifically address any localization technique and assume that, whatever the localization technique used, sensors' location information is available at the PN.
3. Active sensors capture events occurring in their sensing range and transmit data associated with these events straightaway, without any buffering, because sensors are usually not equipped with large (and costly) buffers.
4. All sensors have the same sensing range R_s and the same transmission range R_t. All CHs have the same transmission range $R_t^{CH} > R_t$.
5. Only the CHs can perform data routing. Routing over the overlay network composed of CHs can be performed using one of the energy-efficient routing protocols for WSN proposed in the literature [4]. However, we do not address any specific routing protocol, we only guarantee the existence of a routing topology.
6. Each sensor has an initial energy E_0. The PN has no energy limitation. Besides, we assume that, when a sensor is $Active$, it has a constant energy dissipation during a unit of time, no matter how the events' distribution is.
7. The network is dense enough so that when all the sensors are *Active*, the monitored area is fully covered. Besides, we assume that the graph representing the sensor network is connected (two sensors being connected when they are within the transmission range of each other).
8. Network lifetime is defined as the time separating the instant the network starts operating and the instant at which the network cannot be covered anymore because of the expiration of some nodes.
9. We assume ideal MAC layer conditions, i.e., perfect transmission of data on a node-to-node wireless link.
10. We assume that sensors have ideal sensing capabilities, i.e., inside the sensing range, the quality of sensing does not depend on the distance from the sensor.

4 Problem Modeling

Our problem consists in finding the optimal allocation of states to sensors, which maximizes network lifetime under the integrated constraint of coverage, clustering, and routing. We call this problem **OPT-ALL-RCC**. To maximize network lifetime, we need a trade-off between total energy consumption and energy balancing among sensors. For example, to ensure area coverage, we would prefer to activate more sensors having higher residual energy (and consuming a higher total energy) than few sensors having little residual energy (consuming less total energy but more prone to expiration). On the other hand, any admissible

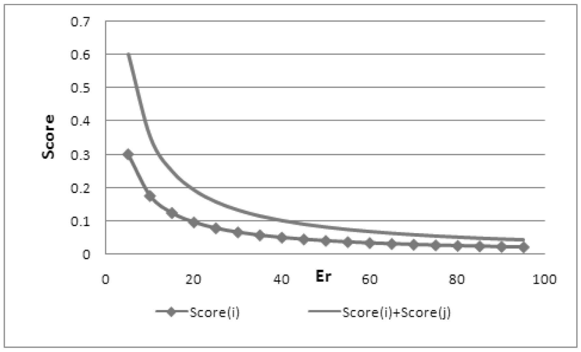

Fig. 5. Shape of the score function.

solution of our model has to ensure full coverage of the monitored area and the existence of a spanning tree connecting all CHs. To model this problem, we first define the following sets and constants:

- Let $S = \{1..N\}$ be the set of sensors.
- Let $C = \{1..M\}$ be the set of cells composing the monitored area.
- Let $\forall\, i = 1..|S|,\ \forall\, j = 1..|S|, \forall\, c = 1..|C|$,

$$d_{ij} = \begin{cases} 1 & \text{if sensor } i \text{ can reach sensor } j \text{ in one hop} \\ 0 & \text{else,} \end{cases}$$

$$D_{ij} = \begin{cases} 1 & \text{if CH } i \text{ can reach CH } j \text{ in one hop} \\ 0 & \text{else,} \end{cases}$$

$$\rho_{ic} = \begin{cases} 1 & \text{if sensor } i \text{ covers cell } c \\ 0 & \text{else.} \end{cases}$$

Then, we define our binary decision variables $\forall\, i = 1..|S|$, $\forall\, j = 1..|S|$:

$$X_i = \begin{cases} 1 & \text{if sensor } i \text{ is } \textit{Active} \\ 0 & \text{else,} \end{cases}$$

$$Y_i = \begin{cases} 1 & \text{if sensor } i \text{ is a CH} \\ 0 & \text{else,} \end{cases}$$

$$Z_{ij} = \begin{cases} 1 & \text{if sensor } i \text{ is connected to CH } j \\ 0 & \text{else,} \end{cases}$$

$$W_{ij} = \begin{cases} 1 & \text{if CH } i \text{ is connected to CH } j \text{ within} \\ & \text{a spanning tree} \\ 0 & \text{else.} \end{cases}$$

To balance energy consumption among nodes, we choose to minimize an objective function that is a linear combination of sensors scores. The score of a sensor i is defined by

$$Score(i) = Log\left(1 + \frac{Ed_i}{Er_i}\right),$$

where

$$Ed_i = \begin{cases} E_{Active} & \text{if sensor } i \text{ is } \textit{Active} \text{ but not CH} \\ E_{CH} & \text{if sensor } i \text{ is CH} \\ E_{Sleep} \approx 0 & \text{else.} \end{cases}$$

As shown in Fig. 5, the logarithmic nature of this score function will tend to accentuate the importance of the residual energy when the latter is small and will give more importance to the dissipated energy when the residual energy is high enough. In other words, when the residual energy is low, sensors will be selected essentially according to their residual energies, favoring the activation of sensors having relatively high residual energy and when the residual energy is relatively high, the optimal solution will tend to activate as less sensors as possible. Thus, we can model our problem by the following optimization system:

Minimize:

$$\sum_{i=1}^{|S|} Y_i.Log\left(1 + \frac{E_{CH}}{Er_i}\right) + (X_i - Y_i).Log\left(1 + \frac{E_{Active}}{Er_i}\right). \quad (1a)$$

Subject to:

$$\forall\, c = 1..|C|,\ \sum_{i=1}^{|S|} X_i.\rho_{ic} \geq 1, \quad (1b)$$

$$\forall\, i = 1..|S|,\ Y_i \leq X_i, \quad (1c)$$

$$\sum_{i=1}^{|S|} Y_i.d_{i0} \geq 1, \quad (1d)$$

$$\forall\, i = 1..|S|,\ \forall\, j = 1..|S|,\ j \neq i,\ Z_{ij} \leq X_i - Y_i, \quad (1e)$$

$$\forall\, i = 1..|S|,\ \forall\, j = 1..|S|,\ j \neq i,\ Z_{ij} \leq Y_j, \quad (1f)$$

$$\forall\, i = 1..|S|,\ \forall\, j = 1..|S|,\ j \neq i,\ Z_{ij} \leq d_{ij}, \quad (1g)$$

$$\forall\, i = 1..|S|,\ \sum_{\substack{j=1 \\ j\neq i}}^{|S|} Z_{ij} + Y_i = X_i, \quad (1h)$$

$$\forall\, j = 1..|S|,\ \sum_{\substack{i=1 \\ j\neq i}}^{|S|} Z_{ij} \leq N_{max}, \quad (1i)$$

$$\forall\, i = 1..|S|,\ \forall\, j = 1..|S|,\ j \neq i,\ W_{ij} \leq Y_i, \quad (1j)$$

$$\forall\, i = 1..|S|,\ \forall\, j = 1..|S|,\ j \neq i,\ W_{ij} \leq Y_j, \quad (1k)$$

$$\forall\, i = 1..|S|,\ \forall\, j = 1..|S|,\ j \neq i,\ W_{ij} \leq D_{ij}, \quad (1l)$$

$$\forall\, H \subseteq S,\ \forall\, s \in H,\ \sum_{j\in H} \sum_{\substack{k\in H \\ k>j}} W_{jk} \leq \left(\sum_{i\in H} Y_i\right) - Y_s, \quad (1m)$$

$$\sum_{j\in|S|} \sum_{\substack{k\in S \\ k>j}} W_{jk} = \sum_{j\in S} Y_j - 1, \quad (1n)$$

$$\mathbf{X}, \mathbf{Y} \in \{0,1\}^{|S|}, \mathbf{Z}, \mathbf{W} \in \{0,1\}^{|S|^2}. \quad (1o)$$

The expression of the objective function (1a) aims at balancing the energy consumption over the network. Equations (1b)-(1o) are the model constraints. Constraint (1b) guarantees a full coverage of the monitored area such that every elementary cell is covered by at least one *Active* sensor. Let us note here that this coverage constraint is valid under the assumption of binary probability (disk) sensing model, where every cell is either covered by a sensor (if it is located inside its sensing range) or not covered at all (if it is outside that sensing range). With probabilistic coverage, the coverage constraint must ensure that every cell is covered up to a certain predefined coverage rate. Hence, the constraint (1b) should be replaced with

$$\forall\, c = 1..|C|,\ Prob\ (c \text{ is covered}) \geq cov\_rate, \tag{2}$$

where cov_rate is a predefined threshold coverage rate. Let $P = \{P_{ic}\}$ be a coverage probability matrix known a priori, where $P_{ic} =$ probability that sensor i covers cell c. Then, (2) is equivalent to

$$\forall\, c = 1..|C|,\ 1 - \prod_{i=1..|S|} (1 - X_i.P_{ic}) \geq cov\_rat. \tag{3}$$

Once linearized, the new coverage constraint (3) will replace constraint (1b) in the above model to have it handle probabilistic coverage.

The rest of our constraints are as follows: constraint (1b) ensures that there exists at least a CH located one hop away from the PN. Constraints (1e)-(1h) ensure that every *Active* and non-CH sensor is connected to at least one CH within its range. Constraint (1i) gives an upper bound on clusters' sizes. Equations (1j)-(1n) describe the routing constraint ensuring that the overlay network composed of CHs is connected, and hence, there exists a tree-like partial subgraph. Equations (1o) are the integrality constraints. To ensure that a spanning tree connecting all the CHs exists in any solution, constraints (1m) and (1n) require the enumeration of all the subsets of S. Even though these constraints represent the theoretical conditions to have a spanning tree in any graph (no cycles and a connected graph), they quickly result in a combinatorial explosion of the number of constraints due to the exponentially increasing number of subsets of S. To circumvent this problem, we will proceed differently: we represent the routing constraint of our problem as a multiflow routing problem. We consider that a virtual flow has to be routed from any CH to, at least, one CH which is one hop from the sink. Indeed, the optimal graph configuration that allows a flow to be routed between any pair of nodes of a connected graph where links have infinite capacity is the minimal-cost spanning tree. To model this virtual flow routing problem, we define a binary variable representing the use of the wireless link lk to convey a flow (i, j), where i, j, k, and l are CHs and i, j are, respectively, the source and destination of the flow. Let

$$\begin{aligned}&\forall\, i,j,k,l \in \{1..|S|\}, i \neq j, k \neq l,\\ &V_{ij}^{kl} = \begin{cases} 1 & \text{if flow } (i,j) \text{ passes through the link } kl\\ 0 & \text{else.}\end{cases}\end{aligned} \tag{4}$$

The following constraints ensure that the network contains a spanning tree connecting all CHs:

$$\begin{aligned}&\forall\, i = 1..|S|, \forall\, j = 1..|S|, j \neq i, \forall\, k = 1..|S|,\\ &\sum_{\substack{l\in S\\ l\neq k}} V_{ij}^{kl} - \sum_{\substack{l\in S\\ l\neq k}} V_{ij}^{lk} = \begin{cases} 0, & \text{if } k \neq i \text{ and } k \neq j,\\ Y_i.Y_j, & \text{if } k = i,\\ -Y_i.Y_j, & \text{if } k = j,\end{cases}\end{aligned} \tag{5a}$$

$$\begin{aligned}&\forall\, i = 1..|S|, \forall\, j = 1..|S|, j \neq i, \forall\, k = 1..|S|,\\ &\forall\, l = 1..|S|, V_{ij}^{kl} \leq Y_i,\end{aligned} \tag{5b}$$

$$\begin{aligned}&\forall\, i = 1..|S|, \forall\, j = 1..|S|, j \neq i, \forall\, k = 1..|S|,\\ &\forall\, l = 1..|S|, k \neq l, V_{ij}^{kl} \leq Y_j,\end{aligned} \tag{5c}$$

$$\begin{aligned}&\forall\, i = 1..|S|, \forall\, j = 1..|S|, j \neq i, \forall\, k = 1..|S|,\\ &\forall\, l = 1..|S|, l \neq k, V_{ij}^{kl} \leq Y_k,\end{aligned} \tag{5d}$$

$$\begin{aligned}&\forall\, i = 1..|S|, \forall\, j = 1..|S|, j \neq i, \forall\, k = 1..|S|,\\ &\forall\, l = 1..|S|, l \neq k, V_{ij}^{kl} \leq Y_l,\end{aligned} \tag{5e}$$

$$\begin{aligned}&\forall\, i = 1..|S|, \forall\, j = 1..|S|, j \neq i, \forall\, k = 1..|S|,\\ &\forall\, l = 1..|S|, l \neq k, V_{ij}^{kl} \leq D_{kl},\end{aligned} \tag{5f}$$

$$\mathbf{V} \in \{0,1\}^{|S|^4}, \mathbf{Y} \in \{0,1\}^{|S|}. \tag{5g}$$

Equation (5a) is the flow constraint ensuring that a feasible path exists between any pair of CHs to convey an elementary unit of flow. Remaining constraints (5b)-(5e) limit the relevance of this virtual flow problem to the overlay network. Constraint (5f) ensures that CHs k and l are neighbors for a flow to pass on the link kl. Finally, (5g) are the integrality constraints. In (5a), we have a nonlinear term that we need to linearize. For this, we define

$$\forall\, i = 1..|S|, \forall\, j = 1..|S|,\ U_{ij} = Y_i.Y_j. \tag{6a}$$

To have a logical equivalence between U_{ij} and $X_i.Y_j$, we add the following constraints:

$$\forall\, i = 1..|S|, \forall\, j = 1..|S|, U_{ij} \leq Y_i, \tag{6b}$$

$$\forall\, i = 1..|S|, \forall\, j = 1..|S|, U_{ij} \leq Y_j, \tag{6c}$$

$$\forall\, i = 1..|S|, \forall\, j = 1..|S|, U_{ij} \geq Y_i + Y_j - 1. \tag{6d}$$

Taking into account the virtual-flow-related constraints (5a)-(5f) and the linearized constraints (6a)-(6d), we end up with a linearized model of *OPT-ALL-RCC*.

Proposition 1. *OPT-ALL-RCC is NP-Complete.*

Proof. To prove the NP-Completeness of *OPT-ALL-RCC*, we will derive a polynomial reduction to the set covering problem which is known to be NP-Complete [27]. For this, we propose to define an instance P of the set covering problem, build an instance I of *OPT-ALL-RCC*, and then show that any algorithm that resolves I is able to resolve P.

Any instance P of the set covering problem is defined by a set of nodes, a set of node subsets, and a cost for each node subset. Let $S = \{s_1..s_N\}$ be a set of N sensors (nodes) and $J = \{S_1..S_N\}$ be a set of N node subsets

($S_j \subseteq S,\ j = 1..N$) such that $\forall\ j = 1..N,\ S_j$ is built from the empty set as follows:

- The node s_j is inserted into S_j.
- All nodes $s_m \in S - \{s_j\}$ that are one-hop neighbors of s_j (i.e., $d_{s_j s_m} = 1$) are added to S_j.

For each $j = 1..N$, we define the cost of subset S_j by $\alpha(j) = Log(1 + E_{CH}/Er_j)$. The instance P being defined, let us consider the instance I of *OPT-ALL-RCC*, with the following input:

- N_{max} = Infinity.
- Each cell of the monitored area is covered by one and only one sensor.
- The residual energy of nodes $s_i \in S$ is equal to $E_0 > E_{CH} > E_{Active}$.
- The transmission power of a CH is such that any potential CHs can reach each other, that is, $\forall\ j,\ m \in \{1..N\}, j \neq m$, if s_j and s_m are elected CH, then $D_{s_j s_m} = 1$.

Since each sensor covers a single cell, any admissible solution will have all its sensors turned on to satisfy the full coverage constraint. We clearly see that any algorithm that is able to resolve the above instance I of *OPT-ALL-RCC* can resolve any instance P of the set covering problem. Indeed, for every sensor s_k $(1 \leq k \leq N)$, designated as cluster head in the solution of I, S_k is a member of the minimum-cost covering set. Such a reduction proves that *OPT-ALL-RCC* is NP-Complete. □

5 Proposed Heuristic

As the considered problem is NP-Complete, we propose a Tabu search heuristic, called TABU-RCC, to tackle to exponentially increasing processing time of the exact solution. TABU-RCC will be run by the PN to find a near-optimal sensor state configuration. As shown in Algorithm 1, TABU-RCC starts with an admissible solution and iteratively performs movements that consist in changing the state of one sensor at a time. The best solution found after the predefined number of iterations is transposed on sensors to form the new network configuration. The network will operate with this configuration for a predefined period T during which residual energies of active nodes and CHs will decrease, then TABU-RCC is run again to find a new configuration based on the new values of residual energies. This new configuration will be kept for another period T and so forth. The periodic execution of TABU-RCC by the PN requires sensors-related information (e.g., residual energies) to be transmitted periodically to the PN (upstream communication) and the newly computed sensor states to be transmitted to the sensors (downstream communication). In our architecture, sensor-related data will be collected exactly in the same manner as the sensed data, i.e., using the cluster-based hierarchical structure of the network. *Active* sensors that have data to report will send it to the PN via their respective CHs. They will append the value of their respective residual energies to the data packets they are sending. When they have no data to send, they will synchronize their energy information with the PN periodically. As for the turned-off sensors, their energy consumption is constant and very low, and can therefore be estimated by the PN whenever needed, as long as they are idle. As far as state assignment to sensors is concerned, the PN will broadcast a notification message holding associations between sensors and their newly computed states *(Sensor ID, Sensor State)*. Only those sensors whose state has changed will have an entry in the notification message while all other sensors will keep their ongoing state. The notification message will be routed to the sensors via their respective CHs.

Algorithm 1: TABU-RCC: Tabu search algorithm of CH election under routing and coverage constraints

- **Initial solution:** the Tabu algorithm starts with a configuration where all sensors are activated as cluster heads. This configuration is obviously admissible;
- **Admissible configuration:** a configuration S is defined by the states of its sensors ($Sleep$, $Active$, or CH). Only feasible configurations (i.e., satisfying model constraints (1b) to (1i)) are considered;
- **Score function:** a configuration is evaluated using the score function given by (1a);
- **Neighborhood investigation:** a search movement $M < i, u, v >$ consists in changing the state (*Sleep*, *Active*, or *CH*) of a single sensor i from state u to state v such that the model constraints (1b) to (1i) are satisfied;
- **Aspiration criterion:** Tabu movements are allowed when the score of the resulting configuration is lower than the score of the best solution s^* found so far over the whole search process;
- **Stop criterion:** The search algorithm stops after a predefined number of iterations.

6 Simulation Results

In this section, we will evaluate the quality of TABU-RCC with respect to the exact (optimal) solution which provides a lower bound of the objective function. To find the optimal solution, we implement our linear integer-variable model using ILOG CPLEX [28]. CPLEX is a mathematical programming and optimization tool that solves linear problems with continuous, integer, or mixed variables, using the branch-and-bound method.

Then, we draw the variation of TABU-RCC's network lifetime when, respectively, the sensing range and the cluster size vary. These measures will show how worth it is to invest in sensors with higher sensing range or higher processing capacity.

Finally, we compare our Tabu search algorithm to EESH [29], a clustering algorithm recently proposed in the literature. EESH elects the set of cluster heads and ensures network connectivity. However, EESH does not handle optimal area coverage. To tackle this issue, we propose an enhanced version of EESH that computes an optimal area-covering subset of nodes (among the noncluster head nodes) by resolving the linear system proposed in [18]. The remaining nodes are then switched off. Our choice of EESH as a comparison reference for our algorithm was

TABLE 1
Computation Time of the
Lower Bound (CPLEX) and TABU-RCC

	Computation time	
Network size	CPLEX	TABU-RCC
9	0.023	0.011
25	155	0.082
49	39987	0.21
64	362	2.33
100	873	6.47
225	1475	10.89

motivated by the fact that EESH is one of the most recent clustering algorithms proposed in the literature and that EESH has been shown to outperform, in terms of network lifetime (which is our main objective to maximize), two of the most popular and well-recognized clustering algorithms for WSN: LEACH [10] and HEED [30]. For all the simulations made, TABU-RCC was run with a tabu list size of 15 and a number of iterations of 10,000.

6.1 Comparative Performance Evaluation: TABU-RCC With Respect To Its Lower Bound (CPLEX)

To evaluate the quality of our heuristic, we considered different network sizes of 9, 25, 49, 64, 100, and 225 sensors and compared the objective function provided by TABU-RCC to the lower bound provided by CPLEX. The measure of the objective functions has no practical interest but is only useful to assess the quality of the heuristic with respect to the exact solution (lower bound). It was difficult to run simulations on bigger network sizes because of the exponentially increasing processing time of CPLEX, as shown in Table 1. In fact, we can clearly see that, while TABU-RCC always converges in few seconds, CPLEX's computation time grows exponentially, which deeply justifies the use of a heuristic. Let us note here that for the network sizes of 9, 25, and 49 sensors, the lower bound used is the value of the objective function given by the solution of the integer-variable system 1, while for network sizes of 64, 100, and 225 sensors, the resolution of the integer-variable system could not be made in a reasonable time, so we made a continuous relaxation of the system 1 and we used its solution to evaluate the solution provided by TABU-RCC. In fact, the relaxed system provides an obvious lower bound and it takes much less time to be resolved than the original integer-variable system.

This explains why the lower bound processing time for 64 sensors reported in Table 1 seems lower than the processing time of the lower bound for 49 sensors.

As shown in Fig. 6, the objective function of TABU-RCC's solutions is very close to that of the lower bound. Also, Fig. 7 shows that the average energy consumed by TABU-RCC's solutions is very close to that of the lower bound. Thus, we can infer that TABU-RCC provides good solutions, close to their lower bound. Even though it was predictable that an exact ILP resolution would not be suitable for large-sized networks, we computed the objective function of CPLEX's solutions for small and medium-sized networks only to assess the quality of the solutions provided by TABU-RCC with respect to optimality.

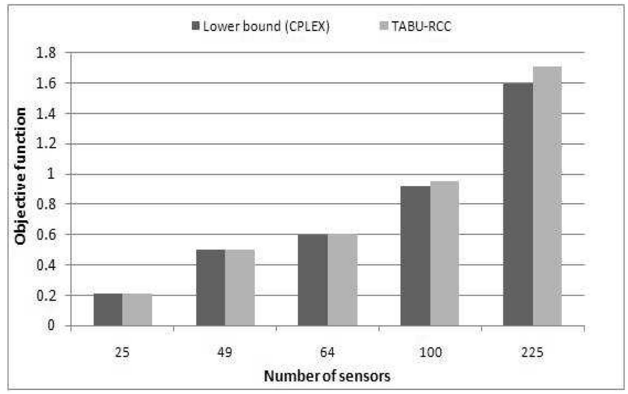

Fig. 6. Value of the objective function generated by TABU-RCC versus CPLEX.

6.2 Performance Evaluation of TABU-RCC: Impact of the Sensing Range

In practice, the value of the sensing range could vary depending on the physical properties of the sensors and on the type of signal they are sensing. To measure the impact of the sensing range, we considered three network sizes of, respectively, 225, 625, and 900 sensors. To measure the network lifetime, we run TABU-RCC iteratively and at every iteration, a sensor's energy is decremented by E_{CH} if it is designated as CH and by E_{Active} if it is assigned the state $Active$. Iterations stop when the monitored area cannot be covered anymore because of the energy exhaustion of some sensors. Fig. 8 shows the variation of the network lifetime with the sensing range, for the considered networks. We see that, for all network sizes, when R_s increases, the network lifetime increases as well. This is due to the fact that, when R_s increases, less sensors are activated to ensure the full area coverage and the connectivity. Hence, less energy is dissipated, which, in average, increases network lifetime.

6.3 Performance Evaluation of TABU-RCC: Impact of the Maximum Cluster Size

In practice, a CH does not have an infinite capacity due to many physical factors like interference, limited CH's processing capabilities, collisions on the MAC layer, etc. To evaluate the impact of the maximum cluster size on the performance of our heuristic, we measured the network lifetime for different network sizes of, respectively, 225, 625,

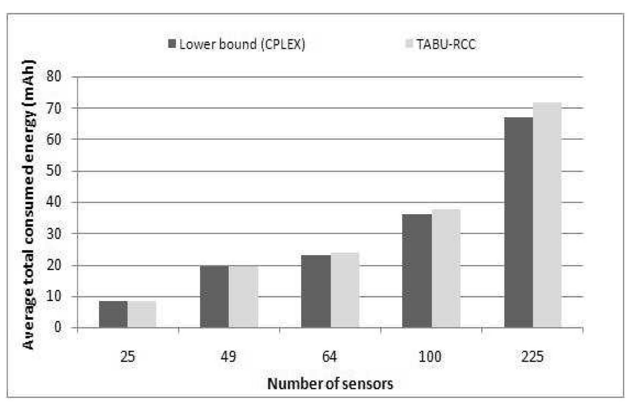

Fig. 7. Average consumed energy using the solution generated by TABU-RCC versus CPLEX.

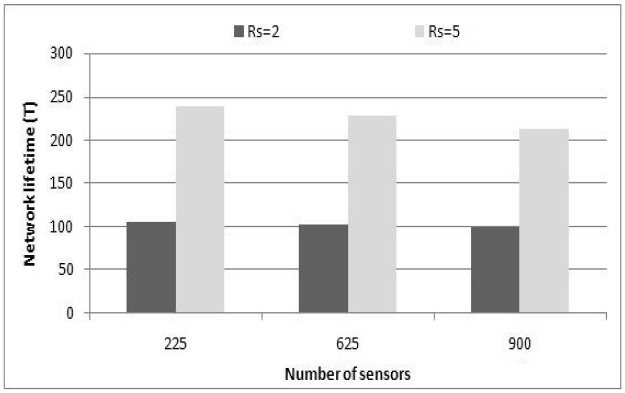

Fig. 8. Variation of the network lifetime with the sensing range, using TABU-RCC.

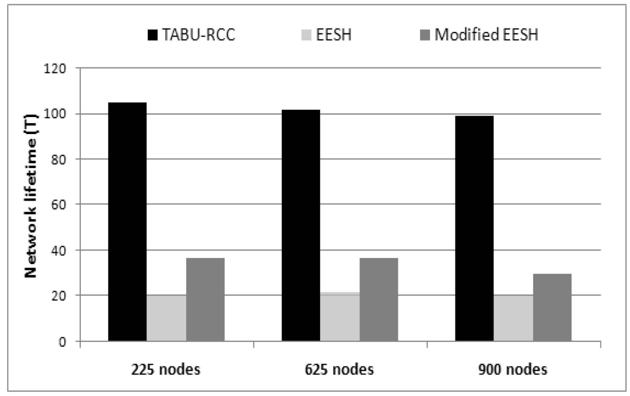

Fig. 10. Comparison of TABU-RCC to EESH and the modified EESH in terms of network lifetime.

and 900 sensors. In Fig. 9, we observe that, for all configurations, when N_{max} increases, the network lifetime increases as well. This is due to the fact that, when N_{max} increases, less CHs are needed to ensure connectivity since a CH can serve more sensors. The leap up in network lifetime becomes salient when the cluster size tends to infinity. In fact, when $N_{max} \rightarrow \infty$, one single CH can ensure the connectivity of all the sensors that can reach it.

6.4 Comparative Performance Evaluation: TABU-RCC versus EESH

To evaluate our TABU-RCC in terms of network lifetime, we compared it to EESH [29]. EESH functions as follows: nodes are promoted cluster heads according to their respective residual energies, their respective degrees, the distance to their neighbors, and the residual energies of these neighbors. For that, EESH evaluates a cost function for every sensor in the network and iteratively elects the node having the greatest cost as CH. This process terminates when all non-CH sensors in the network are connected to at least one cluster head. As EESH does not consider optimal area coverage, we made a small modification of EESH that consists of computing, in each cluster provided by EESH, an optimal subset of non-CH sensors that will be activated while the other sensors are turned off. Fig. 10 depicts the network lifetime provided, respectively, by TABU-RCC, EESH, and the modified version of EESH, for different network sizes. We clearly see that TABU-RCC outperforms the modified version of EESH by providing three times longer network lifetime, for all network sizes. This considerable gain is one of the main benefits of our centralized heuristic.

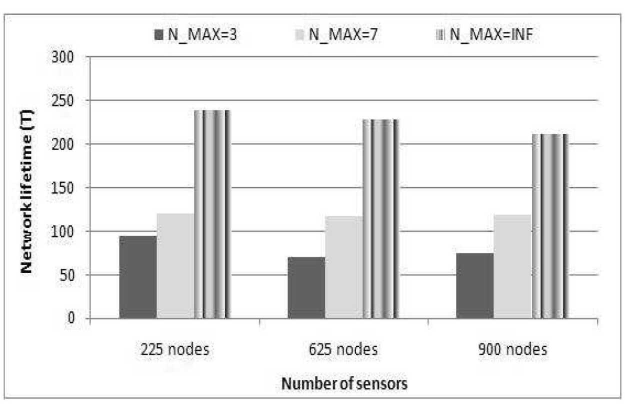

Fig. 9. Variation of the network lifetime with the maximum cluster size, using TABU-RCC.

7 Conclusion

In this paper, we proposed a novel centralized mechanism for near-optimal state assignment to sensors in large-scale cluster-based monitoring wireless sensor networks. Our mechanism is based on a tabu algorithm that computes a near-optimal network configuration in which each sensor can be activated, put in sleep mode or promoted as cluster head. Our mechanism maximizes network lifetime while ensuring the full coverage of the monitored area and the connectivity of the obtained configuration. Connectivity is fulfilled through an optimally computed spanning tree connecting all the cluster heads. Simulations show that our mechanism provides for acceptable results with respect to the exact solutions of the derived ILP model, within low computation times. Despite its centralized aspect, our mechanism exhibits low complexity and low computation times making its practical implementation adaptable for large-scale networks. As future research directions, we intend to develop a more sophisticated heuristic to improve the network lifetime. Furthermore, we intend to consider distance-dependent probabilistic event detection, where the probability that a sensor detects an event is function of the distance of that sensor from the event. Furthermore, we intend to work on distributed algorithms that address energy-efficient clustering under the joint coverage and routing constraint.

References

[1] C.Y. Chong and S.P. Kumar, "Sensor Networks: Evolution, Opportunities, and Challenges," *Proc. IEEE*, vol. 91, no. 8, pp. 1247-1256, Aug. 2003.
[2] M. Cardei, M.T. Thai, Y. Li, and W. Wu, "Energy-Efficient Target Coverage in Wireless Sensor Networks," *Proc. IEEE INFOCOM*, vol. 3, pp. 1976-1984, 2005.
[3] V. Raghunathan, C. Schurgers, S. Park, and M.B. Srivastava, "Energy-Aware Wireless Microsensor Networks," *IEEE Signal Processing Magazine*, vol. 19, pp. 40-50, 2002.

[4] K. Akkaya and M. Younis, "A Survey of Routing Protocols in Wireless Sensor Networks," *Ad Hoc Network J.*, vol. 3, no. 3, pp. 325-349, 2005.

[5] L.M.C. Arboleda and N. Nasser, "Comparison of Clustering Algorithms and Protocols for Wireless Sensor Networks," *Proc. Canadian Conf. Electrical and Computer Eng.*, pp. 1787-1792, May 2006.

[6] M. Younis, P. Munshi, G. Gupta, and S.M. Elsharkawy, "On Efficient Clustering of Wireless Sensor Networks," *Proc. Second IEEE Workshop Dependability and Security in Sensor Networks and Systems*, pp. 78-91, 2006.

[7] H. Karl and A. Wiling, *Protocols and Architectures for Wireless Sensor Networks.* Wiley, 2005.

[8] Y. Yao and G.B. Giannakis, "Energy-Efficient Scheduling for Wireless Sensor Networks," *IEEE Trans. Comm.*, vol. 53, no. 8, pp. 1333-1342, 2005.

[9] S.F. Hwang, Y.Y. Su, Y.Y. Lin, and C.R. Dow, "A Cluster-Based Coverage-Preserved Node Scheduling Scheme in Wireless Sensor Networks," *Proc. Third Ann. Int'l Conf. Mobile and Ubiquitous Systems: Networking and Services*, pp. 1-7, July 2006.

[10] W.R. Heizelman, A. Chandrakasan, and H. Balakrishnan, "Energy-Efficient Communication Protocol for Wireless Micro Sensor Networks," *Proc. IEEE Hawaii Int'l Conf. System Sciences*, Jan. 2000.

[11] V. Mhatre and C. Rosenberg, "Homogeneous vs. Heterogeneous Clustered Sensor Networks: A Comparative Study," *Proc. IEEE Int'l Conf. Comm.*, vol. 6, pp. 3646-3651, June 2004.

[12] M. Inanc, M.I. Magdon, and B. Yener, "Power Optimal Connectivity and Coverage in Wireless Sensor Networks," Technical Report TR-03-06, Dept. of Computer Science, Rensselaer Polytechnic Inst., 2003.

[13] J. Carle and D. Simplot, "Energy Efficient Area Monitoring by Sensor Networks," *Computer*, vol. 37, no. 2, pp. 40-46, Feb. 2004.

[14] X.Y. Li, P.J. Wan, and O. Frieder, "Coverage in Wireless Ad-Hoc Sensor Networks," *IEEE Trans. Computers*, vol. 52, no. 6, pp. 753-763, June 2002.

[15] G. Xing, X. Wang, Y. Zhang, C. Lu, R. Pless, and C. Gill, "Integrated Coverage and Connectivity Configuration for Energy Conservation in Sensor Networks," *ACM Trans. Sensor Networks*, vol. 1, no. 1, pp. 36-72, Aug. 2005.

[16] T. Yan, T. He, and J.A. Stankovic, "Differentiated Surveillance for Sensor Networks," *Proc. First Int'l Conf. Embedded Networked Sensor Systems (SenSys '03)*, pp. 51-62, 2003.

[17] J. Lu, J. Wang, and T. Suda, "Scalable Coverage Maintenance for Dense Wireless Sensor Networks," *Proc. Third Ann. IEEE Comm. Soc. Conf. Sensor and Ad Hoc Comm. and Networks (SECON '06)*, vol. 2, pp. 651-660, Sept. 2006.

[18] A. Chamam and S. Pierre, "Dynamic Sensor Activation for Maximizing Network Lifetime under Coverage Constraint," *Proc. Int'l Symp. Comm. and Information Technologies (ISCIT '07)*, pp. 971-976, Oct. 2007.

[19] S. Lindsey and C.S. Raghavendra, "PEGASIS: Power Efficient Gathering in Sensor Information Systems," *Proc. IEEE Aerospace Conf.*, Mar. 2002.

[20] N. Ahmed, S.S. Kanhere, and S. Jha, "Probabilistic Coverage in Wireless Sensor Networks," *Proc. IEEE Conf. Local Computer Networks (LCN '05)*, vol. 1, pp. 672-681, 2005.

[21] D. Tian and N.D. Georganas, "A Coverage-Preserving Node Scheduling Scheme for Large Wireless Sensor Networks," *Proc. ACM Int'l Workshop Wireless Sensor Networks and Applications (WSNA '02)*, pp. 32-41, 2002.

[22] M. Hefeeda and H. Ahmadi, "A Probabilistic Coverage Protocol for Wireless Sensor Networks," *Proc. IEEE Int'l Conf. Network Protocols (ICNP '07)*, pp. 41-50, Oct. 2007.

[23] Y.-S. Yen, S. Hong, R.-S. Chang, and H.-C. Chao, "An Energy Efficient and Coverage Guaranteed Wireless Sensor Network," *Proc. IEEE Wireless Comm. and Networking Conf. (WCNC '07)*, pp. 2923-2928, Mar. 2007.

[24] N. Patwari, J.N. Ash, S. Kyperountas, A.O. Hero, III, R.L. Moses, and N.S. Correal, "Locating the Nodes: Cooperative Localization in Wireless Sensor Networks," *IEEE Signal Processing Magazine*, vol. 22, no. 4, pp. 54-69, 2005.

[25] J. Bachrach and C. Taylor, "Localization in Sensor Networks," *Handbook of Sensor Networks: Algorithms and Architectures*, I. Stojmenovic, ed., Wiley Interscience, 2005.

[26] H. Chu and R. Jan, "A GPS-Less, Outdoor, Self-Positioning Method for Wireless Sensor Networks," *J. Ad Hoc Networks*, vol. 5, no. 5, pp. 547-557, July 2007.

[27] T.H. Cormen, C.E. Leiserson, R.L. Rivest, and C. Stein, "The Set-Covering Problem," *Introduction to Algorithms*, second ed., Section 35.3, pp. 1033-1038, MIT Press and McGraw-Hill, 2001.

[28] http://www.ilog.com/products/cplex/, 2009.

[29] W. Zhou, H.-M. Chen, and X.-F. Zhang, "An Energy Efficient Strong Head Clustering Algorithm for Wireless Sensor Networks," *Proc. Int'l Conf. Wireless Comm. Networking and Mobile Computing (WiCom '07)*, pp. 2584-2587, Sept. 2007.

[30] O. Younis and S. Fahmy, "HEED: A Hybrid, Energy-Efficient, Distributed Clustering Approach for Ad Hoc Sensor Networks," *IEEE Trans. Mobile Computing*, vol. 3, no. 4, pp. 366-379, Oct.-Dec. 2004.

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