Scalable Coverage Maintenance for Dense Wireless Sensor Networks

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Abstract—Owing to numerous potential applications, wireless sensor networks have been attracting much research effort recently. The critical challenge that wireless sensor networks often face is to sustain long-term operation on limited battery energy. Coverage maintenance schemes can effectively prolong network lifetime by maintaining sufficient sensing coverage over a target region using a small number of active sensors while scheduling the other sensors to sleep. We envision future wireless sensor networks are composed of a vast number of extremely miniaturized sensors (e.g., millimeter-scale) deployed in exceedingly high density (e.g., more than 1000 sensors/m²). Therefore, the key issue of coverage maintenance for the future sensor networks is the scalability to sensor deployment density. In this paper, we propose a novel coverage maintenance scheme, called Scalable Coverage Maintenance (SCOM). SCOM is energy efficient and scalable to sensor deployment density in terms of communication overhead (i.e., number of transmitted and received beacons) and computational complexity (i.e., time and space complexity). We validate our claims through both analysis and simulations.

I. INTRODUCTION

The recent advances in micro-sensor and communication technologies enlarge the possibility of manufacturing inexpensive small wireless sensors with simple sensing, processing and wireless communication capabilities. Limited by their size, small wireless sensors are equipped with restricted power source and storage capacity. For example, the typical Crossbow MICA2 mote MPR400CB [1] has a low-speed 16 MHz microcontroller equipped with only 128 KB flash and 4 KB EEPROM. Powered by two AA batteries, it has a maximal data rate of 38.4 Kbaud and a transmission range of about 150 m. Such small wireless sensors are usually deployed in an ad-hoc manner to monitor a specified region of interest for various applications, such as environment monitoring, target tracking and distributed data storage. The wireless sensors in a network collaborate with each other to monitor surrounding environment and transmit data to sink points through multi-hop communication.

A wireless sensor network is usually densely deployed, i.e., more than sufficient sensors are distributed to fulfill the required functionalities, so as to improve the reliability as well as extend the longevity. One of the critical challenges that such dense sensor networks face is to sustain long-term operation while maintaining sufficient sensing coverage over a target region, which is referred as the coverage maintenance problem in literature.

There are many coverage maintenance schemes proposed. For example, Tian and Georganas [2] presented a node scheduling algorithm to turn off sensors with sensing areas fully covered by the neighbors within sensing range. Randomized as well as coordinated sleep algorithms were proposed in [3] to maintain network coverage using low duty-cycle sensors. The randomized algorithm enables each sensor to independently sleep under a certain probability, while the coordinated sleep algorithm allows a sensor to enter sleep state if its sensing area is fully contained by the union set of its neighbors. An algorithm was proposed in [4] to decide the coverage of a target area by merely checking the coverage state of sensing perimeters. Yan et al. [5] proposed an adaptable energy-efficient sensing coverage protocol, in which each sensor broadcasts a random time reference point, and decides its duty schedule based on neighbors’ time reference points. Co-Grid proposed in [6] schedules sensors by adopting a distributed detection model based on data fusion. Abrams et al. studied a variant of the NP-hard SET K-COVER problem in [7], partitioning
the sensors into $K$ covers such that as many areas are monitored as frequently as possible. Xing et al. [8] studied the relationship between coverage and connectivity, and proposed a coverage maintenance scheme, Coverage Configuration Protocol (CCP), which, when integrated with an existing connectivity maintenance scheme, is able to provide both coverage and connectivity guarantees. In [9], Kumar et al. proposed algorithms to quickly decide whether a deployed region is $K$-barrier covered. Two notions of probabilistic barrier coverage, the weak and strong barrier coverage, are introduced and studied. Cardei et al. [10] proposed an efficient scheme to cover a set of targets with known locations in a randomly and densely deployed sensor network. The target coverage problem is modeled as the maximal set cover problem and two heuristics are proposed and evaluated. Zhang and Huo [11] presented a scheme to optimize coverage maintenance while providing global connectivity by keeping a minimum number of active sensors to minimize coverage redundancy.

We envision future wireless sensors are extremely miniaturized (e.g., millimeter-scale) with very limited processing capability and storage capacity, and a sensor network is composed of a vast number of wireless sensors deployed in exceedingly high density (e.g., more than 1000 sensors/m$^2$) [12] [13]. Thus, the coverage maintenance scheme for future wireless sensor networks must be highly scalable to sensor deployment density in terms of communication overhead and computational complexity. In this paper, we propose a novel coverage maintenance scheme, Scalable COverage Maintenance (SCOM), in which sensors decide their sensing state in a distributive and scalable manner.

The main contributions of SCOM are 1) high scalability to sensor deployment density in terms of communication overhead and computational complexity, 2) a simple algorithm for a sensor to decide coverage redundancy by checking only a small number of locations, 3) high energy efficiency to maintain the required coverage, and 4) load balancing among sensors.

The rest of this paper is organized as follows. Section II specifies SCOM in more detail. Theoretical analysis and simulation results are presented in Section III. Section IV concludes the paper.

II. SCALABLE COVERAGE MAINTENANCE (SCOM)

A. Assumptions

We assume that sensors are static and each sensor knows its own location. Sensors can acquire the location of neighbors through one-hop communication. Such assumptions are reasonably taken by other works (e.g., [2] [4] and [5]) and are supported by the existing research (e.g., [14] [15] [16] and [17]). We also assume that sensors have synchronized timers [18] [19] and are aware of the amount of residual energy. For clarity of algorithm discussion, we further assume that sensors’ communication range, denoted by $CR$, is at least twice the sensing range, denoted by $SR$. This assumption is usually true for real sensors. For example, HMC1002 magnetometer sensors have the SR of approximately 5 m [20] while the CR of MICA2 MPR400CB motes is about 150 m [1]. In the case of the CR less than twice the SR, CASE can work by propagating control beacons through multiple hops.

B. Problem Statement

Definition 1: A location is covered by a sensor if it is within the SR of the sensor. A location is said to be $K$-covered if it is within the SR of at least $K$ sensors. A region is $K$-covered if every location within the region is $K$-covered.

Note that according to the definition, the sensing perimeter of a sensor is not covered by the sensor. SCOM aims to the classic $K$-coverage Maintenance Problem defined as follows:

Definition 2: $K$-coverage Maintenance - Given a sensor group $S$ deployed in region $R$ and a natural number $K$, a subset $S'$ is able to maintain $K$-coverage if it satisfies the follows:

$$\forall v \in R \bigg\{ \begin{array}{ll} C_S(v) \geq K, & C_S(v) \geq K \\ C_S'(v) = C_S(v), & C_S(v) < K \end{array} \bigg\}$$

where $C_S(v)$ and $C_S'(v)$ denote the coverage of the location $v$ by $S$ and $S'$, respectively.

C. Scheme Description

Time is slotted into rounds. At the beginning of each round, SCOM runs in two phases:

1) Decision phase: sensors start with BOOTSTRAP state, and gradually enter the ACTIVE or INACTIVE state according to local coverage and energy information.

2) Optimization phase: sensors optimize the coverage by turning off redundant active sensors while still guaranteeing the required coverage.

In the decision phase, each sensor is initially in BOOTSTRAP state and has an empty active neighbor list. Before making the decision of turning on or off,
each sensor sets a back-off timer $T_{\text{decision}}$ determined by its residual energy,

$$T_{\text{decision}} = \alpha \cdot (1 - p) + \epsilon,$$  \hspace{1cm} (1)

where $p$ is the residual energy percentage level and $\epsilon$ is a small random number uniformly distributed within $(0, \beta]$. $\alpha$ and $\beta$ decide the sensitivity of $T_{\text{decision}}$ to the percentage level of residual energy, that is, larger $\alpha$ accentuates while larger $\beta$ deemphasizes the difference of residual energy among sensors. The choice of appropriate values for $\alpha$ and $\beta$ is out of the scope of this paper, and will be part of our future work. When a sensor’s timer expires, the sensor decides its redundancy by checking whether its sensing region is $K$-covered by the sensors in the active neighbor list, and switches to ACTIVE or INACTIVE state accordingly. Detailed description of the redundancy checking algorithm will be presented in Section II-D. If a sensor decides to turn into ACTIVE state, it broadcasts a TURNON beacon with its coordinates to the neighbors within the CR, which is large enough to cover the neighbors whose sensing regions overlap with the sender. Upon receiving the TURNON beacon, a neighbor adds the sender into the active neighbor list and stores the coordinates of the sender. The decision phase lasts for $(\alpha + \beta)$ time units.

After the decision phase, there may exist redundant active sensors because the sensors turning on later may cover the sensing regions already $K$-covered. In order to turn off the redundant sensors, each active sensor goes through the optimization phase right after the decision phase. An active sensor sets a back-off timer $T_{\text{opt}}$ according to its residual energy,

$$T_{\text{opt}} = \alpha \cdot p + \epsilon,$$  \hspace{1cm} (2)

where $p$, $\alpha$ and $\epsilon$ have the same meaning as in Eq. (1). When a sensor times out, it checks the redundancy based on the active neighbor list and, if it is redundant, switches to INACTIVE state and broadcasts a TURNOFF beacon to its active neighbors. Upon receiving the TURNOFF beacon, an active neighbor removes the sender from its active neighbor list. The optimization phase also lasts for $(\alpha + \beta)$ time units.

In the decision phase, according to Eq. (1), sensors with a higher percentage level of residual energy have shorter back-off period $T_{\text{decision}}$ and thus time out later. Thus, the active sensors with the higher percentage level of residual energy have less chance to turn off. In this way, SCOM uses sensors with more residual energy to provide coverage and thus balances workload among sensors.

D. Redundancy Eligibility Rule

The key operation of coverage maintenance is to decide a sensor’s redundancy given the locations of its neighbors. Obviously, a sensor is redundant if its sensing region is $K$-covered by its neighbors. Here we propose a redundancy eligibility rule, by which a sensor is able to decide whether its sensing region is $K$-covered by its neighbors through merely checking the coverage at a few locations within its sensing region.

We first assume that no two sensors are at the same location, and then extend the proposed eligibility rule to the case of multiple sensors at the same location. We describe the redundancy eligibility rules for two cases: homogeneous SR and heterogeneous SR.

1) Sensors with Homogenous SR: For description clarity, we define a sensor’s critical point set.

**Definition 3:** Critical Point Set - Sensor $i$’s critical point set $S_i$ contains, for each neighbor $n$ of $i$, 1) the intersection points between the sensing perimeters of $n$ and other neighbors within the sensing region of sensor $i$, or if such intersection points do not exist, 2) one intersection point between the sensing perimeters of $n$ and sensor $i$.

For example, in Fig. 1(a), $S_i$ contains three intersection points between neighbors (i.e., $x$, $y$ and $z$) and one intersection point between a neighbor and sensor $i$ (i.e., $v$).

**Theorem 1:** Redundancy Eligibility Rule for Homogenous SR. Given a natural number $K$. 1) If $S_i$ is not empty, the sensing region of sensor $i$ is $K$-covered by its neighbors if and only if each critical point in $S_i$ is $K$-covered by its neighbors. 2) If $S_i$ is empty, the sensing region of sensor $i$ is not $K$-covered by its neighbors.

**Proof:** 1) If the sensing region of sensor $i$ is $K$-covered by its neighbors, obviously each critical point in $S_i$ is $K$-covered. When $S_i$ is not empty, the sensing region of sensor $i$ is divided into sub-regions by the sensing perimeters of neighbors. For example, in Fig. 1(a), sensor $i$’s sensing region is divided into eight sub-regions. Since a sensor’s sensing perimeter is not covered by the sensor itself according to Definition 1, the coverage of a sub-region is always higher than or equal to the coverage of the adjacent critical points. For example, in Fig. 1(a), the coverage of sub-region...
8 is higher than or equal to the coverage of the critical points \(x, y\) and \(z\). Thus, the minimal coverage of the sub-regions is \textit{no less than} the minimal coverage of the critical points. On the other hand, for each critical point, we can always find an adjacent sub-region with equal coverage. For example, in Fig. 1(a), the critical points \(x, y\) and \(z\) have the same coverage as the sub-regions 2, 5 and 7, respectively. Thus, the minimal coverage of the critical points is \textit{no less than} the minimal coverage of the sub-regions. Therefore, the minimal coverage of the critical points equals the minimal coverage of the sub-regions, which means if each critical point in \(S_i\) is \(K\)-covered by sensor \(i\)’s neighbors, the sensing region of sensor \(i\) is \(K\)-covered by its neighbors, and vice versa.

2) Sensors with Heterogeneous SR: When sensors have different SRs, the sensing region of a sensor may be divided into sub-regions even when its critical point set is empty. For example, the sensing region of a sensor with larger SR may contain the sensing region of a sensor with smaller SR. In this case, the sensing region of the sensor with larger SR is divided into sub-regions even when its critical point set is empty. To accommodate this case, we define a sensor’s extended critical point set.

\textbf{Definition 4: Extended Critical Point Set - Sensor} \(i\)’s extended critical point set \(ES_i\) contains 1) the critical points in sensor \(i\)’s critical point set, and 2) a sampling point on each sensing perimeter that is within sensor \(i\)’s sensing region and does not intersect with any other sensing perimeter.

For example, in Fig. 1(b), \(S_i\) contains three critical points, \(x, y\) and \(z\). There are two sensing perimeters contained in sensor \(i\)’s sensing region and do not intersect with other sensing perimeters. Thus, \(ES_i\) also contains \(v\) and \(w\) as the sampling points on the two sensing perimeters. Therefore, \(ES_i\) contains five critical points, \(x, y, z, w\) and \(v\).

\textbf{Theorem 2: Redundancy Eligibility Rule for Heterogeneous SR.} Given a natural number \(K\), 1) If \(ES_i\) is not empty, the sensing region of sensor \(i\) is \(K\)-covered by its neighbors \textit{if and only if} each critical point in \(ES_i\) is \(K\)-covered by its neighbors, and vice versa. 2) If \(ES_i\) is empty, the sensing region of sensor \(i\) is \(K\)-covered by neighboring sensors \textit{if and only if} a sampling point within the sensing region of sensor \(i\) is \(K\)-covered by its neighbors.

\textbf{Proof:} 1) The proof is similar to Theorem 1. We can prove that the minimal coverage of the critical points in \(ES_i\) is equal to the minimal coverage of the sub-regions, which means if each critical point in \(ES_i\) is \(K\)-covered by sensor \(i\)’s neighbors, the sensing region of sensor \(i\) is \(K\)-covered by its neighbors, and vice versa. 2) When sensors have heterogeneous SR, an empty extended critical point set does not necessarily mean that the sensing region does not overlap with others. For example, in Fig. 1(b), \(ES_i\) contains no critical point, but sensor \(i\)’s sensing region is contained in the sensing region of its neighbors. In this case, sensor \(i\)’s sensing region must not be divided into sub-regions. Thus, sensor \(i\) can decide whether its sensing region is \(K\)-covered by checking the coverage of any sampling point within its

![Fig. 1. SCOM - redundancy eligibility rule](image)

(a) Homogeneous SR

(b) Heterogeneous SR

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\(v\) and \(w\) as the sampling points on the two sensing perimeters.
TABLE I
COMMUNICATION OVERHEAD AND COMPUTATIONAL COMPLEXITY

| Scheme         | Transmitted Beacons | Received Beacons | Time Complexity | Space Complexity |
|----------------|---------------------|------------------|-----------------|------------------|
| SCOM           | $O(1)$             | $O(N)$           | $O(1)$          | $O(1)$           |
| SS Scheme      | $O(N)$             | $O(N^2)$         | $O(N)$          | $O(N)$           |
| Basic DS       | 0                  | 0                | $O(N\log N)$   | $O(N)$           |
| 2nd Pass DS    | $O(N)$             | $O(N^2)$         | $O(N\log N)$   | $O(N)$           |

Fig. 2. Critical point set vs. the existing algorithms

For the description above, we assume that no two sensors are at the same location. The redundancy eligibility rule can be easily extended to accommodate the special case of multiple sensors at the same location. For sensors with homogeneous SR, if $S_i$ is not empty, the coverage of the critical points on sensor $i$’s sensing perimeter (e.g., $v$ in Fig. 1(a)) is increased by the number of sensors at the same location as sensor $i$; if $S_i$ is empty, the sensing area of sensor $i$ is covered by the number of sensors at the same location as sensor $i$. In the case of heterogeneous SR, if $ES_i$ is not empty, the coverage of the critical points on sensor $i$’s sensing perimeter (e.g., $z$ in Fig. 1(b)) is increased by the number of sensors at the same location and with the same SR as sensor $i$; in the case of an empty $ES_i$, Sensors’ being at the same location does not impact the algorithm behavior. i.e., we can still use a sampling point to decide the coverage of the sensing region of sensor $i$.

We note that a similar idea was proposed in [21] to study the problem of covering a sphere with circular caps and later developed by [8] and [22] to provide $K$-coverage maintenance for sensor networks. In their algorithms, however, the set of locations to be checked by each sensor includes all the intersection points between the sensing perimeters of any two neighbors or between a neighbor and the sensor itself. Thus, their algorithms require to check more locations to decide redundancy eligibility, and as the result, incurs more computation overhead. For example, in Fig. 2, the proposed critical point set only contains point $x$, while the existing algorithms require to examine all the intersection points, $x, y, z, u$ and $v$. Furthermore, the algorithms proposed in the existing work assume homogeneous caps or sensors and cannot be applied to sensors with heterogeneous SR.

III. PERFORMANCE EVALUATION

In this section, we compare the performance of SCOM with the existing works proposed in [2] and [5].

In the scheme proposed in [2] (hereinafter referred as Sponsor Sector (SS) scheme), every sensor calculates its eligibility for turning off. A sensor is eligible to turn off if its sensing region is contained by the union of the sponsored sectors offered by its active neighbors within SR. A back-off mechanism is used to avoid blind points caused by simultaneous decisions of multiple sensors. After the back-off period, a sensor eligible to turn off broadcasts a TURNOFF beacon to the neighbors within SR. Upon receiving the TURNOFF beacon, every neighbor removes the sensor from the neighbor list so that the sensor will not be counted to decide the eligibility of other sensors.

In the scheme proposed in [5] (referred as basic Differentiated Surveillance (DS)), each sensor randomly generates a time reference point and broadcasts it to the neighbors within twice SR. The target region is covered with a virtual square grid. For each grid point within SR, a sensor decides the working schedule based on its own and neighbors’ time reference points. The final schedule of the sensor is the union of the working schedules for all the grid points. The final schedule can be optimized through exchanging schedule information among
neighboring sensors (referred as 2nd pass Differentiated Surveillance (DS)).

A. Scheme Analysis

Table I summarizes the scalability of different coverage maintenance schemes to sensor deployment density (denoted by $N$ in the table) in terms of communication overhead (i.e., transmitted and received beacons) and computational complexity (i.e., time and space complexity). We can see that SCOM outperforms other schemes except for the communication overhead of basic DS. However, the achievement of basic DS is at the cost of energy efficiency and adaptability to sensor network dynamics such as sensor failure. A sensor’s integrated schedule generated by basic DS is a super set of its schedules for many grid points, and therefore may be more than sufficient to provide the coverage guarantee. Moreover, when executed in multiple rounds, basic DS is not able to restore coverage from sensor failure because sensors are unaware of the failure of neighboring sensors. Although it is possible to use heartbeat signals to check the state of neighbors as described in [5], the communication overhead to transmit and receive heartbeat signals is $O(N)$ and $O(N^2)$, respectively. In contrast, at the beginning of each round, since only working sensors turn on and transmit TURNON beacons, SCOM can easily restore the coverage by substituting failed sensors with working ones.

The high scalability of SCOM can be briefly explained in the follows. Instead of turning off redundant active sensors, SCOM only turns on necessary sensors in the decision phase. Given the required degree of coverage ($K$), the number of sensors turning on in the decision phase is a limited value, which is not related to sensor
deployment density. Since each sensor only communicates to its active neighbors and only considers the active neighbors to make its decision, the communication and computation overhead per sensor remains stable with the increase of sensor deployment density. Similar technique is adopted by [11], [22] and [23], but without specific analysis and evaluation of scalability.

B. Simulation Study

1) Simulation Setup: The simulations are carried out over a square region of 100 m × 100 m with wrap-around in both dimensions. Thus, the results are representative of an infinite system, and therefore apply to typical large-scale sensor networks. Sensors are uniformly deployed in the square region.

In SCOM, the values of $\alpha$ and $\beta$ in Eq. (1) and (2) are set to 10.0 and 1.0, respectively. We simulated both homogeneous and heterogeneous sensor networks. For homogeneous networks, the SR of each sensor is fixed at 10 m. For heterogeneous networks, a sensor’s SR is uniformly chosen from three possible values: 5 m, 10 m and 15 m.

2) Simulation Results: The simulation results are shown for communication overhead, computational complexity, energy conservation and load balancing.

a) Communication overhead: Fig. 3 illustrates the total number of beacons transmitted and received in homogeneous sensor networks. Basic DS is not shown because the beacons to exchange time reference points, which is the only communication overhead of basic DS, can be piggybacked to the location exchanging beacons. Therefore, basic DS incurs no extra communication overhead (as shown in Table I, the number of transmitted and received beacons of basic DS is 0). Fig. 3(a) depicts the total number of transmitted beacons with various sensor deployment densities. We observe that the number of transmitted beacons of SCOM remains stable while the number of transmitted beacons of the other two schemes grows linearly and slowly with the increase of sensor deployment density. The growth rate of SS scheme is lower than that of 2nd pass DS because in SS scheme only redundant sensors need to send beacons while each sensor transmits two beacons for the integrated and optimized schedules in 2nd pass DS. The simulation results confirm the analysis results shown in Table I.

Fig. 3(b) shows that the number of received beacons of SCOM increases linearly with sensor deployment density, while that of 2nd pass DS grows quadratically. More detailed analysis reveals that the growth rate of SS scheme is also quadratic, although much lower than 2nd pass DS. This observation also agrees with Table I.

Fig. 4 describes the number of transmitted and received beacons in heterogeneous sensor networks. We have the similar observation to Fig. 3, SCOM is more scalable than SS scheme and 2nd pass DS in terms of communication overhead.

b) Computational complexity: Note that in all the three coverage maintenance schemes, each sensor decides its working schedule according to the state of its neighbors. Thus, the computational complexity (i.e., time complexity and space complexity) is tightly coupled with the number of neighbors. Here we use the average number of neighbors per sensor to investigate the computational complexity as shown in Fig. 5. Since the average numbers of neighbors in the two phases (i.e., the decision phase and the optimization phase) of SCOM

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Fig. 5. Average number of active neighbors

(a) Homogeneous SR = 10 m

(b) Heterogeneous SR = 5/10/15 m
are different, we show the average numbers of active neighbors in both phases. Because 2nd pass DS always has more computation overhead than basic DS, we only show the result of basic DS. Fig. 5(a) depicts the average number of active neighbors in homogeneous networks. We can see that the average numbers of active neighbors of both phases of SCOM remain constant, whereas that of SS scheme and basic DS rises linearly with the growth of sensor deployment density, which means that the computation overhead per sensor of SCOM keeps stable while the computation overhead per sensor of SS scheme and basic DS increases with network deployment density. If a sensor network is dense enough, the computational complexity of SS scheme and basic DS may overwhelm sensor computation capabilities and makes them infeasible in practice. We also see that SS scheme has less number of neighbors than basic DS because SS scheme only considers neighbors within one SR. Again, this observation conforms to the analysis results in Table I. Fig. 5(b) indicates similar observation for heterogeneous sensor networks.

c) Energy conservation: Fig. 6 illustrates the energy consumption of maintaining coverage for homogeneous sensor networks. In [24], a theoretical lower bound on the active sensor density to achieve 1-coverage is provided as \( \frac{2}{\sqrt{2\pi}SR^2} \), and is calculated in Fig. 6(a) as a baseline for comparison. We can see that SCOM consumes less energy than the other three schemes. For example, the energy consumption of SCOM is about 16% less than that of 2nd pass DS, which is the best performer among the others. This is because SCOM uses actual SR while the DS schemes use smaller conservative SR in order to avoid small sensing holes. From Fig. 6(a),
we also observe that SCOM consumes about 75% more energy than the theoretical lower bound. Fig. 6(b) illustrates the energy consumption to provide differentiated degree of coverage (i.e., $K$-coverage), for which the sensor deployment density is fixed at 8 sensors/SR². Since [5] does not describe how to use 2nd pass DS to provide $K$-coverage, 2nd pass DS is not included here. We can see from Fig. 6(b) that SCOM outperforms both basic DS and SS scheme significantly. The large discrepancy between SCOM and basic DS is due to the fact that a sensor’s integrated schedule generated by basic DS is a super set of its schedules for many grid points, and therefore is more than sufficient to provide the coverage guarantee. Moreover, we notice that, with the increase of the required degree of coverage, the energy consumption of SCOM grows slower than that of basic DS and SS scheme, and the growth rate of SCOM is only slightly higher than the growth rate of the theoretical lower bound. We show the energy conservation of different schemes in heterogeneous sensor networks in Fig. 7. Again, SCOM conserves more energy than other schemes.

d) Load balancing: As described in Section II-C, by setting the back-off timers according to sensor residual energy, SCOM can achieve load balancing by employing sensors with more percentage of residual energy to provide network coverage. Here we compare the load balancing of SCOM and a modified version of SCOM with random back-off timers (referred as SCOM without Load Balancing). In the simulations, each sensor starts with 100% energy and the energy consumption rate is fixed at 10% per round. Fig. 8(a) depicts the network lifetime of maintaining 1-coverage, which is measured as the time from the beginning of the deployment until the network loses 1-coverage of the target region. We can see that SCOM considerably extends the lifetime of networks with various deployment densities. Fig. 8(b) provides a closer look to the load balancing of SCOM by showing the evolvement of the standard deviation of residual energy in a network of 800 sensors. We can see that SCOM lowers the residual energy deviation significantly, which means SCOM better distributes workload among different sensors.

The simulation results presented above confirm that SCOM is highly scalable in terms of communication overhead and computational complexity, and also show that SCOM performs well to conserve energy and balance load among sensors.

IV. CONCLUSION

In this paper, we introduced SCOM that conserves energy while preserving the required sensing coverage by allowing sensors to autonomously decide their active/inactive states. An important property of SCOM is the high scalability to sensor deployment density in terms of communication overhead and computational complexity, which makes SCOM suitable for densely deployed sensor networks composed of simple sensors. We showed that the scalability of SCOM is better than the earlier works through both theoretical analysis and simulation study. Moreover, we demonstrated that SCOM outperforms several existing competitors on energy efficiency through simulation study.

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