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A Hybrid Memetic Framework for Coverage Optimization in Wireless Sensor Networks

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***Abstract*—One of the critical concerns in wireless sensor networks (WSNs) is the continuous maintenance of sensing coverage. Many particular applications, such as battlefield intrusion detection and object tracking, require a full-coverage at any time, which is typically resolved by adding redundant sensor nodes. With abundant energy, previous studies suggested that the network lifetime can be maximized while maintaining full coverage through organizing sensor nodes into a maximum number of disjoint sets and alternately turning them on. Since the power of sensor nodes is unevenly consumed over time, and early failure of sensor nodes leads to coverage loss, WSNs require dynamic coverage maintenance. Thus, the task of permanently sustaining full coverage is particularly formulated as a hybrid of disjoint set covers and dynamic-coverage-maintenance problems, and both have been proven to be nondeterministic polynomial-complete. In this paper, a hybrid memetic framework for coverage optimization (Hy-MFCO) is presented to cope with the hybrid problem using two major components: 1) a memetic algorithm (MA)-based scheduling strategy and 2) a heuristic recursive algorithm (HRA). First, the MA-based scheduling strategy adopts a dynamic chromosome structure to create disjoint sets, and then the HRA is utilized to compensate the loss of coverage by awaking some of the hibernated nodes in local regions when a disjoint set fails to maintain full coverage. The results obtained from real-world experiments using a WSN test-bed and computer simulations indicate that the proposed Hy-MFCO is able to maximize sensing coverage while achieving energy efficiency at the same time. Moreover, the results also show that the Hy-MFCO significantly outperforms the existing methods with respect to coverage preservation and energy efficiency.**

***Index Terms*—Energy-efficient operation, full coverage preservation, network lifetime extension, sensor node scheduling, wireless sensor networks (WSNs).**

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This paper has supplementary downloadable multimedia material available at http://ieeexplore.ieee.org provided by the authors. This support document shows the coverage matrix and some additional information regarding the real-world experiment. Moreover, a detailed performance comparison between the proposed method (Hy-MFCO) and other existing approaches is also provided. This material is 0.82 MB in size.

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

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I. Introduction

WIRELESS sensor networks (WSNs) are composed of a large number of sensor nodes with the capabilities of sensing, wireless communicating, and data processing. These sensor nodes cooperatively perform complicated sensing tasks and data collection/fusion tasks in a specific field. Given the limited energy of sensor nodes, it is critical to implement WSNs following the concept of dynamically energy-efficient management. To this end, a variety of WSN configurations have been extensively explored over the past years. Because of the limited power supply, the main objective of most studies is to maximize network lifetime with efficient energy utilization.

Configuration methods for WSNs have been developed to achieve different goals, such as energy conservation, object tracking, coverage preservation, etc. WSNs must be able to configure themselves to meet the requirements of various applications and environments. Coverage preservation is one of the critical issues that involve how well and how long WSNs can observe a physical phenomenon. Generally, in the research area of preserving coverage, the primary goal is to sustain full coverage as long as possible by assigning all sensor nodes into a fixed number of sets/groups. Nevertheless, such a static WSN configuration is not flexible enough for WSNs to operate in realistic environments due to some unexpected factors. The best solution would be to introduce a dynamic WSN configuration with the ability of adjusting the configuration as needed to maintain high quality of surveillance.

Thus, the purpose of this paper is to deal with both disjoint sets covers (DSC) and dynamic-coverage-maintenance (DCM) problems at the same time in order to maximize the lifetime of WSNs. First, we present a centralized MA-based scheduling strategy to select a minimum number of sensor nodes and arrange them into a maximum number of disjoints sets which will then be activated by turns, i.e., to solve the DSC problem, because the centralized scheduling method is able to generate a near-optimal outcome better than that resulted by the distributed method [1]. Afterwards, in order to match a practically operational circumstance, we consider the DCM problem and prove that this problem is nondeterministic polynomial (NP)-complete. We also use a heuristic recursive algorithm (HRA), based on the concept of recursion [2], to resolve the problem. The HRA is able to recover full coverage during the operation of each set by awaking a minimum number of sleeping nodes, that is, to achieve a dynamic configuration. Consequently, the proposed Hy-MFCO can maximize the lifetime of WSNs as long as possible.

The rest of this paper is organized as follows. Section II gives the related work. Section III presents the problem formulations. In Section IV, we illustrate that the proposed Hy-MFCO is composed of two mechanisms: 1) an MA-based scheduling strategy and 2) a distributed HRA. Section V evaluates the performance of the proposed algorithms in real-world scenarios using a WSN test-bed and computer-based simulations. Based on the experimental results, we conclude this paper with a summary and discuss the future work in Section VI.

II. Related Work

Different ways of sensor node organization can be used to improve the quality of service of WSNs. In Section II-A, we introduced several prevalent approaches with an energy efficient design. In terms of coverage preservation, the static configurations of WSNs were adopted extensively in the past. We comprehensively surveyed three main types of organizing methods related to the static configurations in Section II-B. Finally, the issue of dynamic coverage maintenance with the consideration of actual operation is addressed in Section II-C.

A. Efficient Organization Methods

Organizing sensor nodes into clusters has been proven to be an effective strategy to prolong network lifetime [3]–[5]. In a cluster-based WSN, the energy can be conserved by appropriate election of cluster head nodes which are responsible for managing their cluster members [6], [7]. On the other hand, sensor field configuration can be optimized through searching optimal placement of sensor nodes [8]. For persistent operation to accommodate any changes, the reorganization of WSNs is inevitably required under a dynamic environment. In this regard, mobile sensor nodes/robots are usually employed to improve the object surveillance quality [9]–[13]. They can self-organize a WSN by moving to different places on demand. From the studies on sensor node organization, it is obvious that WSNs can indeed efficiently operate for a longer time by organizing sensor nodes into different types of WSN configurations.

B. Coverage Preservation

In general, the organizing methods used for coverage preservation can be categorized into three main types, namely: 1) disjoint set algorithms; 2) nondisjoint set algorithms; and 3) hybrid algorithms. First, for disjoint set algorithms, a number of disjoint sets are generated under the consideration of maintaining full sensing coverage, and nodes in-between sets are mutually exclusive. For example, Slijepcevic and Potkonjak [14] proposed the most constrained-minimally constraining covering (MCMCC) heuristics to find the maximum number of disjoint sets. After selecting one sensor node to cover a more sparsely populated field (named critical field), the MCMCC heuristics algorithm excludes all other sensor nodes covering the critical field. Therefore, the number of disjoint sets can be as large as possible since only one sensor node would be selected to cover the critical field when organizing a disjoint set. Fig. 1(a) shows an example for monitoring two points of interest (POIs) using four sensor nodes. In this case, two disjoint sets {sensor node 4} and {sensor node 1, sensor node 2} are found all covering both POIs {POI 1, POI 2}. More studies [15]–[18] have been proposed to prolong network lifetime and maximize sensing coverage by formulating these tasks as a DSC problem. Aiming at the same goal of finding the maximum disjoint sets, Cardei and Du [15] transformed the problem into a maximum-flow problem, and presented the maximum covers using the mixed integer programming (MC-MIP) heuristics to finally prolong network lifetime. They proved that the DSC problem is NP-complete. The simulation results showed that the number of disjoint sets produced by the MC-MIP is slightly larger than that generated by the MCMCC. All the approaches introduced here are summarized in Table I in terms of the WSN configuration type, node organization type, and time complexity.

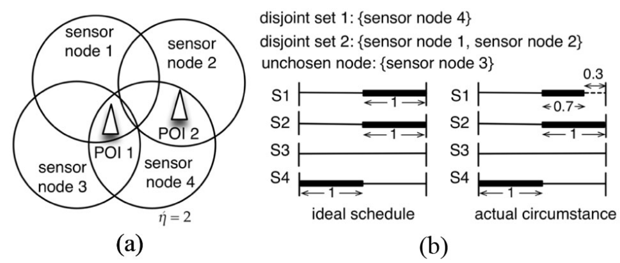

Fig. 1. Example with four sensor nodes and two POIs. (a) Positions of sensor nodes and POIs. (b) Two different on-duty schedules of sensor nodes.

Abrams *et al.* [16] also utilized three node-assignment methods, including a randomized algorithm, a distributed greedy algorithm, and a centralized greedy algorithm, to resolve the DSC problem. Basically, the three algorithms mentioned earlier also belong to the heuristics family that aims to solve the DSC problem. Due to the merits of fast computation and easy implementation, these heuristics soon become popular solutions for such problems. However, the heuristics possibly get trapped in a local optimum despite their many advantages.

Some studies [17]–[19] thus tried to use meta-heuristics to optimize the coverage rather than completely relying on the heuristics. Jia *et al.* [17] employed a nondominated sorting genetic algorithm (NSGA-II) to seek the optimal disjoint sets that meet a required coverage level, since the NSGA-II can produce the Pareto optimal outcome. In the NSGA-II, a binary genetic representation, named chromosome, corresponding to the status (on/off) of every sensor node was used. The NSGA-II would be applied again to the chromosomes to explore a new set until the found set could not meet the lower bound of the coverage level requirement. Furthermore,

TABLE I
LITERATURE REVIEW FOR THE APPROACHES USED TO PRESERVE COVERAGE

Method	Configuration	Organization of nodes	Time Complexity	Description
MCMCC [14]	static	disjoint set	$O(n^2)$	n is the number of nodes
MC-MIP [15]	static	disjoint set	$O(n^2)$	the number of fields is not considered in the computation
Randomized, distributed greedy, and centralized greedy [16]	static	disjoint set	1, $nk\|S_{max}\|$, and $2nk\|S_{max}\|$	$\|S_{max}\|$ is the cardinality of the largest disjoint set, and k is the number of the disjoint sets
NSGA-II [17]	static	disjoint set	-	-
GAMDSC [18]	static	disjoint set	$O((\mu + \lambda) \times n \times m)$	μ is the population size, λ is the number of offspring, and m is the number of POIs
Monte Carlo based GA [19]	static	disjoint set	-	-
MCNCA [20]	static	disjoint set	-	-
MDCS-Greedy, and MDCS-Dist [21]	static	non-disjoint set	$O(n^2 \times m \times w)$	w is the number of directions per sensor
PCL Greedy Selection [22]	static	non-disjoint set	$O(n^2 \times d \times log(d))$	d is the maximum node degree (coverage level)
2-Localized algorithm [23]	static	non-disjoint set	-	-
CWGC [24]	static	non-disjoint set	$(2\log_2(\hat{m}) + n) \times A^*$	$\hat{m}$ is the maximum number of POIs in the sensing area of any sensor
GA [25]	static	non-disjoint set	-	-
Dynamic-CCF [26]	static	disjoint/non-disjoint set	$O(an^2m + an^2 + anm)$	a is the maximum allowed participations of any node in the output sets
Receding-Horizon [12]	dynamic	mobile WSN	-	-
Dynamic path planning [13]	dynamic	mobile WSN	-	-
Distributed POP [27]	dynamic	fixed WSN	$O(g)$	g is the maximum number of neighbors of the node

$^*A = \left\lceil \frac{1}{\varepsilon} \log_{1+\varepsilon}\left(n / \left(1 - H(\hat{m})\varepsilon\right)\right)\right\rceil O\left(n^2 + n\min(m,n)\right)$, $H(\hat{m}) = \sum_{1\le i\le \hat{m}} 1/i$

'-' No time complexity analysis was provided by that study

Lai *et al.* [18] proposed a genetic algorithm (GA) to discover the maximum number of disjoint sets (named GAMDSC). An integer representation was used in the proposed GA. Every allele corresponding to a specific sensor node is represented by an integer ranging from one to $\acute{\eta}$. $\acute{\eta}$ represents the minimum times (frequency) that a POI is covered by sensor nodes. Hence, $\acute{\eta}$ determines the upper bound of the number of disjoint sets to be discovered. The simulation results indicated that GA can yield near-optimal solutions under different system configurations, e.g., network sizes and sensing ranges. It is noted, however, that the meta-heuristics methods often require more computational time to find an optimal solution of a given problem. As a result, the meta-heuristics methods are usually utilized as a prearrangement method before activating a WSN.

For the aforementioned heuristics and meta-heuristics, determining the value of $\acute{\eta}$ by evaluating the frequency that every POI is covered can help the algorithms to search for better solutions. Moreover, $\acute{\eta}$ is treated as the optimal number of disjoint sets that is used to compare with the number of disjoint sets yielded by computational algorithms [20], e.g., $\acute{\eta}$ equals to two in the example of Fig. 1(a), so at most two disjoint sets can be found.

Contrary to the node assignment rule in disjoint set algorithms, however, one sensor node can be assigned to more than one set, which is the main concept in nondisjoint set algorithms [21]–[25]. These algorithms successfully extend network lifetime compared with the disjoint set algorithms under some specific conditions. More importantly, they also indicated that using a nondisjoint set algorithm may extend the operating time of a set whose nodes are available to be reassigned to other sets. However, such circumstances are rare since sensor nodes are not usually placed following a precise scattering pattern in most WSN applications. Finally, a hybrid algorithm capable of producing either disjoint or nondisjoint sets was proposed [26]. However, the experimental results showed that applying the nondisjoint algorithms to WSNs does not provide a significant contribution to improve network lifetime.

C. Dynamic Coverage Maintenance

Although organizing sensor nodes into a number of sets has drawn greater attention in the field of coverage preservation, some questions still remain unanswered. Most of the aforementioned studies [14]–[18], [20]–[26] focused on exploring the maximum number of either disjoint or nondisjoint sets. They suggested that successively activating every generated set is able to prolong the network lifetime if an ideal network is given. As shown in Fig. 1(b), the ideal schedule allows each set to run for a fixed period of time (1 h). However, in practical applications, sensor nodes in WSNs are usually deployed using a randomly scattered pattern, and the distribution of energy consumption for nodes in WSNs will be nonuniform due to the heterogeneity among sensor nodes (e.g., different operation burden, transmission distance, etc.). That is, coverage dynamically varies not only in the spatial domain but in the temporal domain [11]–[13], [27]. Thus, the ideal scheduling is not appropriate. Fig. 1(b) also illustrates that in a practical circumstance sensor node 1 depletes its power after 0.7 working hour which is shorter than the ideal assumption (1 h), so there will be a coverage hole of POI 1, 0.7 h later. In fact, we can employ sensor node 3 to patch the coverage hole at that time to prolong the lifetime of disjoint set 2. Here, we formulate such an issue of dynamic coverage recovery as the DCM problem.

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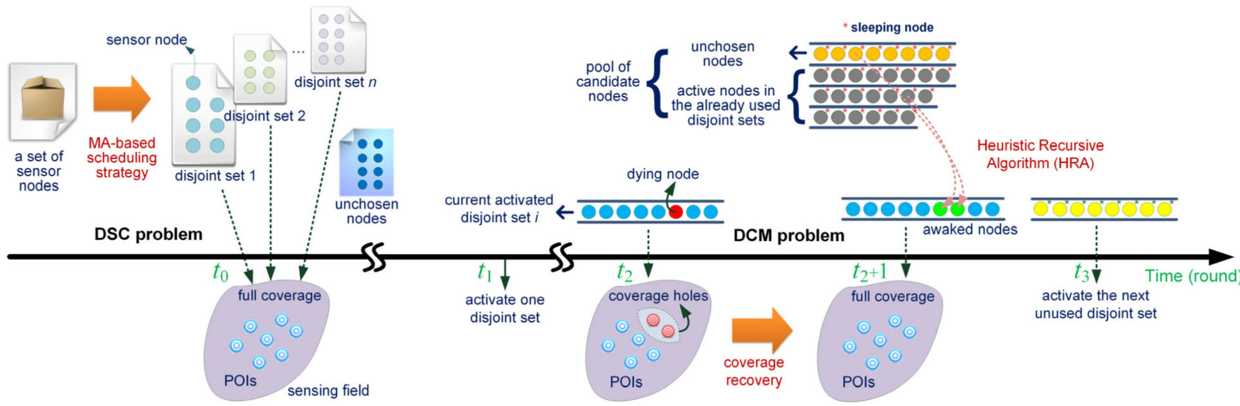

Fig. 2. Conceptual diagram of both the DSC and DCM problems to be solved for maintaining full coverage in this paper.

III. Problem Formulation

Although the sensor node density may be sufficient to meet both coverage and lifetime requirements at the beginning of WSN deployments, the coverage has to be traded for lifetime over a period of time due to power depletion of sensor nodes. In such a case, sensor nodes have to make their best effort to provide coverage as well as save their energy [27]. To accomplish this, we organize sensor nodes into a number of sets (the DSC problem) and switch them on in each set by turns. Meanwhile, we try to extend the working period of every independent set (the DCM problem). We further design a sleep schedule for other off-duty nodes to conserve energy by using the power saving mode of IEEE 802.15.4. Only the minimum nodes are active to cooperatively provide full coverage without redundancy. The conceptual diagram of the hybrid of the both aforementioned questions is depicted in Fig. 2. We divide the network lifetime into rounds, and one round can be regarded as the sampling period of a given WSN. At the beginning of each round, the coverage condition will be evaluated once. In Fig. 2, a WSN is deployed and then organized into n disjoint sets at t_0. After that, a disjoint set is initiated to perform the monitoring task at t_1. At t_2, a sensor node exhausts its power, unable to maintain full coverage. Through solving the DCM problem, two sensor nodes are awaked from the power saving mode at t_2+1 such that full coverage is retrieved. Afterwards, full coverage lasts until t_3. At t_3, full coverage cannot be sustained anymore, and another disjoint set must be initiated to replace the previous one at that time.

Here are some notations that will be used throughout this paper.

$\mathbf{S}$ the set of n nodes of $s_1, s_2, \ldots, s_n$, i.e., $\mathbf{S} = \{s_1, s_2, \ldots, s_n\}$;

$\mathbf{P}$ the set of m POIs of $p_1, p_2, \ldots, p_m$, i.e., $\mathbf{P} = \{p_1, p_2, \ldots, p_m\}$;

$B_j(t)$ the remaining battery life of s_j at round t;

$\mathbf{Cov}$ the collection of subsets of $\mathbf{P}$, which is used to record the coverage of each sensor node. That is, $\mathbf{Cov} = \{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_n\}$, where every set $\mathbf{f}_i$ represents a subset of $\mathbf{P}$ covered by sensor node s_i, $\mathbf{f}_i = \{p_j \mid p_j \in \mathbf{P}$, and p_j is covered by $s_i\}$;

$\mathbf{C}_i$ the disjoint set i corresponds to a subest of $\mathbf{S}$ (i.e., $\mathbf{C}_i \subseteq \mathbf{S}$) created in the beginning stage of a WSN by solving the DSC problem, in which all the members together monitor the whole POIs together;

$\check{\mathbf{C}}$ the collection of all the $\mathbf{C}_i$. Furthermore, $|\check{\mathbf{C}}|$ denotes the number of the generated disjoint sets;

$\mathbf{C}_i(t)$ the composition of disjoint set i at round t, e.g., $\mathbf{C}_i(0) = \mathbf{C}_i$;

$\mathbf{S}_f(t)$ the set of dying nodes which may cause a failure of full coverage at t, and $\mathbf{S}_f(t) \subseteq \mathbf{S}$;

$\mathbf{W}(t)$ the set of nodes to be awaked for patching coverage holes at round t, and $\mathbf{W}(t) \subseteq \mathbf{S}$. Thus, it can be known that $\mathbf{C}_i(t) = \mathbf{C}_i(t-1) \backslash \mathbf{S}_f(t) \cup \mathbf{W}_t$;

$t_{\mathbf{C}i,s}$, $t_{\mathbf{C}i,e}$ the start and end of $\mathbf{C}_i$'s on-period in terms of per round;

$D_{i,\text{on}}$ the duration of $\mathbf{C}_i$'s on-period in which full coverage is achieved, and $D_{i,\text{on}} = t_{\mathbf{C}i,e}$ - $t_{\mathbf{C}i,s}$;

$D_{i,\text{ext}}$ the extension of $\mathbf{C}_i$'s on-period, which is achieved by solving the DCM problem.

The lifetime of the WSN is the sum of every $\mathbf{C}_i$'s on-duty period and its extended time. Thus, the coverage preservation problem can be formulated as the following optimization problem:

$$\text{Max} \sum_{\mathbf{C}_i \in \check{\mathbf{C}}} \left(D_{i,\text{on}} + D_{i,\text{ext}}\right) \tag{1}$$

$$\text{ST} : \forall s_j \in \mathbf{C}_i(t), B_j(t) > 0, \bigcup_{s_j \in \mathbf{C}_i(t)} \mathbf{f}_j = \mathbf{P}. \tag{2}$$

Equation (2) shows that the remaining round number of each node in $\mathbf{C}_i(t)$ during the $\mathbf{C}_i$'s on-period and its extended time must be larger than zero when full coverage continues. If there exists any $B_j(t)$ which is equal to, or less than, zero, it implies that full coverage cannot be sustained due to the use of the fewest nodes. In the following subsections, the aforementioned maximization problem will be divided into two parts: the DSC and DCM problems which are both NP-complete.

A. Maximizing the Number of Disjoint Sets

In essence, the operation duration of a WSN under full coverage mainly depends upon the battery life of nodes covering POIs, such that assigning these nodes to a maximum number

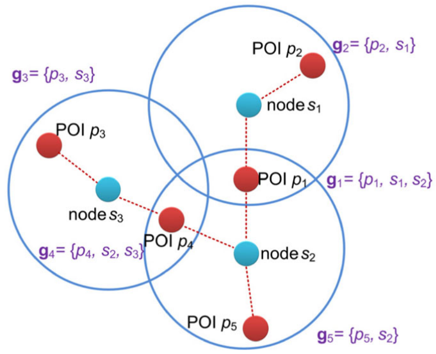

Fig. 3. Illustration for the hyperedges used to depict the relationships between nodes and POIs.

of disjoint sets is crucial for sustaining full coverage as longer as possible. Such a process is formulated as the DSC problem, which has been proven to be an NP-complete problem [15]. Alternatively, solving the maximization DSC problem suggests that the amount of redundant nodes used in preserving full coverage can be minimized.

Definition of DSC: Given a collection **Cov**, find the "maximum" number of disjoint sets for **P** such that each $p_j \in \{\mathbf{f}_i \mid \mathbf{f}_i \in \mathbf{Cov}$ and $s_i \in \mathbf{C}_i\}$, and for any two set covers $\mathbf{C}_i$ and $\mathbf{C}_j$, $\mathbf{C}_i \cap \mathbf{C}_j = \{\phi\}$.

B. Dynamically Patching the Local Coverage Holes by Awaking the Minimum Hibernated Sensor Nodes

As mentioned in the previous section, full sensing coverage cannot be maintained when one node (or more sensor nodes) in a disjoint set exhausts its energy. In order to recover the full sensing coverage, the network needs to select one or more sleeping nodes to patch the coverage holes without redundancy. Such a problem is defined as the DCM problem. To study the DCM problem from the perspective of coverage recovery, we need to define some more notations.

- $\mathbf{g}_i$ — the hyperedge connecting the uncovered POI p_i with available nodes covering p_i. An illustration regarding the representation of $\mathbf{g}_i$ is shown in Fig. 3; for example, the POI p_2 is covered by one node, i.e., s_1, $\mathbf{g}_2 = \{p_2, s_1\}$. For the POI p_1, when it is covered by more than one node (e.g., s_1 and s_2), $\mathbf{g}_1 = \{p_1, s_1, s_2\}$. Note that, in practice, the nodes that cover the p_i but do not have sufficient energy are excluded in every $\mathbf{g}_i$;
- $\mathbf{U}(t)$ — it is the collection of hyperedges that depict the relationship between every coverage hole (i.e., the exposed POIs) and the available sensor nodes covering the hole at round t, i.e., $\mathbf{U}(t) = \{\mathbf{g}_1, \mathbf{g}_2, \ldots, \mathbf{g}_z\}$, and $1 \leq z \leq m$.

With the notations, the definition of the DCM problem and the proof for NP-completeness are described as follows.

Definition of DCM: Given a collection $\mathbf{U}(t)$ composed of z elements at round t, that is $\mathbf{U}(t) = \{\mathbf{g}_1, \mathbf{g}_2, \ldots, \mathbf{g}_z\}$, find the wake-up set of available nodes $\mathbf{W}(t) \subseteq \mathbf{S}$ with a minimal size such that for each $\mathbf{g}_z$ $(1 \leq z \leq m)$ $\mathbf{W}(t) \cap \mathbf{g}_i \neq \{\phi\}$.

Theorem 1: The DCM problem is NP-complete.

Proof: A NP algorithm only needs to guess a given subset of **S** and checks whether at least one member of every $\mathbf{g}_i$ appears in the subset in polynomial time. By using a polynomial-time linear search method, the time complexity is O(nz) when the search method sequentially moves through the collection of $\mathbf{g}_i$ and checks if $\mathbf{g}_i$ intersects with $\mathbf{W}(t)$ for z times. The DCM problem belongs to NP.

The DCM problem can be proved to be NP-hard via a reduction from the minimum vertex cover problem [28]. A minimum vertex cover $\tilde{\mathbf{c}}$ of G is a set of vertices such that for each edge $\mathbf{e}_i = \{u_i, v_i\}$ at least one of u_i or v_i is in the cover. We can construct an equivalent instance G' of the DCM decision problem. The node set **S** in the instance G' of DCM can be viewed as the vertex set in the instance G of the minimum vertex cover problem, with each sensor node being mapped to a distinct vertex in the instance G. The instance G considers whether each edge has at least one vertex in $\tilde{\mathbf{c}}$, while the instance G' considers whether each uncovered POI (expressed by $\mathbf{g}_i$) can be covered by the nodes in $\mathbf{W}(t)$. Then, if there exists a minimum vertex cover $\tilde{\mathbf{c}}$ where at least one vertex of each edge is in $\tilde{\mathbf{c}}$, a corresponding wake-up set with the smallest size that covers all POIs also exists.

On the other hand, suppose that there is a wake-up set with the smallest size for the instance G', we can always find a solution for the instance G of the minimum vertex cover problem. Generating a solution to the instance G' simply becomes equivalent to finding the minimum vertex cover for the hyperedges that connect uncovered POIs and available nodes, such that each hyperedge intersects with the minimum vertex cover. In this regard, the solution of the instance G' readily produces a corresponding solution of the instance G.

G can have a minimum vertex cover if and only if there exists a wake-up set for G, which means that the minimum vertex cover problem can be reduced to the DCM decision problem in polynomial time. As the minimum vertex cover problem is NP-hard, the DCM decision problem is NP-hard. On the other hand, the DCM optimization problem is at least as hard as its decision problem, and thus, is also NP-hard. Additionally, since the DCM problem $\in$ NP, it can be further known that the DCM problem is NP-complete. ■

In the next section, we will present a hybrid memetic framework for coverage optimization (named Hy-MFCO) tackling both the NP-complete DSC and DCM problems with the purpose of maintaining full coverage as long as possible.

IV. Hybrid Algorithm Design

A hybrid framework that consists of an MA-based scheduling strategy and a HRA to optimize the coverage of WSNs is developed. The proposed framework aims at solving two major problems in WSNs, the DSC and DCM problems, thus the energy-efficient coverage can be achieved. Firstly, in the framework, the MA-based scheduling strategy is presented to cope with the DSC problem by organizing sensor nodes into a maximum number of disjoint sets. The MA is used to conduct a consecutive exploring process for finding the disjoint sets [29]. Benefited from the local genetic improvement technique, the MA-based scheduling strategy can quickly obtain a convergent result in finding the maximum number of DSC. Afterward, the second part of this framework, i.e., the HRA, is used to fast activation of several specific nodes to patch coverage holes caused by the failure or energy depletion of nodes. Before we present the proposed algorithm, we first give the definition of notations used here.

x_i the column vector that represents the selection result of nodes for each disjoint set $\mathbf{C}_i$ which is composed of n binary decision variables $\hat{x}_{i,r}$ (1: selected, and 0: nonselected), and $1 \leq r \leq n$;

$\delta_{l,k}$ the binary variable representing whether a given POI p_l is covered by the node s_k, which is calculated at the network initialization stage according to the collection of **Cov.** The definition of $\delta_{l,k}$ is given by

$$\delta_{l,k} = \begin{cases} 1, \text{ if POI } p_l \text{ is covered by node } s_k \\ 0, \text{ otherwise;} \end{cases} \tag{3}$$

$\mathbf{\Phi}_{\mathbf{s}'}$ the coverage matrix that depicts the coverage circumstance for a given node set $\mathbf{S}'$, which can be given as $\mathbf{\Phi}_{\mathbf{s}'} = [\mathbf{\Delta}_{1,\mathbf{s}'}\ \mathbf{\Delta}_{2,\mathbf{s}'} \ldots \mathbf{\Delta}_{m,\mathbf{s}'}]$;

$\mathbf{\Delta}_{l,\mathbf{S}'}$ the coverage vector which is a column vector that depicts the status whether the POI p_l is covered by the nodes in the given node set $\mathbf{S}'$, where $\mathbf{\Delta}_{l,\mathbf{s}'} = [\delta_{l,\mathbf{S}'[1]}\ \delta_{l,\mathbf{S}'[2]} \ldots \delta_{l,\mathbf{S}'[u]}]^T$, $1 \leq l \leq m$, $u = |\mathbf{S}'|$, and $\mathbf{S}'[i]$ denotes the ith element of $\mathbf{S}'$;

$\acute{\eta}$ the minimal frequency that a POI is covered by sensor nodes.

A. Proposed MA-Based Scheduling Strategy

The MA was first introduced by Moscato in 1989 [30], inspired by the concept of meme proposed by Dawkins [31]. It is viewed as being close to a form of the population-based hybrid GA combining with an individual learning procedure, such that a better performance in searching an optimal solution can be obtained with local refinements. In order to solve the DSC problem, the MA is utilized with a dynamic genetic structure to carry out a consecutive exploring process for disjoint sets, i.e., the MA is led by a heuristic to generate a maximal number of disjoint sets (i.e., Maximize $|\check{\mathbf{C}}|$). Every exploring process of the MA for a disjoint set will be terminated when the population fails to satisfy the desired coverage criterion over a length of epochs. In particular, each disjoint set created by the MA will be composed of minimum sensor nodes without redundancy; therefore, the energy resource for a WSN can be conserved and used to recover the loss of sensing coverage later. In this regard, the objective and constraints of each exploring process are

$$\text{Min} \sum_{r=1}^{n} \hat{x}_{i,r}, \forall x_i \tag{4}$$

$$\text{ST} : 0 < \sum_{r=1}^{n} \hat{x}_{i,r} \leq n \tag{5}$$

$$[\mathbf{\Phi}_{\mathbf{s}}]^T \cdot x_i \geq \mathbf{1} \tag{6}$$

$$x_i^T \cdot x_j = 0, \ \ i, \ j \leq \left|\check{\mathbf{C}}\right|, \ \text{and } i \neq j. \tag{7}$$

The objective function depicted in (4) tells that the amount of sensor nodes chosen for every disjoint set must be minimized. Equation (5) stipulates that the number of sensor nodes classified into each disjoint set must be equal to, or less than, n. To achieve full sensing coverage, every POI must be covered by at least one node in a given WSN as defined in (6). In addition, in order to ensure that every disjoint set has a unique composition of nodes without redundancy, (7) stipulates that the intersection of any two disjoint sets should be an empty set.

On the other hand, it can be seen that the frequency of a POI p_j to be covered is bounded between $\acute{\eta}$ and n, depicted as follows:

$$\forall p_j : 1 \leq \acute{\eta} \leq \sum_{k=1}^{n} \delta_{j,k} \leq n, 1 \leq j \leq m. \tag{8}$$

Thus, (8) reflects that $|\check{\mathbf{C}}| \leq \acute{\eta}$, i.e., no more than $\acute{\eta}$ disjoint sets could be found due to the essential constraints of the deployment condition.

1) Encoding Genetic Representation: Genetic representation is a structure that contains candidate solutions for a given problem. Here, we adopt a binary representation that contains a set of decision variables for a subset of sensor nodes. Every allele A_i of a given chromosome ϕ specifies selected/unselected (1/0) status of a corresponding sensor node in the pool of candidate nodes (e.g., for finding $\mathbf{C}_1$, the alleles "$A_1, A_2, \ldots, A_n$" correspond to "$s_1, s_2, \ldots, s_n$"). Using such a genetic representation is able to directly map the solution (chromosome) onto the decision vector x_i.

Besides, a dynamic chromosome structure capable of adjusting the chromosome length is utilized, and the chromosome length of the MA for finding x_i is equivalent to the size of the corresponding "candidate nodes pool," which is defined as $\mathbf{pol}_i$. Therefore, the computational complexity of the scheduling strategy can be significantly reduced when the size of $\mathbf{pol}_i$ decreases. As an example shown in Fig. 4, the chromosome structure for finding $\mathbf{C}_1$ is different from the structure for finding $\mathbf{C}_2$. Through the proposed MA, the first disjoint set $\mathbf{C}_1 = \{s_2, s_3\}$, i.e., $x_1 = [0\ 1\ 1\ \ldots 0]^T$, can be created by picking s_2 and s_3 from $\mathbf{pol}_1 = \mathbf{S} = \{s_1, s_2, \ldots, s_n\}$. Then, the residual nodes (i.e., $\mathbf{S} - \{s_2, s_3\}$) are reviewed as the candidate node pool $\mathbf{pol}_2$ for organizing the next disjoint set $\mathbf{C}_2$. Similarly, with the allele values drawn from the best chromosome "$A_1, A_2, \ldots, A_w$," x_2 can be also determined as $x_2 = [A_1\ 0\ 0\ A_2\ A_3 \ldots A_w]^T$.

2) Operations of the MA-Based Scheduling Strategy: Based on the genetic representation and formulations mentioned in (4)–(8), the MA-based scheduling strategy is applied to find potential solutions for organizing disjoint sets. It comprises two main parts: 1) a scheduling heuristic technique and 2) an MA. The pseudo code of the MA-based scheduling strategy is described in Algorithm 1. Before we introduce the detailed operations of the MA-based scheduling strategy, we define two notations. First of all, $\tilde{\mathbf{a}}_\psi$ is used to denote the allele vector of chromosome ψ, which is defined as $\tilde{\mathbf{a}}_\psi = [A_1\ A_2 \cdots A_u]$, where $u = |\mathbf{pol}_i|$, and $1 \leq u \leq n$. $\mathbf{\theta}_\psi$ is an indicator vector for ψ indicating whether full coverage is satisfied if the nodes are turned on following the decision

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Algorithm 1 Main Procedure of the MA-Based Scheduling Strategy

Input: $\mathbf{P}$, $\mathbf{S}$, $\mathbf{\Phi_S}$
Determine the parameters used in the MA: the population size s, the maximum epoch t, the crossover rate υ, and the mutation rate χ
Procedure:

$i = 1$, $\mathbf{pol}_1 = \mathbf{S} = \{s_1, s_2, \ldots, s_n\}$
repeat
$\mathbf{C}_i$ = MA_operations ($\mathbf{pol}_i$, $\mathbf{\Phi}_{\mathbf{pol}i}$, σ, τ, υ, χ)
// the detailed operations of the MA is described in Algorithm 2
$i = i + 1$
Renew the set of candidate nodes $\mathbf{pol}_i$ by $\mathbf{pol}_i = \mathbf{pol}_{i-1} - \mathbf{C}_{i-1}$
until $\mathbf{C}_i$ fails to guarantee full sensing coverage
Output all the disjoint sets $\mathbf{C}_1$, $\mathbf{C}_2$, $\ldots$, $\mathbf{C}_{i-1}$, and the residual nodes by $\mathbf{pol}_1 - \mathbf{C}_1 - \mathbf{C}_2 \cdots - \mathbf{C}_{i-1}$.

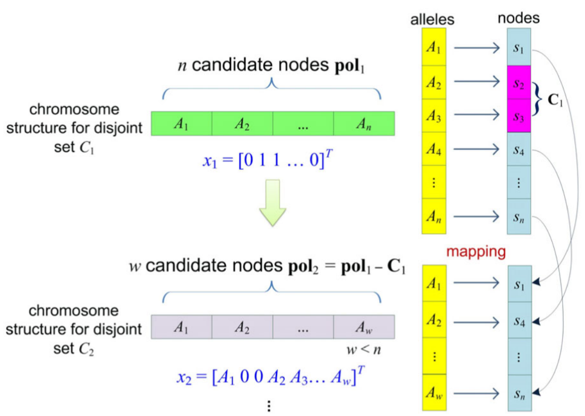


Fig. 4. Chromosome possessing a dynamic structure to accommodate its length to different sizes of disjoint sets.

result of $\tilde{\mathbf{a}}_\psi$. $\boldsymbol{\theta}_\psi$ is computed from a threshold function $\hat{T}$ that can be formulated by

$$\begin{aligned}\boldsymbol{\theta}_\psi &= \hat{T}\left(\tilde{\mathbf{a}}_\psi \cdot \Phi_{\mathbf{pol}i}\right)\\ &= \hat{T}\left(\left[A_1\ A_2\ \ldots\ A_u\right] \cdot \left[\mathbf{\Delta}_{1,\mathbf{pol}i}\ \mathbf{\Delta}_{2,\mathbf{pol}i}\ \cdots\ \mathbf{\Delta}_{m,\mathbf{pol}i}\right]\right)\\ &= \hat{T}\begin{pmatrix}\delta_{1,\mathbf{pol}i[1]} \cdot A_1 + \delta_{1,\mathbf{pol}i[2]} \cdot A_2 + \cdots + \delta_{1,\mathbf{pol}i[u]} \cdot A_u\\ \delta_{2,\mathbf{pol}i[1]} \cdot A_1 + \delta_{2,\mathbf{pol}i[2]} \cdot A_2 + \cdots + \delta_{2,\mathbf{pol}i[u]} \cdot A_u\\ n\\ \delta_{m,\mathbf{pol}i[1]} \cdot A_1 + \delta_{m,\mathbf{pol}i[2]} \cdot A_2 + \cdots + \delta_{m,\mathbf{pol}i[u]} \cdot A_u\end{pmatrix}\end{aligned} \tag{9}$$

where $\hat{T}(\mathbf{H}) = [h_1 \cdots h_m]^T$, and $\mathbf{H}$ is an $m \times 1$ vector. The function $\hat{T}$ is able to return a binary $m \times 1$ vector. The element h_i $(1 \le i \le m)$ of the returned vector is equal to one if the value of the corresponding ith element of $\mathbf{H}$ is equal to, or greater than, one. Otherwise, h_i is equal to zero.

At the beginning of the scheduling strategy, the coverage matrix $\mathbf{\Phi_S}$ is calculated to get the coverage status of a given WSN with a node set $\mathbf{S}$ to monitor POIs in $\mathbf{P}$, and the corresponding parameters in the MA are also determined. After these steps, the MA starts to search for potential solutions to organize sensor nodes into disjoint sets. The residual nodes that do not belong to any disjoint set will be used to recover the loss of sensing coverage later.

Algorithm 2 Memetic Algorithm (MA)

Input: $\mathbf{pol}_i$, $\mathbf{\Phi}_{\mathbf{pol}i}$, σ, τ, υ, χ
Output: the best chromosome ψ_{best} in *population* u_τ
Procedure:

$j = 0$
repeat
Calculate the fitness of every chromosome in the *population* u_j
$j = j + 1$
$u_j = u_{j-1}$
$u_j = crossover(u_j, \upsilon)$
$u_j = mutation(u_j, \chi)$
$u_j = local\_genetic\_improvement(u_j)$
until $j >$ the maximum generation number τ
Output the best chromosome ψ_{best} in the population u_τ

In the proposed MA, the population is initialized randomly. In order to evaluate the goodness of chromosome, every chromosome ψ has a corresponding ranking value computed by a fitness function defined by

$$f(\psi) = \omega \cdot \varpi_\psi - (1 - \omega) \cdot \vartheta_\psi \tag{10}$$

where ω is the weighting coefficient $(0 < \omega < 1)$, ϖ_ψ denotes the coverage ratio, and ϑ_ψ denotes the utilization rate of nodes. ϖ_ψ and ϑ_ψ are defined by

$$\varpi_\psi = \frac{\boldsymbol{\theta}_\psi^T \cdot \boldsymbol{\theta}_\psi}{m}, \vartheta_\psi = \frac{\tilde{\mathbf{a}}_\psi \cdot \tilde{\mathbf{a}}_\psi^T}{u}. \tag{11}$$

According to the fitness function defined in (10), the chromosome that uses lesser sensor nodes to cover all POIs in each disjoint set will result in a larger value of ϖ_ψ and a lower value of ϑ_ψ. The higher fitness value specifies a better solution encoded in the chromosome. The generational process of the MA will repeat until the maximum generation number τ has been reached, and the pseudo code of the MA is described in Algorithm 2. The MA includes three major parts: 1) crossover operation; 2) mutation operation; and 3) a local genetic improvement technique. For the crossover operation, the MA runs a tournament selection to seek better parent chromosomes and performs a single-point crossover with a crossover rate ν. Next, the MA performs the mutation operation with a probability χ that an allele changes its previous value. Finally, the local genetic improvement technique is used to refine the individual chromosome.

The local genetic improvement procedure is applied to assist the MA to achieve the maximal value of $f(\psi)$, and the details of the procedure is described in Algorithm 3. The core concept of the fitness enhancing procedure of an individual chromosome is to decrease the number of alleles whose value equals to one.

For ψ, the value of an allele changes from one to zero if the new fitness value (f'_ψ) is larger than the old one (f_ψ). The local genetic improvement procedure helps the population converge a near optimum solution.

Algorithm 3 Local Genetic Improvement Procedure

Input: ψ
Output: the enhanced ψ
Procedure:

```
k = 1
get the allele vector ã_ψ = [A_1 A_2 ··· A_u]
foreach allele A_k, 1 ≤ k ≤ u
    if A_k = 1
        calculate the fitness of ψ and let f_ψ = f(ψ)
        let A_k = 0, i.e., turn off the sensor node s_k
        recalculate the fitness and let f'_ψ = f(ψ)
        if f'_ψ < f_ψ
            restore the modification by letting A_k = 1
        end if
    end if
end foreach
Output ψ of new alleles.
```

To analyze the performance of the proposed algorithm, we need to know how many nodes are picked to form the disjoint sets by the algorithm. If most of the sensor nodes are selected to form the disjoint sets, it would be hard to patch coverage holes using fewer residual nodes. To further explore this matter, we first analyze the utilization rate of nodes here.

Theorem 2: Given a WSN and a number of POIs, if the algorithm finds $\acute{\eta}$ disjoint sets, the proposed MA-based scheduling strategy achieves an utilization rate of nodes, $\mathrm{OPT}/n \approx \acute{\eta}\ (1/n + m/\Theta) - \mathrm{COV}_{\acute{\eta}}/\Theta$, where Θ denotes the sum of the frequencies that every POI is covered, $\Theta = \sum_{s_j \in \mathbf{S}} \sum_{p_i \in \mathbf{P}} \delta_{i,j}$. $\mathrm{COV}_{\acute{\eta}}$ denotes the sum of the numbers of POIs monitored by the nodes which cover the POI with the minimal covered frequency $p_{\acute{\eta}}$, $\mathrm{COV}_{\acute{\eta}} = \sum_{s_j \in \mathbf{S}_{\acute{\eta}}} \sum_{p_i \in \mathbf{P}} \delta_{i,j}$, and $\mathbf{S}_{\acute{\eta}} = \{s_x \mid s_x \text{ covers } p_{\acute{\eta}} \text{ and } s_x \in \mathbf{S}\}$.

Proof: The utilization rate of nodes is estimated if the algorithm can generate a maximum number of k disjoint sets, i.e., $k = \acute{\eta}$. Let $cov_{\acute{\eta}}^1, cov_{\acute{\eta}}^2, \ldots, cov_{\acute{\eta}}^k$ denote the numbers of POIs monitored by the nodes $s_1, s_2, \ldots, s_k$ ($s_x \in \mathbf{S}_{\acute{\eta}}$, $1 \le x \le k$, $|\mathbf{S}_{\acute{\eta}}| = k$) which all covering $p_{\acute{\eta}}$. Then

$$\mathrm{COV}_{\acute{\eta}} = cov_{\acute{\eta}}^1 + cov_{\acute{\eta}}^2 + \cdots + cov_{\acute{\eta}}^k. \tag{12}$$

In order to achieve full coverage for each disjoint set, the algorithm must assign every node of $\mathbf{S}_{\acute{\eta}}$ to k disjoint sets. That is, there must be "a member" of every disjoint set belonging to $\mathbf{S}_{\acute{\eta}}$.

Let $\mathrm{opt}_1, opt_2, \ldots, opt_k$ denote the actual quantity of nodes selected for k individual disjoint sets

$$opt_x \approx 1 + \frac{m - cov_{\acute{\eta}}^x}{\overline{cov}} \tag{13}$$

where $\overline{cov}$ represents the average number of POIs covered by nodes, and $\overline{cov} = \Theta/n$. Each opt_x can be approximated by using (13). In (13), the number of "1" represents one specific node s_x, and $(m - cov_{\acute{\eta}}^x)/\overline{cov}$ is used to estimate how many nodes are employed to monitor the residual POIs which are uncovered by s_x. Afterward, the number of nodes that OPT picks to form all disjoint sets can approximate by

$$\begin{aligned}\mathrm{OPT} &= opt_1 + opt_2 + \cdots + opt_k \approx k + \frac{km - \sum_{x=1}^{k} cov_{\acute{\eta}}^x}{\overline{cov}} \\ &= k + \frac{km}{\overline{cov}} - \frac{\mathrm{COV}_{\acute{\eta}}}{\overline{cov}}.\end{aligned} \tag{14}$$

As for the utilization rate of nodes, it can be further approximated by

$$\frac{\mathrm{OPT}}{n} \approx \left(k + \frac{km}{\overline{cov}} - \frac{\mathrm{COV}_{\acute{\eta}}}{\overline{cov}}\right)\Big/ n = \acute{\eta}\left(\frac{1}{n} + \frac{m}{\Theta}\right) - \frac{\mathrm{COV}_{\acute{\eta}}}{\Theta}. \tag{15}$$

■

Let e_x define the error term to evaluate the approximation effect on the number of nodes chosen in a set. Based on (14), thus, e_x can be represented as

$$\begin{aligned}e_x &= opt_x - \left[1 + \left(m - cov_{\acute{\eta}}^x\right)\Big/\overline{cov}\right] \\ &= \left(opt_x \cdot \overline{cov} - m + cov_{\acute{\eta}}^x\right)\Big/\overline{cov} - 1.\end{aligned} \tag{16}$$

Then, let $D_x = opt_x \cdot \overline{cov} - m$ so that $e_x = (D_x + cov_{\acute{\eta}}^x)/\overline{cov} - 1$. Thus, we can further find the boundary conditions of e_x as follows.

Lemma 1: $\forall e_x$, *if* $cov_{\acute{\eta}}^x \le \overline{cov}$, then $e_x \le D_x/\overline{cov}$.

Proof: Firstly, suppose the number of POIs covered by a given node in $\mathbf{S}_{\acute{\eta}}$ is less than (or equal to) the average $\overline{cov}$, i.e., $cov_{\acute{\eta}}^x \le \overline{cov}$. Then, it is easy to know $(D_x + cov_{\acute{\eta}}^x)/\overline{cov} \le (D_x + \overline{cov})/\overline{cov}$. Further, it can be simplified by $(D_x + cov_{\acute{\eta}}^x)/\overline{cov} \le D_x/\overline{cov} + 1 \Rightarrow (D_x + cov_{\acute{\eta}}^x)/\overline{cov} - 1 \le D_x/\overline{cov} \Rightarrow e_x \le D_x/\overline{cov}$. ■

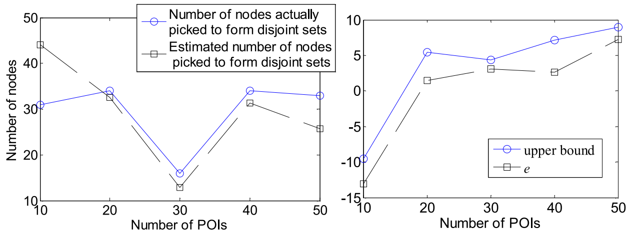
Lemma 1 shows that the estimation error of the quantity of used nodes in each disjoint set has a upper bound depending on whether $cov_{\acute{\eta}}^x \le \overline{cov}$. Although we can individually find the boundary for e_x, it is difficult to estimate the boundary for the sum of the individual errors, $e = \sum_{x=1}^{k} e_x$, representing the estimation error of total amount of nodes chosen in all disjoint sets. However, considering some reasonably assumed situations is able to assist us to realize the boundary of e.

Theorem 3: If every $cov_{\acute{\eta}}^x \le \overline{cov}(1 \le x \le k)$, the total error e of the quantity of the used nodes picked to form all disjoint sets has an upper bound

$$e \le (\overline{cov} \cdot \mathrm{OPT} - km)/\overline{cov}. \tag{17}$$

Proof: Suppose that every $cov_{\acute{\eta}}^x \le \overline{cov}$. According to Lemma 1, we know that $e \le D_1/\overline{cov} + D_2/\overline{cov} + \cdots + D_k/\overline{cov}$. Then, $D_x = opt_x \cdot \overline{cov} - m$, and the bound mentioned earlier becomes $e \le (\overline{cov}\ (opt_1 + opt_2 + \cdots + opt_k) - km)/\overline{cov}$. Hence, it can be seen that $e \le (\overline{cov} \cdot \mathrm{OPT} - km)/\overline{cov}$. ■

According to Theorem 1, if the maximum number of disjoint sets is found by the algorithm, the utilization rate of nodes depends on the intrinsic network conditions including the number of nodes (n), the number of POIs (m), and coverage patterns of a given WSN (i.e., $\mathrm{COV}_{\acute{\eta}}$ and Θ). This supports that the proposed algorithm can choose the fewest nodes to organize the disjoint sets. Based on the proposed framework of Hy-MFCO, on the other hand, using fewer nodes (i.e., a



(a) (b)

Fig. 5. Example to estimate the quantity of node selection. (a) Estimated and actual utilization rates of nodes picked to form the disjoint sets. (b) Error and its upper bound.

lower utilization rate of nodes) to form the maximum number of disjoint sets facilitates searching the best solution to the DCM problem since more candidate nodes could be provided after all the disjoint sets are organized. Fig. 5 shows a practical example to estimate the utilization rate of nodes obtained by the proposed algorithm. For each case in Fig. 5, there are 60 nodes with a fixed sensing range of 180 m and a specific amount of POIs (10–50) being randomly scattered in a 500 × 500 m field (each $cov_{\acute{\eta}}^{x} \leq \overline{cov}$), and through post-verification we know that the proposed algorithm can find the maximum number of disjoint sets. Referring to the result of Fig. 5, indeed, $\acute{\eta}(1/n + m/\Theta) - \mathrm{COV}_{\acute{\eta}}/\Theta$ can be used to approximate the utilization rate of nodes, OPT/n, although its estimation is very difficult.

After the DSC problem is solved by the proposed MA-based scheduling strategy, a HRA is used to cope with the DCM problem such that the loss of sensing coverage can be recovered. The detailed description of HRA will be given in the next section.

B. Proposed HRA

In this section, we present an algorithm named the HRA to cope with the DCM problem. The proposed HRA models the DCM problem by using a recursive formulation $\hat{\mathbf{y}}_\rho$ which is defined as

$\hat{\mathbf{y}}_\rho$ a possible solution (set) that includes at most ρ nodes, and it is created by adding a node s_j from $\mathbf{S}$ to the set $\hat{\mathbf{y}}_{\rho-1}$ if s_j can contribute to the coverage recovery.

The proposed HRA will perform the search epoch at most $\tilde{n}$ times in accordance with the increment in ρ ($1 \leq \rho \leq \tilde{n}$, and $\tilde{n}$ is the number of nodes available to repair the coverage); otherwise, $\hat{\mathbf{y}}_\rho = \hat{\mathbf{y}}_{\rho-1}$. Firstly, in order to evaluate how many $\mathbf{g}_k$ in $\mathbf{U}(t)$ has a nonempty intersection with the current node set composed of the node s_j and $\hat{\mathbf{y}}_{\rho-1}$, a goodness function Q is defined as

$$Q(s_j) = \sum_{k=1}^{z} M\left(\left(s_j \cup \hat{\mathbf{y}}_{\rho-1}\right) \cap \mathbf{g}_k\right) \tag{18}$$

where $1 \leq k \leq z$ (z is the number of the POIs that are not covered), and the indicator function $M(\mathbf{B}) = 1$, if the number of elements in a possible node set $\mathbf{B}$ is more than one; otherwise, $M(\mathbf{B}) = 0$. During performing of the proposed HRA, every new generated $\hat{\mathbf{y}}_\rho$ is recorded and then used in the next loop of the recursive search. Under a variety of compositions of nodes, the purpose of the HRA is to find the smallest wake-up set $\mathbf{W}(t)$ from currently inactive nodes by initiating a consecutive search procedure based on $\hat{\mathbf{y}}_0$. The formulation of the recursive model is defined as follows if $\mathbf{U}(t) \neq \{\phi\}$:

$$\hat{\mathbf{y}}_\rho = \begin{cases} \{\phi\}, & \text{if } \rho = 0 \\ \hat{\mathbf{y}}_{\rho-1} \cup \left(\underset{s_j \in \mathrm{S}}{\arg\max}\, Q(s_j) \colon = \left\{ s_j \middle| s_j \notin \hat{\mathbf{y}}_{\rho-1} \right\}\right), & \text{if } \rho \geq 1. \end{cases} \tag{19}$$

If more than one node is found with the same maximum goodness Q (i.e., some nodes cover the identical POIs), the node with the maximum residual energy index REI(s_j) will be chosen preferentially via (18) and (19). The pseudo code of the proposed HRA is described in Algorithm 4. The search procedure will be terminated when $\sum_k M(\hat{\mathbf{y}}_\rho \cup \mathbf{g}_k)$ is equal to z, i.e., when the lost sensing coverage has been recovered. Otherwise, the search procedure will continue until $\rho = \tilde{n}$. Using this recursive procedure, HRA is able to generate a solution for awaking fewer nodes to recover the loss of sensing coverage. Taking the full coverage into consideration, if there is no sleeping node that can be used to help achieve full sensing coverage, it is necessary to activate the nodes in another unused disjoint set. All of the activated nodes in the previous disjoint set will be switched to the sleeping mode and reawaked if needed.

Note that the HRA will be applied again to maximize the sensing coverage using residual nodes after all disjoint sets are used. The proposed HRA is able to efficiently solve the DCM problem because: 1) it integrates a recording ability into its recursive process and 2) it minimizes the energy consumption of nodes. Moreover, the HRA can be easily implemented on sensor nodes with local information gathered from neighboring nodes.

The time complexity of the HRA in the worst case is $O(n^2)$ through a computational complexity analysis. The formulation of HRA resembles that of dynamic programming (DP) [32], but the execution speed of the HRA is quicker than that required to perform the DP due to its greedy-based characteristics. As a result, the HRA is able to rapidly respond to changes of the network topology, especially for the mission-critical applications of WSNs. A simple example that demonstrates how the DCM problem is solved by the proposed HRA is given based on some assumptions depicted as follows.

Suppose that a given WSN is formed with a set of nodes $\mathbf{S}$, and three exposed POIs, p_1, p_2, p_3, exist in the sensing field. In this case, p_1 is covered by the nodes s_1, s_2, and s_5, p_2 is covered by the nodes s_2, s_3, and s_4, and p_3 is covered by the nodes s_1, s_4, and s_6.

Thus, $\mathbf{U}(t) = \{\mathbf{g}_1, \mathbf{g}_2, \mathbf{g}_3\}$

$$\mathbf{S} = \{s_1, s_2, s_3, s_4, s_5, s_6\}, \mathbf{g}_1 = \{p_1, s_1, s_2, s_5\}$$
$$\mathbf{g}_2 = \{p_2, s_2, s_3, s_4\}, \mathbf{g}_3 = \{p_3, s_1, s_4, s_6\}.$$

Firstly, when $\rho = 1$, in order to recover the exposed POIs, p_1, p_2, and p_3, HRA will look for the node with the maximum goodness Q. In this case, because s_1, s_2, and s_4 have the same goodness value of two (i.e., they all cover two POIs), their REIs (s_1: 0.61, s_2: 0.82, and s_4: 0.78) are utilized to determine $\hat{\mathbf{y}}_1$. The HRA will find the node with the maximum

Algorithm 4 HRA

Input: $\mathbf{U}(t)$, $\mathbf{P}$
Output: $\mathbf{W}(t)$
Procedure:

If $\mathbf{U}(t) \neq \{\phi\}$
  Initially, let $\hat{\mathbf{y}}_0 = \{\phi\}$
  For $\rho = 1$ **to** ñ **do**
    $maxQ = 0$, $pre\_best\_node = \{\phi\}$
    /* $maxQ$ is used to record the best returned value from Q function, and pre_best_node is used to record the best candidate node for every epoch. */
    /* compute $\hat{\mathbf{y}}_\rho$*/
    For $j = 1$ **to** $\tilde{n}$ **do**
      If $Q(s_j) > maxQ$ **and** $s_j \notin \hat{\mathbf{y}}_{\rho-1}$
      let $maxQ = Q(s_j)$, $pre\_best\_node = s_j$, and $\hat{\mathbf{y}}_\rho = \hat{\mathbf{y}}_{\rho-1} \cup s_j$
    Else If $Q(s_j) = maxQ$ **and** $s_j \notin \hat{\mathbf{y}}_{\rho-1}$
      If $\mathrm{REI}(s_j) > \mathrm{REI}\ (pre\_best\_node)$
      let $maxQ = Q(s_i)$, $pre\_best\_node = s_j$, and $\hat{\mathbf{y}}_\rho = \hat{\mathbf{y}}_{\rho-1} \cup s_j$
      End
    End
  End
  If $\sum_k M(\hat{\mathbf{y}}_{\rho-1} \bigcap \mathbf{g}_k\ ) = z$ **then**
    let$\mathbf{W}$(t) $= \hat{\mathbf{y}}_\rho$ and break
  End
End
If $\rho =$ ñ **then**
  let $\mathbf{W}(t) = \hat{\mathbf{y}}_\rho$
End
End.

TABLE II
DEMONSTRATED CASE FOR THE PROPOSED HRA

Node	*REI*	Coverage of POIs	$\rho = 1$		$\rho = 2$	
			$Q(s_i)$	$\hat{\mathbf{y}}_1$	$Q(s_i)$	$\hat{\mathbf{y}}_2$
s_1	0.61	p_1, p_3	2	-	3	-
s_2	0.82	p_1, p_2	2	$\hat{\mathbf{y}}_1$	-	$\hat{\mathbf{y}}_2$
s_3	0.92	p_2	1	-	2	-
s_4	0.78	p_2, p_3	2	-	3	$\hat{\mathbf{y}}_2$
s_5	0.54	p_1	1	-	2	-
s_6	0.42	p_3	1	-	3	-

* $\mathbf{W}(t) = \hat{\mathbf{y}}_2$

value of REI. According to this rule, thus, s_2 will be chosen to form $\hat{\mathbf{y}}_1$. Afterward, for the second round of searching, i.e., $\rho = 2$, s_1, s_4, and s_6 are the possible candidate nodes for forming $\hat{\mathbf{y}}_2$, since all of them can cover the last uncovered POI p_3. Nevertheless, only s_4 is chosen to form $\hat{\mathbf{y}}_2$, because it has the largest REI. Finally, the HRA completes the consecutive search procedure as the termination condition is met; that is, $\sum_k M(\hat{\mathbf{y}}_\rho \cap \mathbf{g}_k) = 3$ $(1 \leq k \leq 3)$, and the final solution $\mathbf{W}(t)$ is set to be $\hat{\mathbf{y}}_2$, which consists of s_2 and s_4. A detailed list regarding the goodness Q and $\hat{\mathbf{y}}_i$ is summarized in Table II.

From the aforementioned description, we know that the HRA is able to determine a wake-up list to repair the lost coverage so as to maintain the full coverage with energy efficiency. Thus, the energy of nodes can be conserved, and the coverage of POIs can be retained. Furthermore, by viewing all POIs as uncovered ones, i.e., $\mathbf{U}(t) = \{\mathbf{g}_1, \mathbf{g}_2, \ldots, \mathbf{g}_m\}$, HRA is able to choose fewer residual nodes with sufficient energy to maintain the coverage as larger as possible after all disjoint sets are used.

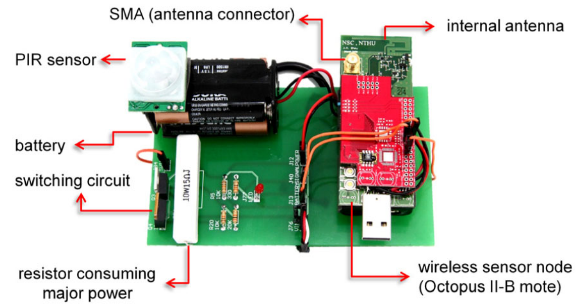


Fig. 6. Configuration of the WMD used in the real-world testing.

V. EXPERIMENTAL RESULTS

In this section, we will evaluate the performance of the proposed hybrid framework through both real-world testing and computer simulations. Firstly, in order to verify the performance of the Hy-MFCO for prolonging network lifetime, a practical test with a detailed analysis under real-world scenarios was carried out. Subsequently, the overall operation performance of the proposed Hy-MFCO was evaluated in uniformly and randomly deployed WSNs, and the results were compared with the performances of using other existing approaches.

A. Implementation of the Hy-MFCO in the Real World

We have applied the proposed Hy-MFCO to real-world scenarios using a WSN test-bed constructed by the Octopus II-B mote [33]. In order to effectively evaluate the performance of the proposed Hy-MFCO, we developed a WSN-based motion detector (WMD) composed of an Octopus II-B mote and a passive infrared (PIR) sensor [34]. The Octopus II-B mote is able to activate or inactivate the PIR sensor via a switching circuit. Moreover, in order to test the robustness of Hy-MFCO, three kinds of resistors (6.8 Ω/10 W, 10 Ω/10 W, and 15 Ω/10 W) were connected to the switching circuit to cause an irregular distribution of energy consumption. In this experiment, we connected 6.8 Ω resistors to 14 WMDs, 10 Ω resistors to 12 WMDs, and 15 Ω resistors to 12 WMDs. The configuration of the WMD is shown in Fig. 6, and the parameter settings of the test-bed are summarized in Table III.

The WMDs used in this paper can operate in two modes: a low-power mode and a general mode. In the low-power mode, the resistors (6.8, 10, and 15 Ω) and the PIR sensor were inactivated, so the power of WMD was mainly consumed by the Octopus II-B mote (for receiving or transmitting messages) and was approximately 30 mA. When operating in the general mode, however, three types of WMDs roughly consumed 600 mA (6.8 Ω), 485 mA (10 Ω), and 340 mA (15 Ω). We collected many used batteries as the power sources for the 38 WMDs in order to increase the energy consumption asymmetry between the WMDs. Although the batteries were not brand new, they were still sufficient to supply electric power required by the WMDs.

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TABLE III
SETTINGS OF THE TEST-BED AND PARAMETERS ADOPTED IN THE MA

Settings of the real world testbed	
Dimension	6 m (length) × 6 m (width) × 2.8 m (height)
POI	2 m (length) × 1.5 m (width)
Sensor node	38 WMDs connected with three kinds of resistors (6.8 Ω/10 W, 10 Ω/10 W, and 15 Ω/10 W)
REI (battery voltage) threshold	1.55 V
Parameters of the MA	
population size σ	100
crossover rate υ	0.5
mutation rate χ	0.07
maximum iteration number τ	20
weighting coefficient ω	0.5

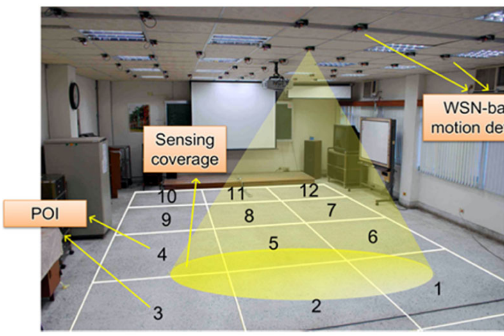

Fig. 7. Test environment used in this paper, including 38 WMDs and 12 POIs, and the yellow ellipse shaped region representing the possible sensing coverage of a WMD.

The experiment was conducted in a room with 12 POIs and a WSN comprising 38 WMDs. Each POI represented a 2 × 1.5 m grid to be monitored by the WSN. In such an experimental environment, the deployed WMDs formed a centralized WSN in which WMDs were able to communicate with the base station (or called the sink node) comprising a laptop and an Octopus II-B mote in charging of transmitting commands/packets among nodes. The main operations of Hy-MFCO were implemented on the JAVA platform installed in the sink node. Note that, in fact, Hy-MFCO is also feasible to be used in large-scale real-world WSNs, because management nodes (e.g., the head nodes in different clusters) can serve as the sink node to perform wide-range monitoring tasks using the proposed Hy-MFCO.

In this experiment, once a person passed through the POI, the movement would be detected by one or more WMDs in the WSN. In order to evaluate the coverage-controlling performance of the proposed Hy-MFCO, a coverage evaluation procedure was done by the person who stood on any POI for 3 s and then moved to next POI in an ascending order of POIs. The POI was in the sensing coverage if one of the WMDs was able to detect any object movement within that POIs grid. By doing so, we could observe the variation of overall sensing coverage of the WSN at any time. The construction of the WSN testbed is shown in Fig. 7.

At first, the coverage matrix $\mathbf{\Phi_S}$ defined in Section IV was obtained through a coverage evaluation procedure. By feeding $\mathbf{\Phi_S}$ into the Hy-MFCO, the disjoint sets which would be applied to the deployed WSN could be determined. The $\mathbf{\Phi_S}$

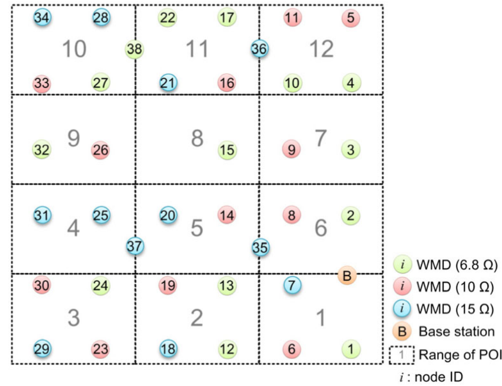

Fig. 8. Relative locations of WMDs and the base station in a given experimental space.

related to the coverage of the WSN is summarized in the supplemental Table I of the supplemental document [35] due to limited space. According to both the coverage matrix $\mathbf{\Phi_S}$ and the battery voltage readings acquired by the WSN, the missing coverage of POIs could be acquired. Once the Hy-MFCO detected that some POIs were not covered by the nodes in the activated disjoint set, it would immediately trigger the HRA to awake some WMDs to recover the loss of coverage. In the experiment, we measured the battery voltage through the analog-to-digital converter installed onboard the Octopus II-B mote and treated the voltage information as the REI. During the operating period, the Hy-MFCO checked the REI of every WMD to determine whether it was necessary to activate some WMDs in the general mode. In addition, a voltage threshold of 1.55 V was used to determine whether a WMD failed, because it was the lowest turn-on voltage for the PIR sensor. Thus, a WMD was viewed as a dead one if its REI was below 1.55 V.

Locations of WMDs and the base station in relation to 12 POIs are depicted in Fig. 8. According to our practical experience after repeated experiments, the parameters of MA were set as follows: the population size σ, 100; the crossover rate ν, 0.5; the mutation rate χ, 0.07; the maximum iteration number τ, 20; and $\omega = 0.5$, as shown in Table III. Then, according to the geographic topology of the deployed WSN, 13 disjoint sets were found by the Hy-MFCO. Only 31 WMDs were included in the yielded disjoint set. The members of every disjoint set $\mathbf{C}_i$ are listed as follows: $\mathbf{C}_1 = \{20, 38\}$, $\mathbf{C}_2 = \{19, 26\}$, $\mathbf{C}_3 = \{16, 18\}$, $\mathbf{C}_4 = \{1, 27\}$, $\mathbf{C}_5 = \{13, 36\}$, $\mathbf{C}_6 = \{12, 17\}$, $\mathbf{C}_7 = \{10, 32\}$, $\mathbf{C}_8 = \{8, 30\}$, $\mathbf{C}_9 = \{14, 33\}$, $\mathbf{C}_{10} = \{2, 7, 21\}$, $\mathbf{C}_{11} = \{5, 15, 23\}$, $\mathbf{C}_{12} = \{6, 22, 25\}$, and $\mathbf{C}_{13} = \{4, 9, 11, 34\}$. The WMDs that belonged to the redundant set included No. 3, 24, 28, 29, 31, 35, and 37, and they were regarded as the candidates for the HRA. Based on the concept of the DCM problem, some of candidate WMDs will be probably switched to the general mode to recover the uncovered POIs.

Fig. 9 shows the curve of the coverage ratios (%) varying over time in the experiment. The coverage ratio was calculated from the results of the coverage evaluation procedure. Combining with the HRA, the disjoint sets generated from the MA-based scheduling strategy could run for 268 min. During this period, 13 disjoint sets were activated one after another, and the HRA woke up sleeping WMDs 7 times to

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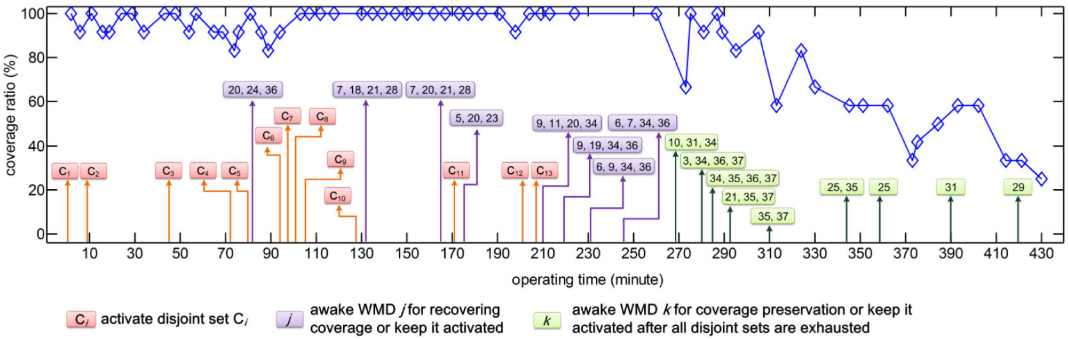

Fig. 9. Evaluated coverage ratio (%) versus time when the proposed Hy-MFCO is applied to a given WSN. The coverage ratio is defined as the number of covered POIs divided by the number of all POIs.

maintain full sensing coverage. The results indicate that the average coverage ratio was 97% computed from 42 coverage-evaluation tests (among the tests, the coverage ratios of 40 tests $\geq$ 10/12) before the 269th min. Additionally, the primary objective of the Hy-MFCO, aiming to maintain full coverage with energy efficiency, was successfully achieved in this real-world experiment.

The slight decreases of the coverage ratio during the experiment were probably caused by some measurement errors when the coverage evaluation procedure was performed. In fact, this problem could be handled by repeating the evaluation procedure or taking the k-coverage technique [36] into consideration, but the detailed discussion of these procedures is out of the scope of this paper. As time passed by, the number of candidate WMDs became larger. Thus, it was easier to recover the loss of sensing coverage for the subsequent disjoint sets. Such a phenomenon is also shown in Fig. 9, where the HRA was conducted four times when $\mathbf{C}_{13}$ was on duty. According to the survey results, the HRA was triggered eight times to extend the operating time by 138 min during the operation of the disjoint sets. In other words, the HRA was able to prolong the network lifetime by 99.2% before all disjoint sets were exhausted at the 268th min. When the nodes in all disjoint sets exhausted their energy, the HRA was conducted again to determine which WMDs should be activated to maintain the larger sensing coverage ratio except that all WMDs were exhausted.

In Fig. 10, we can observe that the average REI of the on-duty WMDs exhibits a repeated descending pattern if an unused disjoint set with a higher average REI was activated. This strategy effectively conserved energy for the entire network, because nodes could be individually activated if necessary.

In summary, the experimental results have confirmed that the Hy-MFCO is indeed able to optimize the coverage of WSNs by appropriately turning on/off sensor nodes. As expected, the Hy-MFCO still produced a good performance on preserving sensing coverage, even when it was tested in a complex and asymmetric WSN environment.

B. Performance Evaluation

In this subsection, we further analyze the performance of the Hy-MFCO on organizing disjoint sets and maximizing network lifetime as it is applied to a variety of deployment environments. All the performance evaluations were conducted through computer simulations on the MATLAB platform.

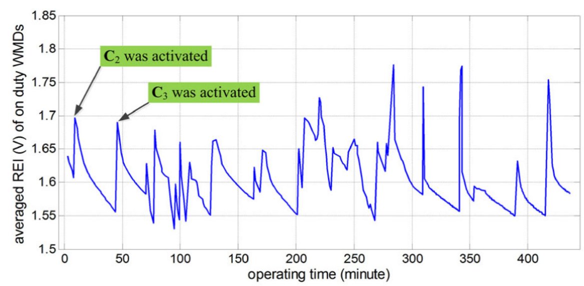

Fig. 10. Average REI of the on-duty WMDs at different time periods.

1) Maximize the Number of Disjoint Sets: Firstly, to test whether the proposed MA-based scheduling strategy is able to produce a near-optimal solution for the DSC problem, and the verification of the solution was done by a series of simulations under various situations after considering a variety of sensing ranges, numbers of POIs, and numbers of nodes. We supposed that a WSN and POIs were randomly deployed in a 500 $\times$ 500 m field, and all nodes were homogeneous. Each simulated case of the paper repeated 30 runs, and the simulation results were compared with those of using the MCMCC [14], the MC-MIP heuristic [15], and a conventional GA (GAMDSC) [18].

According to the simulation results, it is found that the average numbers of the yielded disjoint sets by the MA-based scheduling strategy are larger than those yielded by MCMCC and MC-MIP. When different sensing ranges and numbers of POIs are considered, the average increases of the disjoint set number are 36.1% and 21.8% as compared to MCMCC, and 24.6% and 7.4% as compared to MC-MIP, respectively [as shown in Fig. 11(a) and (b)]. Additionally, as compared to GAMDSC, the average increases of the number of disjoint sets are 2.9% and 0.54% when varying sensing ranges and numbers of nodes, as shown in Fig. 11(c) and (d). Obviously, the Hy-MFCO outperforms MCMCC, MC-MIP, and GAMDSC.

2) Maximize the Network Lifetime While Maintaining Full Coverage: In this section, the outcome of disjoint sets, resulted from the MA-based scheduling strategy, was applied to practical operation of WSNs with a common requirement of full coverage of POIs. Moreover, the HRA was initiated to maintain full coverage as long as possible after each disjoint set of nodes was activated. Due to limited space, more detailed result as compared with several existing approaches (including CoCMA [37], EDGE (4order-4) [38], PEGASIS [39],

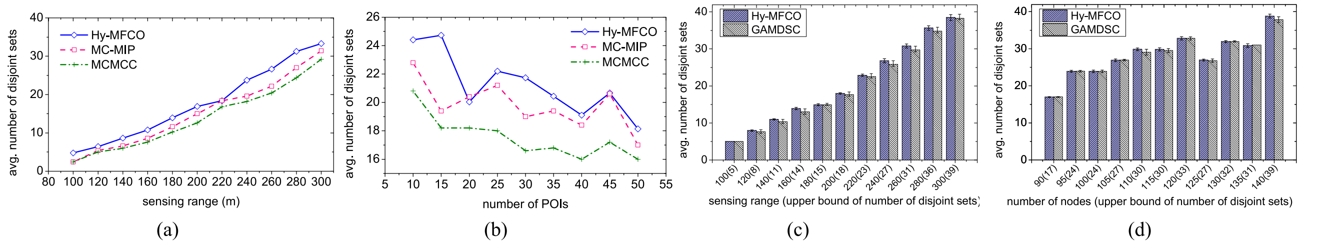

Fig. 11. Performance evaluation of the MA-based scheduling strategy. (a) Comparison of the average numbers of disjoint sets with 90 nodes and 10 POIs, depending on a variety of sensing ranges (100–300 m with an increment of 20 m). (b) Comparison of the average numbers of disjoint sets with 90 nodes and a sensing range of 250 m, depending on a variety of numbers of POIs (10–50 with an increment of 5). (c) Comparison of the average numbers of disjoint sets with 90 nodes and 10 POIs, depending on the upper bounds of the number of disjoint sets ($\acute{\eta}$) determined by different sensing ranges (100–300 m with an increment of 20 m). (d) Comparison of average numbers of disjoint sets with 10 POIs, depending on the upper bounds of the number of disjoint sets ($\acute{\eta}$) determined by different numbers of nodes (90–140 with an increment of 5) with a sensing range of 220 m.

LEACH-Coverage-U [40], and LEACH [3]) and discussion can be found in [35, Sec. 2].

VI. Conclusion

A Hy-MFCO has been presented to optimize sensing coverage of WSNs. The proposed Hy-MFCO comprised two primary components: a MA-based scheduling strategy and a HRA. First, we dealt with the DSC problem using the MA-based scheduling strategy. The goal of the DSC problem is to organize all nodes into a maximum number of disjoint subgroups. The subgroups will be turned on one after another by the proposed hybrid framework. Meanwhile, we encountered another problem while maintaining full sensing coverage, named the DCM problem, which was not discussed by most related studies. Then, we proposed an HRA based on a recursive structure to solve the DCM problem.

The proposed algorithm has been evaluated through real-world experiments and computer simulations. A WSN test-bed was built to put the proposed Hy-MFCO to real-world testing. The experimental results show that the proposed Hy-MFCO is indeed able to retain the coverage of WSNs. Furthermore, several existing algorithms were employed to compare with the proposed Hy-MFCO. The simulation results show that the proposed Hy-MFCO outperforms other algorithms not only in disjoint set generation as opposed to MCMCC, MC-MIP, and GAMDSC, but also in both sensing coverage preservation and network lifetime prolongation as opposed to CoCMA, EDGE (4order-4), PEGASIS, LEACH-Coverage-U, and LEACH. A series of simulations that involved a variety of experimental conditions—including different numbers of nodes (60–160), numbers of POIs (10–50), and sensing ranges (100–300 m)—were conducted to make a comprehensive comparison between the performances yielded by Hy-MFCO and CoCMA The performance of the latter is the best among the methods [EDGE(4order-4), PEGASIS, LEACH-Coverage-U, LEACH, and CoCMA]. The simulation results show that Hy-MFCO improves the network lifetime by 103% on average compared with COCMA under the requirement of full sensing coverage.

The proposed Hy-MFCO can be further improved by integrating the k-coverage technique in the future.

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