Connected Target ε-probability Coverage in WSNs With Directional Probabilistic Sensors

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***Abstract*—Sensing coverage has attracted considerable attention in wireless sensor networks. Existing work focuses mainly on the 0/1 disk model which provides only coarse approximation to real scenarios. In this article, we study the connected target coverage problem which concerns both coverage and connectivity. We use directional probabilistic sensors, and combine probabilistic and directional sensing model features to characterize the quality of coverage more accurately in an energy efficient manner. Based on the analysis of the collaborative detection probability with multiple sensors, we formulate the minimum energy connected target ε-probability coverage problem, aiming at minimizing the total energy cost while satisfying the requirements of both coverage and connectivity. By a reduction from a unit disk cover, we prove that the problem is nondeterministic polynomial (NP)-hard, and present an approximation algorithm with provable time complexity and approximation ratio. To evaluate our design, we analyze the performance of our algorithm theoretically and also conduct extensive evaluations to demonstrate its effectiveness.**

***Index Terms*—Connectivity, probabilistic sensor, target coverage, wireless sensor networks (WSNs).**

I. Introduction

SENSING coverage is a fundamental issue in wireless sensor networks (WSNs). A typical application is to surveil events that occur in a region of interested. These events are regarded as targets, and sensors are randomly deployed in the region to monitor those targets [1]. Sensing coverage measures how well a given target is covered by the network in terms of coverage degree, coverage ratio, activity scheduling, and network connectivity. Three types of coverage exist: target coverage (e.g., [2], [3]), area coverage (e.g., [4]–[6]), and barrier coverage(e.g., [7]–[9]). This article concentrates on the connected target coverage problem.

The connected target coverage problem, further to target coverage, concerns how to guarantee that each sensor node can find an efficient route to the sink, possibly via multi-hop [10]. Existing work focus on three types of optimization, named *minimum sensor connected coverage problem* [11] (minimizing the total number of active sensors), *minimum energy connected coverage problem* [2] (minimizing the total energy cost), and *maximum lifetime connected coverage problem* [12], [13] (maximizing network lifetime). Studies show that the maximum lifetime coverage problem is strongly associated with the minimum energy coverage problem. It has been proven in [14] that if there is a polynomial μ-approximation algorithm for cheapest wireless cover (CWC), then there exists polynomial μ-approximation for max-life wireless coverage (MLWC). The minimum energy problem is a special case of CWC, while the maximum lifetime problem belongs to MLWC. We hence focus on the *minimum energy connected coverage problem* in this article.

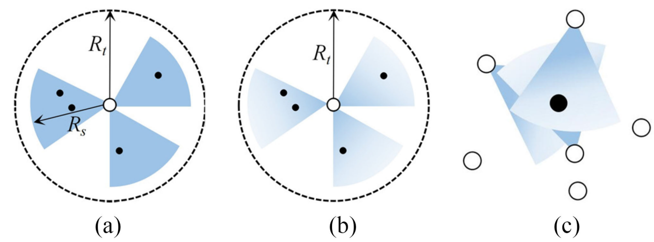

Fig. 1. Sensing model (black point represents target while white point represents sensor). (a) The 0/1 disk sector model. (b) The probabilistic sensing model. (c) An example of sensor combination.

Most of the existing work leverage on the 0/1 sensing model, e.g., in area coverage [4], [15], target coverage [2], [16]–[18], and barrier coverage [19]. For example, a directional sensor based on 0/1 sensing model can rotate in certain directions to monitor different sectors within its sensing range. A target is detected with a probability of 1 within the sectors of a sensor while not detected outside these sectors. Fig. 1(a) illustrates a directional sensor rotates to three directions periodically covering four targets. However, the assumption of a perfect coverage in the 0/1 model is unrealistic, e.g., in the context of detection applications [20]. Commonly, the sensing capability of a sensor is affected by many environmental factors in real deployment, especially for acoustic sensor. The probabilistic sensing model, which can characterize the quality of coverage more accurately, has been proposed with the assumption that sensing probability $p = \lambda(d)$ is a decreasing function of the sensing distance d [21]. Considering the advantages of low-power and realistic sensing, we adopt the directional probabilistic sensors. It is illustrated in Fig. 1(b) where multiple directional sensors of the same kind are embedded into one sensor node and activated simultaneously to detect multiple sectors. It has a communication radius of R_t and detects four targets in its sectors with a probability between 0 and 1. In a probabilistic sensing model, multiple sensors are needed

Manuscript received April 6, 2019; revised August 28, 2019; accepted August 31, 2019. Date of publication September 24, 2019; date of current version September 2, 2020. This work was supported in part by the Key Science-Technology Program of Zhejiang Province, China, under Grant 2017C01022, and in part by the National Natural Science Foundation of China under Grant 61370087. *(Corresponding author: Xianghua Xu.)*

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Digital Object Identifier 10.1109/JSYST.2019.2939178

to detect a target in a manner of mutual sensing. Sensors under mutual sensing manner cooperate with each other to improve the detection probability of a certain target. A target is considered to be covered when the collaborative detection probability by multiple sensors under the mutual sensing manner is beyond the detection probability threshold ε. Considering a typical scenario shown in Fig. 1(c), a target is covered by three sensors nearby.

The probabilistic sensing model has been explored to address the connected target coverage using omnidirectional sensors in [1] and [22]. However, they have been proven inadequate for a variety of reasons. In [22], they make an unrealistic assumption that a target can be always detected with the probability over the detection threshold by at least one sensor. Under this assumption, the probabilistic model is eventually reduced to the 0/1 disk model which only one sensor with a probability beyond ε is required to detect a target. It means that there is at least one sensor very close to the target. However, this assumption is too idealized for the real stochastic deployment to satisfy, especially for a high ε. To achieve the assumption, it requires high density deployment of sensors, leading to much redundancy and a huge waste of deployment cost. The work in [1] retains network connectivity by constructing and maintaining a connected dominated set (CDS) which operates as a backbone network. However, sensors in CDS remain activated in its lifetime even there is no target around, resulting in connectivity energy waste. Studies [2] show that the connectivity cost dominates the total energy consumption in a sensor node. Hence, it is important to find a solution in a global scale to decrease both energy of coverage and connectivity.

We formulate our problem as the minimum energy connected target ε-probability coverage (MECTε-PC) problem under directional probabilistic sensors, aiming to retain network connectivity and detect all targets with at least ε probability. To overcome the deficit of high deployment cost in [22] and connectivity energy waste in [1], we propose two fundamental principles. The first principle is to activate sensors in a mutual sensing manner such that neighbor sensors cooperate with each other to achieve connected target coverage with a probability of ε. Instead of only activating sensors with over probability ε in [22], we choose multiple sensors near a target working cooperatively. Even though sensor deployment does not guarantee the target is covered by at least one sensor with probability ε, we can still achieve the same detection probability threshold through mutual sensing. Our second principle is to activate a sensor if and only if it is used to detect a target or operate as a relay node. Sensors will go into sleep if there is no target around and no message to be forwarded for energy saving.

We prove in this article that the MECTε-PC problem is nondeterministic polynomial (NP)-hard by a reduction from the unit disk cover [23]. Based on the linearization of detection probability in a mutual sensing manner, we propose a flow graph construction to map the MECT ε-PC problem into a minimum weight maximum flow problem. Different with the classic minimum-cost flow problem [24], our objective is to send a maximum flow through a flow network with the minimum node weight. Leveraging on the two principles mentioned above, we design the minimum weight maximum flow algorithm (MWMFA) to approximately address the MECT ε-PC problem by solving the minimum weight maximum flow problem.

It is worth noting that the MWMFA algorithm has two compelling advantages. First, we realize the mutual sensing manner by transferring $-ln(1-\varepsilon)$ flow from a target through multiple neighboring sensors. Based on our analysis of detection probability, a target is assumed to be detected over probability ε if it delivers $-ln(1-\varepsilon)$ flow from the super source created in the flow graph. The flow passing by a target will be transferred by multiple sensors nearby, which will be activated in the mutual sensing manner to detect the target. Second, any sensor picked by MWMFA will be used to detect a target directly or served as a relay node, in this way that none of them is redundant. A certain amount of augmenting paths will be chosen from the super source to the sink one by one. Each augmenting path consists of a detecting sensor (operate to detect a target) and some relay nodes, and all of them will be activated. The detecting sensor is to detect a target, while the relay sensors forward the message from the detecting sensors to the sink. We also design an optimal augmenting path algorithm (OAPA) to find the augmenting path with lower energy cost for both detecting and relay sensors. As a result, all sensors activated by MWMFA will be put into use.

In summary, the article makes the following contributions.

1) We formulate the minimum energy connected coverage problem with directional probabilistic sensors as the minimum energy connected target ε-probability coverage problem, and formally prove that it is NP-hard.
2) We propose MWMFA and mathematically analyze its time complexity and approximation bound. We also design an optimal algorithm, OAPA, to find augmenting path while achieving both coverage and connectivity and prove its correctness.
3) We conduct extensive experiments, and compare our solution with the two recent approaches (i.e., MWBA and LoCQAL). The result shows that our MWMFA outperforms both of them in the total energy cost.

II. Related Work

WSNs have been applied in a wide range of applications such as water pollution, intrusion detection, air quality detection, etc. Sensing coverage is one of the fundamental issues in WSNs. The coverage problem can be divided into three catalogues [10]: target coverage (e.g., [25]–[27]), area coverage(e.g., [6], [28]), and barrier coverage(e.g., [8], [9], [19], [29]). We now focus our discussion on target coverage as follows.

In the early work, Zhao and Gurusamy first propose the concept of connected target coverage in WSNs [30]. They formulate a maximum cover tree (MCT) problem, aiming to prolong the network lifetime by scheduling sensors into multiple sets. Each set denotes a cover tree which is rooted at the sink node that can cover all the targets. They prove that the MCT problem is NP-complete and propose a heuristic algorithm based on a greedy strategy. Han *et al*. [2] first study the minimum connected coverage problem to minimize the total energy cost of both sensing and connectivity. They prove that the problem is NP-hard, and propose an approximation algorithm based on the

Steiner tree algorithm. However, this approach does not apply to probabilistic coverage investigated in this article. Similar to [2] except for the definition of cost, the connected target coverage problem is addressed in [31] and [32], where the objective is to activate minimum sensors for the coverage and connectivity requirements. In [33] and [34], Gupta *et al*. and Mini *et al*. concentrate on how to place the minimum relay nodes to provide desired *k*-connectivity. Roselin *et al*. [35] consider selecting some static nodes among the randomly deployed nodes to achieve target coverage and network connectivity and maximize network lifetime. Han *et al*. [36] analyze the availability and limitations of four different coverage strategies used to maximize network lifetime for wireless sensor networks from an industrial viewpoint. To solve the priority-based target coverage with directional sensors having adjustable sensing ranges, Razali *et al*. [17] present two schemas to maximize the lifetime of the network. Zhu *et al*. [18] consider to select heterogeneous directional nodes to cover targets with different coverage quality requirements and all selected nodes need to connect to a designated sink with the goal is to minimize the cost of the network. Gao *et al*. [37] consider the *k*-sink minimum movement target coverage problem, which is, dispatching mobile sensors from multiple base stations to cover all targets. Cheng and Wang [38] propose the concept of target-barrier, which is a continuous circular barrier enclosing targets with the minimum distance between a target and the barrier is greater than an assigned value. A target-barrier can be used to detect intrusion from outside and to prevent breaching from inside.

Most of the existing work in sensing coverage are based on the 0/1 disk model, and studies [10] show that the probabilistic model is more realistic for practical applications. Several exponential attenuation probabilistic models [20] have been proposed with the assumption that the detection probability is a continuously decreasing function of the sensing distance.

In [7], the detection probability of arbitrary intrusions is presented first and the problem of scheduling sensors to guarantee ε-barrier coverage with energy efficiency is first formulated. They propose a bounded approximation algorithm minimum weight barrier algorithm to schedule active sensors. Zhang *et al*. [39] try to construct a strong barrier coverage with the least number of nodes under the constraint of the minimum detection probability and the maximum error warning probability simultaneously. Kim *et al*. in [22] investigate the connected target coverage problem based on the omni-probabilistic sensing model. They make a strong assumption that all targets are always detected with the probability over the detection threshold by at least one sensor. They define a sensing range for each probabilistic sensor applied to the 0/1 disk model, and propose a heuristic algorithm. They basically convert the probabilistic sensing model into the 0/1 disk model under this strong restriction. The sensors with detection probability below the threshold would be neglected, resulting in much energy waste. Instead, we take an advantage of mutual sensing to achieve detection threshold by operating multiple probabilistic sensors in cooperative manner. Zorbas *et al*. [1] propose a localized algorithm based on mobile nodes to prolong network lifetime under connected probabilistic target coverage. They first ensure connectivity through constructing a CDS, and then determine the operation of three categories of sensing nodes to achieve target coverage. In addition, although the probabilistic sensor is adopted in [20] and [40], however, they fail to take network connectivity into consideration. Karatas [42] considers the hybrid point and barrier coverage, which is used to protect critical facilities located inside the barrier region and prevent illegal border crossing in a heterogeneous sensor network.

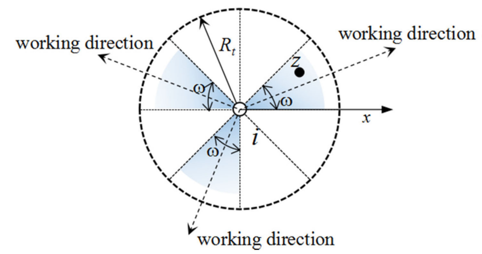

Fig. 2. Directional probabilistic sensor under non-overlapping model. The target z can be detected by the working direction θ of sensor i.

In summary, the probabilistic sensing model has been used in [1], [7], [22], [39] and [41]. Our work is fundamentally different from them. Different from [7] and [39], which focus on probabilistic barrier coverage, we address connected target coverage based on the probabilistic directional sensing model. Target coverage is also considered in [41], which takes no consideration of network connectivity. While connected target coverage is also addressed in [22], we propose the directional probabilistic model instead of the omnidirectional probabilistic model used in their approach. Similarly, the study in [1] focuses on connected target coverage based on omnidirectional probabilistic sensors which is essentially different from our work in sensing model. They propose a localized algorithm (LoCQAL) to determine CDS for connectivity, and use extra mobile sensors to achieve target coverage. In our study, we overcome the disadvantage of scheduling failure in [22], and we avoid the problem that too many redundant relay sensors exist in CDS [1].

III. Preliminary and Problem Formulation

In this section, we present the connected target coverage problem based on directional probabilistic sensors working in a mutual sensing fashion. We first describe the probabilistic sensing model, and then present the network in details, followed by a formal statement of the minimum energy connected target ε-probability coverage problem.

A. Sensing Model

In the context of detection applications, targets usually represent a series of objects which generate some event signals periodically. Sensors deployed in a detected area capture the occurrence of events by receiving the signal from the object [20]. Due to signal path loss in a realistic world, the traditional 0/1 disk sensing model fails to characterize the sensing ability of sensors in detection applications. In this article, we adopt directional probabilistic sensors under a nonoverlapping model, which can characterize the quality of coverage more accurately. As shown in Fig. 2, a directional probabilistic sensor has a finite set of orientations and mutually disjoint sensing sectors. We denote a sensing sector as a working direction with a same detection scope ω. A directional probabilistic sensor has $\frac{2\pi}{\omega}$ working directions, which can be activated simultaneously to detected different sectors within its neighborhood.

In a probabilistic sensing model, sensors detect targets by received energy, which attenuates as distance increases. The sensing quality of a sensor is commonly represented by its detection probability. Several empirical formulas (e.g., [20], [42]–[44]) have been proposed. In this article, we use the exponential probabilistic model proposed in [44]. Combining with the feature of the directional sensing model, we use a more realistic mode—directional probabilistic sensing model. The detection probability of a target z by a sensor i in working direction θ can be characterized by

$$p_{i(\theta)}(z) = \begin{cases} e^{-\alpha d(i,z)}, & \text{if } d(i,z) \leq r_{sk} \text{ and } \angle zi\theta < \frac{\omega}{2} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where α and r_{sk} are parameters representing the physical characteristics of the sensor and $d(i,z)$ is the distance between i and z.

Each active sensor which needs to be connected to the sink (probably though relay nodes) has a transmission radius R_t. Sensors can communicate with each other directly if their Euclidean distance is no more than R_t. We name them relay sensors if they have been just activated for communication.

The energy cost of a sensor contains two factors: sensing and communication. The energy cost of each sensor in each working direction is the same, which is denoted by w_s. Meanwhile, the energy cost of each node for connectivity is also the same, which is denoted by w_c. As shown in Fig. 2, the total energy cost of the sensor is $w_c + 3w_s$, as it activates three working directions and consumes w_c energy to be routed to the sink. For a relay sensor, the sensing cost is zero since it is used for communication only.

B. Network Model

We take stochastic sensor deployment under uniformly distribution in an $L \times L$ two-dimension plane. Let V denote a set of sensors deployed, let D denote a set of targets which appears randomly in the same plane: $D \cap V = \emptyset$. Each target can be detected by multiple sensors nearby, and vice versa. The location information of sensors and targets are assumed to be known through certain localization mechanism [45]. Meanwhile, a sink node is deployed at some location in the plane. All active sensors must be connected to the sink (probably though some relay nodes).

C. Problem Statement

The connected target coverage problem requires that the detection probability of each target is at least ε by activating working directions from the randomly deployed V. Armed with the above probabilistic sensing model and network model, we give the definition of detection probability and problem as follows.

For each target $z \in D$, $p_{i(\theta)}(z)$ denotes the detection probability of z detected by working direction θ of sensor i. If target z is located in the sector of working direction θ, the detection probability is $e^{-\alpha d(i,z)}$, otherwise zero.

Assuming that s_z is the sensor set in which sensors can detect z in a mutual sensing manner, the detection probability of z is $P(z)$ which can be computed by the probability formula, integrating the detection probability of each sensor in s_z, i.e.,

$$P(z) = 1 - \prod_{i \in s_z} \left(1 - p_{i(\theta)}(z)\right) \tag{2}$$

where θ denotes the working directions of i that can detect z. Associating to the detection probability threshold ε, we give the formal definition of the connected target coverage problem under directional probabilistic sensing model as follows.

Minimum energy connected target ε-probability coverage (MECTε-PC): Given a set of sensors $V = \{1, 2, \ldots, N\}$ and a sink randomly deployed in an $L \times L$ two-dimension plane, there are m targets distributed arbitrarily in the plane and required to be detected. The target set is denoted by D. We aim to activate a subset $C \subseteq V$ and working directions S_C of sensors in C with the least energy $w_c|C| + w_s|S_c|$ such that the detection probability of each target in D detected by S_C is at least ε. In addition, the network constructed by the sink and sensors in C is required to be connected.

IV. Theoretical Analysis

We begin by theoretically analyzing the collaborative detection probability, and prove that the MECT ε-PC problem is NP-hard by a reduction from unit disk cover [23]. This is a challenging issue and there is no feasible approach that exists. In this section, we first introduce a network flow model, and then transform the MECT ε-PC problem to a minimum weight maximum flow problem.

A. Analysis of Detection Probability

Given a target z detected by a set of sensors s_z, the detection probability is $P(z) = 1 - \prod_{i \in s_z} (1 - p_{i(\theta)}(z))$. If we require ε-probability coverage, then $P(z) \geq \varepsilon$

$$P(z) = 1 - \prod_{i \in s_z} \left(1 - p_{i(\theta)}(z)\right) \geq \varepsilon. \tag{3}$$

We linearize the formula as follows:

$$P(z) = 1 - \prod_{i \in s_z} \left(1 - p_{i(\theta)}(z)\right) \geq \varepsilon$$

$$\Rightarrow -ln\left(1 - \varepsilon\right) \leq -\sum\nolimits_{i \in s_z} ln\left(1 - p_{i(\theta)}(z)\right).$$

The term $\Psi = -ln(1 - \varepsilon)$ is defined as the *aggregate gain threshold*.

Sensor detection gain $\phi_i(z)$: A target obtains the detection gain from sensor i by $\phi_i(z) = -ln(1 - p_{i(\theta)}(z))$.

Cumulative detection gain $\sum_{i \in s_z} \phi_i(z)$: We achieve a target's cumulative detection gain by aggregating detection gains from nearby sensors.

Obviously, if target z satisfies the detection requirement, then the cumulative detection gain of z is larger than Ψ , i.e.

$$\sum_{i \in s_z} \phi_i(z) \geq \Psi. \tag{4}$$

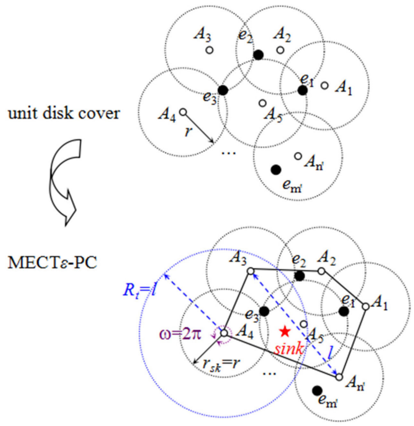

Fig. 3. Example of reduction from unit disk cover to MECT ε-PC. We extend the detection scope ω to 2π and lengthen R_t to l. A sink is created in the convex hull of centers in *A*. The parameter r_{sk} is set as the radius of disk.

B. NP-Hardness

We now prove the NP-hardness of the MECT ε-PC problem by reducing the unit disk cover [23] to our problem. According to the proven NP-hardness, for any instance in the unit disk cover, it should be reduced into MECT ε-PC in polynomial time.

Theorem 1: The MECT ε-PC problem is NP-hard.

Proof: Assuming an instance of unit disk cover, let $P = \{e_1, e_2, \ldots, e_{m'}\}$ denote m' points and a set $A = \{A_1, A_2, \ldots, A_{n'}\}$ denote n' unit disks with radius *r* in a two-dimension plane. The objective is to find a minimum cardinality subset $A^* \subseteq A$, such that each point in *P* is covered by at least one disk in A^*. To reduce the unit disk cover to MECT ε-PC, we take the following steps.

1) At the center of each disk in *A*, we place a probabilistic sensor with detection scope $\omega = 2\pi$. Then, we calculate the convex hull of these centers in *A* using rotating calipers [46] and obtain the corresponding diameter (denoted by *l*).
2) Place m' targets at the location of points in *P*.
3) Deploy a sink node in the convex hull randomly.
4) Set $w_c = 1$ and $w_s = 0$ for each probabilistic sensor. Lengthen transmission radius R_t to diameter *l* of the convex hull.
5) Narrow detection probability threshold ε down to $e^{-\alpha r_{sk}}$. This is a key step in reduction.

An example is given in Fig. 3. Combining (3) and $\varepsilon = e^{-\alpha r_{sk}}$, we have

$$1 > 1 - e^{-\alpha r_{sk}} \geq \prod_{i \in s_z} \left(1 - p_{i(\theta)}(z)\right) \geq 0. \tag{5}$$

Note that probability formula (1) determines that $p_{i(\theta)}(z) \geq e^{-\alpha r_{sk}}$ or $p_{i(\theta)}(z) = 0$. Consequently, (5) holds, if there is at least one detection probability of sensors in s_z larger than $e^{-\alpha r_{sk}}$. It means that the detection probability of a target will go beyond threshold ε when it is located within some disk in *A* according to (5). In other words, if and only if there is at least one sensor far from the target within distance r_{sk}, the target will be detected beyond ε. Furthermore, we have extended transmission radius R_t to *l* and the sink is put in the convex hull. As a result, the distance between any sensor and the sink must be less than R_t. It means any sensor can directly communicate with the sink. None of relay nodes need to be activated. Under this setting, the MECT ε-PC is to find the least $w_c|C| + w_s|SC| = |C|$ sensors to cover all targets, which is exactly the same as unit disk cover. Thus, any instance of unit disk cover can be reduced into MECT ε-PC in polynomial time. Indeed, the unit disk cover is a special case of MECT ε-PC. Toussaint in [46] has proved that the unit disk cover is NP-complete. Therefore, MECT ε-PC must also be NP-hard.

C. Problem Transformation

Both detection probability and detection gain will be very small when the distance between sensor and target is large, especially close to r_{sk}. Furthermore, it will be more cost-effective to obtain the probability with short distance, instead of computing each pair of sensor and target.

Minimum detection probability $p_{\min}$*:* $p_{\min}$ is a threshold predefined by applications. If the detection probability of a target *z* is detected by one sensor *i* is less than $p_{\min}$, we take it as zero, otherwise $e^{-\alpha d(i,z)}$.

Details about how to set $p_{\min}$ based on detection probability threshold ε can be found in our previous work [47].

Detection boundary $d_{\max}$*:* $d_{\max}$ is the maximum detection distance that $p_{\min} = e^{-\alpha d_{\max}}$. The detection probability of target *z* detected by sensor *i* is treated as zero, if the distance between *z* and *i* is beyond $d_{\max}$, otherwise $p_{i(\theta)}(z)$.

We present the minimum detection probability $p_{\min}$ to determine detection boundary $d_{\max}$, aiming to save computation resources. We obtain detection probability and detection gain only when the distance between sensor and target is less than $d_{\max}$, otherwise take them as zero.

The MECT ε-PC problem is a complex problem due to both coverage and connectivity requirements. We now introduce a network flow model to transform MECT ε-PC to the minimum weight maximum flow problem.

Here, we use $\text{dir}(i)$ to denote the working direction candidate set of sensor *i*. For each working direction in $\text{dir}(i)$, the sensor can detect at least one target. We will activate some directions working in a mutual sensing fashion from the candidate set to detect targets. Based on the analysis of detection probability, we build a flow graph $G = (V \cup S_V \cup D \cup \{s\} \cup \{t\}, E)$ to characterize the feature of the network where *V* denotes the randomly deployed sensor set. *D* represents the target set and *t* indicates the sink. *s* is the super source and S_V denotes the virtual vertexes set we create.

We describe the constructing mechanism in details as follows.

1) For $\forall d \in D$, we add directed edge $\langle s, d\rangle$ into *E* with capacity Ψ. We name it virtual edge.
2) For $\forall v \in V$, $\forall \theta \in \text{dir}(v)$, we create a virtual vertex $\theta' = \{\theta, v\}$ and put it into S_V. It will be linked with sensor *v* by adding a directional edge $\langle \theta', v\rangle$ with capacity $+\infty$.
3) For $\forall \theta' \in S_V, \forall d \in D$, if the corresponding sensor *v* in working direction θ can detect *d*, a directed edge $\langle d, \theta'\rangle$ will be added into *E* with capacity $\phi_v(d)$, named sensing edge.

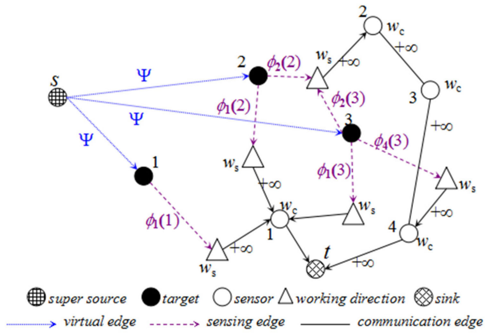

Fig. 4. Example of flow graph. The edge weight represents the capacity. The virtual node representing working direction is only connected toward its corresponding sensor. For example, three virtual nodes are connected toward sensor 1, indicating that sensor 1 has three working directions. This constructing method means a working direction and its corresponding sensor will be activated at the same time.

4) For $\forall v' \in V, \forall v'' \in V$, if $\mathrm{dis}(v', v'') < R_t$, an undirected edge (v', v'') will be added into E and its capacity is $+\infty$, denoted by communication edge.
5) For $\forall v \in V$, if $\mathrm{dis}(v,\ t) < R_t$, then $\langle v,\ t\rangle \in E$ with capacity $+\infty$.
6) The weight of sensor vertex is set to w_c while virtual vertex is set to w_s.

An example of flow graph is shown in Fig. 4. The constructing method of flow graph determines that the flow starts from the super source, passes by virtual edge, sensing edge, communication edge, and eventually arrives at the sink.

Theorem 2: When G' s max flow equals $m\Psi$, the sensors corresponding to max flow satisfy both coverage and connectivity.

Proof: When the max flow reaches $m\Psi$, it means each virtual edge is saturated with flow Ψ passing by. The flow from each target is Ψ, and will be transferred to the sink *t* by sensing edges and communication edges. Assuming for each $z \in D$, s_z denotes the sensor set which transfers flow from z. We can get $\sum_{i\in s_z} \phi_i(z) \geq \sum_{i\in s_z} f(i) = \Psi$ (*f(i)* is the flow value through node *i*). As a result, the detection probability of z is at least ε according to (4). Since Ψ flow from z will eventually arrive the sink *t*, each sensor in s_z can communicate with the sink.

According to Theorem 2, we can reduce the MECT ε-PC problem to the minimum weight maximum flow problem.

Minimum weight maximum flow problem: Based on the flow graph $G = (V \cup S_V \cup D \cup \{s\} \cup \{t\}, E)$ we create, our objective is to find a minimum weight set $C \subseteq V$ and $S'_V \subseteq S_V$, and the subgraph the max flow of $G' = (C \cup S'_V \cup D \cup \{s\} \cup \{t\}, E')$ (G' is constructed in the same way as *G*.) is equal to $m\Psi$.

Without doubt, the minimum weight maximum flow problem is also NP-hard.

V. Algorithm Design

We have proved that the minimum weight maximum flow problem is NP-hard in the previous section. Hence, it is hard to find the optimal solution in polynomial time. Motivated by existing max-flow algorithm, Edmonds-Karp [48] and Dinic [49], we design an approximation algorithm named MWMFA to address the challenge. Finally, we prove its time complexity and approximation ratio in theory.

Algorithm 1: MWMFA.

1: *Create a super source s*
2: *Create* $G = (V \cup S_V \cup D \cup \{s\} \cup \{t\}, E)$
3: $C = \emptyset, S'_V = \emptyset$
4: *invoke OAPA to find a path* $\mu(s,\ t)$ *with maximum* ρ
5: **if** *flow is* 0 **then**
6:     **return** C, S'_V
7: **else**
8:     *send the flow along the augmenting path* $\mu(s,\ t)$
9:     *add nodes into C or* S'_V
10:     *set sensors or working directions active*
11: **goto 4**
12: **end if**

A. Approximation Algorithm

The minimum weight maximum flow problem aims to find a minimum weight set $C \subseteq V$ and $S'_V \subseteq S_V$ to achieve the upper flow value $m\Psi$. Motivated by a classical network flow method Ford-Fulkerson, we first design the key augmenting path algorithm—OAPA.

The basic idea of OAPA is to augment path iteratively with maximum ρ defined as follows:

$$\rho = \frac{\text{augmenting path flow}}{\text{inactive node weights}}.$$

Then, we send the flow along the path to the sink *t*. Different from other maximum flow algorithms such as Edmonds-Karp and Dinic, MWMFA aims to find the augmenting path with larger flow and less node-weight. We activate the corresponding sensors and working directions along the augmenting path, and then put the nodes into *C* and S'_V, respectively.

B. Algorithm Analysis

We first present OAPA based on the shortest path, aiming to find a best augmenting path $\mu(s, t)$ with maximum ρ.

We define the weight graph $WG = (\{o\} \cup S_V \cup V \cup \{t\}, \bar{E})$ as follows, where *o* represents a virtual start with weight zero.

1) For each $s_v \in S_V$, connect o to s_v with a directed edge $\langle o, s_v\rangle$. Set the weight of $\langle o, s_v\rangle$ 0.
2) For each $s_v \in S_V$, we connect s_v to its corresponding sensor *v* in *WG* with a directed edge $\langle s_v, v\rangle$. If node s_v has been activated, assign the weight of $\langle s_v, v\rangle$ 0, otherwise w_s.
3) For each $v' \in V, v'' \in V$, if $\langle v', v''\rangle \in E$ in G, we connect v' and v'' in *WG* with two directional edge $\langle v', v''\rangle$ and $\langle v'', v'\rangle$. If node v' has been activated previously, the weight of $\langle v', v''\rangle$ is set 0, otherwise w_c, as well as $\langle v'', v'\rangle$.
4) For each $v \in V$, if $\langle v, t\rangle \in E$ in *G*, we connect *v* to t in *WG* with a directed edge $\langle v, t\rangle$. If node *v* has been activated before, the weight of $\langle v, t\rangle$ is 0, otherwise w_c.

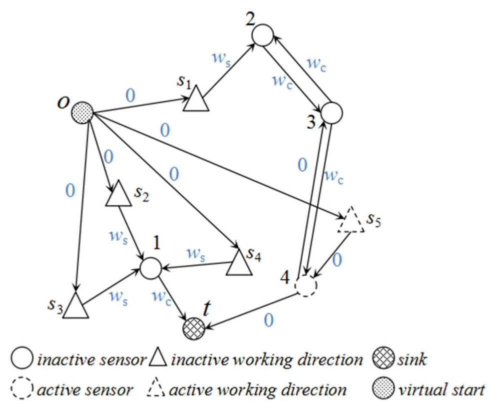

Fig. 5. Assuming the node s_5 and 4 have been activated previously, this figure is an example of *WG* corresponding to the flow graph in Fig. 4. Each weight of directional edge $<u, v>$ in *WG* indicates the node weight of *u*. Thus, the weight of $<4,\ t>$, $<4,\ 3>$ and $<s_5, 4>$ is zero. The node weight of virtual start *o* is also assigned zero.

Fig. 5 is a weigh graph converted from the flow graph showed in Fig. 4. As mentioned above, *flow* represents the flow value in the augmenting path, while *weight* represents the weight of inactive nodes. As for only virtual edges and sensing edges have limited capacity, the *flow* of each augmenting path is determined by the minimum of its virtual edge capacity and sensing edge capacity $\min\{\mathrm{cap}(s,d), \mathrm{cap}(d, s_v)\}$ (cap*(a, b)* represents the capacity of edge $\langle a,\ b\rangle$). Due to each *flow* of the augmenting path is a constant $\min\{\mathrm{cap}(s,d), \mathrm{cap}(d, s_v)\}$, to get the maximum ρ, we need to calculate each minimum *weight* of an augmenting path from *s* to *t*. The weight graph is designed to solve this problem. We make use of the shortest path algorithm, Dijkstra [50]. Each minimum *weight* of an augmenting path from *s* to *t* will be calculated in *WG*. We use an array $\mathrm{route}[x]$ to denote the path from *x* to *t*, an array $\mathrm{dist}[x]$ to denote the distance from *x* to *t*.

Lemma 1: After each invocation of OAPA, some sensing edge or some virtual edge must be saturated.

Proof: The characteristic of our flow graph *G* determines that the flow in $\mu(s,\ t)$ starts from virtual edge, passes sensing edge and arrives at the sink through communication edge. The flow value relies on the capacity of virtual edge and sensing edge due to limited capacity.

Assuming an augmenting path $\mu(s,\ t) = \langle s, d, s_v, v_1, v_2, \ldots, v_k, t\rangle$,$\langle s, d\rangle$ denotes virtual edge, while $\langle d,\ s_v\rangle$ represents sensing edge. It is obvious that the flow in $\mu(s,\ t)$ is $\min(\mathrm{cap}(s,d),\ \mathrm{cap}(d, s_v))$. Thus, $\langle s, d\rangle$ or $\langle d, s_v\rangle$ will be saturated. In either case, $\langle d, s_v\rangle$ will not appear in augmenting path any more. Therefore, after each invocation of OAPA, some sensing edge or virtual edge must be saturated. Meanwhile, OAPA passes every sensing edge by at most once.

Lemma 2: OAPA always finds an augmenting path with maximum ρ.

Proof: Based on the construction of *WG*, the weights of an augmenting path $\mu(s,\ t) = \langle s, d, s_v, v_1, v_2, \ldots, v_k, t\rangle$ found by OAPA starts from *s*, passes by a target *d*, a virtual vertex and some sensors, finally arrives at *t*. Thus, the augmenting path is always legal. In OAPA line 3, we invoke Dijkstra to calculate

Algorithm 2: OAPA.

1: *Create Weight Graph* $WG = (\{o\} \cup S_V \cup V \cup \{t\}, \bar{E})$
2: *Define route[v] to denote the shortest path from v to t*
3: *Call the algorithm Dijkstra with start o, end t*
4: *double* $flow = 0, \rho = 0$;
5: $\mu(s,\ t) =$ **NULL**
6: **for** $d \in D;\ s_v \in S_V$ **do**
7: $\quad flow = min(cap(s,\ d), cap(d,\ s_v))$;
8: $\quad$ **if** *flow* > 0 **then**
9: $\quad\quad$ **if** $dist[s_v] = 0$ **then**
10: $\quad\quad\quad$ **return** *path* $\langle s,\ d,\ route[s_v]\rangle$
11: $\quad\quad$ **else**
12: $\quad\quad\quad$ **if** $\rho < \frac{flow}{dist[s_v]}$ **then**
13: $\quad\quad\quad\quad \mu(s,\ t) = \langle s,\ d, route[s_v]\rangle$
14: $\quad\quad\quad\quad \rho = \frac{flow}{dist[s_v]}$
15: $\quad\quad\quad$ **end if**
16: $\quad\quad$ **end if**
17: $\quad$ **end if**
18: **end for**
19: **return** $\mu(s,\ t)$;

the shortest path from *o* to *t*. Each node in *WG* will get the shortest path from itself to *t*. The weight of each augmenting path $\mu(s,\ t) = \langle s, d, s_v, v_1, v_2, \ldots, v_k, t\rangle$ equals to the total weights of nodes in $\langle s_v, v_1, v_2, \ldots, v_k\rangle$. And it equals to the minimum distance from s_v to *t*, i.e., $w(s_v, v_1) + w(v_1, v_2) + \cdots + w(v_k, t)$. ($w(a,\ b)$ denotes the weight of $\langle a,\ b\rangle$ in *WG*). Therefore, each augmenting path starting from virtual vertex s_v will arrive at *t* with least weights. Meanwhile, the corresponding sensor of s_v can communicate with the sink along the augmenting path based on the constructing method of *WG*. As each virtual node representing a working direction only connects toward its corresponding sensor node, both the working direction and the sensor will be activated simultaneously with ensuring connectivity. OAPA would select the augmenting path with maximum ρ.

Theorem 3: The time complexity of MWMFA is $O(\alpha m \times |V|^2)$, where α is the maximum out-degree of targets.

Proof: Based on Lemma 1, each sensing edge is selected at most once. Hence, OAPA is invoked at most $\sum_{i=1}^{|D|} d(i)$times ($d(i)$ denotes the out-degree of target *i*). The complexity of OAPA is same as that of Dijkstra. Therefore, the time complexity of MWMFA is $O(|V|^2) \times \sum_{i=1}^{|D|} d(i) = O(\alpha m \times |V|^2)$. Indeed, MWMFA is a feasible solution even though it is a centralized algorithm, as for lower time complexity than [4], [7], [51].

Now we show the approximation ratio of MWMFA algorithm. We assume *W* is the weight of both *C* and S'_V calculated by MWMFA, while W_{opt} is the optimum.

Theorem 4: $\frac{W}{W_{\mathrm{opt}}} < \frac{\beta ln(1-\varepsilon)\mathrm{dis}_{\max} w_c}{ln(1-p_{\min}) w_s}$, where $\mathrm{dis}_{\max} = \max_{v\in S_V} \mathrm{dis}(v,t)$ ($\mathrm{dis}(v,t)$ is the minimum hops from *v* to *t*), β is the maximum in-degree of sensor nodes.

Proof: Assuming MWMFA invokes *k* times OAPA, each flow value in augmenting path is denoted by $\phi_1, \phi_2, \ldots, \phi_k$ and inactive node weight is $\Delta_1, \Delta_2, \ldots, \Delta_k$. Therefore, we have $m\Psi = \phi_1 + \phi_2 + \cdots + \phi_k$, $W = \Delta_1 + \Delta_2 + \cdots + \Delta_k$.

Because OAPA finds the augmenting path with maximum ρ, we can obtain

$$\frac{\phi_1}{\Delta_1} \geq \frac{\phi_{\max 1}}{\Delta'_1}$$
$$\frac{\phi_2}{\Delta_2} \geq \frac{\phi_{\max 2}}{\Delta'_2}$$
$$\ldots$$
$$\frac{\phi_k}{\Delta_k} \geq \frac{\phi_{\max k}}{\Delta'_k} \tag{6}$$

$\frac{\phi_{\max i}}{\Delta'_i}$, $i = 1, 2, \ldots, k$ is ρ corresponding to the path with the biggest flow $\phi_{\max i}$ and Δ'_i represents its inactive node weight. Furthermore, in the worst-case scenario, the augmenting path corresponding to the flow value $\phi_{\max i}$ may arrive at the sink without any active sensors. Thus, Δ'_i satisfies the following inequality:

$$\Delta'_i \leq (\mathrm{dis}\,(v_i, t) - 1)\, w_c + w_s \tag{7}$$

where v_i denotes the virtual node.

With (6) and (7), we have

$$\frac{\phi_i}{\Delta_i} \geq \frac{\phi_{\max i}}{(\mathrm{dis}\,(v_i, t) - 1)\, w_c + w_s} \geq \frac{-ln\,(1 - p_{\min})}{(\mathrm{dis}_{\max} - 1)\, w_c + w_s}. \tag{8}$$

According to (6) and (8), we can obtain

$$\frac{\phi_1 + \phi_2 + \cdots + \phi_k}{\Delta_1 + \Delta_2 + \cdots + \Delta_k} \geq \frac{-ln\,(1 - p_{\min})}{(\mathrm{dis}_{\max} - 1)\, w_c + w_s}$$
$$\frac{m\Psi}{W} \geq \frac{-ln\,(1 - p_{\min})}{(\mathrm{dis}_{\max} - 1)\, w_c + w_s}$$
$$W \leq \frac{m\; ln\,(1 - \varepsilon)}{ln\,(1 - p_{\min})} \times ((\mathrm{dis}_{\max} - 1)\, w_c + w_s)\,. \tag{9}$$

The MECT ε-PC problem concentrates on finding the minimum weight C and S'_V. If we only consider coverage without connectivity, we assume W_c is the minimum energy sensors ensuring coverage. Obviously, $W_{\mathrm{opt}} \geq W_c$. Let β denote the maximum in-degree of virtual vertex. It means that one working direction can detect at most β targets. Thus, we must activate $\frac{m}{\beta}$ working directions at least and one sensor communicating with the sink. We have

$$W_{\mathrm{opt}} \geq W_c \geq \frac{m}{\beta} \times w_s + w_c. \tag{10}$$

With (9) and (10), we have

$$\frac{W}{W_{\mathrm{opt}}} \leq \frac{ln(1 - \varepsilon) m((dis_{\max} - 1) w_c + w_s)}{ln(1 - p_{\min}) \times (\frac{m}{\beta} \times w_s + w_c)}.$$

Since communication cost is usually larger than sensing cost [2], i.e., $0 < w_s \leq w_c$, we obtain

$$\frac{W}{W_{\mathrm{opt}}} < \frac{\beta ln\,(1 - \varepsilon)\, \mathrm{dis}_{\max} w_c}{ln\,(1 - p_{\min})\, w_s}.$$

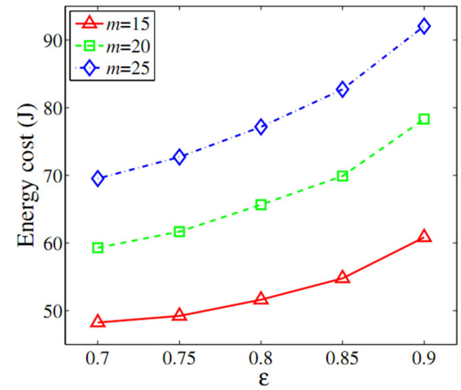

Fig. 6. Performance of MWMFA with different ε and target size m.

Theorem 4 shows the relationship between the solution obtained by MWMFA and the optimal value, and the influence of the threshold of coverage probability and the hop number on the performance of the algorithm. Higher coverage probability threshold ε and more hops $\mathrm{dis}_{\max}$ will lead to higher approximate upper bound, because larger ε usually requires more nodes, while $\frac{w_c}{w_s}$ indicates that connected energy dominates the overall energy consumption of connected coverage. More hops result in more relay nodes in the connection. When more targets may be covered in one working direction, the number of targets covered by one direction of a random deployed node varies largely. Theorem 4 shows that the approximate upper bound of MWMFA will be more higher because of the uncertainty of the random deployment of nodes when increasing the number of nodes or the number of targets covered by one working direction.

VI. Performance Evaluation

In this section, we conduct a series of experiments to evaluate the performance of MWMFA, and compare MWMFA with MWBA [7] and LoCQAL [1]. In our simulation studies, sensors are randomly deployed in a two-dimensional plane with a size of 150×150 m^2. $p_{\min}$ is set to 0.2, and the communication range R_t is set to 40 m. We set the connectivity cost w_c to 2 Joule, and set the sensing cost w_s for one working direction to $\frac{\omega}{2\pi}$ Joule. We adopt the exponential attenuation probabilistic model proposed in [44].

A. Performance

In this section, we evaluate the performance of MWMFA with different parameters including detection scope, number of targets and detection probability ε. We run each experiment 30 times and report the average result of each experiment.

In the first experiment, we evaluate the total energy cost of sensors and working directions activated by MWMFA with respect to number of targets and detection threshold ε. We generate 220 sensors in the region, and fix the detection scope of each working direction to $\frac{1}{3}\pi$. We vary the number of targets to 15, 20, 25, respectively, and also simulate different application scenarios by varying ε to 0.7, 0.75, 0.8, 0.85, 0.9, respectively. As shown in Fig. 6, the total energy increases with number of targets and ε. With more targets and larger ε, more sensors and

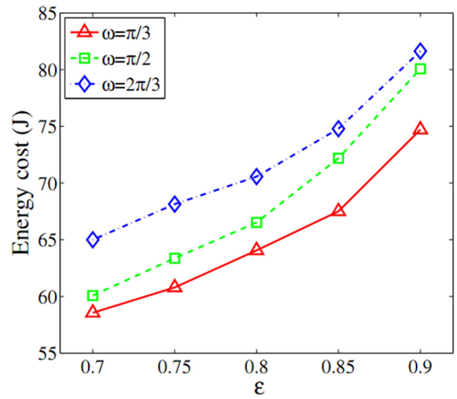

Fig. 7. Performance of MWMFA with different ε and ω.

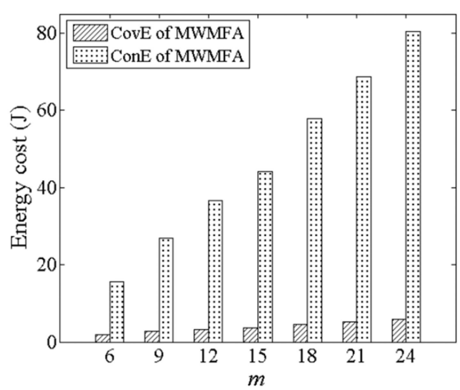

Fig. 8. Energy breakdown with different target size.

their corresponding working directions will be activated to meet both requirements of coverage and connectivity.

In this experiment, we evaluate the performance of MWMFA with respect to detection scope and ε. We generate 220 sensors, then fix the number of targets to 20. We vary the detection scope to $\frac{1}{3}\pi$, $\frac{1}{2}\pi$, $\frac{2}{3}\pi$, respectively, and vary ε to 0.7,0.75, 0.8, 0.85, 0.9, respectively. Fig. 7 shows the total energy cost with different detection scope and ε. As expected, the total energy cost increases with larger detection scope and ε, respectively.

We now have a close look at energy cost, and evaluate how both coverage and connectivity energy vary with different number of targets. We randomly generate 250 sensors and a number of targets ranging from 6 to 24. We fix ε to 0.8 and ω to $\frac{\pi}{3}$. Fig. 8 shows that while both coverage energy (CovE in short) and connectivity energy (ConE in short) by MWMFA grow linearly when target size increases, ConE grows much faster since more relay nodes are needed for each sensing node increased to ensure connectivity.

We also study how both CovE and ConE vary with different detection scope. We randomly generate 250 sensors and 20 targets, and fix probability threshold ε to 0.8. As shown in Fig. 9, with a larger detection scope, we observe more energy spent in coverage and less energy spent in connectivity. This is because a larger detection scope leads to fewer sensors being activated. We also observe that the total energy increases when ω increases.

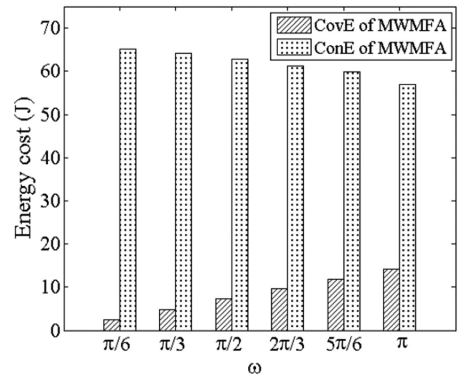

Fig. 9. Energy breakdown with different detection scope ω.

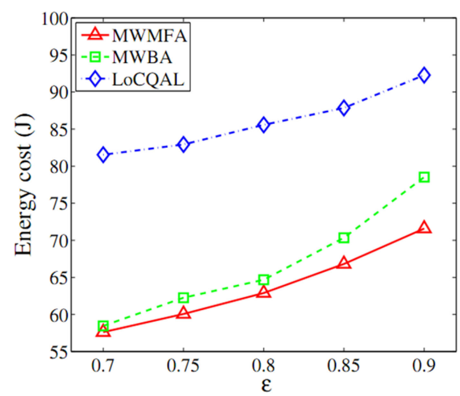

Fig. 10. Impact of ε to MWMFA, MWBA, and LoCQAL.

B. Comparison Study

We now compare MWMFA with MWBA [7] and LoCQAL [1] in terms of the total energy cost versus different ε. LoCQAL represents the state-of-the-art in solving connected target coverage based on the probabilistic sensing model. MWBA is originally designed to address barrier coverage. Since the aim of MWBA is to find a set of nodes with minimum aggregated weight, it can provide a potential solution to max-flow over a certain threshold, which is closely related to our approach.

In this comparison study, we randomly generate 250 sensors and 20 targets in the same region. We fix the detection scope of each working direction to $\frac{1}{3}\pi$, and vary detection threshold ε from 0.7 to 0.9. As shown in Fig. 10 that MWMFA outperforms both MWBA and LoCQAL in the total energy cost. While MWMFA reduces energy cost significantly as compared to LoCQAL, the energy saving to MWBA is comparable with smaller ε. However, MWMFA exhibits better scalability as more energy saving is observed with larger ε. When finding an augmenting path, MWMFA takes only activated sensors into account, while MWBA involves both activated and inactivated sensors. As a result, MWBA may involve more sensors and their working directions than MWMFA, lead to more energy consumption.

In this experiment, we study the energy breakdown comparison. As shown in Fig. 11, while the total energy cost increases for

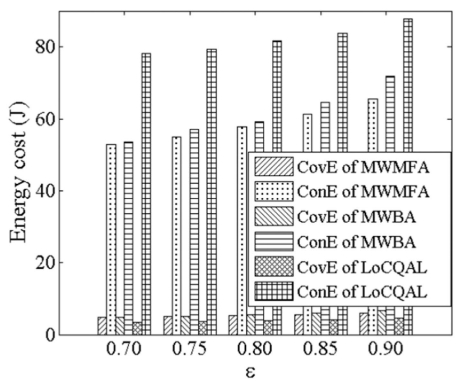

Fig. 11. Energy breakdown comparison.

all the three methods, we observe LoCQAL has a higher energy cost than the other twos. This is because in LoCQAL, the sensors in CDS dominate the total energy cost since they are always activated. When ε increases, only the sensing energy cost will be added on to the total energy cost. In addition, CDS contains many redundant sensors, resulting in huge energy waste.

VII. Conclusion

In this article, we study the connected target coverage problem in WSNs, which aims to efficiently monitor a finite set of targets by sensors. Directional probabilistic sensors with an exponential attenuation probabilistic model are adopted in our network. We conduct theoretical analysis of this model, and prove that the minimum energy connected target ε-probability coverage problem is NP-hard. To solve the problem, we map it to a network flow problem, and propose the MWMFA algorithm with provable time complexity and approximation ratio. Extensive simulation studies demonstrate that the proposed approach outperforms the state-of-the-arts. For our future work, we will further evaluate our approach in a test bed setting, and discover more practical issues for real deployment. For example, instead of a centralized algorithm which maybe expensive in wireless sensor networks, a more practical distributed or localized algorithm will be discovered in our future work.

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