Design of Novel Based Sensing Model for Coverage Area Using Evolutionary Algorithm

R. NITHYA[1], P. JEGADEESHWARI[2]

[1, 2] *Assistant Professor, CK College of Engineering and Technology, Cuddalore, Tamil Nadu, India*

Abstract- The coverage problem in wireless sensor networks(WSNs) can be generally defined as a measure of how effectively a network field is monitored by its sensor nodes. This problem has attracted a lot of interest over the years and as a result, many coverage protocols were proposed. In this survey, we first propose taxonomy for classifying coverage protocols in WSNs. Then, we classify the coverage protocols into three categories (i.e. coverage-aware deployment protocols, sleep scheduling protocols for flat net-works, and cluster-based sleep scheduling protocols) based on the network stage where the coverage is optimized. For each category, relevant protocols are thoroughly reviewed and classified based on the adopted coverage techniques. Finally, we discuss open issues (and recommend future directions to resolve them) associated with the design of realistic coverage protocols. Issues such as realistic sensing models, realistic energy consumption models, realistic connectivity models and sensor localization are covered.

Indexed Terms- Wireless Sensor Network (WSN), Coverage Protocols, Sensing Models, Energy Consumption, Literature Review, and Survey.

I. INTRODUCTION

Wireless sensor networks (WSNs) have attracted significant attention from the research community and industry in the last few years. The main reason for the recent research efforts and rapid development of WSNs is their potential application in a wide range of contexts including military operations, environment monitoring, surveillance systems, health care, and public safety [1] [2]. These applications require the deployment of a number of sensors to cover a given region of interest (ROI) in the network field. Although sensor nodes can work autonomously, they can also work collaboratively to monitor the physical parameters of an environment. Sensor nodes can sense the environment, communicate with neighbouring nodes, and in many cases, perform basic computations on the data being collected

These features make WSNs an excellent choice for many applications [2] running in environments that are hazardous for human presence.

The coverage problem is one of the fundamental problems in WSNs as it has a direct impact on the sensors energy consumption and the network lifetime [5]. The coverage problem can generally refer to how to monitor the network field effectively.

There are several ways to classify the coverage problems in WSNs. Coverage problems can be classified, according to the frequency of network field monitor, into either continuous coverage problems or sweep coverage problems. Continuous coverage problems can be further classified, according to the region of interest for monitoring, into three types: area coverage, point coverage, and barrier coverage. Furthermore, coverage problems can be classified, according to the required coverage degree, into either 1-coverage problems or K-coverage problems.

On the other hand, coverage protocols can be classified based on the connectivity requirement, to either connectivity aware coverage protocols or non-connectivity aware coverage proto-cols. Furthermore, coverage protocols can be classified, ac-cording to the adopted algorithm characteristics, into either distributed protocols or centralized protocols. Centralized coverage protocols can be further classified into either evolutionary algorithm (EA) based protocols or non-EA based protocols. More-over, coverage protocols can be classified according to the sys-tem model of the network. There are four features under the system model: sensor location awareness (aware or unaware), sensor mobility models (static, mobile or hybrid of both), sensor deployment models (deterministic or random), and sensor sensing model. Sensing models are broadly classified, based on the sensing ability, into two types: deterministic sensing models and probabilistic sensing models. Sensing models can also be classified, based on the direction of the sensing range, into either directional sensing models or omnidirectional sensing models. Coverage protocols can also be classified based on when the coverage optimization happens, i.e. into either coverage-aware deployment protocols, when coverage optimization hap-pens before the deployment stage, or sleep scheduling proto-cols, when coverage optimization happens after the deployment stage. Sleep scheduling protocols can be further classified, based on the network topology, into either cluster-based sleep scheduling protocols or sleep scheduling protocols for flat net-works. A detailed description of the various dimensions of the classification discussed above is given in Section II. Fig. 1 shows the taxonomy for classifying coverage protocols in WSNs.

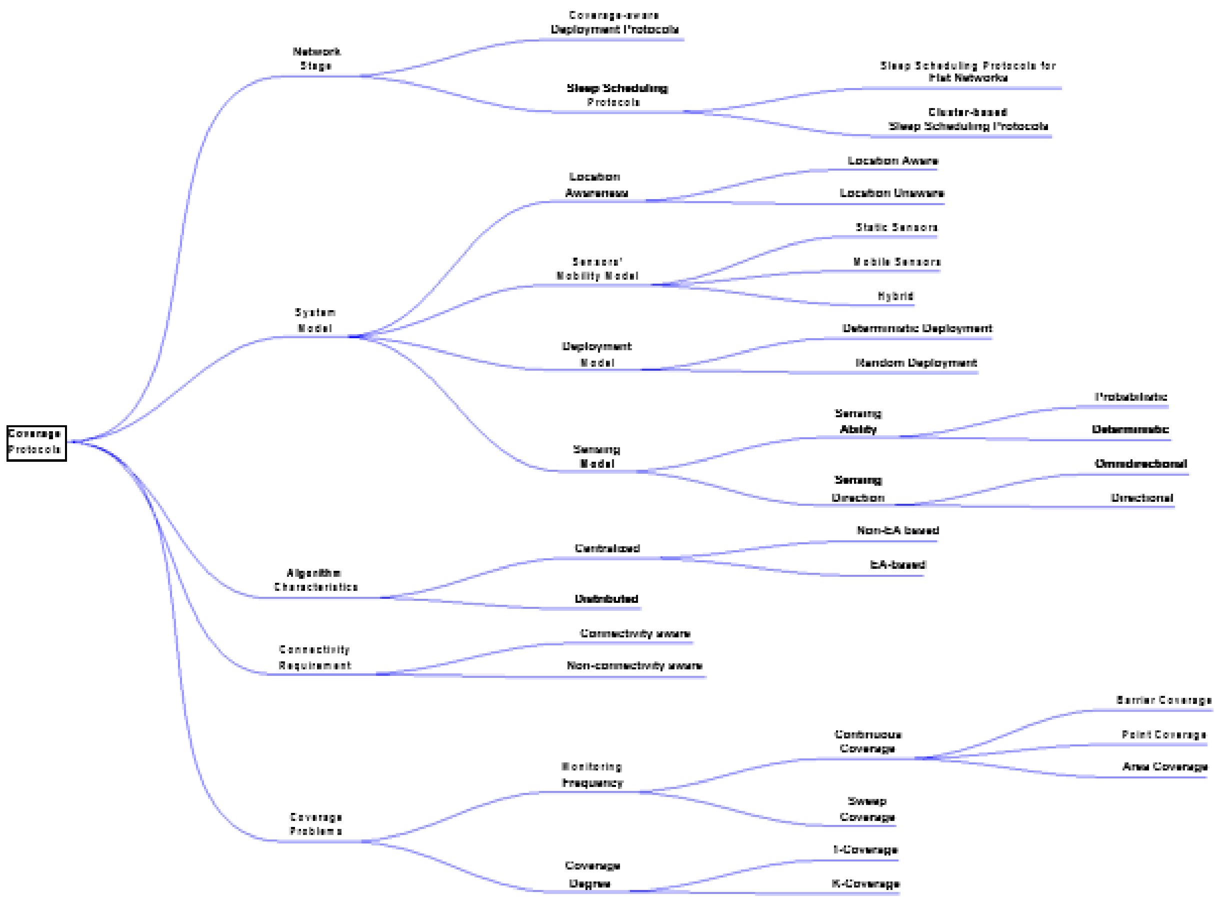


Fig. 1: Taxonomy for classifying coverage protocols in WSNs

viewed coverage protocols are broadly classified based on the protocol characteristics (distributed vs. clustered) and the sensor nodes location information (location-aware vs. location-unaware). The review considers area coverage protocols only, for both deterministic sensor nodes deployment and random sensor nodes deployment. Finally, the review focuses on coverage protocols that use static nodes only and that are based on the boolean sensing model (a detailed

sensing model classification is presented in Section II.C).

The relationship between coverage and connectivity in WSNs is analyzed in [7]. In this review, the coverage protocols are classified into three categories: coverage deployment strategies, sleep scheduling mechanisms, and adjustable coverage radius protocols. This survey however, mainly focuses on coverage protocols that adopt the boolean sensing model.

A comprehensive survey on barrier coverage in WSNs is given in [8]. The reviewed barrier coverage protocols are mainly classified into two categories: barrier coverage for static sensor nodes and barrier coverage for mobile sensor nodes. The pro-tocols are further classified based on the following criteria: the sensing range direction (omnidirectional vs. directional), the sensing model (boolean, probabilistic and full-view), and the coverage requirement (weak *k*-barrier coverage vs. strong *k*-barrier coverage). Moreover, several optimization problems in barrier coverage are studied.

Another review of barrier coverage is given in [9]. However, the focus of this review is barrier coverage for directional sensor nodes only. The examined protocols are classified, based on the coverage requirement, into four categories: strong barrier and weak barrier, *1*-barrier and *k*-barrier, worst and best-case coverage and exposure path coverage, and any-view coverage and full-view coverage.

In [10], the coverage issue is discussed as a topology control technique in WSNs. The studied coverage protocols are classified into three categories respectively: area coverage protocols, barrier coverage protocols and sweep coverage protocols. Area coverage protocols are further classified based on the types (i.e. static, mobile or hybrid) of sensors available in the WSNs and the coverage requirement (*1*-coverage or *k*-coverage). More-over, barrier coverage protocols are studied for both deterministic and probabilistic sensing models.

The author of [11] presents a brief survey on *k*-coverage problems and protocols. The protocols were mainly classified, into two categories: *k*-coverage verification protocols and sleep scheduling protocols for *k*-coverage problems.

A. Review of evolutionary algorithm (EA)-based sleep scheduling protocols is given in [12]. The authors highlight the main reasons behind adopting EA in sleep scheduling protocols. Moreover, the reviewed sleep scheduling protocols are classified, based on the EA they adopted, into four categories: swarm intelligence (ant colony optimization (ACO), particle swarm optimization (PSO), and pulse-coupled biological oscillators (PBO)) protocols, genetic algorithms (GA), differential evolution (DE), cellular automata, and protocols which uses

B. Omnidirectional Sensing Model

Omnidirectional sensing model is a special case of directional sensing model [28] where $\alpha = 360^\circ$. Omnidirectional sensors cover a unit of a circle and they have only one working direction. Many legacy sensor nodes equipped with temperature, humidity, and magnetic sensors are omnidirectional sensors.

C. Boolean Sensing Model

Boolean (deterministic/disk) sensing model is the simplest and most commonly used sensing model [29]. In this model, if a point (or event) P in the network field is located within the sensing range R of sensor node S, then it is assumed that P is covered/detected by S. The sensing area of S is defined as a disk centered at S with a radius of the sensing range R.

In this model, the coverage function, C(S, P), of sensor node S and point P is given by the following equation:

$$C(S,P) = \begin{cases} 1, & \text{if } d(S,P) \leq R \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Where d(S, P) is the Euclidean distance between sensor node s and point P.field, such as buildings, railway track, power stations and mines, result in extra loss and more variation in the received signal power of both the sensing signal and the signal emitted from targets or events. Moreover, the sensing ability of a sensor is non-uniform and asymmetric in all directions around the sensor due to their hardware configuration and software implementation. Therefore, the sensing radius of a sensor node should not be modelled uniformly in all directions since signals from different directions, corresponding to different propagation paths, suffer from different amounts of *shadowing* loss. The variations in the received signal strength due to obstructions in propagation path is known as *shadowing*.

The shadow fading sensing model given in [33] is the first model to consider the impact of the shadowing effects on the coverage problem in WSNs. In this model, the coverage function, C(S, P), represents the probability that sensor S covers/detects P in a shadowed environment. This coverage probability depends on the shadowing fading parameter σ, the Euclidean distance d(S, P) between sensor node S and point Pas well as an average sensing radius $\bar{ }$. The coverage function,RC(S, P), is given by the following equation [33] [34]:

D. Probabilistic Sensing Models

The probabilistic sensing model was firstly proposed by [30] as a more realistic extension of the Boolean sensing model. This model was motivated by the fact that sensor detections are usually imprecise and the quality of sensing gradually decreases with increasing distance away from the sensor [31]. Therefore, the coverage function, C(S, P), needs to be expressed in probabilistic terms. The probabilistic sensing model is further classified into two models: the Elfes sensing model and the shadow fading sensing model.

(a) The Elfes Sensing Model. Two sensing radii are de-fined in the Elfes sensing model [32], R_{min} and R_{max} where R_{min}defines the starting of the uncertainty in the sensor detection. If a point (or event) P in the network field is located within the sensing range R_{min} of sensor node S, then it is assumed that P is definitely covered/detected by S. If point P is located beyond the sensing range R_{max}, then it is definitely not covered/detected by S. Otherwise, point P is covered/detected by S with probability p. The coverage function, C(S, P), is given in the following equation:

$$C(S, P) = \begin{cases} p = e^{-\lambda(d(S,P)-R_{min})^{\gamma}}, & \text{if } R_{min} < d(S, P) < R_{max} \\ 1, & \text{if } d(S, P) \le R_{min} \\ 0, & \text{if } d(S, P) \ge R_{max} \end{cases} \quad (2)$$

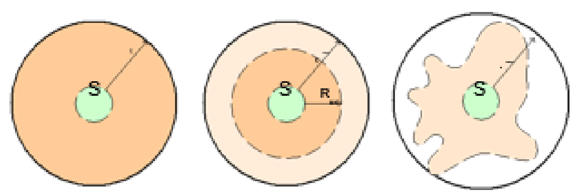
Where the λ and γ parameters are adjusted according to the physical properties of the sensor. It should be noted that the Elfes sensing model is considered a more general model, where it becomes a boolean sensing model when $R_{min} = R_{max}$.

(b) The Shadow Fading Sensing Model. In the aforementioned sensing models, the sensing radius of a sensor node has a constant value in all directions around it. Therefore, its sensing ability depends only on the distance between the sensor node and the point of interest. However, obstructions in the network

$$C(S, P) = \frac{1}{\bar{A}} \int_0^{R_{max}} Q\left(\frac{10\beta \log_{10}\left(\frac{d(S, P)}{\bar{R}}\right)}{\sigma}\right) \times 2\pi d(S, P)\, dr \quad (3)$$

Where β denotes the signal power decay factor and R_{max} denotes the maximum practicable sensing range. dr is a small increment in distance d(S, P) which represents a small difference in the distance due to the sensor size. More details aboutthese variables or how to calculate $\bar{ }$ can be found in [33] [34].R

Fig. 2 illustrates the shape of the sensing area for the aforementioned sensing models.



(a) Deterministic sensing model
(b) Elfes sensing model
(c) Shadow fading sensing model

Fig. 2: The shape of the sensing area for different sensing models

In this survey, we classify coverage protocols, based on the network stage where the coverage is optimized, into either coverage aware deployment protocols or sleep-scheduling proto-cols. Sleep-scheduling protocols are further classified, based on the network topology, into either cluster-based sleep scheduling protocols or sleep scheduling protocols for flat networks, as shown in Fig. 1. The following three sections give a detailed review of such protocols.

II. COVERAGE-AWARE DEPLOYMENT PROTOCOLS

Coverage-aware optimal sensors deployment can be defined as the process of determining the optimal locations of sensors in a network field such that the coverage requirement of an application is met. The coverage whole problem, which refers to finding regions that are not covered by any sensor, is a sub-problem of deployment protocols [35]. Mobile sensors are used to solve such problem by adapting their position in order to fill up sensing holes and eventually increase the area coverage [36]. The Maximum Coverage Sensor Deployment Problem (MCSDP) is an example of deployment problems that aims at finding the minimum number of sensors to achieve maximum coverage of the surveillance area. Most deployment problems are NP-hard problems with many conflicting objectives. Therefore, centralized evolutionary approaches are often used to solve various deployment problems [13] [16] [17].

PSO-based deployment algorithm, PSODA, is proposed into solve the deterministic deployment problem for point coverage in WSNs. In PSODA, the MCSDP is modelled as a constrained optimization problem and the main objective of the algorithm is to minimize the number of sensors while satisfying the coverage constraints for all the target points. The ROI is divided into small cells and the center of each cell is a potential position for a sensor. PSODA contains one binary 0/1 decision variable for each position in the network area where the value of 1 indicates that a sensor should be deployed at this position and 0 indicates the opposite. The fitness function uses a weighted-sum approach that combines two sub-objectives: the first one is used to minimize the number of sensors to be deployed and the second one is used to minimize the dissatisfaction of the coverage constraints.PSODA assumes that the sensors follow the Elfes sensing model and all the sensors are static and homogeneous. A modified PSO which uses a new position updating procedure for a faster convergence was adopted to solve the premature convergence problem of traditional PSO. Although PSODA was primarily developed to solve the point coverage problem, it can be adopted for applications that require full area coverage. It should be noted that the PSODA protocol does not consider the connectivity between the sensors and the BS.Constrained Pareto-based Multi-objective Evolutionary Approach, CPMEA, is proposed in [16] to solve the deterministic deployment problem in WSNs. Unlike PSODA, CPMEA treats the coverage requirement as an objective rather than a constraint. Moreover, CPMEA aims at maintaining the full connectivity between each sensor node and the BS by modelling the connectivity requirement as a constraint. CPMEA uses the Pareto-dominance concept to formulate the objective functions. The main objective is to find more than one Pareto-optimal sensor-layouts that can maximize the coverage and lifetime simultaneously while maintaining full connectivity between the sensors. The decision variables in CPMEA represent the desired positions of the sensor nodes. However, instead of generating a col-lection of random layouts without considering the connectivity, the initial population is generated in two steps. The first step consists of generating a number of random tree topologies that connect the BS to the sensor nodes. Then in the second step, the positions of sensor nodes are randomly generated based on the BS position and the tree structure. CPMEA assumes thatthe sensors follow the boolean sensing model and all sensors are static and homogeneous.

GA-based deployment protocol was proposed in [17] to ensure both coverage and connectivity of a given set of targets. The goal of the protocol is to select the minimum number of the potential positions for the sensors such that two requirements are met: k-coverage and m-connectivity. The objective function was defined as a weighted-sum of three scaled sub-objectives: minimizing the number of deployed sensor nodes, maximizing the total achieved coverage and maximizing the connectivity. Each individual in the GA population has a length equals to the number of the potential positions of the sensors. Each gene can have a value of either 1 or 0 to indicate whether a sensor should be installed at that location or not. [17] assumes that the sensing range is equal to the communication range and all sensors follow the boolean sensing model. It is also assumed that all the sensors are static and homogeneous.

Another approach for solving the sensors deployment problem in WSNs is to find an optimal deployment pattern. In this approach, it is assumed that the ROI is divided into virtual grids and every sensor is deployed at the intersection points of the grid. The grid shape can either be square, triangle, hexagon, etc. The goal of the deployment protocol is to estimate the pattern (grid shape) and the optimal distance between the sensors. For example, the authors in [38] developed a protocol to address the problem of finding a regular node deployment pattern that uses the minimum number of sensors to provide *k*-coverage and *m*-connectivity. The main idea of the proposed protocol is to find a deployment pattern that satisfies three conditions: the network area is *k*-covered, the sensor nodes are *m*-connected, and the number of deployed sensors is minimized. The main goal of this protocol is to estimate the locations and the optimal distance be-tween sensors for three different deployment patterns: triangle, square, and hexagon. The protocol then chooses the deployment pattern to be used to deploy minimum number of sensors while meeting the coverage and connectivity requirements. The protocol assumes a boolean sensing model and all sensors are static and homogeneous.

Another approach for coverage-aware deployment is to de-ploy and reposition mobile sensors to meet the coverage requirement of a certain application. MobiBar [39] is a protocol of such design that is proposed for barrier coverage applications. MobiBar is a distributed deployment protocol that utilizes mobile sensors to construct *k* distinct complete barriers and hence provides *k*-barrier coverage. The goal of MobiBar protocol is to achieve a final deployment that provides the maximum achievable barrier coverage by repositioning the mobile sensors. The authors of MobiBar defined a *baseline* as the line that is parallel to the border of the network area to which other barriers should be constructed parallel to it. MobiBar assumes that sensors located on adjacent barriers are able to communicate. These connected barriers are referred to as the connected barrier component. Each barrier in MobiBar has a priority which decreases as the distance between the baseline and the barrier increases. Initially, all sensors move towards the baseline to increase the connectivity of the network. The first sensor to reach the base-line elects itself as a leader of the connected barrier component. Then this leader chooses at most four neighbour sensors, each of

Table 3: Comparison of coverage aware deployment protocol

Coverage Protocol	Year Published	Main Goal(s)	Sensing Model	Location Awareness	Protocol Characteristics Dist.	Cent.	EC.
[17]	2015	Provide full area K-coverage/M -connectivity	Boolean	N/A			
[38]	2015	Provide full area K-coverage/M -connectivity	Boolean	N/A			
MobiBar [39]	2017	Provide K-barrier coverage	Boolean	Yes			
PSODA [37]	2016	Solve the MCSDP/Point coverage	Elfes	N/A			
CPMEA [16]	2016	Provide full area coverage/connectivity	Boolean	N/A			
MSCOLER [40]	2018	Provide targeta K-coverage/connectivity	Boolean	Yes			

required level of coverage. Network lifetime prolongs when the number of such sets increases. Hence, the goal of this approach is to determine the maximum number of DSCs. Since both the OCP and the DSC problems are well-known NP-hard optimization problems, EAs can be used to solve them [43] [44].

A variant of PSO, Binary PSO (BPSO), is adopted in a centralized Binary PSO-based sleep scheduling protocol [45] to solve the OCP. BPSO assumes that the sensors are homogeneous, randomly deployed in the network field and adopt the boolean sensing model. The coverage problem was modelled as a constrained 0/1 programming problem to determine whether a sensor should be in active mode (with value 1) or in sleep mode (with value 0). The goal of the protocol is to minimize the number of active sensor nodes while maintaining full area coverage constraint. Moreover, the protocol was extended to find the maximum number of DSCs. This is done by initially minimizing the number of active sensor nodes. These active nodes form the first set and are marked as unavailable. Then, the unassigned sensor nodes form another network topology. This process continues till the last network topology cannot provide full coverage for the area.

A multi-layer GA, (mlGA), is adopted in [44] to find the maximum number of DSCs. The goal of the *mlGA* protocol is to find the maximum number of DSCs and to ensure that each DSC is assigned the minimum number of sensors which provides full coverage. The mlGA protocol employs a post-heuristic opera-tor, in which the unassigned sensors may be used to enhance the coverage of each set of covering sensors or *set cover* for brevity. Similar to the BPSO protocol, the mlGA protocol identifies the maximum number of DSCs gradually. However, the mlGA protocol assumes that the sensors adopt the Elfes sensing model to reflect the uncertainty in sensor's sensing ability. It should be noted that the random initialization and update of the population individuals in both *BPSO* and *mlGA* may result in infeasible set cover solutions that do not meet the required coverage constraint. In this case, a repair function is adopted to repair these individuals (i.e. set covers) and hence further move toward the optimal solutions space. The repair function usually works by drawing a random sensor from the set of the unassigned sensors and adding this sensor into an infeasible individual solution. This process continues till the coverage constraint of each infeasible individual is met.

An Energy Efficient Connected Coverage (EECC) algorithm was proposed in [46] to find the maximal number of non DSCs that ensure target coverage and connectivity while minimizing sensors redundancy around the targets. Authors of EECC argued that non-disjoint cover sets provide a longer network lifetime compared to the disjoint cover set as they may generate morecover sets, which in turn will prolong the network life time. The sensors are classified into sensing and relay nodes according to its coverage. If the sensor does not cover any of the targets, its coverage is null and it is termed as relay node. A sensor which covers a target is termed as a sensing sensor. Sensing sensors are further classified, based on the number of targets it covers, into three types: single coverage sensor, multi coverage sensor, and critical coverage sensor. Each sensor has a heuristic value derived from its sensing coverage and connectivity to the BS. The value of the coverage heuristic prioritize the sensing node according to its contribution towards coverage while the value of connectivity heuristic prioritize the relay sensor according to its connectivity to sensing nodes and sink. Although the authors have proved that their problem formulation is NP-complete, they have used greedy approach to select the sensors to include in the cover, based on their heuristic values.

GA-based protocol to find the maximum number of non DSCs to provide K-coverage for a predetermined number of tar-gets was proposed in [47]. Each sensor cover is enough to cover all the targets in the field. The network lifetime of the sensor covers is calculated as the minimum lifetime of a sensor that belongs to that cover, i.e. the sensor that has the minimum remaining energy. The energy-efficient target coverage problem is then formulated as a maximization problem that aims to maximize the aggregated network lifetime among all the sensor covers. Firstly, the adopted GA algorithm determines the optimal cover heads that are responsible for transferring the data to the BS. Then, the algorithm forms the covers based on the coverage range of each sensor, the expected consumed energy, the distance to the BS, and targets positions. Authors assumed that the sensors are mobile and can move freely in the network field, to collect environmental data, without adhering to any specific sensor mobility model. Moreover, a cover management method that switches between different sensor covers was proposed. It was also assumed that all the sensors can transmit directly to the BS.

III. CLUSTER-BASED SLEEP SCHEDULING PROTOCOLS

Though both the *Cluster Heads (CHs)* selection problem and the coverage problem have been extensively studied separately, only a few protocols considered them together. Most of existing clustering protocols focus only on selecting CHs to reduce or balance the network's energy consumption, while how to cover the network area effectively is out of the scope of these existing solutions. The following paragraphs describe papers that con-sider clustering and coverage simultaneously.

Table 4: Comparison of sleep scheduling protocols for flat networks

Coverage Protocol	Year Published	Main Goal(s)	Sensing Model	Location Awareness	Protocol Characteristics		
					Dist.	Cent.	EC.
CMSS [41]	2015	Minimize # of active sensors/Full area coverage	Boolean	Yes			
CAOP [42]	2015	Minimize # of active sensors/Full area coverage	Boolean	Yes			
BPSO [45]	2015	Find maximum # of DSCs/Full area coverage	Boolean	Yes			
mIGA [44]	2015	Find maximum # of DSCs/Full area coverage	Elfes	Yes			
EECC [46]	2017	Find maximum # of non DSCs/Target coverage	Boolean	Yes			
[47]	2018	Find maximum # of non DSCs/Target coverage	Boolean	Yes			

Distributed, Cluster-based Coverage-aware protocol, ECDC that can be adapted for different applications is proposed in [25]. The network area in ECDC consists of randomly deployed static sensor nodes. The main idea behind the protocol is that sensors having higher remaining energy and/or deployed in a densely populated area, and/or cover more POIs are more likely to be selected as CH candidates. Two coverage importance metrics are introduced to measure the coverage importance for each sensor node: one for the point coverage problem and the other for the area coverage problem. In the point cover-age problem, the point coverage importance of a sensor node is determined by the number of POIs covered by that sensor node only. The higher the number of POIs covered by a sensor node, the larger the point coverage importance of that sensor node. In the area coverage problem, the area coverage importance of a node is determined by the number of neighbours. The fewer nodes around a sensor node, the greater the area coverage importance of that sensor node. The clustering process of ECDC is divided into rounds, each of which consists of a cluster set-up phase and a data transmission phase. In the cluster set-up phase, the sensor nodes compete for the CH role based on their relative residual energy and their coverage importance. At the end of this phase, sensor nodes with relatively higher residual energy and smaller coverage importance will be chosen as CHs. In the data transmission phase, a routing tree is constructed to connect the elected CHs to the BS. The CHs aggregate data from their cluster members and then send data to the next hop nodes on the constructed routing tree. It is assumed that the selected CHs are within the communication range of each other and each CH can either send its data directly to the BS or can send its data to a neighbouring CH. The ECDC protocol uses a Time Division Multiple Access (TDMA) mechanism to avoid inter-cluster and intra-cluster collisions.

Balanced clustering algorithm (BCA) is another distributed clustering protocol that was proposed in [48]. Similar to the ECDC protocol, the BCA protocol operates in rounds and favours sensors that are deployed in a densely populated area to act as CHs candidates. Moreover, the BCA protocol creates a set of equally balanced, in terms of their coverages, clusters (i.e. to make the coverage area of each cluster approximately the same). The coverage area of a cluster is defined as the union of the coverage areas of all cluster members. In BCA, each sensor calculates its probability of becoming a CH based on its sensing population, which is defined as the number of sensor nodes that are located within its sensing range. Once a sensor node be-comes a CH, it uses its sensing population information to put some nodes into sleep mode in order to save their energy. To do so, a CH selects a random number of sensors to put to sleep.

This number should not exceed a specific threshold which is determined by the CH. However, the absence of redundancy check in this process leads to potential coverage holes.

Another distributed Coverage-Preserving Clustering Protocol (CPCP) is proposed in [49]. The CPCP defines several cost metrics that combine the remaining energy of a node with its contribution to network coverage. For example, the minimum-weight coverage cost metric is defined such that nodes deployed in densely populated network areas and that has higher remaining energy are better candidates to act as CHs and/or to stay active. The operation of CPCP consists of five phases. In the first phase, the sensors exchange information about their remaining energy and each node calculates its coverage cost based on that information. In the second phase, each sensor decides whether or not to become a CH for the current round based on its activation time. Every sensor determines its activation time based on its current coverage cost. A sensor that does not hear an announcement message, from any other sensor node, during its activation time will declare itself to be a new CH upon the expiration of its activation time. In order to avoid creating non-balanced clusters, a sensor node announce its role as a CH within a prespecified cluster range. In the third phase, a multi-hop route between the CHs and the BS is constructed. In the fourth phase, the clusters are formed such that each non-CH node joins the closest CH. In the final phase, each sensor decides whether it will stay active or not for the current round. This decision is based on its coverage cost. In order to take this decision, every node defines an activation time based on its current coverage cost. Doing that will allow sensors that have lower coverage cost to announce them-self earlier as active nodes. Every node will determine its status upon the end of its activation time. If a sensor node determines that its sensing area is completely covered by its neighbouring nodes, it turns itself off for the current round. However, this activation method is not efficient, as it cannot guarantee to find all redundant nodes in each round. Moreover, the main operation of CPCP depends mainly on the values of the activation timers. So the decision of whether a sensor will stay active or not is not taken at the beginning of the round. This decision could be taken by the node anytime during the round, depending on its activation time. This will lead to unnecessary consumed energy by the redundant nodes who are waiting their timer to expire to take the decision to be inactive. Moreover, although the authors of CPCP recommended the activation time to be proportional to the coverage cost, no specific recommendation was given on how to set this value.

The authors in [50] developed a centralized, cluster-based coverage-aware protocol for target tracking applications. The network area consists of both randomly deployed static sensor

Table 5: Comparison of cluster-based sleep scheduling protocols

Coverage Protocol	Year Published	Main Goal(s)	Sensing Model	Location Awareness	Protocol Characteristics Dist.	Cent.	EC.
[50]	2009	Increase coverage rate/Point coverage	Boolean	Yes			
BCA [48]	2015	Create equally balanced clusters/Area coverage	Boolean	Yes			
CPCP [49]	2009	Clustering/Area coverage	Boolean	Yes			
ECDC [25]	2014	Increase coverage rate/Point/Area coverage	Boolean	Yes			
MOEAD-CCP [51]	2014	Clustering/Full area Coverage	Boolean	Yes			
NSGA-CCP-3D [52]	2018	Clustering/Full area Coverage/3D WSN	Boolean	Yes			

Consequently, network lifetime is decreased because more (redundant) sensors than required are kept active.

- On the other hand, boolean sensing model may also overestimate the sensor's sensing capacity by assuming that all the points located within its uniform sensing range are covered. This in turn may result in coverage holes in the network and the coverage requirement of the application is not met.

The Elfes sensing model II.C.4.a was proposed to solve those problems by defining two sensing ranges for a sensor. However, the coverage area for each sensing range is still uniformly distributed and hence it shares the same problems as the Boolean sensing model.

Several empirical studies have shown that the shape of the sensing area of a sensor may not be a regular disk [55] [56][57] The impact of location errors, sensing signal irregularity and packet loss on the Coverage Configuration Protocol [58], CCP, were studied and investigated in [55]. Experimental results shown that CCP performance degrades with the location errors increase, sensing signal irregularity and packet losses. More-over, the impact of radio irregularity on the sensor communication was confirmed and quantified in [56]. According to [57], the radio irregularity in WSNs is caused by three main factors:

- Anisotropy: a signal transmitted by a sensor node experiencesvarious path losses at different directions.
- Continuous variation: the signal path loss varies continuouslywith incremental changes of the propagation direction from a transmitter.
- Heterogeneous sending powers: sensor nodes may transmitradio signals at different sending powers, even though they are from the same manufacturer. This is caused due to the hardware differences between sensors and different battery level of the sensors.

The shadow fading sensing model was proposed as a first at-tempt to construct a more realistic sensing model by simulating the path loss around the sensors. However, a careful look at the coverage protocols in the literature will reveal that this model has rarely been used to model the coverage of the sensor in WSNs. Moreover, the shadow fading sensing model is isotropic in the sense that the path losses in different directions are the same [57]. To illustrate this, the path loss at distance d, P L (d)is calculated using the following equation [59]:

$$PL(d) = PL(d_0) + 10\beta \log_{10}\left(\frac{d}{d_0}\right) + N(0,\sigma) \quad (4)$$

Where d is the distance from the sender, d_0 is the reference distance, P $L(d_0)$ is the path loss at a reference distance d_0, β is the path-loss exponent, N (0, σ) is a zero-mean Gaussian random variable with standard deviation σ.

The Radio Irregularity Model (RIM) was proposed in [57] tosimulate the three factors that cause radio irregularity in WSNs. In RIM, the irregularity of a radio pattern is denoted by parameter Degree of Irregularity, DOI. DOI is defined as the maximum path loss percentage variation per unit degree change in the direction of radio propagation. Accordingly, the path loss model is modified based on the DOI to generate 360 different path loss values for different directions. In RIM, the DOI-adjusted path loss at direction θ and distance d, P L (d, θ) is calculated using the following equation [59]:

$$PL(d,\theta) = \left(PL(d_0) + 10\beta \log_{10}\left(\frac{d}{d_0}\right)\right) \times K_\theta + N(0,\sigma) \quad (5)$$

Where K_θ is the path-loss coefficient at direction θ and is computed as follows:

$$K_\theta = \begin{cases} \text{if } \theta = 0 : K_\theta = 1 \\ \text{if } 0 < \theta < 360 : \quad \text{if } B(1, 0.5) = 0 : K_\theta = K_{\theta-1} + W(b_1, b_2) \times DOI \\ \qquad K_\theta = K_{\theta-1} - W(b_1, b_2) \times DOI \end{cases} \quad (6)$$

Where $|K_0 - K_{395}| < DOI$, B (n, p) is a Binomial random variable with n trials and success probability p, and W $(b_1, b_2)$is a Weibull random variable with scale parameter b_1 and shape parameter b_2.

RIM is a thoughtfully designed model that reflects the signal irregularity phenomena in WSNs [60] [59]. It has been used and studied recently in many WSNs protocols such as [61] [62][64] [59]. However, most of these protocols focus on localization methods or link quality estimation. To the best of our knowledge, RIM has not yet been studied or used to model the coverage problem in WSNs.

- Realistic Coverage-aware Clustering Protocols

Clustering sensor nodes is an efficient topology control method to maximize the network's energy efficiency. Many clustering protocols have been used in various WSNs applications. However, most of these protocols focus only on selecting the optimal set of CHs to reduce or balance the energy consumption of a given network, while how to cover the network area effectively is overlooked. Moreover, the performance of these protocols is limited by the challenges on determining an accurate radio model for the sensor nodes in the network. A commonly employed energy consumption model is presented in [65] [66]. The energy consumption in this model is calculated

- Realistic Connectivity Model The index statej refers to the energy states of the sensor:statej

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