Deployment strategies in the wireless sensor network: A comprehensive review

Sanay Abdollahzadeh, Nima Jafari Navimipour

Department of Computer Engineering, Tabriz Branch, Islamic Azad University, Tabriz, Iran

ARTICLE INFO

Article history:
Received 17 June 2015
Revised 26 May 2016
Accepted 15 June 2016
Available online 21 June 2016

Keywords:
Wireless sensor networks
Deployment
Coverage
Connectivity
Energy efficiency

ABSTRACT

Wireless Sensor Networks (WSNs) have come across several challenges such as node deployment, the reduction of power consumption, secure routing, bandwidth allocation, Quality of Service (QoS), and so forth. Since sensor deployment is an important matter due to its influence on cost and the network capability of WSN, the focus of this study is the deployment issue and related concerns such as coverage, connectivity, and energy efficiency, which have a great impact on the performance of WSNs. To the best of our knowledge, there are no studies that analyze and review the current scope completely. In this paper, some important research in the scope of sensor deployment will be investigated and analyzed as well as identifying their main specification. The deployment problem is classified based on few important factors and four deployment strategies and their related results are studied in each class. Also, the advantages and disadvantages along with important challenges of several strategies have been discussed so that more efficient deployment strategies can be developed in future.

© 2016 Elsevier B.V. All rights reserved.

1. Introduction

With the development of distribution environments such as the grid computing [30,44,70], cloud computing [12,43,47], Peer-to-Peer networks [46], Expert Cloud [8,26,28,43,50,54], electronic management [52,53,68,84,10], knowledge management [85,24] and MapReduce [45], nowadays, Wireless Sensor Network (WSN) becomes more popular than before. It is an emerging paradigm of computing and networking, which can be defined as a network of minuscule, diminutive, inexpensive, and keenly intellectual devices, called sensor nodes. Sensor nodes are spatially distributed and they work cooperatively to communicate information gathered from the monitored field through wireless links and send them to a sink, which either uses the data locally or communicates it to other networks [59]. The development of WSNs was originally motivated by military applications [78], for example in battlefield surveillance they could be used to detect, locate, or track enemy movements. WSNs are currently employed in many industrial and civilian application areas including industrial process monitoring and control [57], environment and habitat monitoring [5,15,79], healthcare applications [4], home automation [66], and traffic control [42]. In the case of natural disasters [89], sensor nodes can sense and detect the environment to forecast disasters in advance. The wide range of potential WSN applications call for a rapidly growing multi-billion dollar market, but this would require further major progress in WSN standards and technologies to support new applications [21]. Despite the continuous development of WSNs, there are still several research challenges related to wireless sensor communication due to the restricted features of low priced sensor node hardware and the common necessity for the nodes to work for long time periods. Besides, there are challenges originating from close interaction between the WSN and the environment that need to be investigated, namely uncertainty related to sensors readings, harsh deployment environments and combining sensory data from multiple sensors [64].

For most WSNs, a major design step is to selectively decide the locations of the sensors in order to maximize the covered area of the targeted region. This particular problem has different appellations in the literature, e.g. placement, coverage or the deployment problem in WSNs [32]. The deployment of sensors can be random (e.g. dropping sensors in a hostile terrain or a disaster area) or deterministic (e.g. placing sensors along a pipeline to monitor pressure and/or temperature, and boundary surveillance) [27], and it depends mainly on the type of application, the environment, and the sensors themselves. The planning strategy of the deployment problem affects transmission rate of the sensors as well as the coverage and lifetime of the whole system, making the deployment a very critical issue in WSNs [74].

In general, poor deployment of sensor nodes leads to inefficient network connectivity or redundancy of coverage. A well-chosen deployment strategy will not only reduce cost but also extend the...
network lifetime; therefore, the deployment of a WSN is a critical problem. Deployment planning requires consideration of several objectives such as energy consumption, sensing coverage, network lifetime, network connectivity, and so forth. Often these objectives conflict with one another, and operational trade-offs must be established during network design [76].

In this paper, we classify the deployment methods and algorithms proposed in the literature for both predetermined and random deployments. This classification is based on the most important objectives used for modeling and solving the deployment problem. The deployment strategies are classified into four main categories: increasing the coverage, enhancing the connectivity, improving energy efficiency and optimizing the lifetime, and finally multi-objective deployments. To the best of our knowledge, a comparative study on the deployment issue considering these categories has not been conducted as of yet. [81] categorizes different approaches based on their node positioning techniques (static vs. dynamic [41]), and compares them based on their objectives and methodologies. However, it does not consider multi-objectivity of the strategies. [88] investigate the coverage and connectivity issues from different aspects of deployment strategy, sleep schedule mechanism and coverage radius. We have investigated state-of-the-art strategies in each category and depicted their advantages and disadvantages. We have compared all presented strategies based on some important factors regarding deploying sensors, such as load balancing, energy distribution, scalability, sensor’s sensing range, a region of interest, network cost and so on. As well, a side-by-side comparison of all discussed strategies is presented, and few open issues are addressed.

The basic concepts and preliminaries are provided in the next section. Section 3 discusses related papers and research in the scope of sensor deployment under four main categories. The taxonomy and comparison of analyzed strategies are presented in Section 4. Section 5 maps our open-ended issues and finally Section 6 concludes the paper.

2. Basic concepts and preliminaries

The solutions to deployment issues in WSNs involve many basic theories and assumptions. In this section, some basic knowledge regarding WSN will be presented, and deployment concepts, and few definitions that are required to further understand the rest of the paper are provided.

2.1. Preliminary definitions

Definition 1. (Random deployment). In many practical cases, the random scattering of WSNs might be essential, because of the large scale of the required network or the inaccessibility of the terrain. Node placement must meet two conditions; nodes should not be placed too close, which would result in a small covered area and little information would be retrieved. Additionally, if nodes are placed too far apart, many would be isolated and as a result, data would not reach the sinks [76]. Random deployment may require much more redundant sensors to be deployed in order to achieve given specification.

Definition 2. (Pre-determined deployment). In pre-determined deployment, the locations of the nodes are specified. This type of deployment is mostly used in applications where sensors are expensive or their operation is meaningfully affected by their position, namely by placing imaging and video sensors, populating an area with highly precise seismic nodes, positioning WSN applications underwater, monitoring manufacturing plants etc. [20].

Definition 3. (Self-deployment). More recently, self-deployment is proposed as a technique assuming the sensors’ own mobility. For example, potential fields [80] or virtual force based approaches [33] are used to spread sensors out from a compact or random initial configuration to cover an unknown area.

Definition 4. (Energy hole). Sensor nodes which are close to the sink have larger energy consumption because they carry heavier relay traffic. As a result, sensor nodes in this area tend to die early when their energy diminishes as a result of what is called an energy hole [22]. The non-uniform distribution of energy in any part of the network may stop the functioning of that part of the network, leading to a phenomenon known as the energy hole problem. In order to solve the energy hole problem, a concept of non-uniform deployment for the sensor network has been proposed. In this concept, the area closer to the sink should have higher sensor density which enables a larger number of sensors to share the load of data-forwarding. [35].

Definition 5. (Heterogeneous wireless sensor network). Heterogeneous WSN contains sensor nodes with various abilities, such as a different processing power and sensing range, so deployment and topology control are more complicated when compared to homogeneous networks [7]. Energy consumption and lifetime tend to be the most important issues to have been found in heterogeneous WSNs, increasing the balance in energy usage enhances the network’s lifetime [51].

Definition 6. (Homogeneous wireless sensor network). In homogeneous networks, each of the nodes is similar in battery energy and hardware complexity. Homogeneous wireless sensor networks with pure static clustering might increase the risk of cluster head nodes being overloaded with transmissions of extended range to remotely located base stations. Furthermore, extra processing is required for the protocol coordination and data aggregation [75].

Definition 7. (Relay nodes). Relay nodes can have extra storage space and much more powerful transceivers compared to sensor nodes. They can be used in order to forward sensed data for long distances in large monitored sites, and energy at Sensor nodes is saved for further data sensing and gathering [87].

Definition 8. (Redundant node). The redundant node refers to the node that can be removed from the network without affecting the process of receiving the targeted data. On the contrary, the redundant node is a unique source of information in the monitored site that cannot be recovered by the other nodes in the network [86].

Definition 9. (Mobile node). Mobile nodes have all the features of the fixed nodes; in addition, they enjoy mobility feature. Since coverage and connectivity are crucial for WSNs, the failure of a node may cause the network to be partitioned into disjoint segments or brought along with a hole in the original coverage area. A mobile node can act as a router when it is in a low or even no coverage area, and it can accomplish the recovery task [88].

Definition 10. (Voronoi partition). Given k points in a plane, the plane is partitioned into k sub-regions according to the nearest-neighbor-rule [9] such that every sub-region called Voronoi cell is dominated by a point called Voronoi center which is closest to all the points in this sub-region. As an example, a Voronoi diagram is shown in Fig. 1 [36].

Definition 11. (mobile sinks). Mobile sinks are special nodes which visit the WSN at regular intervals in order to collect sensed data, thus, eliminate the need for multi-hop communications and reduce energy consumption significantly Yu, Zhang et al., [83]. Consequently, the use of mobile sinks extends the network lifetime when employed. It is not feasible to employ multi-hop communi-
cations when sensors are sparsely deployed, and the mobile sink is often employed in such situations [14].

2.2. Sensing model

The sensing model is a mathematical model that describes the probability of an event or target detection of a sensor. Several types of sensing models can be found in the literature, but more generally they can be categorized as binary and probabilistic sensing models.

2.2.1. The binary sensing model

The recognition possibility of the event concerned is one within the sensing range; otherwise, the probability is zero. The definition of this model is depicted in the Eq. (1) [67], where it is assumed that the sensor has a fixed sensing range ($r$).

$$P(S_i) = \begin{cases} 
1, & \text{if } d(S_i, P) < r \\
0, & \text{Otherwise} 
\end{cases}$$  

(1)

Where $d(S_i, P)$ is a distance between point $S_i$ and point $P$ and, $P(S_i)$ depicts the probability of the event of interest is one within the sensing range of the $i$th sensor.

According to Wang et al. [77], there are two kinds of binary sensing models: perfect and imperfect binary sensing models. In the perfect binary sensing model, each node is able to recognize in case the target falls within its sensing range $R$ (as shown in Fig. 2(a)). In the imperfect or frail binary sensing model, the target is always diagnosed within the inner disk of radius $R_{in}$ (as shown in Fig. 2(b)); however, it is discovered only with some nonzero probability in an annulus among this inner disk and the outer disk of radius $R_{out}$.

Although the binary sensor model is simpler, the uncertainty factor in the measurement is not taken into consideration. In reality, measurements by a sensor node are imprecise and it is not likely that physical signals fall suddenly from high, full-strength values to zero, as the binary model assumes. This means there could possibly be a chance to diagnose an event happening at ranges greater than the sensing radius.

2.2.2. Probabilistic sensing models

A probabilistic sensing model is much more practical considering that the occurrence being sensed, sensor design, and environmental circumstances are all stochastic in nature. As an example, noise and interference in the natural environment can be modeled by stochastic processes. Sensors produced through the same manufacturer are not deterministically equivalent in behavior; alternatively, sensors’ features are usually modeled using statistical distributions. Dhillon and Chakrabarty [13] have proposed a simple probabilistic sensing model which is described in Fig. 3 (assuming an exponential decay of the probability of detection with Euclidean distance).

2.3. Coverage and connectivity

The coverage of a sensor network delivers the quality of surveillance, which the network can offer, for instance, how well a region of interest is supervised by means of sensors, and how efficiently a sensor network can identify intruders. For an effective design and employment of sensor networks in various application scenarios, the coverage of a sensor network relies on numerous parameters [37]. The coverage problem can be divided into two categories: 1-coverage problem and $k$-coverage problem. In $k$-coverage problems, each target in the sensing field must be covered by at least $k$ different working sensors, whereas, in the 1-coverage problem, it needs to be covered by at least one sensor (Rebai et al., 2015). Also, Liu et al. [38] have divided coverage deployment strategies into two main categories: static and dynamic coverage.

2.3.1. Static coverage

The goal of static coverage is to improve the overall sensing performance of a sensor network by optimizing sensors’ locations [69]. It can be stated as developing a sensor distribution algorithm.
to make the exposure area of the sensors be the least or to minimize the overlapped sensing area of sensor nodes, as shown in Fig. 4 (a) and (b) respectively. The difficulty in this issue is the definition of the detecting range and its influence on the entire network. The interest is to fully cover the monitored area with the least number of sensor nodes [38].

2.3.2. Dynamic coverage

Dynamic coverage is defined by the use of a mobile sensor network and results from the consistent mobility of sensors. While sensors move around, locations that were uncovered at the beginning will be covered at a later time, therefore, a wider area is covered over time, and intruders that might never be discovered in a fixed sensor network can now be detected by mobile sensors. On the other hand, this advancement in coverage is accomplished at the cost that an area is covered only part of that time period, alternating between covered and not covered. Fig. 5 depicts the coverage of mobile sensor networks where the solid disks being covered at the given time are instant. Also, in the union of the shaded region and the solid disks, the region is covered during the time interval [37].

Khanjary et al. [29] have defined the network connectivity as a graph-theoretic concept which enables sensors to communicate with each other in order to forward their data to the sink. A network can be modeled as a graph in which vertices are the sensor nodes and edges are the communication link between nodes. In this case, a connected network means underlying graph is connected. A WSN is called m-connected if elimination of any \((m-1)\) sensors does not leave the communication graph disconnected [55]. Due to [18], some characteristics like quality, robustness, and throughput of a sensor network are directly affected by the degree of coverage and connectivity.

2.4. Lifetime

There are several definitions for WSNs lifetime in the literature, and an inappropriate definition might lead to incorrect lifetime estimation. This may cause a waste of resources. Models in the literature differ in the way they consider a WSN to be still operational. These models can rely on the connectivity of the deployed nodes or on a percentage of alive nodes (which have enough energy to accomplish their assigned tasks) in the network. Connectivity-based (CB) and Percentage of Alive Nodes (PAN) models are defined as follows, respectively:

CB: The lifetime of a WSN is the time span from deployment to the instant when a network partition occurs. This happens when one or more nodes are not able to communicate with the base station.

PAN: The lifetime of a WSN is the time span from deployment to the instant when the percentage of the alive nodes falls below a specific threshold. However, losing a few nodes may not significantly affect the overall wireless sensor network performance, especially when redundant nodes and communication links (edges) are used in tolerating high probabilities of disconnected nodes, as they did in environmental applications. Generally, in environment monitoring, several nodes are assigned to measure single specific criteria of the monitored space, such as temperature in forestry fire detection [1]. Consequently, the concept of node redundancy should be addressed. In addition, lifetime models relying on the aforementioned definitions do not take into consideration the node type which could be cluster head, a relay node or sensor node.

The definition of sensor lifetime is further divided into three approaches, namely FND, HNA and LND for defining lifetime based on the kind of service the network provides. For the scenarios where it is important to know when the first node dies, the First Node Dies (FND) metric is proposed, which indicates a value for this event. Furthermore, in some scenarios sensors are placed near to each other. The adjacent sensors can record related or identical data so that the loss of a few nodes would not decrease the quality of the service the network provides. For these cases, the Half Of the nodes Alive (HNA) metric serves well as it estimates a value

Fig. 3. A probabilistic sensor model. The chance of detection in the gray annulus decreases with distance from the sensor [31].

Fig. 4. Static coverage problem where a grey part represents exposure area in a and overlapped area in b [38].

Fig. 5. Coverage of mobile sensor network: the left figure shows the initial network configuration at time 0 and the right figure depicts the effect of sensor mobility during the time interval \([0, t]\) [37].
for the half-life period of a network. The final metric, Last Node Dies (LND) suggests a value for the overall lifetime of the network [71].

3. Deployment strategies

Sensor deployment is one of the most important issues in WSN because an efficient deployment scheme can reduce the deployment cost and enhance the detection capability of the wireless sensor networks. In addition, it can enhance the quality of monitoring in wireless sensor networks by increasing the coverage area. Based on our observation, all the deployment strategies that are introduced by researchers have been based on the four most important objectives used for modeling and solving the deployment problem. These objectives are coverage maximization, connectivity enhancement, energy efficiency and lifetime optimization, and multi-objectivity.

3.1. Coverage maximizing

Coverage has attracted significant research interest because of its relationship with optimization associated with resources in a sensing field. Maximizing the coverage and preserving less expensive deployment have always been a challenging task, particularly when the monitoring area is unidentified and perhaps dangerous [88]. Subsequently, coverage is one of the significant functionality metrics for sensor networks due to the fact that it demonstrates how perfectly a sensor field is supervised. In this subsection research that falls under this scope is discussed and analyzed.

3.1.1. Ant colony optimization-greedy based approach

Liu and He [29], have considered the challenge of coverage in grid-based WSN with a guarantee-connectivity and low-cost (GCLC), and they have proposed the ACO–Greedy deployment solution, to settle this approach. This approach improves ant colony optimization (ACO), by adding the new character, ants’ greedy migration. ACO is a well-known intelligent algorithm where complicated combined behavior emerges from the behavior of ants. As one of the vast majority of thriving swarm intelligence algorithms, it is extremely efficient for solving NP-hard combinatorial optimization problems. In the ACO–Greedy based approach the deployment field consists of discrete grid points on which sensors can be stationed and can recognize the Points of Interests (POIs) inside the sensing radius. The objective of the GCLC problem is defined as searching for a set of as a small number of points as possible among the candidate grid points, hence a node is deployed on each individual grid point of the set. Eventually, all of the POIs can be covered by deployed nodes. Each member of the set is named a Point of Solution (PoS). In addition, each individual PoS has to be attached to the sink through one hop or multiple hops. To give a Point of the sink, in which the black dots represent POIs and the red ones represent PoSs. In this case, the green stars are the sink, in addition, the shadows symbolize the sensing/communication range of the nodes. The advantages of this strategy are that this method can quickly complete the full coverage, and markedly decrease the deployment cost. In addition, ACO–Greedy can dynamically adjust the sensing/communication radius to alleviate the energy-hole problem and balance the power consumption among sensor nodes, and as a result, it can prolong the network lifetime in grid-based WSNs. However, by adding more nodes to the areas with heavier traffic, the cost will increase.

3.1.2. Genetic algorithm based approach

Younim and Yong–Hyuk [82] have considered an efficient Genetic Algorithm (GA) using a Monte Carlo normalization method to design an effective analysis function. The reason for using the normalization technique is to overcome the inherent redundancy of the genotype space which slows down the GA convergence. The so-called redundancy happens as a result of the fact that different variations of three sections of a chromosome are translated into the similar candidate solution. Thus, authors have used random parent selection in their proposed normalized GA, which is an odd choice since it is mediocre in terms of convergence speed to the more commonly used Roulette Wheel or Tournament selection methods. However, in this strategy, computation time is lowered without having a decrease in solution quality by means of implementing a technique that begins with a few numbers of arbitrary trial samples and progressively enlarges the number for subsequent generations. One of the advantages of the genetic algorithm method in comparison to random deployment and current methods is that it is approximately twice as faster, and demonstrates substantial performance advancement in the level of quality. In addition, another advantage is that high-quality sensor deployment for any set of heterogeneous static sensors without the management of a human can be reached by this strategy.

3.1.3. Glowworm swarm optimization based approach

Liao et al. [34], have introduced a sensor deployment structure dependent on Glowworm Swarm Optimization (GSO) in order to optimize the coverage after an initial random deployment of the sensors. Swarm intelligence is a type of artificial intelligence based on the cooperative manners of decentralized, self-controlled systems. It emphasizes the research of the collective behavior that is prepared from a population of undemanding agents interrelating locally with one another and with their environment. Even though there is no centralized control determining the behavior of the agents, the agents follow some straightforward rules to interact locally with other agents that usually set off an overall pattern to develop. In this strategy, each sensor node is deliberated as exclusive glowworms releasing a luminant material called luciferin and the amount of luciferin is determined by the distance between the sensor node and its adjacent sensors. A sensor node is attracted to the direction of its neighbors that have a lower intensity of luciferin and chooses to move towards one of them. Using this method, the coverage of the sensing field is maximized when the sensor nodes tend to reposition themselves towards the area which has lower sensor density. In Fig. 7, there are five glowworms with different luciferin levels. Each glowworm will endeavor to move towards its neighbors that have a higher intensity of luciferin. Here li(t) represents the luciferin level of glowworm i at time t. As an instance, glowworm b will move towards its neighbors c and e as the value of lb(t) is less than lc(t) and le(t). The directions of movement of the glowworms are presented by directed lines. This deployment method is easily scalable for large sensor networks because there is no centralized control dictating the behavior of the agents, and simulation results showed that the GSO-based sensor deployment approach can provide high coverage with limited movement of the sensor nodes which can be listed as the advantages of this strategy. As a disadvantage, neighbor oscillation is problematic [6], where a node experiences repeated deviations of its set of neighbors. Although some efforts were made to decrease the oscillation situation, it causes a reduction in the coverage rate.

3.1.4. Holes detection and healing based approach

Senouci et al. [63], have researched a solution to the issue of hole detection and healing in mobile WSNs. They presented a comprehensive and a distributed virtual forces-based local healing solution for the detection and healing of holes called HEAL (Holes detection and healing). HEAL is a distributed and localized algorithm that operates in two distinct phases. The initial phase con-
consists of three sub-tasks; hole identification, hole discovery and border detection. The authors have proposed a Distributed and localized Hole Detection algorithm (DHD) that operates over the Gabriel Graph of the network. DHD has very low complexity and deals with holes of various forms and sizes despite the nodes distribution and density. The next phase deals with the hole healing with a new concept, hole healing area. It consists of two sub-tasks; hole healing area determination and node relocation. The researchers have proposed a distributed virtual forces-based local healing approach based on the Hole Healing Area (HHA), in which the forces will be effective. This allows a local healing where only the nodes located at an appropriate distance from the hole will be involved in the healing process. Hole Manager (HM) will be responsible for the hole-healing announcement. After determining the HHA, the HM informs the nodes involved in the healing process. Nodes that receive forces from the hole center, move towards it. The researchers have tried to balance the tradeoffs between attractive and repulsive forces to recover the hole without side effects (Fig. 8). The hole center applies an attractive force on every node within the HHA located at a certain distance. At the same time to minimize the overlapped coverage, a repulsive force exists between nodes within the certain range. Experimental results showed that HEAL provides a cost-effective and accurate solution for hole detection and healing in mobile WSNs. But considering the environment as an obstacle free area is a disadvantage for this strategy.

To conclude this section, we will present a comparison of the reviewed deployment strategies which are based on maximizing coverage in Table 1. The comparison is carried out in terms of the algorithm type, type of sensors deployed, the adopted sensing model, advantages and disadvantages of each strategy.

### 3.2. Maximizing the connectivity

In device deployment (i.e. the number and positions of devices) several factors such as coverage, connectivity, lifetime, and etc. must be considered. However, in environments where there are harsh conditions such as in forests, connectivity is one of the most important factors. Connectivity can be considered as a primary/secondary objective or as a constraint in the deployment problem.

#### 3.2.1. Optimized 3D deployment with lifetime constraint -based approach

Al-Turjman et al. [3], have introduced a 3D deployment approach, known as the Optimized 3D deployment with Lifetime Constraint (O3DwLC), which is applicable for relay nodes in environmental applications. Increasing network connectivity and maintaining an effective lifetime period at the same time, without exceeding cost limitations is a difficult design objective for WSNs. Gratifying this sort of objective turns into additionally a much more elaborate challenge with 3D configurations and extreme operational situations included in common large scale natural environment tracking applications. To achieve this, the researchers have used the grid model vertices characteristic that can be organized in different structures (e.g. Cubes, octahedrons, pyramids, etc.) in 3D space to provide more accurate estimates in terms of the spatial properties of the targeted data. This strategy refers to
the two-phase deployment strategy in which the first phase is used to place a minimum number of relay nodes on the grid vertices to establish a connected network. The second phase is used to choose the optimal positions of extra relay nodes required to maximize the network connectivity with constraints on cost and lifetime. In this research, a two-layer hierarchical architecture is assumed as a natural choice in large-scale environmental applications. The lower layer consists of sensor nodes that sense the targeted phenomena and send measured data to Cluster Heads (CHs) in the upper layer, as shown in Fig. 9(a). The upper layer consists of cluster heads and relay nodes which have a better transmission range (= r) and communicate periodically with the base station to deliver the measured data in the lower layer. Cluster heads aggregate the sensed data and coordinate medium access, in addition to supporting relay nodes in transferring data from other CHs to the BS in the upper layer. Assuming sensor nodes have enough energy to perform their effortless tasks, this work has focused on the upper layer devices which are relay nodes and cluster heads. Fig. 9(b) depicts the 3D grid model assumed in this strategy, where the grid edge length is supposed to be equal to a relay node transmission range r. It is assumed that all relay nodes have a common transmission range r. In this cubic grid model, each SN is placed near the phenomena of interest for more accurate estimates in terms of the spatial properties of the collected data. CHs are then placed on the most appropriate grid vertices; which can serve the largest number of sensor nodes distributed around each cluster head. The base station is placed based on the application requirements in a fixed position and it is the data sink for the system. Then, the method tries to optimize the relay nodes’ positions on the 3D grid to get cluster heads connected to the base station efficiently; in terms of cost and network lifetime. This deployment planning is applicable for other types of grid models, and not only the cubic one and this strategy optimizes network connectivity while guaranteeing particular network life span and limited cost in outdoor environments with harsh conditions. However, when the available number of functional nodes cannot tolerate the failure, the WSN connectivity decreases dramatically and network partitions occur and cause prominent degradation in WSN connectivity even when O3DwLC strategy is used.

3.2.2. Independent genetic-algorithm-based approach

Al-Turjman et al. [1], have introduced the average connectivity percentage, a grid-based deployment metric, with the purpose of illustrating the deployed network connectivity when sensor situations are subject to arbitrary errors around parallel grid locations. In this study, authors have indicated properties of the grid connectivity and examined its behavior in real life scenarios, where node positioning is subject to human or machinery mistakes and the communication range is subject to sudden circumstances which could affect its shape in the 3D space. Thus, the key sources of connectivity failures and problems are addressed. In this strategy, a generic approach is used to measure and evaluate the proposed metric which is independent of the random error distributions, grid-shape, and distinct environment-based channel properties. Two deployment scenarios have been applied: the grid-based deployment with bounded uniform errors and with unbounded normal errors. Based on the numerical accomplishments, quantified outcomes of the positioning errors and grid edge length on the average connectivity percentage are outlined. Fig. 10(a) depicts the arbitrary shape of the communication range since it, in reality, has an arbitrary shape and it is constructed by a set of spheres as shown in Fig. 10(b). These spheres vary in numbers and sizes from one arbitrary shape to another. An advantage of this method is being resilient to the random placement errors and unpredictable communication ranges. Node failures which occur because of limited energy and mobility of obstacles are counted as a disadvantage.

3.2.3. Standard semi-definite programming based approach

Ibrahim et al. [23], in their strategy aimed to improve the connectivity of a given network by adding a set of relays to it. They proposed a network maintenance algorithm, which is concerned about keeping the network from getting disconnected, and finds the best locations for a given set of relays. The proposed algo-

### Table 1
Comparison between maximizing coverage-based deployment strategies.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Algorithm</th>
<th>Type of sensors</th>
<th>Sensing model</th>
<th>Advantages</th>
<th>Disadvantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Liu and He [39]</td>
<td>ACO-greedy algorithm</td>
<td>Homogenous/Fixed</td>
<td>Deterministic</td>
<td>Decreasing cost and Power balancing</td>
<td>Adding nodes leads to increase in cost</td>
</tr>
<tr>
<td>Yousif and Yong-Hyuk [82]</td>
<td>Normalized GA</td>
<td>Heterogeneous</td>
<td>Deterministic</td>
<td>Fast coverage, good performance, cost decreasing</td>
<td>Consider no obstacles for ROI and is not applicable to mobile sensors</td>
</tr>
<tr>
<td>Liao, Kao et al. [34]</td>
<td>GSO</td>
<td>Mobile</td>
<td>Deterministic</td>
<td>Decentralized control</td>
<td>Oscillation</td>
</tr>
<tr>
<td>Senouci, Abdelhamid et al. [61]</td>
<td>Artificial Potential Fields-based algorithm (APF)</td>
<td>Homogenous/Mobile</td>
<td>Deterministic</td>
<td>Low sensor movement, localized protocol and low complexity.</td>
<td>The border holes are not addressed.</td>
</tr>
</tbody>
</table>

Fig. 9. (a) Two layers hierarchical architecture and (b) Cubic 3-D grid model for the targeted wireless sensor network deployment where dashed lines and empty circles represent grid edges and vertices, respectively [1].
Algorithm obtains the best relays’ locations through a multi-level approach. In each level, the search problem can be formulated as a standard semi-definite programming (SDP) optimization problem. Finding the optimum locations for such relays is a difficult problem due to the continuous nature of this problem, which results in an infinite number of possible solutions. In this study, the researchers overcame this problem and proposed a network maintenance algorithm, which specifies the near-optimum locations for an available number of relays \( K \geq 1 \) to maximize the Fiedler value of the network. The researchers characterized the network connectivity by the Fiedler value, which is the second-smallest eigenvalue of the Laplacian matrix representing the network graph, this way they aimed to find the optimum locations for a given set of relays in order to maximize the Fiedler value of the resulting graph. First, they divided the network area into a certain number of equal regions and represent each region by a relay in its center. Second, they chose the best \( K \) relays’ locations by solving a Semi-Definite Programming (SDP) optimization problem. Third, they refined this solution by dividing each obtained relay’s region into a number of smaller regions and repeating the same procedure. This algorithm consists of a number of stages, which are called levels. Finally, the authors chose the best location after a number of levels, where each relay could be deployed. This method can increase the Fiedler value by 35% after adding one relay only. This result is very close to what can get by random addition schemes and exhaustively search for the optimum location. However, this proposed algorithm requires only 1/20 of the time taken by the exhaustive search scheme. This proposed network-maintenance algorithm can be implemented through utilizing low-altitude unmanned air vehicle (UAVs). But as a disadvantage of this method the researchers have noted that for a disconnected network, the proposed algorithm does not guarantee that it can reconnect this network by adding a predetermined set of relays to it.

3.2.4. Optimal 3D grid deployment based approach

Al-Turjman et al. [2], proposed an optimal 3D grid Deployment (O3D) strategy for forestry applications where connectivity is optimized. By considering a WSN as a graph, the researchers measured how well the WSN is connected using the second smallest eigenvalue of the graph Laplacian [16]. This eigenvalue is called algebraic connectivity as well. Increasing the algebraic connectivity means increasing the required number of nodes and links disjoint paths in the graph leading to the robust network architecture and a more reliable WSN. The researchers used integer linear programming to solve the SDP optimization placement problem. They assumed the data samples are taken frequently by sensor nodes and transmitted back to the base station via data aggregation centers (or Cluster Heads (CHs)) based on a synchronized schedule. CHs relay information to BS through RNs while aggregating the sensed data and coordinate medium access. The researchers assumed SNs and CHs placement is determined by the application in order to achieve the desired data sampling, and they focus on the issue of optimal placement of relay nodes in a 3D forestry space. It is obvious that not all of the grid vertices can be RN candidate positions. This is due to the forestry environmental parameters, such as obstacles or unreachable places. Therefore, they identified the RN placement problem as a given specific sensing task with specified SNs, CHs, and BS locations, determine the number and positions of RNs that maximizes the connectivity between the SNs (or CHs) and the BS with a constraint on the maximum number of RNs. 3D forest description can be achieved from the laser imagery (LiDAR) technology [17]. LiDAR makes a laser scan for the forest from an airplane. Then it provides images which describe the trees density and heights in addition to other obstacles specifications on the site. Since SNs (or CHs) and BS are placed to satisfy the desired application, they may not be initially connected as shown in Fig. 11(a). Therefore, they have used a Minimum Spanning Tree (MST) algorithm to connect these SNs (or CHs) to the BS using a minimum number of RNs as shown in Fig. 11(b). The proposed O3D strategy is evaluated and compared to two possible random deployment strategies, Random 3D grid deployment (R3D) and Random 3D grid deployment with Optimal Backbone (R3DwOB). Simulation results show that the O3D can achieve high reliability. However, coverage energy consumption is relatively high when O3D is applied. This is because the authors have an operational path from all CHs to the BS even in the presence of 40% & 50% of edge and node failure, respectively. In addition, using the O3D strategy they can set a threshold on the minimum number of
required RNs to maintain the connectivity of WSN in an environment of a specific PNF or PEF. (Fig. 12).

Table 2 compares the reviewed algorithms in this section in terms of the algorithm used, the type of deployed sensors, adopted sensing model, advantages, and disadvantages of each one.

### 3.3 Energy efficiency and lifetime optimization

Energy consumption is one of the most important issues in WSN because the nodes are energy constrained, and battery replacement is almost impractical [25]. Therefore, energy balance is a key metric impacting the performance of WSNs. Also, how to design a flexible deployment and broadcasting model for nodes is a problem in WSNs. In general, the wireless sensor is battery-powered. It is usually impossible or impractical to recharge the battery. So the lifetime of WSN is mainly determined by battery life. Preserving the sensor’s energy is a key to keeping the network operational for longer periods of time [72,65]. Protocols for WSNs need to be designed in a way that the limited battery power in the sensor nodes is effectively used [58].

#### 3.3.1 Improved non-uniform load routing based approach

Tiegang et al. [73], proposed a new deployment strategy of WSN that gathers several means to minimize cost. The regular hexagonal cell architecture is employed to build a network that satisfies the constraints of coverage and connectivity. Based on the analysis of energy consumption of sensors and sink and cost of the network, an energy allocation theorem, and an integer programming model are presented to minimize the cost per unit area. The key issue is to determine the number of layers of the network when other parameters are fixed. Furthermore, a scheme of the multi-sink network is proposed for a large monitored area. In order to balance the energy consumption of sensors on the identical layer, a uniform load routing algorithm is presented. The numerical analysis and simulation results show that the waste of energy and cost of WSN can be effectively reduced by this strategy.

#### 3.3.2 Heterogeneous node deployment scheme based approach

Halder and Bit [19], developed an allocation-wise predetermined Heterogeneous Node Deployment Scheme (HNDS). The present scheme is an improvement over their earlier scheme discussed in Section 3.3.1 which dealt with the prolonging of the network lifetime deploying homogeneous nodes only, whereas the present scheme deals with the deployment of heterogeneous nodes. This strategy is produced based on the principle of energy balancing derived from their observations which revealed that the energy imbalance in WSNs occurs due to the relaying of data from different parts of the network towards the sink. In order to reach an improved energy balance, it is recommended to deploy relay nodes along with sensor nodes to manage the imbalance and enhance the lifetime of the network. Here, by a location-wise predetermined strategy, not only the number of nodes in an area is determined, but also, the exact locations within the area are predetermined. Heterogeneity has been introduced by using two types of nodes: sensor nodes and relay nodes. The researchers have considered the RHC architecture as a network model for this strategy. The nodes are static and uniformly distributed within the network with a given node density. They have considered periodic data gathering applications in which each sensor node uniformly generates n bits of data and sends the data to the sink at a fixed time-interval q(t). In the first phase of deployment, SNs are deployed in the center of each cell to ensure coverage. In the second phase, RNs are placed at locations according to their priorities which are set as per the locations’ amount of work pressure in terms of energy consumption for relaying data of their neighboring
nodes. In case there is no dearth of nodes’ availability, all the prioritized locations are to be filled with nodes; otherwise, according to the availability, nodes are to be placed on the heavily loaded vertex first, then at moderately loaded and finally at the lightly loaded vertex. This way, a certain level of performance is maintained even in the presence of a limited number of nodes. However, if there is any dearth of SN nodes, the deployment scheme cannot be implemented. The simulation results also show that this scheme does not compromise with other network performance metrics such as end-to-end delay, packet loss, throughput while achieving the design goal. However, the deployment strategy may be made more realistic by considering a 3D environment. The scheme must be analyzed for further improvement considering QoS parameters.

3.3.3. Swarm-intelligence-based sensor selection algorithm based approach
Restuccia and Das [61], have defined the problem of lifetime optimization in WSNs in the presence of uncontrollable and random sink mobility while guaranteeing QoS constraints on data reliability and throughput. The paper considers applications where the sensing area is divided into subareas and proposed Swarm-Intelligence-based Sensor Selection Algorithm (SISSA) runs independently in each subarea. SISSA schedules a contention-free channel access scheme during each MS visit and facilitates lifetime by ensuring only nodes with the highest residual energy transmit. In this way, the remaining nodes save energy and the transmitting nodes are allowed to increase their channel access time resulting in spectacularly lower duty-cycle for each sensor and thus saving energy and optimization of a lifetime. SISSA allows sensor nodes to have the same channel access time, regardless of the number of the nodes in the network. Furthermore, by allowing only a subset of nodes to communicate during each visit, the allocated time slot for each nodes increases, resulting in the increase in network lifetime. The Authors introduce an ideal scheme that demonstrably maximizes network lifetime and contrast the lifetime provided by SISSA. The efficiency of the model is tested experimentally and compared to that of the ideal scheme. The results prove that SISSA offers on the average the 56% of the lifetime provided by the ideal scheme in all the considered parameter sets and conclude that SISSA is highly scalable and energy efficient. However, the paper is not considering interferences and needs to be evaluated with more efficient MS discovery algorithms.

3.3.4. Dual beacon discovery protocol for mobile elements
Restuccia et al. [60], have provided a performance analysis of a hierarchical discovery protocol for WSN Mobile Elements (MEs) named Dual Beacon Discovery protocol (2BD), while minimizing the energy consumption of sensor nodes. The communication phase between the sensor nodes and the MEs is thoroughly analyzed and the obtained results suggest that 2BD is capable of providing a significant reduction in energy consumption, compared with classical solutions, and increasing the lifetime of sensor networks consequently. This happens especially when the ME discovery phase takes rather long times. Due to hierarchical nature of the protocol, the nodes are assumed to switch between low and high duty cycles. While sensors operate with low duty cycle during the discovery phase, in order to save energy, they switch to high duty cycle as they realize the ME is at the point of entering its transmission range. A periodic emission of two different beacon messages, Short-Range Beacons (SRBs) and Long-Range Beacons (LRBs), provides the sensor nodes with information about the actual ME location. SRBs and LRBs are transmitted with different transmission powers. SRBs are used to notify the sensor node that the ME is within its transmission range so that data exchange can occur. LRBs can be received within a larger area compared to SRBs, hence, they are utilized to notify the sensor node that the ME is approaching.

Random mobility scenario provides no information about the ME mobility pattern. Hence, 2BD best operates with these scenarios where the arrival time of ME at sensor nodes is not predictable, but the sensor node has to always stay in the discovery phase. Accordingly, energy saving obtained by 2BD in random mobility patterns might be very high. Also, the hierarchical mechanism also reduces the network’s traffic and offers some proximity search capabilities [49]. Nevertheless, where a relatively accurate prediction of the arrival time of ME is available, 2BD protocol becomes less efficient, especially in the curvilinear scenario.

Table 3 provides a comparison among the reviewed algorithms in this section in term of the deployed sensors and adopted sensing models. Advantages and disadvantages of each are mentioned as well.

3.4. Multi-objective deployments
During the deployment of sensor nodes, there are some objectives which are desired to be satisfied, namely the coverage of the region, the total energy consumed through the WSN, the lifetime of the network, connectivity and the number of deployed sensors. Previous research shows there have been attempts to reach several of the above-mentioned objectives through various optimization processes, both by mathematical/numerical programming and evolutionary computing techniques. The objectives were sometimes modeled as constrained single-objective functions. The problems can be modeled as constrained single-objective functions by aggregating several weighted objectives. However, multi-objective approaches have always been favorable in considering all aspects of sensor node deployment, as will be discussed in this section.

3.4.1. Multi-objective particle swarm optimization-based approach
Pradhan and Panda [56], have introduced an energy-efficient sensor deployment based on the multi-objective Particle Swarm Optimization algorithm (MOPSO). The MOPSO, as all multi-objective evolutionary algorithms, provides a set of non-dominated solutions, which form the Pareto front. It is assumed there is fuzziness in each objective due to the imprecision in the nature of the judgment of the decision maker. This fuzziness can be defined by membership functions representing the degree of fuzziness. When the number of solutions at the center of the Pareto front is very large and it is difficult to distinguish between the solutions, providing almost equal weight to each objective, then the fuzzy mechanism can be used to find a compromise solution. The fuzzy mechanism looks at the way the solutions contribute to each objective and assigns a fuzzy variable. It shows a possible way of finding a compromise solution in case the solutions are close to one another. In this study, the best-compromised solution on the Pareto front is selected by a fuzzy based mechanism. In this strategy, it has been assumed that each node knows its position in the search space and all sensor nodes are homogeneous and have equal energy and mobility. The two objectives of the coverage and lifetime are taken into consideration while maintaining a full connectivity of the network. During the optimization process, sensor nodes dynamically organize themselves to form a fully connected network. The mobility of the nodes provides a way to avoid time consumption and expensive deployment techniques. Lifetime is defined as the time until one of the participating nodes runs out of energy; also, the stochastic sensor model is used in this research. In practice, a WSN is divided into multiple sub-regions for easy layout, organization, and management. Since the stochastic sensor model is accepted practically, the size of the sub-region and its corresponding density and edge effects should be considered. These two objectives compete with one another. The coverage objective will try to spread out the nodes to maximize coverage, resulting in a
high energy loss and short lifetime. On the other hand, the lifetime objective will try to arrange the nodes as close as possible to the high energy communication node (HECN) to reduce loss in energy, resulting in poor coverage. As a consequence, in a multi-objective optimization problem, a set of trade-offs exists giving rise to multiple solutions. Each solution in this set represents a particular performance trade-off between the multiple objectives and these solutions are considered as optimal solutions. The popularity of MOPSO is attributed to its simple implementation, population-based approach and success in handling continuous search spaces. MOPSO needs exceptionally low computational time, which makes it a very promising candidate for engineering optimization problems where the computational cost is a vital issue. This approach considers obstacles which need modeling and detailed analysis and this is not usually preferred.

3.4.2. Incremental deployment-based approach

Lin et al. [36], have proposed an incremental deployment algorithm to deploy a static sensor network by taking into account practical communication constraints and the probabilistic sensor sensing model. The researchers adopted the idea of exploring under-deployed regions taking into account the practical communication constraints of sensors during the deployment process. Two important metrics are considered to evaluate the performance of sensor deployment, namely, coverage and topology connectivity. The goal is to use the least number of sensors to cover an area and maintain communication connectivity in a real environment setting. In order to do so, by deploying one or multiple autonomous agents, it is checked how a real setting environment affects the communication and sensors are deployed accordingly. The Voronoi partition is applied to help determine the moving direction during deployment, and to detect which agents deploy sensors one-at-a-time. This is done for the purpose of using a less number of sensors to cover the area while maintaining communication connectivity. The probabilistic sensor sensing model is used to evaluate the area coverage, and loop packet loss probability is used as a metric system to evaluate the communication quality. In this method, mobile sensors are subject to either attractive or repellent forces, according to the distances between their neighbors and themselves. The deployment process is terminated when every sensor arrives at a location with zero composite artificial force from its neighbors. Using more autonomous deploying agents clearly increases the deployment efficiency and shortens the time, i.e. if they collaborate in an effective way. As shown in Fig. 13, sensors s21; s22; s23; s24 are deployed by the agent and these locations are known by the agent a, while s11; s12; s13; s14; s15 are not deployed by the agent a, so these locations are not known by agent a, temporarily. The researchers assumed that all deployed sensors have their own location information, and once an unknown deployed sensor s12 is within the communication range of agent a, agent a can obtain the location of this sensor. Through communication, the agent can get the locations of the other sensors s11; s12; s13; s14; s15 which is able to communicate with s12 in a single hop or multiple hops. Any agent can know the location of all deployed sensors based on this scheme, at the end. Both simulations and experiments demonstrate the success of the algorithm and applicability in practical situations. However, how to optimize the deploying path to reduce total time has not been studied as of yet.

3.4.3. Multi-objective evolutionary algorithm based approach

Sengupta et al. [62], have formulated a deployment task as a constrained multi-objective optimization (MO) problem in which the goal is to locate a implemented sensor node layout in order to increase the region of coverage, minimize the net energy consumption, maximize the network lifetime, and decrease the number of deployed sensor nodes while keeping connectivity between each sensor node and the sink node for appropriate data transmission. They assumed a tree structure between the deployed nodes and the sink node for data transmission. In this WSN problem, the sink node is the root. Other sensor nodes are connected to the sink as shown in Fig. 14. This method implements a multi-objective evolutionary algorithm (MOEA) generally known as the MOEA/D-DE, which uses a decomposition method to convert the problem of the approximation of the Pareto fronts (PF) into a number of single-objective optimization problems. The proposed approach makes use of differential evolution (DE), as its search method, which is one of the most effective real parameter optimizers in current use. By means of introducing a new fuzzy dominance based decomposition technique, the original MOEA/D becomes altered. The proposed algorithm presented a fuzzy Pareto dominance concept, by which the two solutions can be compared and the scalar decompo-
sition method can be used when one of the solutions fails to dominate the other in terms of a fuzzy dominance level. The efficiency of this strategy is compared with original MOEA/D-DE and Non-dominated Sorting Genetic Algorithm (NSGA-II), which is another popular MOEA. The best trade-off solutions from the MOEA/DDF based node deployment scheme have also been compared with the original DE, an adaptive DE-variant (JADE), the original particle swarm optimization (PSO), and a variant of PSO. Evaluations made by the authors prove MOEA/DDF to be superior to other algorithms and produces minimum energy. Also, the proposed multi-objective formulation of the problem adds more flexibility to the decision maker in choosing the necessary threshold of the objectives to be realized. For instance, the decision maker can choose any specified coverage threshold as required by the application and can get a much lower energy rate and a longer lifetime than would have been possible in the full coverage situation. During the single objective optimization procedure, such freedom of decision making is not possible. This can be attributed to the least number of nodes. As one node breaks down the functioning is hampered to a large extent. Having reached the coverage threshold by 10 nodes, the optimizer will try to place the extra nodes closer to the sink node. Due to the addition of the extra node net, energy consumption may be increased, but the energy consumed by the individual node decreases. Therefore, in situations where lifetime is a more important criterion than the number of nodes, the decision maker can choose any number of nodes to meet demand.

3.4.4. Multi-objective evolutionary algorithm based on decomposition approach

Konstantinidis et al. [32], have considered an energy-aware transmit power level assignment to maximize the network lifetime while tackling the deployment problem. In other words, the authors have defined a multi-objective Deployment and Power Assignment Problem (DPAP). Using the Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D), the DPAP is decomposed into a set of scalar sub-problems, which are categorized according to the objective preference and handled in parallel by the use of the neighbor area's data and problem-specific evolutionary operators, in a single run. The suggested operators adjust to the demands and objective choices of each sub-problem dynamically throughout the development, leading to the substantial enhancement of the entire performance of MOEA/D. The researchers have proposed the SMAC medium access control, in which it has been observed that there are no collisions at any sensor during data communication. Utilizing this technique, they have been able to implement the simple but relevant path loss communication model as in [40]. In the multi-objective DPAP defined in this strategy, there is no available solution that can optimize all objectives simultaneously. Consequently, they focused on attaining a set of Pareto optimal solutions, or an approximated value. The Pareto optimal solutions, however, which are close to the objective space, should have many similarities with one another in the search space, recalling the Proximate Optimality Principle (POP) [38]. The POP is a fundamental assumption in most heuristics. A solution representation based on DPAP and several DPAP-specific, MOEA/D-based evolutionary operators are proposed, namely, the M-tournament selection, the adaptive crossover, and the adaptive mutation operators, which are highly interrelated with one another and adapt to the needs and objective preferences of each sub-problem dynamically, during the evolution. Simulation results showed the superiority of the problem-specific MOEA/D against the NSGA-II in several network instances, providing a diverse set of high-quality network designs to facilitate the decision maker's choice.

3.4.5. Maximum connected load balancing cover tree-based approach

Chen et al. [11], have proposed an algorithm called MCLCT (maximum connected load balancing cover tree) to achieve full coverage while maintaining BS-connectivity of each sensing node. MCLCT consists of two components: COR, a coverage optimizing recursive heuristic, and PLB, a probabilistic load-balancing strategy for routing path determination. The COR heuristic finds a maximum number of cover sets based on the global information of WSN. Subsequently, the PLB strategy chooses the best parent node to broadcast sensed data through neighbor nodes. Based on their experimental findings, the authors claim that the combination of the COR and PLB algorithms is feasible in achieving full coverage and connectivity of WSNs. Throughout MCLCT, energy consumption among the nodes is smooth, since the sensing and a transmitting load of the nodes can be shared. Authors indicate that the lifetime can be improved since MCLCT is capable of taking advantage of node's energy effectively. A node will not always operate in the same mode (sensing/relying/sleeping) which allows the algorithm to dynamically determine the appropriate operation mode of the nodes likewise the routing paths, and leads to the construction of routing topology called dynamic cover tree. Authors define the objective of the MCT problem as constructing several connected cover trees, which facilitates achieving a longer network lifetime and full coverage. In fact, the better performance of the proposed MCLCT mainly due to the energy saving method designed for sensing nodes and the coverage recovery strategy as well as the load balance mechanism developed for relaying nodes. However, coverage healing and uniformity of sensor deployment are not considered in the proposed approach. Moreover, the applied assumption of knowing the position of the nodes after the random deployment is a strong assumption that could be using a considerable amount of the network energy. The main advantage of MCLCT is efficient consumption of energy, which is accomplished owing to COR and PLB strategies. Nevertheless, neither sensor deployment uniformity nor coverage healing is taken into account in MCLCT.

Table 4, presents a comparison among the reviewed algorithms in this section in term of the deployed sensors and adopted sensing models. Advantages and disadvantages of each are mentioned as well.

4. Results and comparison

Since sensors are capable of processing and communicating data, forming networks, they can be employed to solve many problems in different fields of application. Hence, sensors can be applied in the following fields: infrastructure security, environmental and habitat monitoring, industrial sensing, traffic control. Depending on the type of environment and preferred application, the deployment of sensors can vary based on their scope of use, and the chosen deployment strategy varies based on the desired application and its objective.

In this section, we will compare the reviewed deployment algorithms according to their features. If the table is completely observed, it can be seen that different algorithms are suitable for
different scenarios. Table 5 shows a summarized form of the features of all research strategies studied in the previous section. For instance, if the cost is not of utmost importance, and the operation is affected by sensor position, then the HNDS-based approach would be more appropriate. When the considered region is a forest or may have bad weather conditions, it is considered one of the strategies to cover the area in all three dimensions. They provide an inherent trade-off between connectivity and lifetime and it should be taken into account when choosing a strategy. Similarly, there is another tradeoff between the lifetime of the network and the quality of connectivity. If all of the mentioned factors are equally significant, one might choose one of the 4th type strategies.

5. Open-ended issues

During recent years, a lot of attention has been paid to deployment issues in WSNs. However, many other issues are still open to research regarding the approaches that have been suggested recently.

5.1. Coverage and connectivity issues

Many types of research have been conducted addressing coverage and connectivity issues. However, there are still a lot of challenges and problems in this area which need to be solved.

5.1.1. Improve coverage and connectivity control algorithms

To solve more extensive coverage problems, finding the greatest coverage area and finding the proper distribution of the given properties, the radio range, and the density of nodes have become important challenges in the field of WSNs. Moreover, there is no work capable of restoring the k-connectivity of a k-connected WSN in a distributed and efficient manner. Restoring the k-connectivity through a generic algorithm that will work for any given k would definitely be an interesting research topic. Beside of the so far
mentioned open-ended issues, the regulation of the coverage degree, modulation of sensing frequency, determination of neighbor node coverage boundaries, finding the greatest coverage area given the radio range and distribution of nodes, or finding the proper distribution of the given properties, the radio range, and the density of nodes are also important.

5.1.2. Improving coverage hole's detection and recovery mechanism

Although many different researches have been conducted to clarify coverage and connectivity issues, only a few of them concentrate on coverage holes. One of the challenges is how to detect such holes, another one is how to repair these holes. The challenges regarding coverage holes include detecting and repairing of these holes. Furthermore, the probable ignorance of significant sensing overlaps or voids among sensors leads to poor network coverage, which interprets the importance of coverage hole as a hot research area.

5.1.3. Improving node failure detection and connectivity recovery algorithms

Most published studies focus on the recovery, assuming that the impact of the failure is determined. Whereas, there is no algorithm capable of determining the scope of the failure in a distributed manner. Existing node failure detection algorithms should be improved or redesigned to boost their accuracy. Moreover, in Underwater Wireless Sensor Networks, the nodes are more prone to failure compared to terrestrial WSNs, because of the corrosion and fouling. This is why the UWSN may get partitioned and some of the nodes might not be able to communicate with the others and with the surface station. Exploiting the controlled mobility to restore the connectivity in such 3D network is a challenging task. Leverage of cross-layer techniques can enhance the robustness of the failure detection and tolerance [48]. For instance, node and link failures are often difficult to distinguish and there is a high probability that false alarms would be triggered for node movement. The employment of a combined link and network layers can lead to the significant reduction of the frequency of false positives. Additionally, conflicts may occur at any time and new network factors such as network re-deployment, data packet loss, and network delay can be considered in deployment strategies.

5.1.4. Design effective sensing models

Considering the existing works on coverage and connectivity issues which are mostly based on the disc sensing model or the probabilistic sensing model, the fact that the sensing range can be affected by real geography environment and communication jamming is well known. Therefore, further research regarding the design of sensing models from theoretical aspects to the real world applications is essential.

5.2. Energy efficiency

Despite the fact that many protocols have been developed to maximize the energy efficiency, still they need to be reconsidered to further fulfill the requirements of WSN like energy, delay, and reliability in a more effective manner. In the future, the energy consumption due to sensor movement in the presence of obstacles must be considered while calculating lifetime. The analysis of the energy consumption model considering signal strength, retransmission and interference must be taken into account in future works. In the actual network, nodes have infinitesimal energy consumption, even if they do not communicate. So energy consumption in the real world must be considered. The energy consumption should also be considered in k-Connectivity.

6. Conclusion

In this paper, the most important research in the scope of sensor deployment and the identification of its main specification has been analyzed. The deployment strategies have been classified into four main categories based on their objectives: increasing the coverage, enhancing the connectivity, improving energy efficiency and optimizing the lifetime, and multi-objective deployments. We reviewed and analyzed contemporary strategies in each category and depicted their advantages and weaknesses. As well, all presented strategies are compared based on some important factors involving deploying sensors, such as load balancing, energy distribution, scalability, sensor's sensing range, a region of interest, network cost, and so on. Moreover, side-by-side comparison of all discussed strategies is done. We showed that diverse strategies might be suitable for various scenarios. For instance, if the operation is affected by the sensor's position, the Deploying Heterogeneous Nodes strategy would be more appropriate. When the considered region is a forest or has bad weather conditions, it is better to choose one of the strategies that cover the area in all three dimensions. When making a choice among available strategies, it should be taken into account whether the coverage is of greater importance or the connectivity. We concluded that if all mentioned factors are equally significant, it is better to choose one of the multi-objective strategies.

Acknowledgements

Authors are thankful to their collaborator Mr. Atabak Maherkia for the fruitful discussions and useful comments on writing this work.

References


C. Song, L. Liu, G. Feng, Y. Fan, Persistent awareness coverage with maximum coverage frequency for mobile sensor networks, Cyber Technology in Automation, Control and Intelligent Systems (CYBER), 2013 IEEE 3rd Annual International Conference on, IEEE, 2013.


