Area coverage estimation model for directional sensor networks

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Abstract: Recently, directional sensor networks (DSNs) have received a great deal of attention owing to their wide range of applications in different fields. A directional sensor has a smaller angle of sensing range compared to an omni-directional sensor. Coverage is one of the fundamental problems of directional sensor networks at present, which reflects how well the environment is monitored. In this paper, we propose a coverage estimation model to estimate coverage problem with boundary effect. In order to guide initial deployment of DSNs and better meet requirements with certain initial coverage probability effectively, a novel probability-based area coverage estimation model with boundary effect, named PCPMB, is proposed. Simulation results show that our proposed model outperforms the previous proposed model without boundary effect.

Keywords: directional sensor networks; area coverage; coverage estimation; node estimation.


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1 Introduction

In recent years, wireless sensor networks (WSNs) have attracted a lot of attention owing to their wide application in environment monitoring, battlefield monitoring, agricultural monitoring and some other aspects, and more scholars begin to engage in relevant studies (Lan et al., 2002). WSNs composed of a large number of sensors are always classified into omnidirectional sensor networks and directional sensor networks (DSNs). Omni-directional sensor networks are adopted to make simple data collection (such as temperature and humidity) from the surroundings (Ma and Tao, 2006). Aiming at collecting more data like audios, images and videos under the complex and changing monitoring environment, directional sensor networks with stronger communication and processing capacities have emerged (Wang et al., 2009). Different from conventional omni-directional sensors that always have an omni-angle of sensing range, directional sensors have a limited angle of sensing range due to technical constraints or cost considerations. The sensing range of each directional sensor is a sector of disk. Moreover, each sensor has ability to adjust the sensing orientation and communicate with neighbouring directional sensors (Amac and Gokhan, 2011).

Owing to the distinguishing characteristics of DSNs, such as rotatable sensing orientation and limited sensing range, there are several challenges in DSNs. One of the challenges is that energy of sensor is limited and sensing range is a sector-disk (Kim et al., 2013). Besides, coverage reflects how well the monitoring region is monitored by sensors, and this is a fundamental and challenging problem of wireless networks. In the case of random deployment, sensing range of a directional sensor is determined by sensor position, sensing radius and sensing offset angle. All these factors determine a field of view (FOV) of directional sensors. Depending on which target is covered, coverage problem could be classified into three categories (Torkestani et al., 2013): area coverage, target coverage and barrier coverage. Area coverage deals with a problem of covering infinite points within monitoring region, it aims to maximise coverage area with minimal number of directional sensors so that the entire area is almost covered by DSNs. Target coverage aims at covering all the finite points within monitoring regions. Barrier coverage is adopted to minimise the probability of undetected penetration through a barrier, and is used to detect intruders attempting to penetrate a protected region.

This paper mainly aims to study area coverage prediction by consideration of boundary effect. Sensing range of different sensors may overlap with others or fall outside monitoring region after random deployment of DSNs, sensors outside boundary of monitoring region are called boundary sensors. Previous coverage estimation models of DSNs ignore all boundary sensors, and number estimation without considering boundary effect is inaccurate. Therefore, we need to derive an analytical expression for area coverage with considering boundary effect. Boundary effect is fully considered, and a novel probability-based networks coverage estimation model with boundary effect is proposed. Simulation results show that our proposed model yields better results than the previous models without boundary effect.

The remainder of this paper is organised as follows: Related work is discussed in Section 2. In Section 3, the problem statement and sensing model are proposed. In Section 4, we propose a novel coverage estimation model for guiding the deployment of DSNs. Some experimental results are presented and discussed in Section 5. Finally, we conclude this paper in Section 6.

2 Related work

Coverage as a fundamental and challenging issue has received a lot of attention from scholars recently. A lot of studies of coverage are achieved. In Tao et al. (2007), authors presented a rotating sector sensing model and a novel algorithm based on virtual potential field theory, which was first proposed to solve area coverage problem of DSNs, an innovative concept of centroid was introduced, but coverage loss problem was unsolved, because boundary effect was not considered. Tao and Wu (2015) summarised barrier coverage problem of directional sensor networks, and introduced strong barrier, weak barrier and full-view coverage, etc. Target coverage problem was introduced and modelled as disjoint cover sets problem. Yong et al. (2013) studied an interference management strategy for multiuser twoway transmission network, and proposed a multiple-input multiple-output precoding matrix for reducing the decoding complexity. Sushmita and Bimal (2011) proposed two deterministic key predistribution schemes which make communication faster and efficient in wireless sensor networks. A robust communication architecture was proposed to realise stable monitoring in complex and harsh environments (Ming et al., 2012). Each cover set can entirely monitor all targets within monitoring region, besides, target coverage problem has been proved as NP-complete problem (Cardei and Du, 2005). Mohamadi et al. (2013) first proposed target cover sets problem based on learning automata, four learning automata-based algorithms are proposed to solve this problem and several pruning rules are suggested to improve the performance of algorithms. The polytype target coverage problem in heterogeneous wireless sensor networks was studied, an integer linear programming algorithm based on clustering was proposed to maximise the network lifetime (Xing et al., 2014).

Cheng et al. (2007) studied maximal directional area coverage problem, and proved NP-completeness of the proposed algorithm; they presented a distributed-greedy algorithm to solve this problem. Dai et al. (2014) proposed a coverage enhancing algorithm based on virtual potential field involving the concepts of overlapping centroid and effective centroid, coverage probability is efficiently enhanced. Sharmin et al. (2015) studied area coverage problem based on network lifetime and proposed a cluster-based algorithm to select active sensors and their sensing orientations to optimise coverage probability and extend the network lifetime effectively. In Zhao and Zeng
(2010), authors presented a virtual centripetal force-based coverage enhancing algorithm and introduced the concept of sensing area grid, by establishing the relationship between centripetal force and adjusting orientation, each sensor rotated its corresponding angle according to the value of centripetal force. Rotating orientation was decided by the direction of centripetal force, the coverage probability could be enhanced. In order to optimise area coverage of DSNs, Chen et al. (2013a) proposed a coverage-enhancing algorithm based on overlap-sense ratio. By adjusting the sensing orientation of each sensor, coverage probability is increased with minimising the number of active sensors of DSNs, the proposed algorithm could effectively improve the coverage probability, and extend the network lifetime.

In Jing and Abouzeid (2006), a distributed greedy algorithm was proposed to increase area coverage. Chen et al. (2013b) studied coverage-enhancing algorithm through considering boundary effect. Xiao et al. (2009) proposed a path coverage enhancing algorithm based on improved potential field, for conventional virtual force is easy to reach local convergence, and also introduced common coverage probability to enhance path coverage.

In Ma and Li (2005), authors proposed a novel model based on probability to guide the network initial deployment and then established the relation named as CPMOB between initial coverage probability $P_{cov}$, sensor radius $r$, sensor number $N$, sensor sensing offset angle $\alpha$ and monitoring region $\Omega$.

$$P_{cov} = 1 - \left(1 - \frac{\alpha r^2}{\Omega}\right)^N$$

In other words, if the coverage probability of a given monitoring region is at least $P_{cov}$, the number of deployed directional sensors should be represented in equation (2). This model is used to predict and guide initial deployment of DSNs, it could help improve efficiency and accuracy of deployment.

$$N \geq \frac{\ln (1 - P_{cov})}{\ln (\Omega - \alpha r^2) - \ln \Omega}$$

In Zhao and Zeng (2012), authors have established a probability-based coverage model named as NDMOB between sensor density $\lambda$, sensor radius $r$, sensor sensing offset angle $\alpha$. The NDMOB equation is shown as $P_{cov} = 1 - e^{-\lambda \alpha r^2}$, authors have proved that PMOB and NDMOB obtain the same approximate results, when sensor sensing range is much smaller than monitoring region. In both of the above two models, boundary of monitoring region is neglected and the sensing range of all sensors is assumed to deploy within the monitoring region. Because of ignoring the boundary sensors and boundary sensing range, the value of estimation of the above models has a larger error compared with the real experimental value.

To the best of our knowledge, we are the first to study coverage estimation problem with boundary effect in directional sensor networks. In order to improve accuracy of coverage estimation model, by considering boundary effect of DSNs, we propose a novel model named PCPMB which is based on probability. Different from the models (CPMOB and NDMOB), we divide monitoring region into two subregions, called inner region and boundary region. We use the total probability formula to establish coverage model proposed in this paper and to guide the deployment of DSNs for a given coverage probability accurately.

3 Problem definition

In this paper, a number of directional sensors randomly deployed within a square monitoring region are considered. Each sensor of DSNs can be rotated to cover different regions and operates with a uniform sensing range at each unit of time. In order to guide the initial deployment of DSNs and better meet the requirements of certain initial coverage probability effectively, it is necessary to establish an accurate coverage model to solve this problem.

3.1 Network model

In this section, a directional sensing model of DSNs is described, and main assumptions are suggested for coverage estimation problem. Different from the omnidirectional sensor networks, each sensor of DSNs can sense events within a sector in its FOV. Figure 1 shows the directional sensing model could be denoted by a quintuple $(P_i, \alpha, r, d_i, \beta_i)$, where $P_i (x_i, y_i)$ represents the location coordinates of sensor $n_i$. $r$ is the radius of a sensing region and indicates the maximum sensing range of sensor. $d_i$ is a unit vector called sensing orientation that divides FOV into two equal parts, it represents sensing orientation of sensor $n_i$. $\alpha$ is called sensing offset angle, where $2\alpha$ describes the FOV. Intersection angle $\beta_i$ between the sensing orientation of sensor and horizontal coordinate $X$ axis represents the orientation angle, where $\beta_i \in [0, 2\pi]$.

Figure 1 Illustration of directional sensing model

Note: $P_i (x, y)$ represents position coordinates of node $n_i$, $r$ represents sensing radius, $d_i$ represents sensing direction of node $n_i$, $2\alpha$ represents FOV and $\beta$ represents the included angle between $d_i$ and horizontal coordinate $X$, which is called direction angle.
Assumption 1 All directional sensors are homogeneous. Specially, all sensors have the same sensing angle, sensing radius, and communication radius.

Assumption 2 All directional sensors are randomly deployed within the square monitoring region with side length of \( L \).

Assumption 3 All directional sensors are located at fixed position and know their own positions.

3.2 Problem definition

Sensors are randomly deployed within a square monitoring region, in order to make it easy to describe coverage estimation problem with considering boundary effect, we divide a monitoring region into two sub-regions, called inner region and boundary region, defined as follows.

**Definition 1:** The distance between the point within monitoring region and boundary of monitoring region is less then sensing radius \( r \), this point is called boundary point. A special region composed of boundary points is called boundary region (also called outer region). In Figure 2, \( \Omega \) represents the monitoring region, \( \Omega_2 \) denotes the boundary region.

**Definition 2:** As showed Figure 2, the region within the monitoring region \( \Omega \) except boundary region \( \Omega_2 \) is called inner region. \( \Omega_1 \) denotes the inner region.

**Definition 3:** After directional sensor networks are randomly deployed, sensors within boundary region \( \Omega_2 \) are called boundary sensors, meanwhile, the monitoring region \( \Omega \) in which boundary sensors deployed has boundary effect. The boundary sensor can be denoted by \( \psi \), where \( \psi = \{node|node_i \in \Omega_2\} \).

Figure 2 Illustration of a monitoring area \( \Omega \) divided into two parts

![Illustration of a monitoring area](image)

Notes: \( O \) is the origin of a coordinate system. \( \Omega_1 \) represents the inner area in which \( s_1 \) located, and \( \Omega_2 \) represents the border area in which \( s_2 \) is located.

3.2 Problem definition

The following main notations are used throughout this paper to describe the coverage estimation problem.

- \( L \) denotes the length of a square monitoring region
- \( P_{cov} \) denotes the initial area coverage probability of DSNs
- \( \Omega \) denotes the monitoring region
- \( \Omega_1 \) denotes the inner region of monitoring region
- \( \Omega_2 \) denotes the boundary region of monitoring region
- \( \lambda \) denotes the sensor density of DSNs
- \( \mu(s) \) denotes the area of FOV of sensors
- \( N \) denotes the sensor number of DSNs
- \( r \) denotes the sensor sensing radius
- \( \alpha \) denotes the sensing offset angle.

4 Proposed model

In this section, through fully considering boundary effect in DSNs, a novel probability-based networks coverage estimation model with the boundary effect is proposed. Then, the feasibility of the proposed model will be proved.

4.1 Coverage estimation model

When DSN is randomly deployed, because sensors are scattered in the square monitoring region, some part of the sensors will fall in the boundary region, and some sensors will fall in the inner region. Boundary effect has an adverse influence on the accuracy of traditional coverage estimation models, such as CPMOB and NDMOB, because both of these models ignored boundary effect. Aiming to get more accuracy coverage estimation for guiding initial deployment and evaluating sensor scale of DSNs, boundary effect must be taken fully into account. For conveniently describing boundary effect caused by boundary sensors, the monitoring region is divided into two sub-regions (boundary region and inner region) shown in Figure 2. According to total probability formula, area coverage probability after initial deployment could be denoted as:

\[
P_{cov} = P(\Omega_1)P_i + P(\Omega_2)P_e
\]  

(3)

where \( P(\Omega_1) \) represents the probability of sensors falling in inner region, \( P(\Omega_2) \) denotes the probability of sensors falling in boundary region, \( P_i \) represents the coverage probability of the inner region in which no boundary sensors exist and \( P_e \) indicates the coverage probability of the boundary in which each sensor refers to boundary sensors.

As it is shown in Figure 2, all sensors randomly deployed in the monitoring region \( \Omega \) submit to uniform distribution. According to the uniform distribution formula,
the probabilities of sensors falling in inner region $\Omega_1$ and boundary region $\Omega_2$ could be denoted as:

$$P(\Omega_1) = \frac{(L - 2r)^2}{L^2}$$

(L4)

$$P(\Omega_2) = \frac{4r(L - r)}{L^2}$$

(L5)

When sensors fall in inner region, the entire sensing range of sensor lies in monitoring region and it is regarded as ignoring boundary effect problem. Thus, the coverage probability of inner region could be concluded as:

$$P_i = 1 - e^{-\lambda \mu (s)}$$

(L6)

When sensors falls in boundary region, part of the sensing range inevitably falls outside of monitoring region, such as sensor shown in Figure 2, the coverage probability of boundary region is considered to be a total boundary coverage problem, the coverage loss caused by boundary sensors can be denoted as $g(\lambda)$, called loss function. Then, the coverage probability of boundary region could be concluded as:

$$P_e = P - g(\lambda)$$

(L7)

where $\lambda$ denotes sensor density of DSNs deployed, according to experimental and theoretical analysis, we assume the loss function could be expressed as:

$$g(\lambda) = \frac{1}{6} (\lambda \mu(s))^2 e^{-\lambda \mu(s)}$$

(L8)

On the basis of the above deduction, through taking boundary effect into account, the coverage estimation model with boundary effect of DSNs could be concluded as:

$$P_{cov} = \frac{(L - 2r)^2}{L^2} \left(1 - e^{-\lambda \mu(s)}\right) + \frac{4r(L - r)}{L^2} \left(1 - e^{-\lambda \mu(s)} - \frac{1}{6} (\lambda \mu(s))^2 e^{-\lambda \mu(s)}\right)$$

(L9)

then:

$$P_{cov} = 1 - e^{-\lambda \mu(s)} - \frac{2r(L - r)}{3 \lambda L^2} (\lambda \mu(s))^2 e^{-\lambda \mu(s)}$$

(L10)

From equation (10), if the initial coverage probability of a randomly deployed directional sensor networks is at least $P_{cov}$, the number of deployed directional sensors should be concluded as:

$$N \geq \Omega \times \lambda$$

(L11)

4.2 Feasibility analysis

In this section, the feasibility of the proposed model, named as PCPMB, is analysed. To do so, probability properties (Lemma1) and convergence of boundary effect (Lemma2) should be proved.

Lemma 1: The proposed model PCPMB based on probability meets probability attributes.

Proof: When no sensor falls in monitoring region, means sensor density $\lambda \rightarrow 0$, it could be concluded that:

$$\lim_{\lambda \rightarrow 0} P_{cov} = \lim_{\lambda \rightarrow 0} \left(1 - e^{-\lambda \mu(s)} - \frac{2r(L - r)}{3 \lambda L^2} (\lambda \mu(s))^2 e^{-\lambda \mu(s)}\right) = 0$$

When the entire monitoring region is filled with nodes, means node density $\lambda \rightarrow \infty$, it could be concluded that:

$$\lim_{\lambda \rightarrow \infty} P_{cov} = \lim_{\lambda \rightarrow \infty} \left(1 - e^{-\lambda \mu(s)} - \frac{2r(L - r)}{3 \lambda L^2} (\lambda \mu(s))^2 e^{-\lambda \mu(s)}\right) = 1$$

As $e^{-\lambda \mu(s)}$ is monotone decreasing function of $\lambda$, then $P_{cov} = 1 - e^{-\lambda \mu(s)} - \frac{2r(L - r)}{3 \lambda L^2} (\lambda \mu(s))^2 e^{-\lambda \mu(s)}$ is the monotone increasing function of $\lambda$. Thus, it could be concluded that: $0 \leq P_{cov} \leq 1$.

Lemma 2: Convergence of boundary effect: when sensor sensing range is much smaller than monitoring region, namely it is approximate to no boundary effect existing in monitoring region, the results of PCPMB and NDMOB are approximately equal.

Proof: When node sensing range is much smaller than monitoring area, area of the node sensing range could be approximate to: $\mu(s) = \alpha r^2 = \frac{L^2}{n}$. Hereinto, $n$ represents ratio of the area of monitoring area to the area of sensing range. When sensing range is much smaller than monitoring region, it means $n \rightarrow \infty$, then the ratio $f$ between PCPMB model and NDMOB model could be expressed as:

$$f = \frac{1 - e^{-\lambda \mu(s)} - \frac{2 r(L - r)}{3 \lambda L^2} (\lambda \mu(s))^2 e^{-\lambda \mu(s)}}{1 - e^{-\lambda \mu(s)}} = 1 - \frac{2 r(L - r) (\lambda \mu(s))^2 e^{-\lambda \mu(s)}}{\frac{2 \lambda \mu(s)^2}{3 \lambda L^2} \frac{L^2}{n^2} \frac{L^2}{n^2} - 1}$$

Then, set $x = \frac{L^2}{n^2}$, it could be concluded that:

$$f = 1 - \frac{2 r(L - r) \frac{L^2}{n^2} \frac{L^2}{n^2} - 1}{\frac{2 \lambda \mu(s)^2}{3 \lambda L^2} \frac{L^2}{n^2} \frac{L^2}{n^2} - 1}$$

As $x \rightarrow 0$, then $e^x - 1 \approx x$. Hence we have

$$\lim_{x \rightarrow 0} f = \lim_{x \rightarrow 0} \left(1 - \frac{2 r(L - r) x^2}{3 \lambda L^2 e^{x^2} - 1}\right) = \lim_{x \rightarrow 0} \left(1 - \frac{2 r(L - r) x}{3 \lambda L^2}\right) = 1$$

which completes the proof of the Lemma 2.

From Lemma 1 and Lemma 2, it can be known that the proposed model PCPMB has the same probability properties.
in comparison with the traditional model CPMOB and NDMOB. It could be concluded that PCPMB is feasible and effective.

5 Simulation results

In this section, we evaluate the performance of our proposed model through simulations using MATLAB software. We focus on analysing the effect of different parameters on models CPMOB and PCPMB. Experimental simulation parameters are shown in Table 1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Length of area $L$</td>
<td>500 m, 600 m, 700 m</td>
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<tr>
<td>Area coverage $P$</td>
<td>0–1</td>
</tr>
<tr>
<td>Sensor number $N$</td>
<td>60–400</td>
</tr>
<tr>
<td>Sensing radius $r$</td>
<td>30–100 m</td>
</tr>
<tr>
<td>Sensing offset angle $\alpha$</td>
<td>$\pi/6 - \pi/3$</td>
</tr>
</tbody>
</table>

Table 1 Experimental parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Variation</th>
</tr>
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<td>Nodes</td>
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<td>------------</td>
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<td>98.8672</td>
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<tr>
<td>400</td>
<td>99.1029</td>
</tr>
</tbody>
</table>

Table 2 Comparison results of CPMOB, NDMOB, PCPMB and experimental value

5.1 Instance analysis

In order to get more clearly comparison results between model theoretical value and actual experimental value. Suppose radius of all sensors $r = 60$ m, sensor sensing offset angle $\alpha = \pi/4$ and monitoring region $\Omega = 500$ m $\times$ 500 m. Through calculating and comparing the theoretical coverage probability of CPMOB, NDMOB and PCPMB based on different sensor scales, as it is shown in Table 2. Here, $P_1$ represents the theoretical coverage probability of CPMOB, $P_2$ represents the theoretical coverage probability of NDMOB, $P_{cov}$ represents the theoretical coverage probability of PCPMB. $P_{exp}$ denotes the actual experimental coverage probability. The theoretical coverage probability of PCPMB is approximate to actual experimental value compared to models CPMOB and NDMOB, this is because our proposed model takes boundary effect into account, boundary effect could cause coverage loss. On the contrary, the models CPMOB and NDMOB ignore boundary effect, assume all sensors fall in the monitoring region, hence the theoretical coverage probability of these two models is larger than the actual experimental value. It means, at the same given initial coverage probability of a randomly deployed DSNs, our proposed model can accurately estimate the sensor scale of DSNs.

5.2 Coverage estimation analysis

Because the theoretical values of models CPMOB and NDMOB are similar, comparing PCPMB with CPMOB helps demonstrate accuracy and efficiency of PCPMB. A series of simulation experiments are used to illustrate the influences on PCPMB and CPMOB with three different key parameters: sensor scale, sensing radius and sensor sensing offset angle. For these three parameters, the theoretical coverage probability of PCPMB will be compared with theoretical coverage probability of model CPMOB and the actual experimental value to judge the accuracy of the models.

From the changing curve in Figure 3, we can figure out that when $r$ and $\alpha$ are certain, area coverage probability increases with sensor scale $N$ and it increases rapidly. When sensor scale $N$ is very large, the three curves tend to be consistent, that is because when sensor scale $N$ is very large, the entire monitoring region will be totally covered, namely coverage probability is 1. At the same time, under the same sensor scale, the error between coverage probability of PCPMB and experimental real coverage probability is very small. It means the theoretical value of PCPMB is approximate to the actual experimental value compared to the model CPMOB. So the coverage estimation using proposed model at initial deployment be more accurate.

Besides, the influences of sensing radius $r$ and sensing offset angle $\alpha$ to CPMOB, PCPMB and actual experimental coverage probability are also similar. By considering the sensor scale is certain, the sensor radius or sensing offset angle could be changeable, it has influence on our proposed model and model CPMOB. When sensor scale is certain, the sensing range increases with the increase of sensor sensing radius and sensing offset angle, so that the coverage probability will also constantly increase. From Figures 4 and 5, it could be concluded that the error between PCPMB and experimental real coverage probability is smaller, which indicates that it has relatively good performance at coverage probability estimation. The theoretical value of PCPMB is approximate to actual experimental value compared to the model CPMOB, it is concluded that PCPMB is more likely to match the actual situations.
5.3 Node scale estimation analysis

From the changing curve in Figure 6, it could be concluded that with area coverage probability increasing, number of the sensors required by initial random deployment roughly increases exponentially. At the same time, with network monitoring region increasing, number of the sensors required to get the same coverage probability also increases rapidly. This is because with the increasing of the monitoring region, more sensors are needed to be randomly deployed to obtain the same coverage effect.

From Figure 7, it could be noted that with area coverage probability increasing, number of the sensors required by deployment in monitoring region also increases correspondingly and it increases relatively rapidly. When initial area coverage probability is low, the influence of boundary effect on the network is small and the two curves tend to be consistent. Under the same area coverage probability, the sensor scale of model PCPMB is larger than its of model CPMOB, this is because the model CPMOB
neglects boundary effect in DSNs, which means that sensing range of sensors always falls within the monitoring region. But our proposed model takes full consideration of the boundary effect, so more sensors are deployed to reach the same coverage probability. At the same given initial coverage probability of a randomly deployed DSN, our proposed model can accurately estimate the sensor scale of the DSN.

6 Conclusions

In this paper, a novel probability-based area coverage estimation model is proposed for DSNs. Boundary region and inner region are presented to compute the coverage probability. In model PCPMB, when sensing range of sensor lies in boundary region, coverage loss function is adopted to accurately evaluate coverage probability. Compared with other model CPMOB, the proposed model is more accurate and effective to estimate coverage and the number of sensors. The simulation results show that our proposed model outperforms the existing models in terms of coverage and node number prediction.

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