A Realistic Sensing Model for Event Area Estimation in Wireless Sensor Networks

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Abstract. A lot of research works have been reported so far for event area localization and estimation in self-organized wireless sensor networks deployed to monitor a region round the clock. In most of the works, it has been assumed that a node is affected whenever it lies within the event region. But in reality, each node does not sense just its point of location but covers a region defined by its sensing range and extracts an aggregated view of the sensed region. Unfortunately, so far no sensing model takes into account this fact. In this paper, a new realistic model of sensing is proposed for continuous event region, and based on that a lightweight localized algorithm is developed to identify a minimal set of boundary nodes based on 0/1 decision predicates to locate and estimate the event area in real time with high precision. Extensive simulation studies and testbed results validate our proposed model and also show that using only elementary integer operations and limited communication, the proposed scheme outperforms existing techniques achieving a 5–10% precision in area estimation with 75–80% reduction in network traffic even for sparse networks.

Keywords: Wireless sensor networks (WSN) · Affected area · Boundary node · Uniform area sensing model · Digital circle

1 Introduction

Recent technological advances have made the use of small and low-cost sensor devices technically and economically feasible for the purpose of sensing ground data from a region of interest (*RoI*). Typically, a sensor node is capable of sensing data from an area within its sensing range r_s and also can communicate via wireless links with other neighboring nodes within its transmission range r_c. After deployment, each node periodically senses data and cooperatively forwards it through the network to a gateway node, often referred to as the *sink node*,

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thus forming a wireless sensor network (WSN). WSN can provide a fine global view through the collaboration of many sensors, each capturing a local snapshot at regular intervals. In critical situations, like forest fire, chemical spills, natural disasters, it is crucial to report the event to the sink immediately to estimate the affected area and its location. It is obvious that in case, all affected nodes attempt to send data to the sink, preferably via multihop paths to ensure energy efficiency, the network will get congested increasing the end-to-end packet delay and energy consumption. Hence, it is a great challenge to select a minimal subset of affected nodes, using lightweight in-node computation to define the event region boundary satisfying the precision requirement of the application.

So far, a lot of research works have been reported addressing the event boundary detection and area estimation problem in 2D WSN. Most of the approaches reported till now are based on either the computation-intensive classical techniques of computational geometry, or some simpler greedy heuristics. In [1], a boundary face detection technique has been proposed by adopting the planarization algorithm. They have also mentioned that the estimation of area affected by any event is more desirable rather than the detection of exact boundary of the event region. Authors, in [2–4], have used the graph-theoretic models, relative neighborhood graph, and Gabriel graph methods to detect the boundary of an event area. In [5], authors proposed an angle based boundary detection algorithm to detect the event boundary.

In most of the earlier works, on event boundary detection, it has been assumed that a sensor node gets affected if and only if it lies within the event area. But in reality, a sensor node senses a region around it and is affected only if a substantial portion of its sensed region lies within the event area. Though a large number of abstract sensing models are already in place and widely being used to solve the problems related to *coverage*, *boundary detection*, *event area estimation* etc., unfortunately, so far no sensing model has captured this fact [6]. To alleviate the problem, in this paper, a realistic model of *uniform area sensing* has been proposed considering the fact that a sensor actually captures an aggregated view of its sensed region, not just a point under its coverage, as has been assumed in the earlier models.

In this paper, following the proposed realistic model of sensing, a lightweight distributed algorithm has been proposed that involves elementary integer operations only to localize and estimate the event region without compromising the accuracy. Extensive simulation studies have been done to compare the performance of the proposed technique with earlier works. Simulation results and testbed experiments show that the proposed technique performs significantly better in terms of selection of boundary nodes and area estimation accuracy even for sparse networks with reduced computation and communication overhead.

The rest of the paper is organized as follows. Section 2 presents the proposed sensing model. Section 3 describes the lightweight area estimation technique under uniform area sensing model. Section 4 evaluates the performance of the proposed method with earlier works by simulation and testbed results. Finally, Sect. 5 concludes the paper.

2 Proposed Model

It is assumed that n number of homogeneous sensor nodes $\mathscr{S} : \{s_1, s_2, \ldots, s_n\}$ with uniform sensing range r_s and communication range r_c are randomly distributed over a 2D region A. In most of the earlier works, following the existing models of sensing, it is assumed that a node gets affected if and only if it lies within the event area, as if a node just senses its point of location. But in reality, each node covers not just its point of location but a region around it determined by its sensing range.

With homogeneous nodes, the area covered by a node in 2D is assumed to be a circular region with sensing radius r_s. Given an irregular-shaped event area A' as shown in Fig. 1, a node s_{12} lying outside A' may report that it is affected since a major portion of its coverage area lies within the event region. On the contrary, a node s_5 lying within A' may remain unaffected since most of the area covered by it lies outside the even area. Hence, the condition that a node should lie within the event region is neither necessary nor sufficient to affect it, as has been considered so far. Appropriate sensing model is required to represent the scenario.

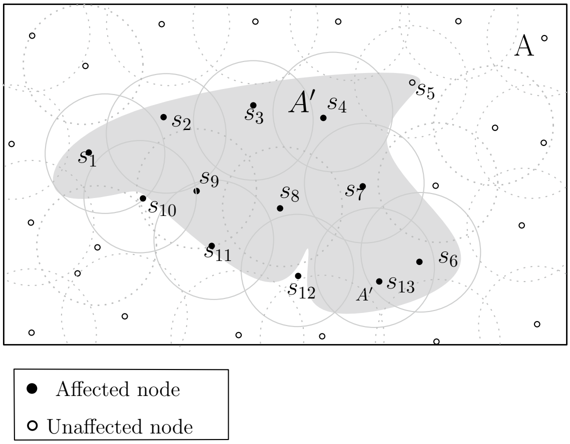

Fig. 1. An event area (shaded) and the affected and unaffected sensors, assuming uniform circular coverage

2.1 Sensing Models

In the literature, so far, various abstract sensing models, either directional or omnidirectional, have been proposed and used widely [6]. Considering only the omnidirectional ones here follows a classification of the existing sensing models.

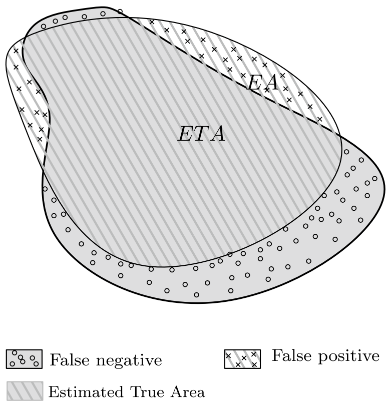

Fig. 2. Actual event area and estimated event area with false positive and false negative

- *Deterministic Sensing Model*: The probability that a sensor at location S detects an event at point P is represented by the *coverage function* given by:

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

  where $d(S,P)$ is the Euclidean distance between S and P [7].
- *Probabilistic Sensing Model*: Considering the fact that the quality of sensing actually depends on various parameters like the distance $d(S,P)$, the presence of obstacles, various probabilistic sensing models have been proposed so far [8].
  - *Elfes Sensing Model*: In this model [9], the *coverage function* is given by:

$$C(S,P) = \begin{cases} 1 & \text{if } d(S,P) \leq r_{\min} \\ p_r = e^{-\lambda(d(S,P)-r_{\min})^{\gamma}} & \text{if } r_{\min} < d(S,P) < r_{\max} \\ 0 & \text{if } d(S,P) \geq r_{\max} \end{cases}$$

    It is to be noted that the deterministic sensing model is a special case of this model with $r_{\max} = r_{\min} = r_s$. where λ and γ are adjustable parameters according to the physical properties of the sensor.
  - *The Shadow Fading Sensing Model*: This model [10] is proposed to take into account the *shadowing loss* of signal due to the presence of obstacles on signal path between S and P, where

$$C(S,P) = \frac{1}{A} \int_{0}^{r_{\max}} Q\left(\frac{10\beta log_{10}(\frac{d(S,P)}{\bar{r}})}{\sigma}\right) \times \ 2\pi d(S,P)dr,$$

    β is the signal power decay factor, dr represents a small increment in distance $d(S,P)$, σ is the shadow fading parameter, and $\bar{r}$ is the average sensing radius, respectively.

It is interesting to see that in each of the models, the *coverage function* actually assumes that an event always occurs at a point P. But in case of events like fire, smoke, oil spill, the event spreads with time over a continuous region, and each sensor actually senses an aggregated view and detects its impact over its covered area. So the above models are not adequate to represent an event spanning over an area. Hence, a new sensing model is proposed in this paper.

Definition 1. *Uniform Area Sensing Model*: In this proposed model, it is assumed that each sensor S senses a uniform circular area $\mathscr{A}$ of radius r_s, its sensing range. In case of an event spanning a continuous region $\mathscr{A}'$, the sensor data is given by:

$$D(S, \mathscr{A}') = \frac{1}{\mathscr{A}} \int_{\mathscr{A}} \delta_a . da,$$

where

$$\delta_a = \begin{cases} 1 & \text{if } a \in \mathscr{A}' \\ 0 & \text{otherwise} \end{cases}$$

Now, a sensor is *affected*, if and only if $D(S, \mathscr{A}') \geq p$, a predetermined threshold, $0 < p \leq 1$.

It is obvious that this model is more appropriate to estimate the event area in case of events like fire, gas pollution, oil spill, where not a single point but a continuous area is affected. It is to be noted that under this model, given an event area as shown in Fig. 1, the sensor nodes s_{12} and s_5 can be identified accurately as affected and unaffected nodes, respectively, provided the threshold is decided appropriately during design time.

2.2 Topology Graph and Data Model

It is obvious that for collaborative computing and data gathering, the nodes need to communicate with each other and they forward their data to the sink node via multihop paths for energy-efficient data forwarding. However, it has been already proved that with $r_c \geq 2r_s$, connectivity is guaranteed in case of full coverage [11]. So, we assume $r_c = 2r_s$ throughout the paper. For data gathering, the underlying topology graph must remain connected, as defined below.

Definition 2. Topology Graph: A wireless sensor network is represented by an undirected *topology graph* $G(V, E)$, where V is the set of nodes and E is the set of edges such that an edge $e(i, j) \in E$, if and only if sensor node s_i can communicate with node s_j directly, i.e., $d(s_i, s_j) \leq r_c$, where $d(s_i, s_j)$ is the Euclidean distance between nodes s_i and s_j, and vice versa, with $s_i, s_j \in V$.

In our proposed model, sensor nodes do not require the actual data value within the event area. It is assumed that in case, the sensed data crosses a predetermined threshold p, the node is considered to be *affected*.

3 Event Area Estimation Based on Uniform Area Sensing Model

Under the *uniform area sensing model*, proposed above, a sensor node is affected if and only if substantial part of its covered area is within the event region. Hence given the set of all affected nodes, the event boundary can be identified as a sequence of intersecting real circles covered by a minimal set of boundary nodes. However, with real circles, it is not easy to estimate the bounded area [12]. Some concepts of digital geometry were applied to ease the computation in [13]. For completeness, an outline of the scheme is included in the following subsection.

3.1 Real Circle Versus Digital Circle

In [12], from computational geometry approach, authors proposed an $O(n\ log\ n)$ algorithm to compute the area covered by a random set of real circles. Since complex computations are involved, the technique is not feasible for sensor nodes with elementary computing and storage capacities. Later, in [13], authors have shown that complex computation can be avoided if the real circles are approximated by digital circles following the concepts of digital geometry. Authors in [14] studied the performance of the digital circle approach *(DCA)* to solve the boundary detection and event area estimation problem for an irregular-shaped event region. Though the proposed area estimation technique based on digital circle simplifies the computation significantly, the boundary node detection and intersection point computation require complex computation and data structures. To make the computation even simpler, in this paper we propose a lightweight distributed approach outer angular algorithm *(OAA)* involving elementary integer operations only.

3.2 Outer Angular Algorithm (OAA)

To simplify the computation of event area estimation based on the proposed realistic sensing model, we assume that the sensor nodes are equipped with directional antennae, and knows the angle of arrival of the signal received from its adjacent neighbors. With that information, each node (having some *affected* and some *unaffected* neighbors) creates a circular sorted neighbor list with its state, based on the angle of arrival of signal. During traversal through the circular list, in a certain direction (clockwise/anticlockwise), if it identifies a state transition between successive neighbors, it selects the *unaffected* node as the *reporting node* to define the boundary of the event region. After selection, the reporting nodes, send their ID's to the *sink* node to compute the area of the polygonal region defined by the reporting nodes. An outline of the procedure is given in **Algorithm 1**.

Algorithm 1: OAA

Input: circular sorted list of neighbors $NL(s_i)$
Output: List of reporting nodes B_o

for each node s_i;
broadcast a hello message with status flag at regular interval;
if *node* s_i *receives a hello message from its neighbor* s_j **then**
  update the (0/1) flag bit in the circular list NL;
end
After receiving hello message from all neighbors, node s_i traverses through the circular list and if any transition found, then include the unaffected node s_j model, such as in B_o;
broadcasts *selected*(B_o) message;
if *receives selected*(B_o) *message* **then**
  if the node id is present in B_o then send its location with flag bit to *sink* via multihop path;
end

In [5], based on the *point coverage sensing* model, an angle-based approach was followed for event area estimation. But it always underestimates the event area. In this paper, a new angle-based algorithm based on the realistic *uniform area sensing* model is presented and the performance comparison by simulation shows that OAA significantly outperforms [5] in accuracy of event area estimation.

4 Performance Evaluation

For performance comparison with Algorithm 1, some distributed techniques proposed earlier have been simulated under the proposed *uniform area sensing* model, such as inner angular algorithm (IAA) [5], digital circle algorithm (DCA) [13], and BDCIS algorithm [2] respectively.

For simulation, n number of sensor nodes are uniformly and randomly distributed over an area A. An irregular-shaped event area A' also termed as *True Event Area* (TA) is generated by diffusion process presented in [15]. Figure 2 shows an arbitrary-shaped event region *TA* and the estimated event region *EA* that defines both *False Negative* (*FN*) and *False Positive* (*FP*) areas.

4.1 Simulation Results

For simulation studies over 200×200 region, different event regions are created by changing the source cells randomly and the experiments are repeated for different networks. The algorithms are implemented using *Java*. The simulation parameters are presented in Table 1. Here the performance of *OAA*,*DCA*, *IAA* and *BDCIS* methods has been compared under the *Uniform Area Sensing Model* with different values of threshold p.

Variation of Estimated True Area (ETA): Figures 3, 4 and 5 show *DCA* and *OAA* methods are always able to report almost 100% of the *TA* compared to other methods discussed in this paper.

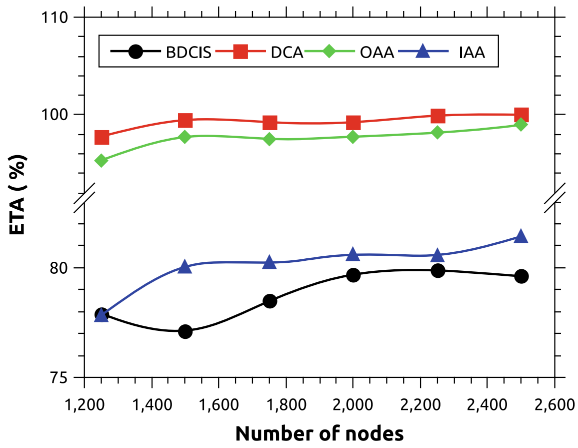

Fig. 3. Percentage of estimated true area for $p = 0.50$

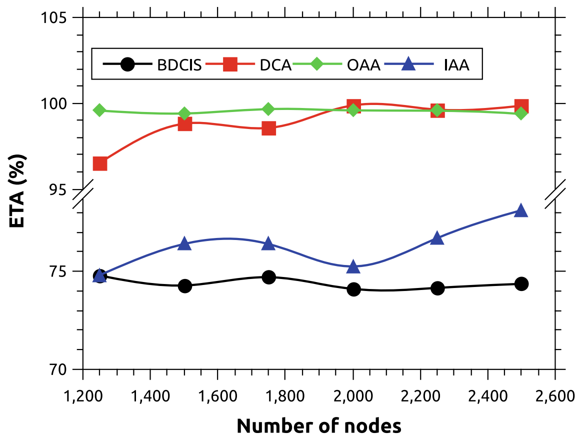

Fig. 4. Percentage of estimated true area for $p = 0.60$

Variation of Error: Figures 6 and 7 show the variation of error (False Positive + False Negative) in percentage. From the previous results, it is clear that OAA and DCA methods can always estimate almost 100% of the event area for $p = 0.5$ to 0.7 but error is high if the value of p is low.

Number of Nodes Reported: Figures 8 and 9 show the variation in the number of *reporting* nodes with n. It is obvious that with the increase in node density the number of reporting nodes also increases, resulting best performance by OAA and DCA with almost 70–85% reduction in the number of nodes reported, and hence in network traffic.

Computation Overhead: By observing the percentage of estimated area, error percentage and number of reporting nodes we can say, both OAA and DCA methods perform well but in terms of execution time and number of computation as

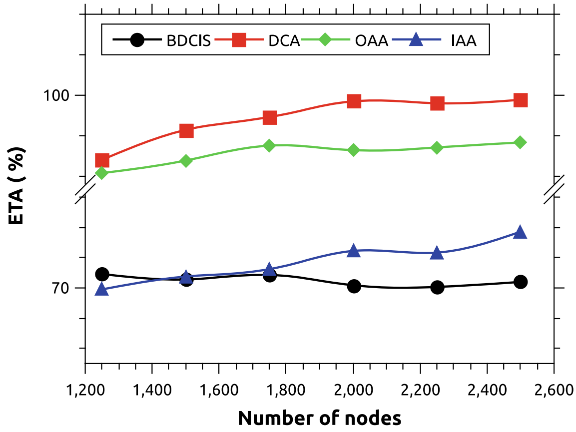

Fig. 5. Percentage of estimated true area for $p = 0.70$

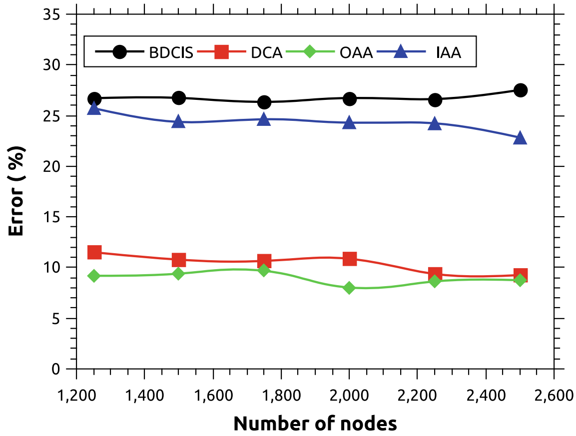

Fig. 6. Percentage of error for $p = 0$

shown in Figs. 10 and 11, OAA method performs significantly better than DCA. OAA method needs significantly less number of integer operations compared to DCA method. Moreover, DCA technique needs floating-point operations, which is not required for OAA method.

4.2 Testbed Implementation

To validate our proposed model, we set up a simple indoor experimental testbed. Fourteen *JN5168-001-M00* sensenut modules with light sensor are deployed randomly over a 400×400 square unit region. From device specifications, the communication range r_c in indoor varies from 25 to 30 m and at outdoor 75–80 m. An irregular-shaped event region is generated using light sources and shadows. Some existing algorithms for boundary detection and area estimation with the

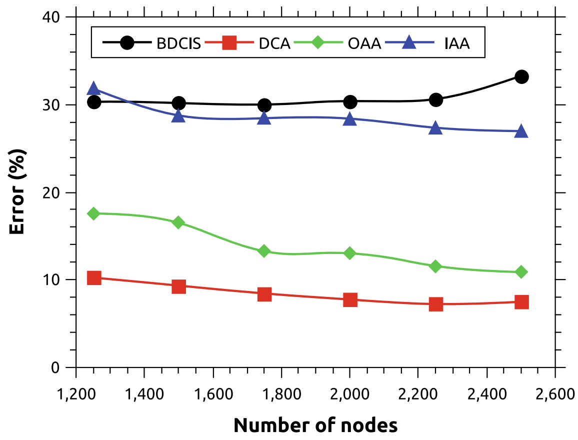

Fig. 7. Percentage of error for $p = 0.70$

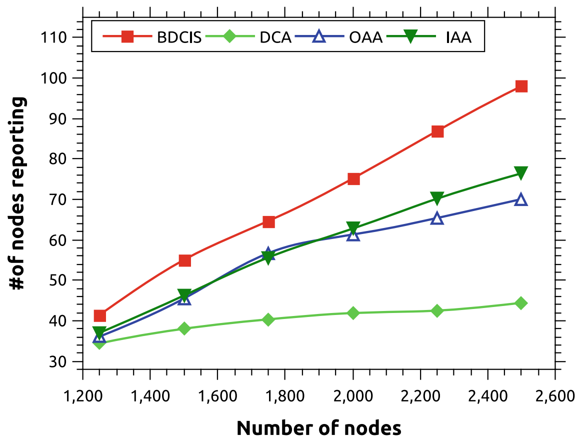

Fig. 8. Number of nodes reporting for $p = 0.60$

proposed one are implemented on this testbed. This experiment is executed 20 times, and each time it runs for 300 s. Initially, during the switch-off condition, each sensor node measures a light intensity of 0 Lux. But, as the light is switched on, the illumination increases rapidly and the maximum data value in nodes is 280 Lux. For this experiment, we consider the threshold value $p = 0.6$ and 0.7, respectively. Table 2 shows the percentage of the estimated area and the percentage of estimated true area for different methods. Though the testbed experiment has been done with small number of sensor nodes only, still it shows the same trend as observed by simulation. Hence, it is evident that with significantly less computation and communication overhead the proposed *OAA* technique with the *uniform area sensing model* is more suitable for event area estimation in wireless sensor networks, even in a sparse network.

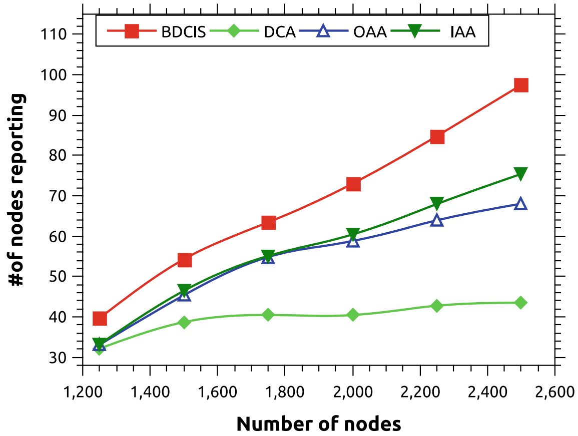

Fig. 9. Number of nodes reporting for $p = 0.70$

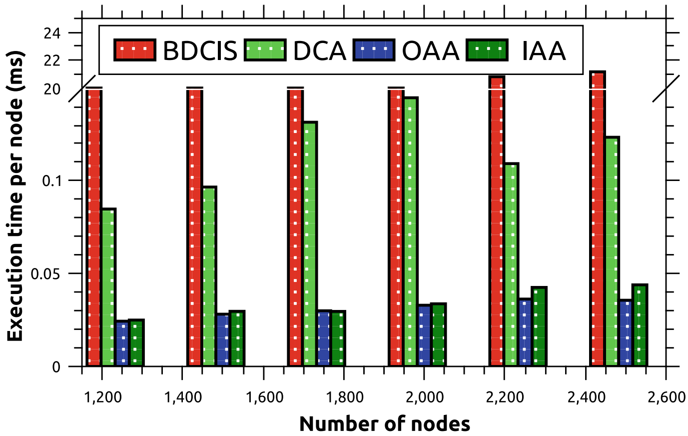

Fig. 10. Execution time per node in milliseconds

5 Conclusion

In this paper, it has been shown that for wireless sensor networks monitoring a region against events like forest fire, oil spill, chemical pollution, where the event spreads over a continuous area, the existing sensing models are not adequate. Hence, a new, more realistic model, namely the *Uniform Area Sensing* model is proposed here. Based on that model, a localized lightweight technique is developed to estimate the event area using only elementary integer operations. Performance comparison by simulation and experimental results show that the proposed algorithm outperforms the earlier works achieving a 5–10% precision in area estimation with 75–80% reduction in reporting traffic even for sparse networks, provided the threshold p is determined appropriately.

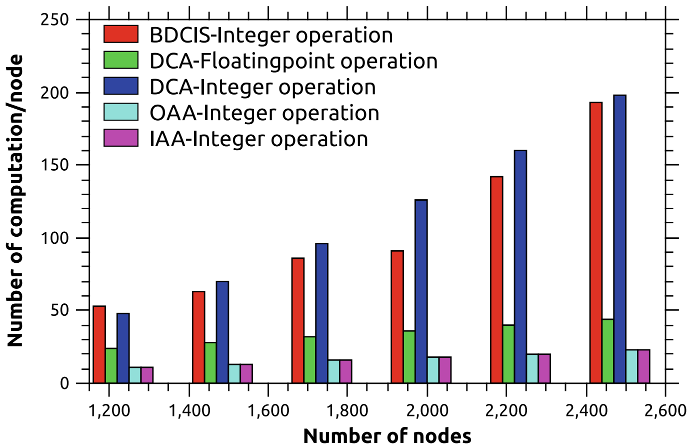

Fig. 11. Number of computation per node

Table 1. Simulation parameters

Parameter	Value
A	200×200
n	1250–2500
r_s	4 unit
r_c	8 unit
l	1 (unit cell)
p	0.50–0.70

Table 2. Performance summary for different methods on testbed

Method	$p = 0.60$		$p = 0.70$	
	% of EA	% of ETA	% of EA	% of ETA
OAA	99.54	90.39	94.44	87.51
DCA	104.69	87.98	100.06	92.37
IAA	82.17	82.17	79.8	75.23
BDCIS	89.58	74.19	84.49	70.39

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