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Efficient Topology Extraction Technique for Wireless Sensor Networks

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Abstract

Wireless sensor networks have been widely used in many applications especially environmental monitoring. Thanks to the sensors small size and low cost, a large number of nodes can be easily deployed in hazardous areas by airplanes passing over it. Deploying the nodes using this random mechanism causes different node densities in different subregions of the area of interest. One of the challenges in such applications is the recognition of the topology structure after deployment. In this paper, we propose an efficient technique to help nodes to construct boundary cycles around each subregion of specified density-level. These cycles help in describing the layout the deployed network. The main contribution of this technique is the ability to work in sparse networks with the same efficiency as in dense networks. Evaluation of our proposed technique shows that it uses less average node degree in different simulation scenarios and achieves about 50% decrease in energy consumption than Heuristic Boundary Cycles Finding Technique.

Keywords: *Wireless Sensor Network, Random Deployment, Boundary Node, Interior Node, Transmission Range, Topology Extraction, Boundary Cycles.*

1. Introduction

Wireless Sensor Networks (WSNs) are networksof spatially distributed nodes called sensors. Sensors have good special characteristics which make WSNs differ from traditional wireless ad-hoc networks. These features allow it to be used in a wide range of discriminative applications. Sensor nodes are tiny ships called motes with a sensing, processing, and communication devices embedded on it. What make it different are its sensing capabilities. It enables them to monitor physical phenomenon in real environments such as, but not limited to, pressure, temperature, and moisture. Examples of WSN applications are: i) area monitoring where specific phenomenon has to be recognized such as air pollution[1, 2], forest fire detection [3, 4], disasters detection[5, 6], ii) health-care[7, 8],and iii) civil services [9, 10]. One of the challenges in WSNs is the used deployment method. According to the size of the application, one from two deployment methods can be used. The first one is planned deployment. It is used in small sized applications where a small number of sensors have to be deployed in the area of interest. The location of these sensors has to be studied and analyzed before deployment. This study helps in deciding the minimum number of sensors that is needed to satisfy the application requirements of coverage. The second deployment method is random deployment. It is used in large scale applications which especially serve in remote and rugged areas. In these situations, it is difficult for human to get through the area of the network. Therefore, helicopters are usually used to pass over these areas and scatter sensors. Random deployment method always suffers from holes in coverage. Because sensors are lightweight, it can be easily affected by air while dropping. Moreover, antennas may be poorly placed. So, it is always recommended to use a large number of nodes, from hundreds to thousands, to compensate the unused nodes and achieve good coverage rate. However, this is not a good solution because of its high cost. As mentioned in [11], a 300×300 network, 95% coverage rate can be achieved using 300 nodes while 100% coverage rate can be achieved using 600 nodes. Extra 300 nodes for only more 5% increase in coverage have to be considered. Therefore, random deployment with a minimum number of nodes achieving desired coverage followed by relocation techniques which try to solve coverage errors was proposed. However, all of them assume sensors are mobile to be able to move and optimize its location in the network [12]. Also, assuming all deployed nodes to be mobile is not a wise cost. Therefore, in this paper, we propose a topological extraction technique for randomly deployed WSNs. The aim of topological extraction is to provide sufficient information to describe the layout of the network, i.e. the relation between points and subregions of high density or voids. After that, this information can be used by a mobile robot to place more nodes in holes or low coverage subregions to optimize the coverage in the networks. The remaining of the paper has been organized as follows: Section 2 covers the related work. Section 3 shows the problem formulation of our work. Definitions and assumptions are shown in Sections 4 and 5 respectively. The details of the proposed technique are shown in Section 6. Evaluation of the proposed technique is shown in Section 7.Finally; we conclude our work in Section8.

2. Related Work

In this paper, we try to identify the shape of the network by describing it with a set of connected polygons that define each subregion with constant density. The aim is to collect sufficient information to recognize boundary nodes which define vertices of polygonal subregions and interior nodes inside it to extract the topology layout. Previous research made in this area tries to solve this problem such as in[13]. Kröller et al. proposed a topology extraction technique for large sensor networks. İt is based on a sufficient nodes density. The technique istestedon a network with 60,000 sensors arranged along intersected streets. Nodes are deployed as strips representing streets and connected at the intersection of two streets. The technique constructs a flower-based graph of the connections between nodes along the street until it detects the boundary nodes of each street. The technique also identifies nodes which lie in the intersection cores between intersecting streets. Clusters are finally defined for intersections and streets. The average node's degree in this technique is about 20. In [14], Wang et al. proposed a technique to define the boundary nodes of the whole network area and recognize holes inside the network. This method depends on constructing the shortest path tree at one selected node. Paths of the tree are continuous with enough number of nodes achieving full connectivity. However, it diverges before a hole and meets again after it. The technique was tested on a network with enough density, i.e. average node's degree is about 10. In [15], Lederer et al. used a set of landmark areas in the network boundary with sufficient density to detect the shape of the network. Voronoi diagram for these landmarks and its dual combinatorial Delaunay complex is constructed. This technique figures out the correct network layout without flips where parts of the network can fold over each other. Selected landmarks used to capture important topological information then it is used to reconstruct the network layout. The performance of this technique increases with higher nodes density and higher density of landmarks. The average node degree is ranging from 6 to 10. In [16], Liu et al. proposed a skeleton extraction technique. The aim of this technique is to recognize nodes which figure the shape of the network. This is based on the idea that skeleton nodes have larger neighborhood size than others. The average node degree is ranging from 7 to 10. From our review, all the previous techniques depend on high average node degree with a defined network structure and holes shapes which are not the case in randomly deployed networks. Figure 1 shows examples of used topologies in the previously proposed techniques and

Table 1summarizes the main differences between thesetechniques.

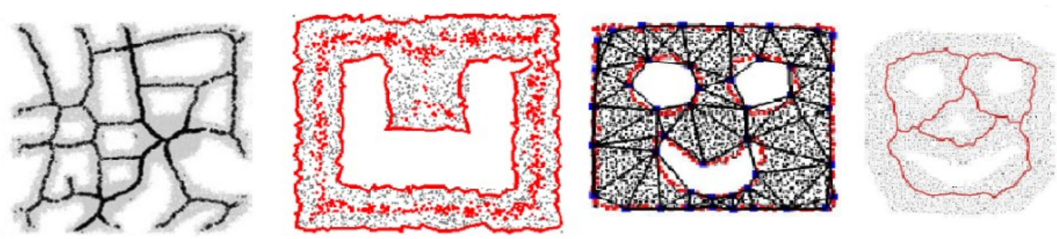

Figure 1.Examples of topologies used in previous works[13-16]

Table 1Comparision between different topology extraction mechanisms

Technique	**Design criteria**	**Average network degree to achieve good results**
[13]	Use very complex connectivity structure which is flowers.	20
[14]	Suffer from repetitiveflooding to construct the shortest path tree at each node.	10
[15]	Depends on the selection of uniformly distributed landmarks on the boundaries which fail in low-density networks	6-10
[16]	Four stages are passed to define the final skeleton nodes which consume a high number of messages.	7-10
Proposed	Depends on transmission range adaptation according to a general network information	3-5

3. Problem formulation

Topology extraction problem is a main issue in wireless sensor networks. From our review, it is always solved in high-density networks with a very large number of nodes that can achieve a relatively constant density all over the area of the network. In such networks, the shape of the network can be identified by finding the nodes with the highest degree which construct the skeleton of the topology. Added to that, when holes appear, it can be easily identified where the decrease in the degree can be easily observed. However, this assumption does not practically hold in real applications as the distribution of nodes is always random. By analyzing nodes densities in randomly deployed networks, we can notice that there is no constant level of density if we divide the network into small units of area. This division yields areas with different densities starting from high density to holes without nodes inside it. The network appears as if it is divided into a set of subregions with different density levels of nodes as shown in Figure 2. The variation of density all over the network causes problems in the coverage and the connections between nodes. Therefore, in this paper, we focus on randomly deployed networks to extract spatial topological features which may help in additional redeployment process to overcome these shortages. Topological description for such networks can be a set of polygons, one for each subregion with specific density level. These subregions can be recognized by a cycle of boundary nodes resides at the border of them. The benefit of our proposed technique is that it can work in any network density. Even if the network is sparse or dense, the proposed technique can extract the layout of the network.

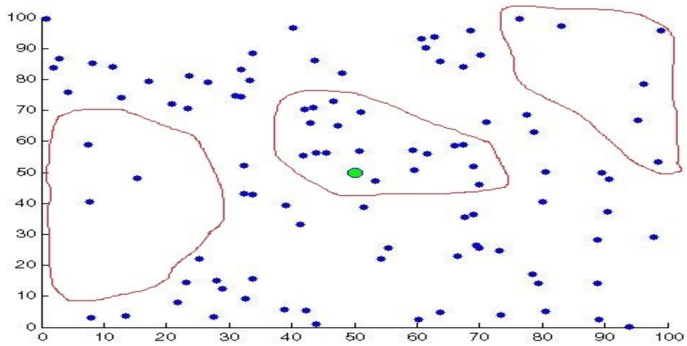

Figure 2.Random distribution of 100 nodes in a 100×100m^{2}network.

Our proposed technique aims to define each subregion in randomly distributed WSNs by defining nodes which border each subregion to show if it contains nodes or empty. Simple spatial analysis can be done on the neighboring information between nodes. This analysis aims to define the type of the node in its subregion. A node can be interior one surrounded with enough number of neighborsin its subregion or resides at the border of it. The identification of boundary nodes is a famous problem in WSNs applications such as surveillance, and monitoring applications. To recognize these nodes, the proposed techniques mainly depend on the adaptation of the transmission range value of each node to recognize boundary nodes sharing the same subregion with it. This adaptation is based on two parameters of the deployed network which are the number of nodes and the area of deployment. Relating the transmission range value to these two values helps the proposed technique to work with any network density.

4. Definitions

Each sensor node has Omni-directional antenna which enables communication within a maximum determined area. The transmission area is a disk centered at the node. The radius of the disk is the transmission range of this node. Two nodes within each other's transmission ranges are neighbors and can communicate directly. According to the node’s transmission range, the number of neighbors can differ.

5. Assumption

In our proposed protocol, we use the following assumptions:

- The location of nodes is fixed after deployment.
- The number of nodes is N.
- Nodes are randomly distributed in a $W \times H$ network area.
- Nodes can adapt their communication range and use different values for different purposes.
- Nodes can estimate the distance to neighbors.

6. Proposed Technique

The proposed technique consists of three phases which are: (1) Transmission range adaptation, (2) Nodes classification, and (3) Boundary cycles construction. The details of each step are shown as follows:

(1) TransmissionrangeAdaptation

İn the first phase, nodes adapt their communication range to a value which depends on the number of deployed nodes and the area of study. In [17], Bettstetter studied the relation between the transmission range and the number of neighbors $n$of each node which is defined as the degree of the node $d(n)$. He study this relation in a network when$N$ nodes are randomly deployed in an area $A = W \times H$. He assumed a uniform random distribution with large N, i.e. a constant node density can be measured as $\rho = \frac{N}{A}$ andnode's transmission radio range $r_0$covers atransmission area $A_0 = \pi r_0^2$, and computed the probability that the network has a minimum node degree $d_{min} \geq n$, which is given by:

$$P(d_{min} \geq n) = \left(1 - \sum_{i=0}^{n-1} \frac{(\rho\pi r^2)^i}{i!} . e^{-\rho\pi r^2}\right)^N \quad (1)$$

In our work, we want to minimize the transmission range value of the nodes to detect only the nearestneighbors which enable it to recognize the distribution of its surrounding subregion.

So, we use Equation (1) to calculate the transmission range value to be used by all nodes of the network to achieve an average network degree equals 3. The idea behind using this value will be clear after reading the second phase of the proposed technique.

Using Equation (1),$P(d_{min} \geq 3)$can be solved at a choosen threshold *(Th)* as follows:

$$(1 - \sum_{i=0}^{2} \frac{(\rho\pi r^2)^i}{i!} \cdot e^{-\rho\pi r^2})^N \geq Th \quad (2)$$

The optimal value of Th is 1. A close value to 1 has been chosen for Th which is 0.999999. Therefore, using the last equation, the minimum value of $r$form the range $[1, max(W, H)]$ can be calculated. For example, if *N=100*, and *W=H=500*; the transmission range is in the range [1, 500]. But to achieve an average network degree equals 3 we make mediation for the resulted value of transmission range. In Table 2, sample of different transmission range values to be applied for different network areas and different number of nodes. The value calculated in this step is the initial transmission range that will be used by all nodes to test if it is interior node or not.

Table 2Values of transmission range for different network sizes

N	*H=W*	*r*
50	200	29
100	200	21
200	400	42
400	600	22

(2) Nodes Classification

The aim of this step is to define a set of nodes which are used as vertices of polygons to define subregions of the network. These subregions can be empty subregions or high-density subregions. Therefore, in this step, nodes are classified to interior nodes surrounded with enough number of nodes and boundary nodes which surround each subregion. For this purpose, we use a border detection technique proposed by Shukla et al. in[18]. Many other techniques were proposed, but we choose this one because each node needs only its 1st hop neighbor's information to decide if it is interior or boundary one. It is used in a distributed algorithm and by one step it can differentiate between nodes as interior or boundary node. The node will be interior one if it is enclosed in a triangle of three neighbor nodes. Otherwise, it will be a boundary node. The difference between interior and boundary nodes is shown in Figure 3. İn the previous step; we choose to achieve average network degree equals three to enable nodes to test the triangle condition to determine its type.

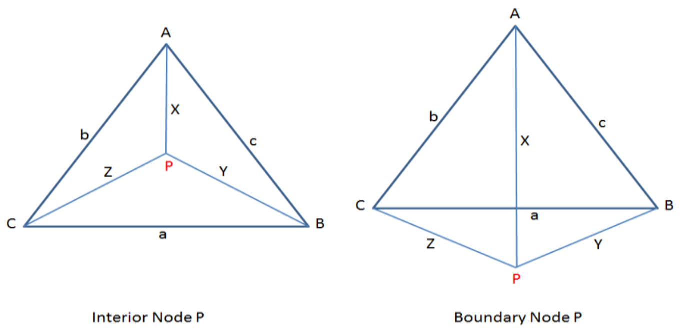

Figure 3.The difference between interior and boundary node [18].

(3) Boundary cycles construction

Nodes which are classified as boundary nodes are used to describe the layout of the topology. Each node broadcast advertisement message to its neighbors to announce its type. Upon receiving this information, each node constructs a neighboring table which contains all its 1sthopneighbors' type. Boundary nodes neighboring table contains additional information about its boundary neighbors. It has to know the direction to reach these neighbors to be able to construct the cycle which will surround this area. Figure 4shows an example of simple subregion with nodes N1 and N2 as interiors and N3, N4, N5, N6 as boundary nodes. Constructed tables according to this subregions shown in Tables 3, 4 and 5. After this, topological cycle construction procedures start by each boundary node. It summarizes this information to construct edges table which define all edges constructed by boundary nodes in the network.

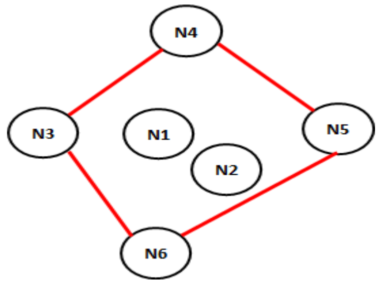

Figure 4. Example of interior and boundary nodes constructing a subregion

Table 3. Neighboring table of interior node N1

Neighbours ID	Neighbours Type
N2	Interior
N3	Boundary
N4	Boundary
N5	Boundary
N6	Boundary

Table 4. Neighboring table of N3 boundary node

Neighbours ID	Neighbours Type	Boundary Neighbour Directions
N1	Interior	
N2	Interior	
N4	Boundary	Clockwise
N6	Boundary	Counterclockwise

Table 5. Edges table of N3 boundary node

Edge ID	Starting Node	Ending Node
E1	N3	N4
E2	N3	N6

From this table, a boundary cycles construction process is started to define all polygonal border lines for each subregion. The polygonal borders recognized by a loop of nodes which starts and ends at the same node. For example, the polygon in Figure 4is N3-N4-N5-N6-N3. Given the estimated distance between each two adjacent boundary node and the direction from one to the other, each boundary node can detect its closed boundary cycle.

7. Evaluation of the Proposed Technique

We test the proposed technique at different deploymentscenarios;Figure 5shows three different deployment scenarios in a $500 \times 300m^2$ network area. The first scenario (A) presents a uniformly deployed low-density network using 250 nodes. The second scenario (B) presents a uniformly deployed high-density using 450 nodes. And the last scenario (C) presents a non-uniformly deployed network using 300 nodes. We can notice that the defined boundary cycleshelps to define the distribution of the dense and sparse subregions for the three cases.

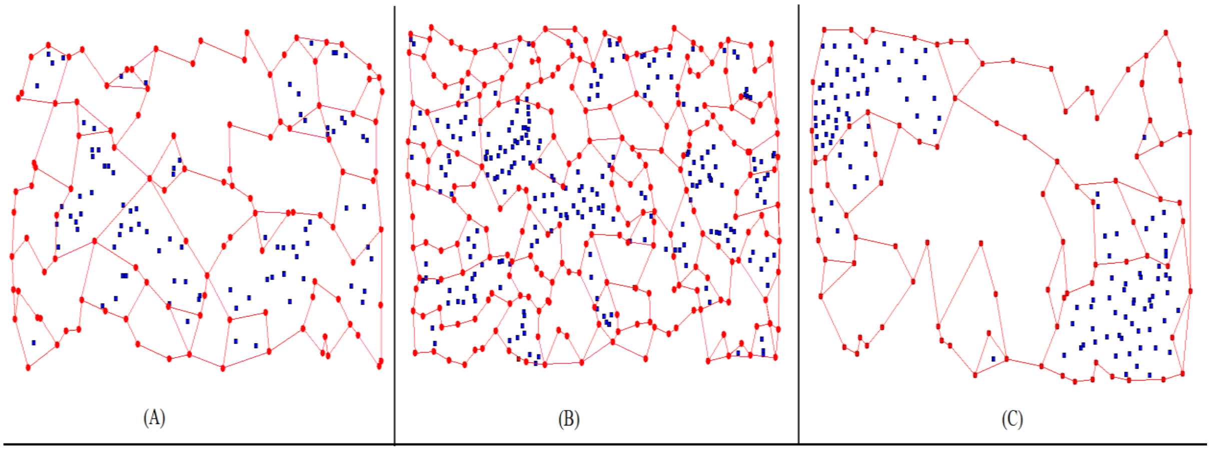

Figure 5.The topological structure of different random deployment scenarios. (A) Low-density uniformly distributed network (B) High-density uniformly distributed network (C) Non-uniformly distributed network.

To evaluate the performance of the proposed protocol, we compare it with the protocol presented in [19].It proposed a Heuristic Boundary Cycles Finding technique. We choose this one because it assumed the least average degree used than all other techniques mentioned in the related work. The author assumed (5-9) average degree in the centralized scenario and (6-9) in the distributed case in low-density networks. This technique is based on choosing a seed node with the local highest degree among its neighbors. The technique starts at this node and begins to gradually augment a boundary cycle by adding more nodes to this cycle. These nodes have to be neither is olatedwith degree equals 0 nor an end-node with degree equals 1. This process is repeated until it hits the boundary of the network. If more than one cycle is constructed, merging process for these cycles begins. In this protocol, all nodes are involved in the construction of the boundary cycles. On the contrary, our technique uses an average network degree equals three, and the step of transmission range adaption selects a set of boundary nodes to define subregions. Only these nodes are involved in the construction of topological boundary cycles which causes a less number of messages and less energy consumption during the process of boundary cycles construction. Therefore, the benefit of our technique is the prediction of the nodes which will help in the process of topology extraction in advance. To present the efficiency of our technique, we preview a sample scenario in Figure 6, to show the resulted topological boundary cycles resulted from the two techniques. We also measure the average number of exchanged messages and the average consumed energy by nodes involved in the construction process of the boundary cycles. These values are measured for a $400 \times 400\mathrm{m}^2$ network with a number of nodes ranging from 200 to 500 nodes. These values are viewed in Figure 7 and Figure 8.

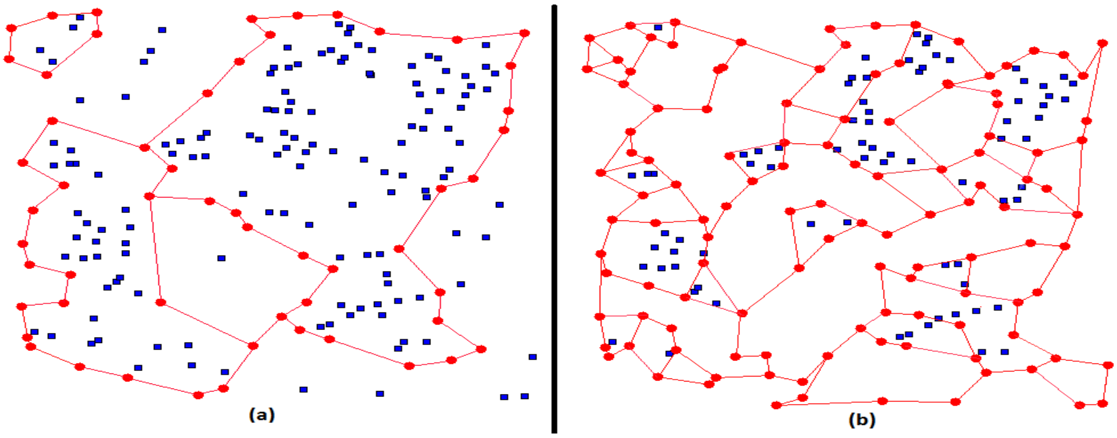

Figure 6.Comparison between (a) technique presented in [19] and (b) our proposed technique

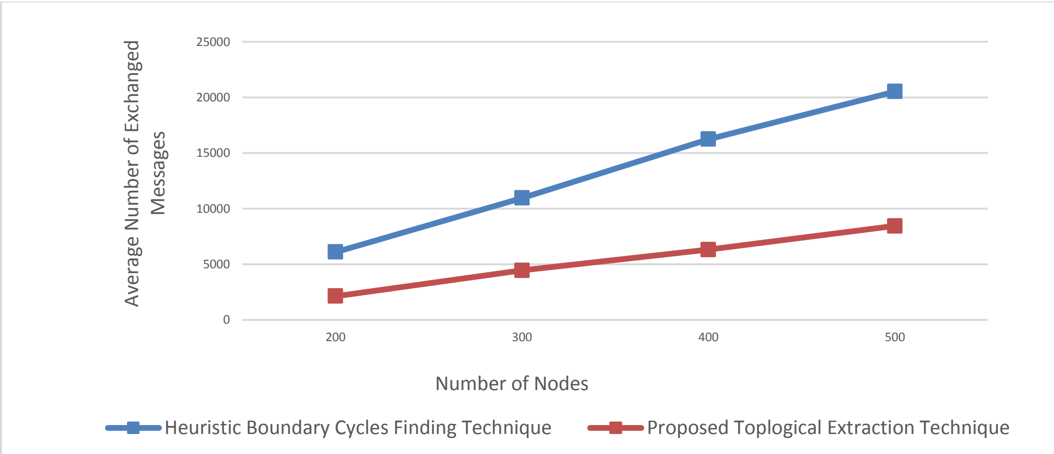

Figure 7.Average number of exchanged messages for the construction of boundary cycles.

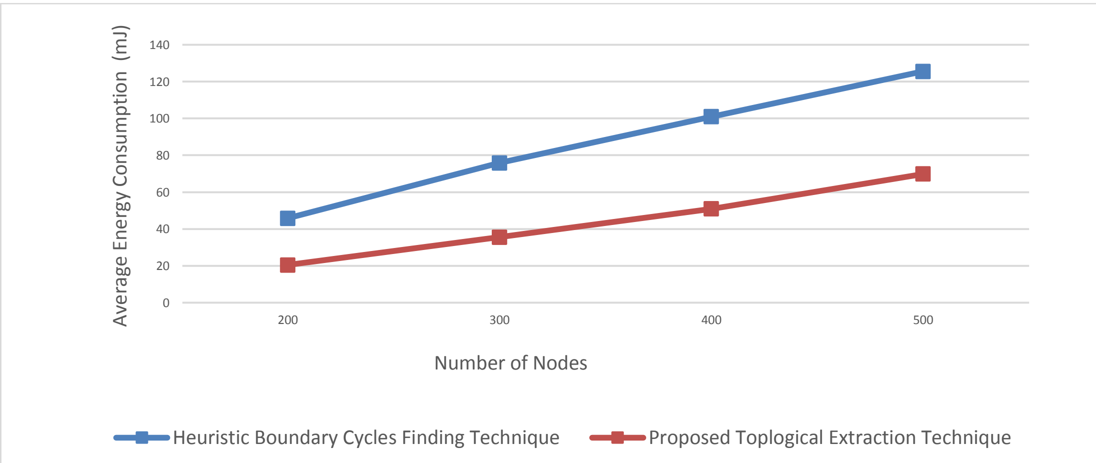

Figure 8.Average energy consumption for the construction of boundary cycles.

8. Conclusion and Future Work

In this paper, we propose a technique which defines the layout of randomly deployed WSNs. This is done by defining boundary lines that border the polygonal subregions of similar density level resulted from the random distribution of sensors in the network. Our technique depends on node's transmission range adaptation by choosing a value which depends on the total number of distributed nodes and the area of the network. It is adapted to be able to test the type of each node in its own subregion. Each node can be interior or boundary one. Other techniques discussed in this paper depend on a high density of the distributed nodes. Some of them consider aclear defined figure of holes, for example, concave regions or separated holes not near to each other. These conditions of deployment are not feasible for many real applications. Future work includes the refinement of the constructed polygons to merge adjacent empty subregions and the use of defined boundary links to guide a redeployment process to enable movement of nodes from high-densitysubregions to low-density subregions and holes.

References

[1] A. Al-Ali, I. Zualkernan, and F. Aloul, "A mobile GPRS-sensors array for air pollution monitoring," *IEEE Sensors Journal,* vol. 10, pp. 1666-1671, 2010.

[2] K. K. Khedo, R. Perseedoss, and A. Mungur, "A wireless sensor network air pollution monitoring system," *International Journal of Wireless & Mobile Networks,* pp. 31–45, 2010.

[3] J. Lloret, M. Garcia, D. Bri, and S. Sendra, "A wireless sensor network deployment for rural and forest fire detection and verification," *Sensors,* vol. 9, pp. 8722-8747, 2009.

[4] E. H. Putra, M. Y. Hariyawan, and A. Gunawan, "Wireless Sensor Network for Forest Fire Detection," *TELKOMNIKA (Telecommunication Computing Electronics and Control),* vol. 11, pp. 563-574, 2013.

[5] N. A. A. Aziz and K. A. Aziz, "Managing disaster with wireless sensor networks," in *13th International Conference on Advanced Communication Technology (ICACT).* 2011, pp. 202-207.

[6] R. Ohbayashi, Y. Nakajima, H. Nishikado, and S. Takayama, "Monitoring system for landslide disaster by wireless sensing node network," in *SICE Annual Conference,*, 2008, pp. 1704-1710.

[7] A. Darwish and A. E. Hassanien, "Wearable and implantable wireless sensor network solutions for healthcare monitoring," *Sensors,* vol. 11, pp. 5561-5595, 2011.

[8] Y.-D. Lee and W.-Y. Chung, "Wireless sensor network based wearable smart shirt for ubiquitous health and activity monitoring," *Chemical Sensors and Actuators B,* vol. 140, pp. 390-395, 2009.

[9] M. Ceriotti, L. Mottola, G. P. Picco, A. L. Murphy, S. Guna, M. Corra*, et al.*, "Monitoring heritage buildings with wireless sensor networks: The Torre Aquila deployment," in *Proceedings of the 2009 International Conference on Information Processing in Sensor Networks*, 2009, pp. 277-288.

[10] X. Laisheng, P. Xiaohong, W. Zhengxia, X. Bing, and H. Pengzhi, "Research on traffic monitoring network and its traffic flow forecast and congestion control model based on wireless sensor networks," in *ICMTMA'09. International Conference on Measuring Technology and Mechatronics Automation* 2009, pp. 142-147.

[11] M. R. Senouci, A. Mellouk, and A. Aissani, "Random deployment of wireless sensor networks: a survey and approach," *International Journal of Ad Hoc and Ubiquitous Computing,* vol. 15, pp. 133-146, 2014.

[12] V. Sharma, R. Patel, H. Bhadauria, and D. Prasad, "Deployment schemes in wireless sensor network to achieve blanket coverage in large-scale open area: A review," *Egyptian Informatics Journal,* vol. 17, pp. 45-56, 2016.

[13] A. Kröller, S. P. Fekete, D. Pfisterer, and S. Fischer, "Deterministic boundary recognition and topology extraction for large sensor networks," in *Proceedings of the seventeenth annual ACM-SIAM symposium on Discrete algorithm*, 2006, pp. 1000-1009.

[14] Y. Wang, J. Gao, and J. S. Mitchell, "Boundary recognition in sensor networks by topological methods," in *Proceedings of the 12th annual international conference on Mobile computing and networking*, 2006, pp. 122-133.

[15] S. Lederer, Y. Wang, and J. Gao, "Connectivity-based localization of large-scale sensor networks with complex shape," *ACM Transactions on Sensor Networks (TOSN),* vol. 5, p. 31, 2009.

[16] W. Liu, Y. Yang, H. Jiang, X. Liao, W. Wei, B. Li*, et al.*, "A General Framework of Skeleton Extraction in Sensor Networks," *IEEE Sensors Journal* 2015.

[17] C. Bettstetter, "On the minimum node degree and connectivity of a wireless multihop network," in *Proceedings of the 3rd ACM international symposium on Mobile ad hoc networking & computing*, 2002, pp. 80-91.

[18] S. Shukla and R. Misra, "Angle based double boundary detection in wireless sensor networks," *Journal of Networks,* vol. 9, pp. 612-619, 2014.

[19] L. Sitanayah, A. Datta, and R. Cardell-Oliver, "Heuristic algorithm for finding boundary cycles in location-free low density wireless sensor networks," *Computer Networks,* vol. 54, pp. 1630-1645, 2010.