Optimal Deployment of Mobile Sensor Networks and Its Maintenance Strategy

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Abstract. Sensor network deployment and its maintenance are very challenging due to hostile and unpredictable nature of environments. The field coverage of a wireless sensor network (WSN) can be enhanced and consequently network lifetime can be prolonged by optimizing the sensor deployment with a finite number of sensors. In this paper, we propose an energy-efficient fuzzy optimization algorithm (EFOA) for movement assisted self-deployment of sensor networks based on three descriptors – energy, concentration and distance to neighbors. The movement of each sensor node is assumed relatively limited to further reduce energy consumption. The existing next-step move direction formulas are improved to be more realistic. We also propose a network maintenance strategy in the post-deployment phase based on the sensor node importance level ranking. Simulation results show that our approach not only achieves fast and stable deployment but also greatly improves the network coverage and energy efficiency as well as prolongs the lifetime.

Keywords: Sensor networks, fuzzy logic, deployment, mobility, coverage

1 Introduction

Sensor networks which are composed of tiny and resource constrained computing devices, have been widely deployed for monitoring and controlling applications in physical environments [1]. Due to the unfamiliar nature of such environments, deployment and maintenance of sensor networks has become a challenging problem and has received considerable attention recently.

Some of the work [2], [3], [4] assume that the environment is sufficiently known and under control. However, when the environment is unknown or inhospitable such as remote inaccessible areas, disaster fields and toxic urban regions, sensor deployment cannot be performed manually. To scatter sensors by aircraft is one of the possible solutions. However, using this scheme, the actual landing position cannot be predicted due to the existence of wind and obstacles such as trees and buildings. Consequently, the coverage may not be able to satisfy the application requirements. Some

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researchers suggest simply deploying large amount of static sensors to increase coverage; however it often ends up harming the performance of the network [5].Moreover, in many cases, such as during in-building toxic-leaks detection [6], chemical sensors must be placed inside a building from the entrance of the building. In such cases, it is necessary to take advantage of mobile sensors, which can move to the appropriate places to provide the required coverage.

To address this issue, a class of work has recently appeared where mobility of sensors is utilized to achieve desired deployment [7], [8], [9], [10], [11], [12]. Typically in such works, the sensors detect lack of desired deployment objectives such as coverage holes, estimate new locations, and move to the resulting locations. For example, in [9], the authors present the virtual force algorithm (VFA) as a new approach for sensor deployment to improve the sensor field coverage after an initial random placement of sensor nodes. The cluster head (CH) executes the VFA algorithm to find new locations for sensors to enhance the overall coverage. However none of the above work can well handle the random movement and unpredictable oscillation in deployment. In [13], fuzzy logic theory is applied to handle the uncertainty in sensor network deployment problem. Their approach achieve fast and relatively stable deployment and increase the field coverage as well as communication quality. However, their fuzzy inference system has only two antecedents, number of neighbors of each sensor and average Euclidean distance between sensor node and its neighbors, without energy consumption considered at all, which is one of the most critical issues in sensor networks.

In this paper, our contribution relies on the two propose strategies. The first is an energy-efficient fuzzy optimization algorithm (EFOA) for movement assisted self-deployment of sensor networks. It outperforms [13] in three aspects. The first is that we take the energy level of sensor node as one of the antecedents in fuzzy rules; the second is that the mobility of sensor nodes is set to be relatively limited, i.e., the movement distance is bounded by communication range, so that energy consumption can be further reduced; the last is represented by the more realistic next-step moving direction equations we derived. The second strategy we propose for network maintenance in the post-deployment phase is based on the derived sensor node importance level ranking.

The rest of the paper is organized as follows. Section 2 briefly introduces the overview of fuzzy logic system and preliminaries. In section 3 the Energy-efficient Fuzzy Optimization Algorithm (EFOA) is explained in detail for mobile nodes deployment design. In section 4 network maintenance strategy is proposed based on sensor node importance ranking. Simulation and performance evaluations of this work are presented in Section 5. We conclude with a summary and discuss future work in Section 6.

2 Technical Preliminaries

2.1 Fuzzy Logic Systems

The model of fuzzy logic system consists of a fuzzifier, fuzzy rules, fuzzy inference engine, and a defuzzifier. We have used the most commonly used fuzzy inference technique called Mamdani Method [14] due to its simplicity.

The process is performed in four steps:

1) Fuzzification of the input variables *energy, concentration and average distance to neighbors* - taking the crisp inputs from each of these and determining the degree to which these inputs belong to each of the appropriate fuzzy sets.
2) Rule evaluation - taking and applying the fuzzified inputs to the antecedents of the fuzzy rules. It is then applied to the consequent membership function.
3) Aggregation of the rule outputs - the process of unification of the outputs of all rules.
4) Defuzzification - the input for the defuzzification process is the aggregate output fuzzy set *moving* distance and the output is a single crisp number.

Information flows through the fuzzy inference diagram as shown in Figure 1.

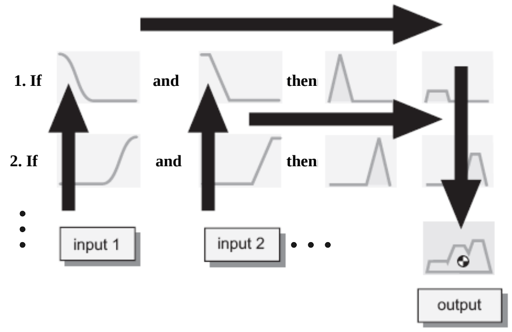


Fig. 1. Fuzzy inference diagram

2.2 Coverage

Generally, coverage can be considered as the measure of quality of service of a sensor network. In this paper, coverage [10] is defined as the ratio of the union of areas covered by each node and the area of the entire Region of Interest (ROI), as shown in Eq. (1), and binary sensing model [10] is adopted. Here, the covered area of each node is defined as the circular area within its sensing radius. Perfect detection of all interesting events in the covered area is assumed.

$$C = \frac{\bigcup_{i=1,\ldots,N} A_i}{A} \quad (1)$$

where
A_i is the area covered by the i^{th} node;
N is the total number of nodes;
A stands for the area of the ROI.

In order to prevent recalculating the overlapped area, the coverage here is calculated using Monte Carlo method by creating a uniform grid in the ROI [11]. All the grid points being located in the sensing area are labeled 1 otherwise 0, depending on whether the Euclidean distance between each grid point and the sensor node is longer or shorter than sensing radius. Then the coverage can be approximated by the ratio of the summation of ones to the total number of the grid points.

If a node is located well inside the ROI, its complete coverage area will lie within the ROI. In this case, the full area of that circle is included in the covered region. If a node is located near the boundary of the ROI, then only the part of the ROI covered by that node is included in the computation.

3 Proposed Deployment Approach: EFOA

3.1 Assumptions and Model

Let *G(V, E)* be the graph defined on *V* with edges $uv \in E$ iff $uv \leq R$. Here *uv* is the Euclidean distance between nodes *u* and *v*, *R* is the communication range. A sensor can detect any event within its sensing range *r*. Two sensors within *R* can communicate with each other. Neighbors of a sensor are nodes within its communication range. Detection and communication is modeled as a circle on the *2-D* sensor field.

According to the radio energy dissipation model, in order to achieve an acceptable Signal-to-Noise Ratio (SNR) in transmitting an *l* bit message over a distance *d,* the energy expended by the radio is given by [15]:

$$E_T(l,d) = \begin{cases} lE_{elec} + l\varepsilon_{fs}d^2 & if\ d \leq d_0 \\ lE_{elec} + l\varepsilon_{mp}d^4 & if\ d > d_0 \end{cases} \quad (2)$$

where E_{elec} is the energy dissipated per bit to run the transmitter or the receiver circuit, ε_{fs} and ε_{mp} are amplifier constants, and *d* is the distance between the sender and the receiver. By equating the two expressions at $d=d_0$, we have $d_0 = \sqrt{\varepsilon_{fs} / \varepsilon_{mp}}$. Here we set electronics energy as E_{elec}=50*nJ/bit*, whereas the amplifier constant, is taken as ε_{fs} =10$pJ/bit/m^2$, ε_{mp} = 0.0013$pJ/bit/m^2$, the same as in [15].

To receive *l* bit message, the radio expends:

$$E_R(l) = lE_{elec} \tag{3}$$

For simplicity, assume an area over which n nodes are uniformly distributed and the sink is located in the center of the field, so the distance of any node to the sink or its cluster head is $\leq d_0$.

3.2 Energy-efficient Fuzzy Optimization Algorithm

Expert knowledge is represented based on the following three descriptors:

- Node Energy - energy level available in each node, denoted by the fuzzy variable energy,
- Node Concentration - number of neighbors in the vicinity, denoted by the fuzzy variable concentration,
- Average distance to neighbors - average Euclidean distance between sensor node and its neighbors, denoted by the fuzzy variable d_n.

Table 1. Fuzzy rule base (d_n=average distance to neighbors, d_m=moving distance)

No.	energy	concentration	d_n	d_m
1	low	low	close	close
2	low	low	moderate	vclose
3	low	low	far	vclose
4	low	med	close	moderate
5	low	med	moderate	close
6	low	med	far	vclose
7	low	high	close	moderate
8	low	high	moderate	close
9	low	high	far	close
10	med	low	close	moderate
11	med	low	moderate	close
12	med	low	far	close
13	med	med	close	far
14	med	med	moderate	moderate
15	med	med	far	close
16	med	high	close	far
17	med	high	moderate	moderate
18	med	high	far	moderate
19	high	low	close	far
20	high	low	moderate	moderate
21	high	low	far	moderate
22	high	med	close	vfar
23	high	med	moderate	far
24	high	med	far	moderate
25	high	high	close	vfar
26	high	high	moderate	far
27	high	high	far	far

Legend: vclose=very close, vfar=very far, med=medium.

The linguistic variables used to represent the node energy and node concentration, are divided into three levels: *low, medium* and *high*, respectively, and there are three levels to represent the average distance to neighbors: *close, moderate* and *far*, respectively. The outcome to represent the moving distance d_m was divided into 5 levels: *very close, close, moderate, far* and *very far*. The fuzzy rule base includes rules like the following: IF the energy is *high* and the concentration is *high* and the distance to neighbor is *close* THEN the moving distance of sensor node *i* is *very far*.

Thus we used $3^3 = 27$ rules for the fuzzy rule base. We used triangle membership functions to represent the fuzzy sets *medium* and *moderate* and trapezoid membership functions to represent *low, high, close* and *far* fuzzy sets. The developed membership functions and their corresponding linguistic states are represented in Table 1 and Figures 2 through 5 respectively.

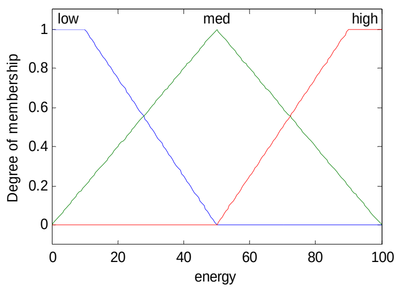


Fig. 2. Fuzzy set for fuzzy variable *energy*

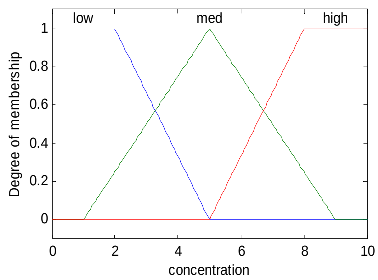


Fig. 3. Fuzzy set for fuzzy variable *concentration*

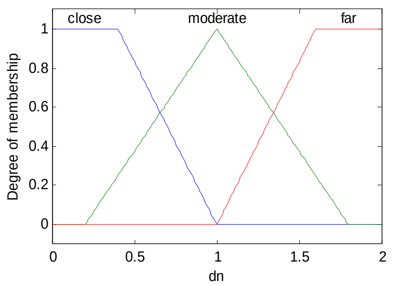


Fig. 4. Fuzzy set for fuzzy variable dn

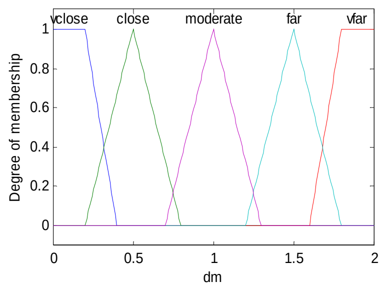


Fig. 5. Fuzzy set for fuzzy variable d_m

For the defuzzification, the Centroid is calculated and estimated over a sample of points on the aggregate output membership function, using the following formula:

$$Cen = \left(\sum \mu_A(x) * x\right) / \sum \mu_A(x) \tag{4}$$

where, $\mu_A(x)$ is the membership function of x in A. The membership function maps each element of X to a membership value between 0 and 1.

The control surface is central in fuzzy logic systems and describes the dynamics of the controller and is generally a time-varying nonlinear surface. From Fig. 6 and Fig. 7 obtained by computation in Matlab Fuzzy Logic Toolbox, we can see that although the concentration for a certain sensor is high, the moving distance can be smaller than some sensor with higher energy or sensor with fewer neighbors but more crowded. With the assistance of control surface, the next-step moving distance can be determined.

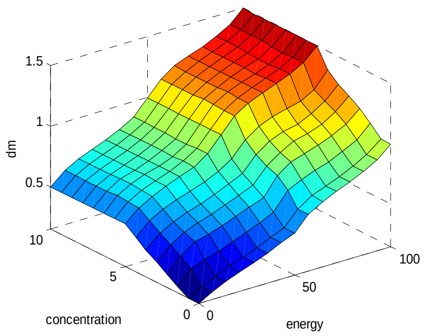


Fig. 6. Control surface (concentration, energy vs d_m)

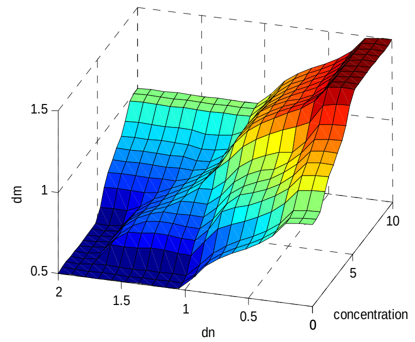


Fig. 7. Control surface (d_n, concentration vs d_m)

The next-step move direction is decided by virtual force. Assume sensor i has k neighbors, $k=k_1+k_2$, in which k_1 neighbors are within threshold distance d_{th} to sensor i, while k_2 neighbors are farther than d_{th} distance to sensor i. The coordinate of sensor i is denoted as $C_i = (X_i, Y_i)$, and that of neighbor sensor j is $C_j = (X_j, Y_j)$. The next-step move direction of sensor i is represented as Eq. (5) and (6), which are the improved version of moving direction equation in [13]. It is improved in the sense that threshold distance is set here so that attraction and repulsion forces can be represented in the equations. Thus after getting moving distance d_m and direction (angle α), sensor i clearly knows its next-step moving position.

$$\vec{v} = \frac{1}{\left|\vec{C}_i - \vec{C}_j\right|^2}\left(\sum_{j=1}^{k_1}(\vec{C}_i - \vec{C}_j) + \sum_{j=1}^{k_2}(\vec{C}_j - \vec{C}_i)\right) \tag{5}$$

$$\tan(\alpha) = \frac{Y(\vec{v})}{X(\vec{v})} \tag{6}$$

The threshold distance d_{th} here is set to a proper value $\sqrt{3}r$ which is proved as follows: We attempt to make distance between 2 sensor nodes moderate, i.e., not very close and not very far. This kind of stable structure is illustrated in Figure 8. Non-overlapped sensor coverage style is shown in Figure 8(a), however, an obvious drawback here is that a coverage hole exists which is not covered by any sensor. Note that an alternative way is to allow overlap, as shown in Figure 8(b) and it ensures that all grid points are covered. Therefore, we adopt the second strategy.

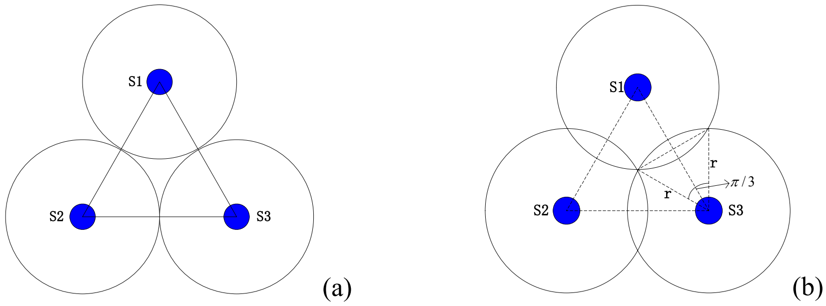


Fig. 8. Non-overlapped and overlapped sensor coverage cases

In Fig. 8(b), it is obvious that $\triangle S_1S_2S_3$ is equilateral triangle. Because the sensing radius is r, through some steps of simple geometry calculations, we can easily derive the distance between two sensor nodes in the latter case $S_1S_2 = S_2S_3 = S_1S_3 = 2\times\sqrt{3}r/2 = \sqrt{3}r$.

4 Proposed Network Maintenance Strategy

After the first stage deployment, the network maintenance is also necessary to be considered due to the uncertain environment. Thus, it is actually the post-deployment stage after the fuzzy optimization deployment stage and a certain period of network operation. The characteristic of the network in this situation is heterogeneous. The proposed network maintenance strategy is based on the sensor node importance level ranking. First, we take the importance level calculation of the node n as an example. Assume the total number of nodes in the network is N. Let the probability that node i can sense grid point j be denoted by $S_i(P_j)$, and then the probability $C(P_j)$ that grid point j is sensed by the whole network is derived as:

$$C(P_j) = 1 - \prod_{i=1}^{N}(1 - S_i(P_j)) \tag{7}$$

$$= 1 - (1 - S_n(P_j)) \times \prod_{i \neq n}^{N}(1 - S_i(P_j))$$

If delete node n, then the probability $C(P_j)$ becomes

$$C(P_j) = 1 - \prod_{i \neq n}^{N}(1 - S_i(P_j)) \tag{8}$$

For point j, the detection probability loss due to the deletion of node n becomes

$$\Delta C_n(P_j) = S_n(P_j) \times \prod_{i \neq n}^{N} (1 - S_i(P_j)) \tag{9}$$

Considering the importance difference of each node in the network, the detection ability loss of the whole network after deleting node *n* is:

$$\Delta C_n = \sum_j \Delta C_n(P_j) \times \nabla(P_j) \tag{10}$$

in which $\nabla(P_j)$ is the temporal gradient of sensing value at grid point *j*. The higher the gradient value the more often the interesting events occurrence. We assume that sensor measurement physically has a range ($0 \sim x_{\max}$); if the sensing vale $v > x_{\max}$, then let $v = x_{\max}$.

According to importance level indicator ΔC_n, the importance level ranking of each node in the network can be sorted. Consequently we can either deploy several new sensor nodes close to the most important nodes or remove redundant nodes from "quiet" spot to the vicinity of those "busy" nodes as a backup.

5 Performance Evaluations

The proposed EFOA algorithm is evaluated first. For the convenience of comparison, we set the initial parameters the same as in [13]: various number of sensors deployed in a field of 10×10 square kilometers area are investigated; the *r* and *R* used in the experiment are *1km* and 2*km* (2*km* and 4*km*) respectively. So d_n should be ranged as 0~2 (0~4), not 0~10 as set by [13]. We assume each sensor is equipped with an omni-antenna to carry out the task of detection and communication. Evaluation of our EFOA algorithm follows three criteria: field coverage, energy consumption and convergence. Results are averaged over 100 Monte Carlo simulations.

Figure 9 shows that the coverage of the initial random deployment, fuzzy optimization algorithm (FOA) proposed in [13] and our proposed algorithm EFOA when *r=1km* and *R=2km*. The FOA and EFOA algorithm have similar results that both of them can improve the network coverage by 20% ~ 30% in average.

Figure 10 gives the results when *r=2km* and *R=4km*, the coverage comparison between random deployment, FOA and EFOA. In the case when 20 sensors are deployed, initially the coverage after random deployment is around 86%. After FOA and EFOA algorithm are executed, the coverage reaches 97%. The coverage is dramatically improved in the low density network. The above two figures indicate that instead of deploying large amount of sensors, the desired field coverage could also be achieved with fewer sensors.

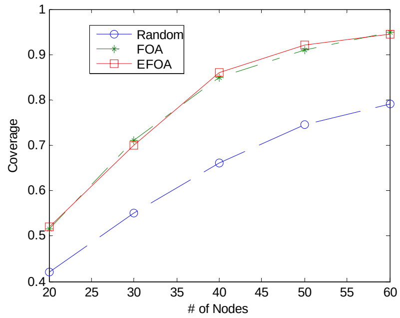


Fig. 9. Coverage vs. # of Nodes (*R=2, r=1*)

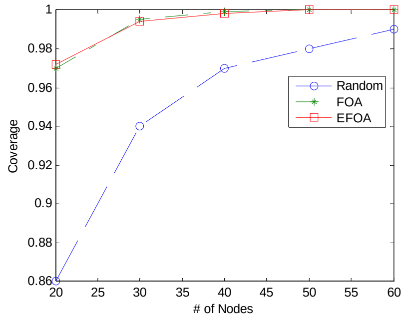


Fig. 10. Coverage vs. # of Nodes (*R=4, r=2*)

Figure 11 shows the total number of nodes that remain alive over time where each node begins with *2J* of energy and when *R=4km* and *r=2km*. The number of nodes in EFOA remains the same for a long time and they die out quickly almost at the same time while the first node dies early in FOA. The reason is that after some operation time, the network display heterogeneous characteristics, however, FOA doesn't consider the residual energy of nodes, so the energy difference among sensors becomes significant as time goes on. Network lifetime is the time span from the deployment to the instant when the network is considered nonfunctional. When a network should be considered nonfunctional, it is generally the instant when the first sensor dies or a percentage of sensors die and the loss of coverage occurs. Thus the lifetime is prolonged in EFOA compared with FOA.

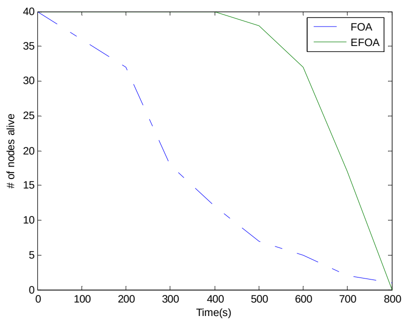


Fig. 11. # of nodes alive over time where each node begins with *2J* energy. (*R=4, r=2*)

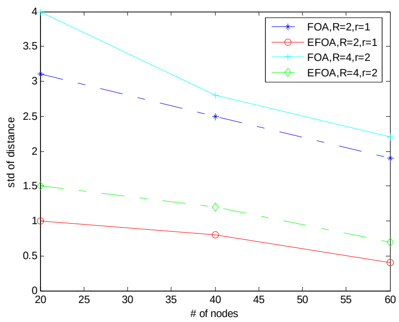
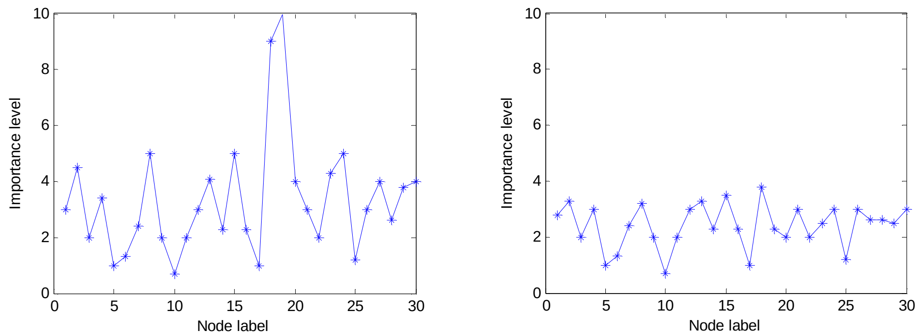


Fig. 12. Standard deviation of distance traveled verses number of nodes

Figure 12 shows EFOA has lower standard deviation of distance compared with FOA in both cases when *R=4km*, *r=2km* and *R=2km*, *r=1km* with various number of nodes. When the standard deviation of distance traveled is small, the variation in energy remaining at each node is not significant and thus a longer system lifetime with desired coverage can be achieved.

The network maintenance strategy is simulated thereafter as Figure 13 shows. The parameter $x_{\max}$ is set to be 50, sampling period is 5*s*.Total number of nodes in the network is 30, and two of the most importance nodes are the nodes labeled as 18 and

19 which have the highest importance level. After adding four new nodes close to node 18 and 19, the importance level distribution become nearly uniform compared with the case before executing network maintenance strategy. Thus the working load of the "busy" nodes can be shared by the backup nodes and the lifetime can be further prolonged.



(a) Before maintenance strategy (a) After maintenance strategy

Fig. 13. Importance level verses node serial number

6 Conclusions and Future Work

In this paper, an energy-efficient fuzzy optimization algorithm (EFOA) for self- deployment of mobile sensor networks was proposed. It was based on three descriptors – energy level of nodes, concentration and average distance to neighbors. The movement of each sensor node was assumed to be relatively limited for further reducing energy consumption. The existing next-step move direction formulas were also improved to be more realistic. Our approach has a great advantage to deal with the randomness in sensor deployment as well as minimize energy consumption. We also proposed a network maintenance strategy in the post-deployment phase based on the sensor node importance level ranking. Simulation results showed that our approach not only achieved fast and stable deployment but also greatly improved the network coverage and energy efficiency as well as extended the lifetime.

In the future work, the integration of environmental factors and realistic sensing model will be investigated.

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