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Expanding Ring Search Energy Analysis and Optimization for Wireless Sensor Networks

Xiuxiu Wen, Huiqiang Wang, Guangsheng Feng, Hongwu Lv,
Junyu Lin, Qiang Zhu

College of Computer Science and Technology, Harbin Engineering University
Harbin, 150001, China
wenxiuxiu@hrbeu.edu.cn

Abstract

Expanding Ring Search (ERS) is an advanced flooding technique exploring for targets progressively. It is widely used to locate destinations or information in wireless sensor networks. In this paper, a fundamental problem concerning the best ERS strategy to minimize energy cost in wireless sensor networks is addressed. We propose a model for estimating the average energy cost of ERS strategies, and a model for comparing the energy cost of an ERS strategy with pure flooding. The second model is then used to prove that incremental ERS strategies are inefficient in large-scale wireless sensor networks. Furthermore, we propose an ERS strategy optimization algorithm SSetOpt, which can be applied to both dense wireless sensor networks and sparse ones. The simulation results show that the strategy obtained by SSetOpt can cost 5% less energy than prior works when the network is sparse, say, the average degree is less than 30..

Keywords: *wireless sensor networks; broadcasting; costing; search problems*

1. Introduction

Wireless sensor networks consist of wireless sensors with finite power, which makes it important to design energy efficient search method. Expanding Ring Search (ERS) is a flooding method. It has extensive applications in target discoveries in wireless networks, such as those widely utilized in the route discovery process of routing protocols[1,2,3], those used in wireless sensor networks for sensor discoveries[4,5], or those used in Ad Hoc networks for service discoveries[6,7]. ERS explores for the target progressively by increasing the searching range after each search fails. Under ERS a request is broadcasted and propagated in the network. A preset TTL value is carried in the request and every time the packet is relayed, the TTL value is decremented. This continues until TTL reaches zero and the propagation stops. Therefore, the searching range is controlled by the TTL value. The preset TTL values compose an ERS strategy [1].

There have been a number of works on ERS energy cost analysis. Most of them were focusing on the problem of how ERS strategies can affect the energy cost of route discovery in protocols, *i.e*. AODV, DSDV or FSR. Perkins selected AODV to compare the routing loads in two cases: with and without ERS strategies[8]. The comparison based on simulations was presented in [9]. A detailed framework consisting of modeling of routing overhead generated by three widely used proactive routing protocols (DSDV, FSR and OLSR) was presented in [2]. These works provided an understanding about effectiveness of ERS strategies in routing protocols in terms of routing load reduction. Different from their works, we try to obtain the best ERS strategy.

Only a few works were focusing on ERS strategy optimization. Hassan and Jha studied the optimum threshold for the incremental ERS strategies[10]. The authors developed a theoretical model for analyzing the expected broadcast cost as a function of threshold , and argued that there was an optimum value of , which minimizes the

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expected cost of broadcasts. Extensive numerical experiments validated their theoretical model by considering a large number of random network topologies of different sizes and path lengths. However, the theoretical model can only be used to obtain the optimum ERS strategy under the condition that the searching range increases only by one hop after each failed search. Chang and Liu revisited the TTL-based controlled flooding search extensively, which was not confined to the incremental ERS strategies [11]. They proposed an analytical model by counting all the nodes involved in request receptions during the searching process. A search strategy optimization method based on dynamic programming was proposed. Because the energy consumed by receptions is much smaller than transmissions, Cheng[12] and Jing[1] analyzed the cost of ERS as the number of nodes involved in request transmissions respectively. Cheng investigated geography-based and hop-based flooding control methods, and provided a general formula to determine good parameters for two-tier and three-tier schemes[12]. While Jing proposed another analytical model, and obtained a strategy close to the optimum based on the analytical model in dense wireless sensor networks with the source node located at the origin[1].

We focus on a fundamental problem concerning the best ERS strategy to minimize energy cost for wireless sensor networks. It has been shown that different ERS strategies can cause different energy cost [9, 13, 14, 15]. Therefore, it is interesting to identify the best ERS strategy for networks. In this work, we analyze the running process of ERS strategies in wireless sensor networks, and propose an ERS strategy optimization algorithm SSetOpt. Our contributions can be summarized as follows:

- We propose a model for estimating the average energy cost of ERS strategies. This model is briefer than the prior works. Because we do not have assumptions on network density or successive search ranges, our model is more adaptive than the prior works.
- We prove that incremental ERS strategies are inefficient in large-scale wireless sensor networks. Existing works find this phenomenon by simulations, but the reason is not fully discussed. We find the reason is that the successive search ranges are too close. We propose a theorem about the reason, and derive a lower bound of network radius when pure flooding should be used instead of incremental ERS strategies.
- We propose an ERS strategy optimization algorithm SSetOpt, which can be applied to both dense wireless sensor networks and sparse ones. The simulation results show that the strategy obtained by SSetOpt can reduce energy cost by 5% compared with prior works when the network is sparse, say, the average degree is less than 30.

The rest of this paper is organized as follows. In Section 2, we present two analytical models, energy cost analytical model and relative cost ratio analytical model. We prove that incremental ERS strategies are ineffective in large-scale wireless sensor networks using relative cost ratio analytical model in Section 3. The ERS strategy optimization algorithm SSetOpt is proposed in Section 4. Section 5 presents results of simulations which verify our conclusions. We conclude our work and state future work directions in Section 6.

2. ERS Energy Cost Analysis

2.1. Assumptions and Notations

The wireless sensor network is connected. We assume that a single destination exists in the network and is equally likely to be located in one of the non-source nodes. Throughout our paper, we use the following notations:

- $|A|$: the radix of set A.
- N : the total number of nodes in the network.
- s : the source node that employs ERS.

- R : the minimum hops required to reach the farthest node from s .
- A_x : the set of all nodes that can be reached within x hops from s .
- d : the distance (minimum hops) between s and the target, also an integer-valued random variable taking value between 1 and R .
- $F(x)$: the percentage of nodes that can be reached within x hops from s .
- $SSet$: ERS strategy. $SSet = \{L_1, L_2, L_3, \cdots, L_n\}$, where L_i is an integer representing the preset TTL value in the i th search, and $L_i + 1 \le L_{i+1}$.
- B : the energy cost of $SSet$, also a random variable.

2.2. Energy Cost Analytical Model

We propose an energy cost analytical model by counting all the nodes involved in request transmissions.

When s wants to discover a destination, the first search is started with TTL value L_1 . A request with TTL value L_1 is broadcasted. The number of nodes involved in sending request will be $|A_{L_1}|$, and the number of nodes requested will be $|A_{L_1+1}|$. Therefore, the incurred cost of the first search writes

$$E(B \mid d \le L_1 + 1) = |A_{L_1}| \tag{1}$$

Each node has equal probability to be the destination, so the probability that the destination is successfully located in the first search is approximately equal to the ratio of nodes requested in the first search over the network.

$$P\{d \le L_1 + 1\} = |A_{L_1+1}| / N \tag{2}$$

The i th search is started with TTL value L_i , if the $i-1$ th search fails. The number of nodes involved in sending request will be $|A_{L_i}|$, and the number of nodes requested will be $|A_{L_i+1}|$. The expected cost when the destination is located in the i th search should be the sum of $|A_{L_i}|$ and $\sum_{j=1}^{i-1} |A_{L_j}|$, which is the energy already cost before this search. Thus we can get:

$$E(B \mid L_{i-1} + 1 < d \le L_i + 1) = \sum_{j=1}^{i} |A_{L_j}| \tag{3}$$

The success probability of the i th search is

$$P\{L_{i-1} + 1 < d \le L_i + 1\} = (|A_{L_i+1}| - |A_{L_{i-1}+1}|) / N \tag{4}$$

Thus, we arrive at the following formula of the average energy cost.

$$\begin{aligned} E(B) &= E(E(B \mid d)) \\ &= E(B \mid d \le L_1 + 1) \times P\{d \le L_1 + 1\} + \\ &\quad \sum_{i=2}^{n} P\{L_{i-1} + 1 < d \le L_i + 1\} \times E(B \mid L_{i-1} + 1 < d \le L_i + 1) \\ &= |A_{L_1}| \times (|A_{L_1+1}| / N) + \sum_{i=2}^{n} \left(\sum_{j=1}^{i} |A_{L_j}| \times ((|A_{L_i+1}| - |A_{L_{i-1}+1}|) / N) \right) \end{aligned}$$

$F(x)$ is the percentage of nodes that can be reached within x hops from s . Substituting $F(x) = |A_x| / N$ in the equation above, we obtain the energy cost analytical model as

$$E(B)=N(F(L_1)+\sum_{i=2}^{n}F(L_i)\times(1-F(L_{i-1}+1))) \tag{5}$$

2.3. Relative Cost Ratio Analytical Model

We propose a relative cost ratio analytical model for comparing the energy cost of an ERS strategy with pure flooding in this section. The cost of the last search of $SSet$ is $|A_{L_n}|$ as we have explained. To make sure the destination can be detected in probability 1, the request in the last search should be received by all the nodes in the network, which makes the last search turn into pure flooding. Therefore, $|A_{L_n}|$ is also the energy cost of pure flooding. Comparing the energy cost of ERS with pure flooding, we can get relative cost ratio analytical model as follow.

$$\varphi(SSet)=(|A_{L_n}|-E(B))/N=\sum_{i=2}^{n}(F(L_{i-1}+1)F(L_i)-F(L_{i-1}))$$

Our goal is to find the best ERS strategy $SSet$ that can maximum φ. We analyze several inefficient ERS strategies in next section, and propose our optimization algorithm in Section Ⅳ

3. Inefficient ERS Strategies

Incremental ERS strategies have been widely used and studied in these years[9,14]. Researchers have proved that they can help to reduce energy cost in route discovery procedure of route protocols. However, we find some contrary phenomenon through our experiments, so it is important to figure out why, and then to decide when pure flooding should be used instead of ERS strategies. We first derive a necessary condition under which an ERS strategy is inefficient, and then give a lower bound for the radius of network where pure flooding should be used.

Theorem 1: $SSet=\{L_1,L_2,L_3,\cdots,L_n\}$ is an ERS strategy. For any $\varepsilon\le 1/12$, if $F(L_1)<\varepsilon$, $F(L_n)=1$, and $F(L_i)-F(L_{i-1})<\varepsilon$, then $\varphi(SSet)<0$.

Proof of Theorem 1:

$L_{i-1}+1\le L_i$, and $F(x)$ is an increasing function, then we can get $F(L_{i-1}+1)\le F(L_i)$.

$$\begin{aligned}\varphi(SSet)&=\sum_{i=2}^{n}(F(L_{i-1}+1)F(L_i)-F(L_{i-1}))\\&\le\sum_{i=2}^{n}F(L_i)F(L_i)-F(L_{i-1})<1+\sum_{i=1}^{n}F(L_i)^2-\sum_{i=1}^{n}F(L_i)\end{aligned}$$

$\varepsilon\le 1/12$, then there must be a K satisfying $2\le K\le 1/6\varepsilon$. $F(L_i)$ can be seen as monotonic sequence f_i in the range of $(0,1]$, so $f_i^2-f_i<0$. We focus on f_i in the range of $[K\varepsilon,1-K\varepsilon]$.

$$\varphi(SSet)<1+\sum_{i=1}^{n}(f_i^2-f_i)<1+\sum_{K\varepsilon\le f_i\le 1-K\varepsilon}(f_i^2-f_i)$$

$f_1<\varepsilon$, $0<f_i-f_{i-1}<\varepsilon$, and $f_n=1$, then the number of elements of sequence f_i in the range of $[K\varepsilon,1-K\varepsilon]$ is $\lfloor((1-2K\varepsilon)/\varepsilon)+1\rfloor$ at least, and $f_i^2-f_i\le K^2\varepsilon^2-K\varepsilon$. Assuming that f_m is the smallest element greater than $K\varepsilon$, we get

$$\varphi(SSet) < 1 + \sum_{i=m}^{m-1+\lfloor((1-2K\varepsilon)/\varepsilon)+1\rfloor} (f_i^2 - f_i)$$
$$< 1 + ((1-2K\varepsilon)/\varepsilon) \times (K^2\varepsilon^2 - K\varepsilon)$$
$$= 1 + (1-2K\varepsilon)(K^2\varepsilon - K) = 1 + K(3\varepsilon K - 1) - 2K^3\varepsilon^2$$
$$< 1 + K(3\varepsilon K - 1)$$

$2 \le K \le 1/6\varepsilon$, therefore $3K\varepsilon \le 1/2$. $\varphi(SSet) \le 1 + K(1/2 - 1) = 1 - K/2 \le 0$

The intuition behind this result is that an ERS strategy is inefficient if the successive search ranges are too close. It also implies that the search strategy with intensive search ranges, incremental ERS strategies for instance, should be carefully used in the network with large radius, where the condition of Theorem 1 can be satisfied easily. Incremental ERS strategies (TTL_a in short) increase the TTL value by a constant integer a after each failed search, i.e. $L_i = i \times a$. Using Theorem 1, we can deduce the theorem below.

Theorem 2: If $F(x) = (x/R)^m$, $SSet = \{L_1, L_2, L_3, \cdots, L_n\}$ is an incremental ERS strategy TTL_a, where a is a small integer, $n = \lfloor (R-1)/a \rfloor + 1$, $L_i = i \times a$ for $1 \le i < n$, and $L_n = R$, then $12a(2^m - 1)$ is a lower bond for R making $\varphi(SSet) < 0$.

Proof of Theorem 2:

$$F(L_{i+1}) - F(L_i) = ((a \times (i+1))/R)^m - ((a \times i)/R)^m < (a^m/R^m) \times (i^{m-1} \sum_{k=0}^{m-1} C_m^k)$$

Because $a \times i \le L_n = R$, we can get $i \le R/a$.

$$F(L_{i+1}) - F(L_i) < (a^m/R^m) \times \left((R/a)^{m-1} \sum_{k=0}^{m-1} C_m^k \right) = (a/R) \times (2^m - 1)$$

If $R > 12a(2^m - 1)$, then $F(L_{i+1}) - F(L_i) < 1/12$, and $F(L_1) = (a/R)^m < 1/12$, which satisfies the condition of Theorem 1, thus $\varphi(SSet) < 0$.

Theorem 2 implies that TTL_a is inefficient in large uniformly distributed wireless sensor networks, where the ratio of nodes reached within x hops can refer to the type $F(x) = (x/R)^m$. $m = 1,2,3$ correspond to a linear wireless sensor network, a wireless sensor network placed on land, and a wireless sensor network placed underwater respectively.

4. ERS Strategy Optimization

4.1 SSetOpt

To get the best strategy, let opt be the maximum $\varphi(SSet)$ under the condition $|SSet| \le S$, and the strategy corresponding to opt is the best strategy which is donated by $SSet^*$. Thus we have the ERS strategy optimization problem as follow.

$$opt = \max\{\varphi(SSet)\} = \max \sum_{i=2}^{n} (F(L_{i-1}+1)F(L_i) - F(L_{i-1})), n \le S$$

We donate the maximum $\varphi(SSet)$ under the condition that $|SSet| \le r$ and the TTL value of the first search is m by $Q(m,r)$, where $1 \le m \le R-1, 1 \le r \le S$. The value of m is $R-1$ at most, since the request with a preset TTL value of $R-1$ can reach all the nodes. When the request reaches the node at the distance of R, the TTL is just decreased to 0, and the node receives the request without making any transmissions. This is reasonable since it is already the farthest node from s.

$$Q(m,r)=\max_{L_1=m;n\le r}\{\sum_{i=2}^{n}F(L_{i-1}+1)F(L_i)-F(L_{i-1})\}\tag{6}$$

Thus, the value of opt can be obtained by solving $R-1$ related sub-problems:

$$opt=\max_{1\le m\le R-1}\{Q(m,S)\}\tag{7}$$

$Q(m,r)$ can be rewrite as

$$Q(m,r)=\max_{m+1\le k\le R-1}\{F(m+1)F(k)-F(m)+Q(k,r-1)\}\tag{8}$$

$Q(m,r)$ can be obtained recursively as shown in Eq. (8). We should note $Q(R-1,r)=0$, since an ERS strategy costs the same amount of energy as pure flooding when the TTL value of the first search is $R-1$. If $r=1$ and $1\le m\le R-2$, $Q(m,r)$ corresponds to the strategy that there is only one search, and the searching range is not big enough to cover the whole network. This strategy makes no sense, and we assign -1 to $Q(m,r)$. Thus, we have

$$Q(m,r)=\begin{cases}-1 & ,1\le m\le R-2, r=1\\ 0 & m=R-1, r\ge 1\end{cases}\tag{9}$$

It requires $R-m$ comparisons to calculate $Q(m,r)$. If $F(m+1)F(k)-F(m)+Q(k,r-1)$ is the maximum one of the $R-m$ items in Eq. (8), then k is the optimal TTL value of the next search when the current search with TTL value m fails. Let $pre(m,r)$ be the k corresponding to $Q(m,r)$.

When we solve Eq. (7) and (8), it is obvious that some sub-problems are solved over and over, thus dynamic method can be applied. There is a triple-nested loop structure in the optimization algorithm, the running time is $O(S\times R^2/2)$.

4.2. Searching based on SSetOpt

The source node knows the locations of other nodes. It first obtains the $F(x)$ according to the locations, and gets an ERS strategy, $SSet*$, according to the SSetOpt. (The input, S ,of Algorithm 1 can decide the optimization level of the strategy obtained.)

$$SSet*=\{L_1*,L_2*,L_3*,...,L_n*\}, n\le S$$

When the source node wants to discover a destination by flooding, the first search is started with TTL value L_1*. A request with TTL value L_1* is broadcasted. When a node receives the request, it checks whether it is the target. If so, it sends a reply to the source node; if not, it checks whether the TTL of the request is larger than 0. If the answer is yes, it decreases the TTL value by one and broadcasts the request; if no, it does nothing.The i th search is started with TTL value L_i*, if the $i-1$th search fails.This process continues until the target is found or the number of searches reaches n

5. Simulation

5.1 Simulation Setup

We compare SSetOpt with the strategies in [1], California Split[9] and TTL_2 in this Section. The network is distributed in a circle terrain with radius denoted by Rmax. Each node transmits a received request exactly once, and the request reaches every other node within transmission radius, $Tr=50$ m. Nodes disregard multiple copies of the same request. We subsequently assume all transmissions are correctly received. The strategy of Jing ($n=2$) is $\{\lfloor (R-1)/2\rfloor, R-1\}$, and the strategy of Jing ($n=3$) is $\{R/3,(R-1)^2/(2R-25/9),R-1\}$, where R is estimated by $Rmax/Tr$. The strategy of California Split is $\{1,2,4,8,...\}$, and TTL_2 uses the strategy $\{2,4,6,8,...\}$. The simulation scenarios: (i) Density: We consider a network with $Rmax = 300$ m and the source node fixed at the origin, and N is varied from 400 to 4000 in increments of 160. (ii) Source node locations: We consider a network with $Rmax = 300$ m and $N = 1000$. The distance between the terrain center and the source node location, X, is varied from 0 to 150 m in increments of 25 m. (iii) Terrain radius: We consider a network with the source node fixed at the center and 0.00127 nodes per square meter, and $Rmax$ is varied from 300 m to 1300 m in increments of 100 m.

5.2. Density

The energy cost presented in Figure 1 shows that pure flooding is the most energy consuming strategy. Jing ($n = 2$) and SSetOpt ($S = 4$) can reduce the energy cost by 25% compared with pure flooding when $N > 1500$ as we can see from Figure 2. It also shows that SSetOpt ($S = 4$) costs 5% less energy than Jing ($n = 2$) and 13% less energy than Jing ($n = 3$) when $N > 1500$ and the average degree is less than 30 according to our statistics. Comparing with TTL_2, SSetOpt has an energy saving of 5% when $N > 1500$. Through our experiment, we find that some nodes cannot be located using Jing ($n = 2,3$), because these nodes cannot be reached in $\mathrm{R} = \mathrm{Rmax} / \mathrm{tr}$ hops though they are within Rmax meters from the source, thus we have to add another search with a large TTL value to make sure that the destination can be detected in the probability of 1. The sparser the network is, the more these nodes exist. Jing ($n = 2$), the strategy for dense networks, does not consider these nodes. This is the reason why its performance decreases fast with network density. By adding another search, Jing ($n = 2$) becomes a three-tire strategy. If $S = 2$, the number of searches in the strategy obtained by SSetOpt is 2, which is less than that of Jing ($n = 2$). This is the reason why SSetOpt is better than Jing ($n = 2$) when $S \geq 3$.

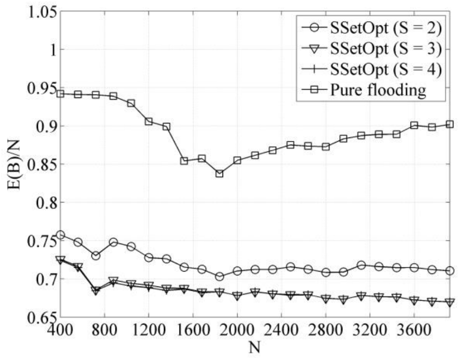

Figure 1. The Energy Cost of SSetopt at Different Density

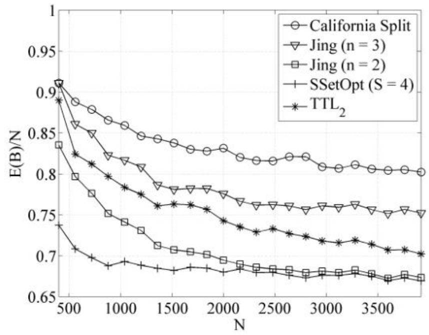

Figure 2. The Comparison of Energy Cost at Different Density

Since California Split, pure flooding and TTL_2 do not need the knowledge of network topology, while the others do, so in small networks with the source node located at the origin, if the knowledge is unknown, the best strategy is TTL_2 as we can see from Figure 2, but if the knowledge is known, the best one is our method.

5.3. Source Node Locations

The previous test considers the ideal scenario, where the source node is located at the origin. We conduct another test to see the effect of source node locations on energy cost. The results are presented in Figure 3 and Figure 4. With the increase of X , the energy cost of TTL_2 increases fast, exceeding California Split and Jing ($n=3$), and becomes the most energy consuming strategy as we can see from Figure 4. The performance of Jing($n=3$) is worse than Jing($n=2$). Comparing with Jing ($n=2$), SSetOpt has an energy saving of 5%. Therefore, if the source node is not located at the origin and the knowledge of topology is unknown, TTL_2 is not a good strategy since its energy cost is hard to predict as we can see from Figure 4. Thus the knowledge is necessary. If the knowledge is known, SSetOpt is better than other strategies.

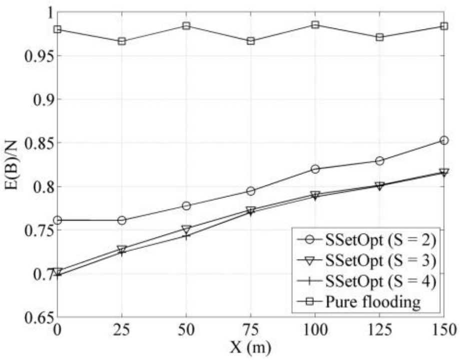

Figure 3. The Energy Cost of SSetopt at Different Source Node Locations

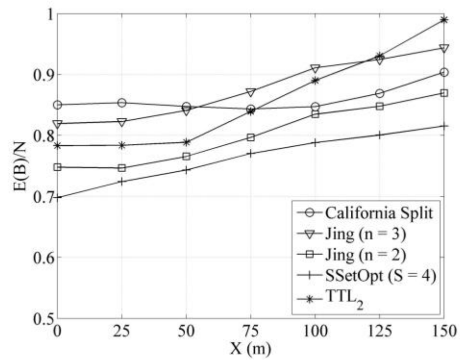

Figure 4. The Comparison of Energy Cost at Different Source Node Locations

6. Conclusions

ERS is a widely used flooding technique for locating destinations or information in wireless sensor networks. We focus on the problem concerning the best ERS strategy in the networks with various density, not confining to the dense ones. We analyze the running process of ERS strategies, and propose two analytical models, energy cost analytical model and relative cost ratio analytical model. We prove that the incremental

ERS strategies are inefficient in large-scale wireless sensor networks, and give a lower bound $12a(2^m - 1)$ of the network radius when pure flooding should be used instead of TTL_a, which increases the TTL value of next search by a constant integer a after each search fails. We also propose an optimization algorithm, SSetOpt, for obtaining the best ERS strategy with searching attempts less than S. The simulation results show that the strategy obtained by SSetOpt can reduce the energy cost by 25% compared with pure flooding in dense networks with small radius. Comparing with the strategies in [1], SSetOpt has a less amount of energy cost over 5%, when the network is sparse, say, the average degree is less than 30.

We assume that the percentage of nodes reached with x hops from the source node is known as a prior. In some applications, $F(x)$ is unknown. How can the source node obtain $F(x)$ automatically, and generate an optimal ERS strategy? Moreover, the performance of SSetOpt decreases with the increase of network radius. How to combine ERS with other techniques to solve this problem? Our future work will focus on these questions.

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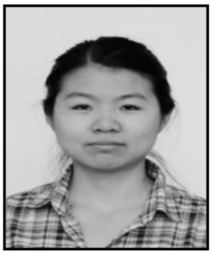

Xiuxiu Wen, She received her B.E. degree in computer science and technology from the Harbin Engineering University (HEU), Harbin, China, in 2011. She is recently working towards her Ph.D. degree at HEU. Her research interests involve cross-layer design and information sensing. Recently, she focuses on the efficient discovery strategies for wireless network.

Huiqiang Wang, He received the B.E. degree in computer science and technology from Harbin Institute of Technology (HIT) in 1982, received M.E. and Ph.D. degrees in Technology of Computer Application from HEU in 1985 and 2005 respectively. From 2001 to 2002, he was at Queen's University, Ontario, Canada, as a senior visiting scholar. Since then, he has been engaged in teaching and researching at computer networks and communications.

Guangsheng Feng, He received his B.S., M.S and Ph.D. from HEU in 2003, HIT in 2005, and HEU in 2009 respectively. Now, he is engaging in teaching and researching at Cognitive Networks. He is a full stuff at HEU. His research interests involve cross-layer design, information sensing and wireless channel access control.

Hongwu Lv, He received his B.S. and Ph.D. from HEU in 2006 and 2011 respectively. Now, he is engaging in teaching and researching at Performance Evaluation. He is a full stuff at HEU. His research interests involve Markov chains and fluid-flow approximation.

Junyu Lin, He received his B.S. and Ph.D. from HEU in 2007 and 2014 respectively. Now, he is engaging in researching at ubiquitous network architecture. He is a full stuff at HEU.

Qiang Zhu, He received his B.S. and M.S. degree in computer science and technology from the Harbin Engineering University in 2009 and 2011. He is recently working towards his Ph.D. degree at HEU. His research interests involve network virtualization and cloud computing.