

# Multi-Path Planning for Mobile Element to Prolong the Lifetime of Wireless Sensor Networks\*

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## Abstract

*Mobile elements, which can traverse the deployment area and convey the observed data from static sensor nodes to a base station, have been introduced for energy efficient data collection in wireless sensor networks (WSNs). However, most existing solutions only plan a single path for the mobile element, which may lead to quick energy depletion for the sensor nodes that are far away from the path. In this paper, for data collection in WSNs, we study the multi-path planning (MPP) problem for the mobile element to prolong the lifetime of WSNs. Observing the intractability of the problem, two MPP heuristic schemes, namely fixed-K and adaptive-K, are proposed. The central idea of these schemes is to plan multiple paths and have the mobile element follow them in turn to balance the energy consumption on individual sensor nodes, thus extending the lifetime of WSNs. The proposed schemes are evaluated through extensive simulations. The results show that, compared to that of the single path solution, the multi-path approaches can extend the lifetime of WSNs by up to **four times**. Moreover, the adaptive-K scheme treats the sensor nodes more fairly with less variation on their energy consumptions.*

## 1 Introduction

In the recent past, the popularity of wireless sensor networks (WSNs) has been manifested by their deployment in many real-life applications (e.g., habitat study [13] and ecology monitoring [19]). With potentially a large number of sensor nodes scattered in a region of interest, one of the challenging problems in WSNs is how to efficiently aggregate the data sampled at each node to a base station, which has the computational power to store and process all the collected data [1, 7]. Note that, sensor nodes are generally

battery powered and it is hard (if not impossible) to replace those batteries after their deployment. Therefore, developing energy efficient data collection schemes is ultimately important to reduce the energy consumption on individual sensor nodes, and thus extending the lifetime of WSNs.

In conventional WSN deployments, the data aggregation is normally achieved through *multi-hop data forwarding* schemes [1]. In these schemes, for the sensor nodes that are far away and can not reach the base station in a single hop, their data will be relayed by their neighbors that are closer to the base station. However, the major shortcoming of such schemes is that the energy for the sensor nodes that are close to the base station will be quickly depleted due to their high data transmission activities, thus limiting the lifetime of WSNs.

To address this problem, the mobility of base stations has been exploited, where the base station moves around in the field to collect data from sensor nodes [3, 4, 8]. For the cases where the base station are not moveable, energy efficient data collection schemes that exploit *mobile elements*, which can move around the deployed field and convey the data from each sensor node to the base station, have been studied [9, 10, 17, 23, 24]. The main challenge in these schemes is how to control the mobility of the mobile elements for efficient data collection while satisfying various constraints (e.g., before buffer is full on each sensor node [10]). More recently, considering the constraint that the mobile element may not be reachable from every sensor node, the *hybrid* approaches that combine the idea of multi-hop data forwarding and mobile elements have been explored [12, 21, 23]. Here, the data is first aggregated locally using multi-hop schemes to some rendezvous points. Then, the mobile element visits only these rendezvous points to pick the data up [12, 23].

Note that, in most of the existing studies involving mobile elements, only a *single* path is calculated for each mobile element and the same path is followed repeatedly during data collection [12, 21, 23, 24]. However, such solutions with a single path for the mobile element may still

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lead to *uneven* energy depletion rates for the sensor nodes in WSNs, especially for the cases where the mobile element needs to collect data directly from every sensor node but it cannot visit the location of all sensor nodes (due to, for example, energy budget of the mobile element or time limitations). The sensor nodes that are far away from the path will need to transmit their data to the mobile element at higher power levels and thus use up their energy budget more quickly. For WSNs that rely on *all* their sensor nodes for normal operations, such uneven energy depletion will lead to limited lifetime of WSNs.

Different from the existing single-path solutions, in our preliminary study, we have proposed the idea of exploiting multiple paths for the mobile element in WSNs to extend the WSN's lifetime [25]. However, no detailed algorithm and simulation results were reported in the preliminary work.

In this paper, for the problem of data collection in WSNs using a single mobile element that collects data *directly* from every sensor node, we study systematically the *multi-path planning (MPP)* problem. The key idea is to calculate multiple paths for the mobile element, which will be followed *in turn* during data collection in order to *balance* the energy consumption on individual sensor nodes, thus to extend the lifetime of the WSNs. After showing the intractability of the problem, we study two MPP heuristic schemes, *fixed-K* and *adaptive-K*, based on different path planning strategies. The proposed heuristic schemes are evaluated through extensive simulations. The results show the superiority of the proposed multi-path schemes on extending the lifetime of WSNs when compared to that of single-path solutions (e.g., up to 4 times with 20 paths).

The remainder of the paper is organized as follows. Section 2 presents the system models and states our assumptions. Section 3 illustrates the problem with a motivational example and formalizes the problem. The multi-path planning heuristics are presented in Section 4 and simulation results are discussed in Section 5. Section 6 discusses the related work. Section 7 concludes the paper and points out the directions for our future work.

## 2 System Models and Assumptions

The WSN considered in this work consists of a set  $\Phi$  of  $n$  sensor nodes, a base station (BS) and a mobile element. The  $n$  sensor nodes are statically deployed in the field of interest where node  $N_i$  ( $i = 1, \dots, n$ ) is at location  $(x_i, y_i)$ , which is assumed to be known a priori. So does the location of the base station at  $(x_0, y_0)$ . Departing from the base station, the mobile element needs to travel through the field, collect data *directly* from all the sensor nodes and return to the base station for conveying the collected data (and/or recharging) within a given time interval  $T$ . Here, the time interval  $T$

could be determined by the data sampling rate and buffer size on the sensor nodes [10], or by the amount of available energy (after being fully recharged) to drive the mobile element. We further assume that the mobile element moves at a constant speed  $S$  and the maximum length of its *travel path (PH)* should be no more than  $L = S \cdot T$ .

Suppose that the *distance* from a sensor node to the travel path of the mobile element is  $d$  (which is defined as the minimum distance from the location of the sensor node to the nearest point on the travel path). During data collection, when the sensor node transmits its data to the mobile element through wireless communication, it is well-known that the required transmission power directly depends on the distance  $d$ , which can be modeled as [15]:

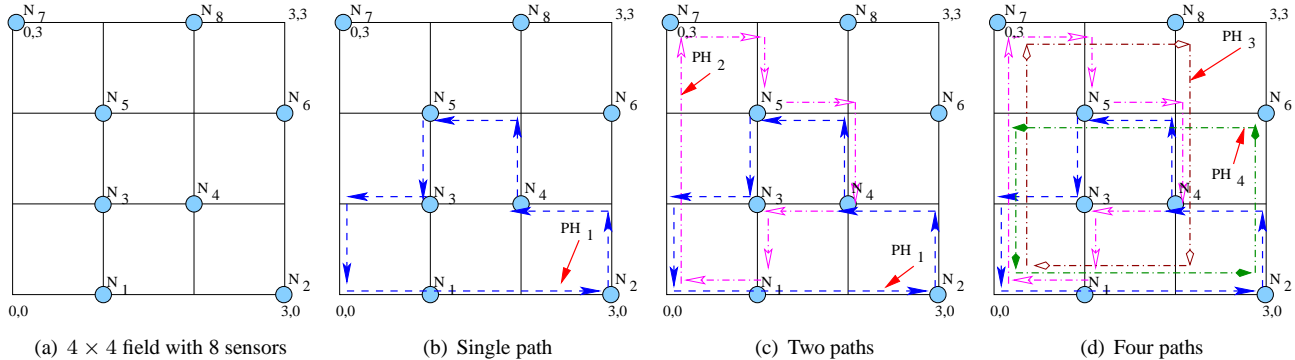
$$P(d) = \gamma + \alpha d^\beta \quad (1)$$

where  $\gamma$  and  $\alpha$  are system dependent parameters and  $2 \leq \beta \leq 4$ . And, in general,  $\gamma$  is a small constant.

Modern sensor nodes normally have a few discrete power levels that can transmit data in different ranges (e.g., Tmote Sky sensors have 32 different power levels [16]). In this paper, we assume that the sensor nodes considered have  $m$  different power levels, which are represented as  $m$  couples:  $(P_1, R_1), \dots, (P_m, R_m)$ , where  $R_i$  is the transmission range when sensor nodes transmit at power level  $P_i$ . Here, the maximum transmission power level  $P^{max} = P_m$  limits the maximum transmission range to be  $d^{max} = R_m$ . For instance, Tmote Sky sensor nodes can transmit up to 125 meters at its maximum transmission power level [16]. Note that, the maximum distance from any sensor node to the travel paths of the mobile element should be no more than  $d^{max}$  (otherwise, the mobile element will not be able to directly collect the data from such sensor node). Moreover, the minimum transmission power level  $P^{min} = P_1$  allows the sensor nodes to transmit data up to distance of  $d^{min} = R_1$  (e.g., when Tmote Sky sensor nodes transmit at the lowest power level, the smallest range is measured to be around 0.15 meter).

Assuming that the sensor nodes have the same constant sampling rate, the amount of data collected at each node will be the same during any time interval  $T$ . Suppose that the wireless data transmission speed does not depend on the transmission power (which only affects the transmission range), the data transmission time  $t$  will be a constant value. Suppose that  $d_i$  is the distance from the location of sensor node  $N_i$  to a travel path  $PH$ . When the mobile element follows the path  $PH$  during one round of data collection, the amount of energy consumed by the sensor node  $N_i$  for transmitting its data to the mobile element will be  $E_i = P_x \cdot t$ , where the power level  $P_x$  corresponds to  $R_x$  with  $R_{x-1} < d_i \leq R_x$ . That is, the energy consumption of a sensor node to transmit its data depends solely on  $d_i$ .

Therefore, if the mobile element could *visit* the location



**Figure 1. Motivational example: path planning for the mobile element.**

of *each* and *every* sensor node (that is, the distance from every sensor node to the travel path of the mobile element is no more than  $d^{min}$ ), all sensor nodes can transmit their data to the mobile element at their minimum power level  $P^{min}$  with minimized energy consumption, which in turn maximizes the WSN's lifetime. In this paper, we consider the cases where the path length  $L$  of the mobile element is not enough for it to visit all the sensor nodes. Therefore, for the sensor nodes that are not on the mobile element travel path during one round of data collection, they need to transmit at a power level higher than  $P^{min}$  for the mobile element to successfully receive their data. Moreover, we assume that the WSN is functional only if *all* sensor nodes are alive (i.e., when *any* sensor node uses up its energy and dies, the WSN will die). In other words, assuming that all sensor nodes have the same energy budget at their initial deployment, the lifetime of the WSN depends on the sensor node that consumes the highest amount of energy.

In what follows, before formally presenting the problem, we illustrate the problem through a concrete example.

### 3 Motivational Example

We consider an example with 8 sensor nodes placed on a  $4 \times 4$  grid field as shown in Figure 1(a). Here, the base station is located at  $(0, 0)$ . For illustration purpose, we assume that the mobile element needs to follow the grid on the field. Suppose that the grid size is 1 and the path length limit of the mobile element is 10. It can be easily seen that it is not possible for the mobile element to visit each and every sensor node during one round of data collection within its path length limit.

Assume that the power consumption for the sensor nodes is modeled as in Equation 1 and  $\gamma = 0$ ,  $\alpha = 1$ ,  $\beta = 2$ ,  $P^{max} = 2$  (i.e.,  $d^{max} = \sqrt{2}$ ),  $P^{min} = 0.1$  (i.e.,  $d^{min} = \sqrt{0.1}$ ) and the transmission time  $t = 1$ . If a path  $PH_1$ , as shown in Figure 1(b), is planned for single path schemes, after 12 rounds of data collection, the energy consumption for the sensor nodes to transmit their data is shown in the

	$PS_1$	$PS_2$	$PS_3$
$N_1$	1.2	1.2	1.2
$N_2$	1.2	12.6	9.6
$N_3$	1.2	1.2	6.6
$N_4$	1.2	1.2	3.9
$N_5$	1.2	1.2	3.9
$N_6$	12	12	9.3
$N_7$	24	12	9.6
$N_8$	12	12.6	9.3

**Table 1. Energy consumed by the sensor nodes for transmitting data during 12 rounds of data collection with different sets of paths. Here,  $PS_1 = \{PH_1\}$ ,  $PS_2 = \{PH_1, PH_2\}$  and  $PS_3 = \{PH_1, PH_2, PH_3, PH_4\}$ .**

second column (i.e., labeled as *path set*  $PS_1$ ) in Table 1. Here, we can see that node  $N_7$  consumes 24 units of energy, which is much more than that of other sensor nodes.

Instead of always following the same path  $PH_1$ , we may calculate two paths ( $PH_1$  and  $PH_2$ , as shown in Figure 1(c)) and let the mobile element follow them alternatively. In this case, for 12 rounds of data collection, the mobile element will follow each path 6 times and the overall energy consumption of each node is shown in the third column (labeled as path set  $PS_2$ ) of Table 1, with the maximum energy consumption being 12.6 units for nodes  $N_2$  and  $N_7$ . Note that, during any round of data collection, the mobile element needs to collect data from all the sensor nodes, regardless of whether they are on its travel path or not during that round of data collection. Recall that the WSN is assumed to be able to operate until the first node uses up its energy. Therefore, we can easily see that using two paths can almost *double* the lifetime of the WSN when compared to that of the single path option.

Intuitively, the lifetime of the WSN can be further improved if more paths can be exploited. Figure 1(d) shows one solution with four paths ( $PH_1, PH_2, PH_3$  and  $PH_4$ ).

After each path is followed 3 times, the corresponding energy consumption for the nodes during 12 rounds of data collection is shown in the fourth column (labeled as path set  $PS_3$ ) of Table 1. Here, the maximum energy consumption for the nodes is only 9.6 units (for nodes  $N_2$  and  $N_7$ ). Compared to that of the case with two paths, the four-path option can achieve about 25% more lifetime for the WSN.

### 3.1 Problem Formulation

Assuming that the WSN under consideration can operate until the *first* node uses up its energy and dies, for a given path number  $K$ , the objective of this work is to find an efficient approach to construct the appropriate set of  $K$  paths for the mobile element, such that the energy consumption for the most energy-hungry sensor node is minimized.

Define  $E_{i,j}$  as the energy consumption for the sensor node  $N_i$  when the path  $PH_j$  is followed by the mobile element, we have:

$$E_{i,j} = P(d_i^j) \cdot t \quad (2)$$

where  $d_i^j$  is the shortest distance from the path  $PH_j$  to the location of sensor node  $N_i$  and  $P(d_i^j)$  is the corresponding power level. Moreover, when the constructed  $K$  paths are followed in turn by the mobile element, the *average* energy consumption for sensor node  $N_i$  during one round of data collection is defined as:

$$E_i = \frac{\sum_{j=1}^K E_{i,j}}{K}. \quad (3)$$

Therefore, the *multi-path planning (MPP)* problem can be formally stated as follows. For the WSN with  $n$  static sensor nodes being deployed in the field at known locations, construct the set of  $K$  paths  $PS = \{PH_1, \dots, PH_K\}$  for the mobile element, so as to:

$$\text{Minimize} \left( \max_{\forall i} E_i \right) \quad (4)$$

subject to

$$|PH_j| \leq L, \forall j \quad (5)$$

$$d_i^j \leq d^{max}, \forall i \forall j \quad (6)$$

where  $|PH_j|$  stands for the length of path  $PH_j$ . Here, the first condition (Equation 5) states that, the length for any constructed path should be within the path length limit  $L$ ; and the second condition (Equation 6) ensures that the distance from any sensor node to any path is within the maximum distance limit  $d^{max}$  for the mobile element to collect data directly from all sensor nodes when it follows the paths constructed.

### 3.2 Intractability of the MPP Problem

We next show that the general MPP problem is NP-complete and outline the reasoning. We do this in stages. First, we show that when  $K = 1$ , the problem is NP-complete. This can then be used to show that the version with  $K$  paths is NP-complete as well using restriction.

For the case of  $K = 1$ , we redefine the problem as the *Sensor Power Problem*: given  $n$  points  $N_1 \dots N_n$ , what is the minimal power range a mobile element can use to communicate with all the sensors while its travel path has a maximum length of  $L$ ? To show the problem is NP-complete, we can adopt the decision version of the sensor power problem and name it *Sensor Power Decision Problem*, which is stated as follows: given  $n$  points  $N_1 \dots N_n$  and a range  $\epsilon$ , is  $\epsilon$  range sufficient for the mobile element to communicate with all the sensors while traveling on a path with the maximum length of  $L$ ?

Next, we use decision version of *travel salesman problem (TSP)* with neighborhoods for reduction to show NP-completeness [2]. *TSP with Neighborhoods Problem* can be stated formally as: given  $n$  points  $N_1 \dots N_n$  with respective neighborhoods  $\epsilon_1 \dots \epsilon_n$ , is there a path with length  $X$  that allows the salesman to visit all the neighborhoods? We reduce sensor power decision problem to TSP with neighborhoods as follows: set  $\epsilon_i = \epsilon$ ,  $1 \leq i \leq n$  and  $M = L$ . Solving this TSP with neighborhood problem will solve sensor power decision problem. It is known that TSP with neighborhood problem is NP-complete [2]. Therefore, sensor power decision problem is NP-complete and sensor power problem is NP-complete as well. Since one path version of the problem is NP-complete,  $K$  path version of sensor power problem is also NP-complete.

## 4 Multi-Path Planning (MPP) Heuristics

From the motivational example, we can see that the lifetime of WSNs under consideration depends on not only the number of paths (i.e.,  $K$ ) to be constructed, but also the track of each path (i.e., where it goes and the distance from the path to every sensor node). Recall that, due to the path length limitation, we assume that *any* constructed travel path within the path length limit cannot enable the mobile element to *pass by* (with the distance being no more than  $d^{min}$ ) the location of each and every sensor node. Therefore, to maximize the lifetime of a WSN, the planned paths should aim to *balance* the energy consumption on the sensor nodes. That is, if a sensor node is far away from one path (thus consumes more energy for transmitting its data during that round of data collection), it should be on or close to other travel paths of the mobile element.

Define a *feasible* travel path for the mobile element as the one that satisfies the constraints represented by Equa-

tions 5 and 6. That is, its length should be no more than the path length limit  $L$  and the distance from the path to *any* sensor node should be no more than the maximum distance limit  $d^{max}$ . Moreover, without exceeding the path length limit  $L$ , the constructed travel path should be as close to the sensor nodes that are not on the path as possible. Following these guidelines, in this work, we study multi-path planning (MPP) heuristics based on the idea of *seed nodes*, where a partial path is first constructed based on a subset of sensor nodes (defined as *seed nodes*) and then expanded to consider other non-seed nodes.

In what follows, we first address how to construct a single feasible travel path for the mobile element that will pass by a subset of *seed nodes*. Then, based on different strategies to select the subsets of seed nodes, we propose two MPP heuristics: *fixed-K* and *adaptive-K* schemes.

#### 4.1 Single Path Construction with Seed Nodes

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##### Algorithm 1 : SinglePathConstruction

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- 1: **Input:** location of all sensor nodes and base station, and the set  $\Psi_j$  of seed nodes;
  - 2: **Step 1:** Get path  $PH_j$  from  $\Psi_j$  using TSP heuristics;
  - 3: **Step 2:**//extend path to ensure  $d^{max}$
  - 4: **while** ( $\exists N_i \in \Phi - \Psi_j$  such that  $d_i^j > d^{max}$ ) **do**
  - 5:   //Here,  $d_i^j$  is the distance from  $N_i$  to  $PH_j$ ;
  - 6:   Expand path  $PH_j$  to ensure  $d_i^j \leq d^{max}$ ;
  - 7: **end while**
  - 8: **if** (Length of path  $PH_j: L_j > L$ ) **then**
  - 9:   The construction of  $PH_j$  fails and exits;
  - 10: **end if**
  - 11: **Step 3:**//further path extension to length limit  $L$ ;
  - 12: **while** Length of path  $PH_j: L_j < L$  **do**
  - 13:    $N_m = \text{PickNodeForFurtherExpansion}()$ ;
  - 14:   Calculate path increase  $\Delta$  for  $PH_j$  to reach  $N_m$ ;
  - 15:   **if** ( $\Delta \leq L - L_j$ ) **then**
  - 16:     Expand  $PH_j$  to reach  $N_m: d_m^j = d^{min}$ ;
  - 17:   **else**
  - 18:     Expand  $PH_j$  with length increase as  $L - L_j$ ;
  - 19:   **end if**
  - 20: **end while**
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For a given subset of seed sensor nodes  $\Psi_j \subset \Phi$  ( $j = 1, \dots, K$ ), the outline for constructing the  $j$ 'th path is shown in Algorithm 1. Basically, there are three steps. First, exploiting the existing heuristic solutions for the TSP (e.g., the minimum spanning tree based approach [5]), an initial *partial* travel path can be constructed by solving the corresponding TSP problem with the seed nodes. Note that, the initial path will pass by all the seed nodes, which enables the seed nodes to transmit their data to the mobile element at the minimum power level  $P^{min}$ .

Then, in the second step, the initial partial path will be *minimally* expanded. That is, if the distance from a non-seed sensor node to the path is no more than  $d^{max}$ , the sensor node can transmit its data directly to the mobile element with a higher power level, but no path expansion is needed. However, for the non-seed sensor nodes that have the distance being more than  $d^{max}$ , the path will be expanded iteratively to ensure that the distance from the path to all sensor nodes is no more than  $d^{max}$  (i.e., the constraint of Equation 6). This will ensure that the mobile element can collect the data from all sensor nodes directly while it follows the path. The details of the path expansion are shown in the next subsection. If the length of the expanded path is no more than the path length limit  $L$  (i.e., the constraint of Equation 5), a feasible path is obtained; otherwise, the heuristic fails to construct a feasible path with the selected seed nodes (in this case, the algorithm can declare a failure, or choose another set of seed nodes).

If a feasible path is obtained in the second step with the path length being less than  $L$ , the path will be *further* expanded in the last step to reach as many non-seed nodes as possible. That is, following a certain strategy (which is different for the fixed-K and adaptive-K heuristics, as discussed below), some non-seed nodes that are far away from the path will be selected (line 13) and the path is expanded to pass by them one by one until the length of the path reaches the limit  $L$ .

**Path Expansion** Note that, in Algorithm 1, there are two important steps of path expansion. For the non-seed nodes that are far away from the initial partial path with the distance being more than the maximum transmission range  $d^{max}$ , the first path expansion (i.e., Step 2) needs to reduce the distance to be no more than  $d^{max}$  and to obtain a feasible travel path. In the further path expansion (i.e., Step 3), the path is expanded with the goal of passing by as many sensor nodes as possible within the path length limit  $L$ . However, the principle on how to expand the path is the same for these two steps and is discussed next.

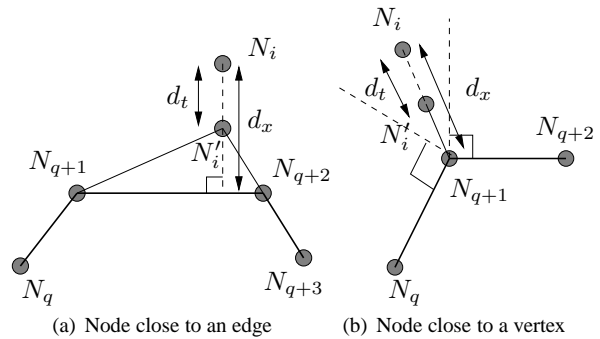


Figure 2. Addition of a node to a path

Suppose that the path to be constructed is  $PH_j$  ( $j = 1, \dots, K$ ) and the distance from  $PH_j$  to a non-seed node  $N_i$  is  $d_x$ . Depending on which point on the path  $PH_j$  has the minimum distance to  $N_i$ , as illustrated in Figure 2, there are two different cases for expanding path  $PH_j$ .

In the first case, as shown in Figure 2(a), the closest point to node  $N_i$  is on one edge of path  $PH_j$ , which is from node  $N_{q+1}$  to node  $N_{q+2}$ . If the distance  $d_x$  is larger than the target distance  $d_t$ , one virtual node  $N'_i$  will be added such that the distance from  $N'_i$  to the node  $N_i$  equals  $d_t$ . Here, we have the target distance  $d_t = d^{max}$  for the path expansion in Step 2 which ensures the feasibility of the expanded path. For the further path expansion in Step 3, for simplicity, we adopt a greedy approach and set  $d_t = d^{min}$ . That is, for the selected non-seed sensor nodes, the further path expansion enables the mobile element collect data from such nodes even when they transmit the data with the minimum power level  $P^{min}$ .

Note that, the location of the virtual node  $N'_i$  can be easily obtained from the position of nodes  $N_i$ ,  $N_{q+1}$  and  $N_{q+2}$ . After that, the path  $PH_j$  will be expanded by *adding* two new edges (one is from node  $N_{q+1}$  to the virtual node  $N'_i$  and the other is from  $N'_i$  to node  $N_{q+2}$ ) while *removing* the edge from node  $N_{q+1}$  to node  $N_{q+2}$ . Here, the path length of  $PH_j$  will increase by  $\Delta = |N_{q+1}, N'_i| + |N'_i, N_{q+2}| - |N_{q+1}, N_{q+2}|$ .

The second case is shown in Figure 2(b), where the closest point on the path  $PH_j$  to the node  $N_i$  is at one vertex  $N_{q+1}$ . The same as before, if the distance from node  $N_{q+1}$  to vertex  $N_i$  is  $d_x$  and larger than the target distance  $d_t$ , one virtual node  $N'_i$  will be added and two *overlapped* edges will be added to the path  $PH_j$ : one is from  $N_{q+1}$  to  $N'_i$  and another is from  $N'_i$  to  $N_{q+1}$ . Similarly, the location of the virtual node  $N'_i$  can be determined by setting the distance from  $N'_i$  to  $N_i$  as  $d_t$ . And the path length of  $PH_j$  will increase by  $\Delta = 2 \cdot |N_{q+1}, N'_i|$  (that is,  $2 \cdot (d_x - d_t)$ ).

## 4.2 Fixed-K MPP Scheme

From Algorithm 1, we can also see that the selection of seed nodes is *crucial* since these sensor nodes are assured to be able to transmit their data at the minimum power level  $P^{min}$  when the mobile element follows the corresponding generated travel path. Depending on *when* and *how* the seed nodes are selected, we first discuss the *fixed-K* heuristic scheme, where the seed nodes are *statically* determined for each path to be constructed. Here, to guarantee that each sensor node to serve as a seed node and on *at least* one of the generated travel paths, the fixed-K heuristic scheme first statically divides the sensor nodes into  $K$  subsets (with  $\lceil \frac{n}{K} \rceil$  seed sensor nodes in each set), where the  $j$ 'th subset will serve as the set of seed nodes when the  $j$ 'th path is constructed using Algorithm 1.

Note that, for the fixed-K scheme, the paths will be constructed *independently*. That is, the construction of one path does not depend on other paths. More specifically, after a feasible path is created following the first two steps in Algorithm 1, during the further path expansion in Step 3, the non-seed sensor nodes that have the largest distance to the path will be selected (line 13 in Algorithm 1), regardless how much energy it consumes while the mobile element follows other  $(K - 1)$  paths.

## 4.3 Adaptive-K MPP Scheme

Instead of determining the seed nodes for all the paths statically, the *adaptive-K* scheme chooses the seed nodes for the  $j$ 'th path construction based on the energy consumed by the sensor nodes during the data collection when the first  $j - 1$  ( $j = 2, \dots, K$ ) paths are followed by the mobile element. Here, to achieve better balance on the energy consumption of the sensor nodes, a subset of sensor nodes that consume the highest amount of energy when the mobile element follows the first  $j - 1$  paths will be selected as seed nodes. That is, the construction of the  $j$ 'th path will depend on previous constructed paths. For the first path, the seed nodes can be randomly selected.

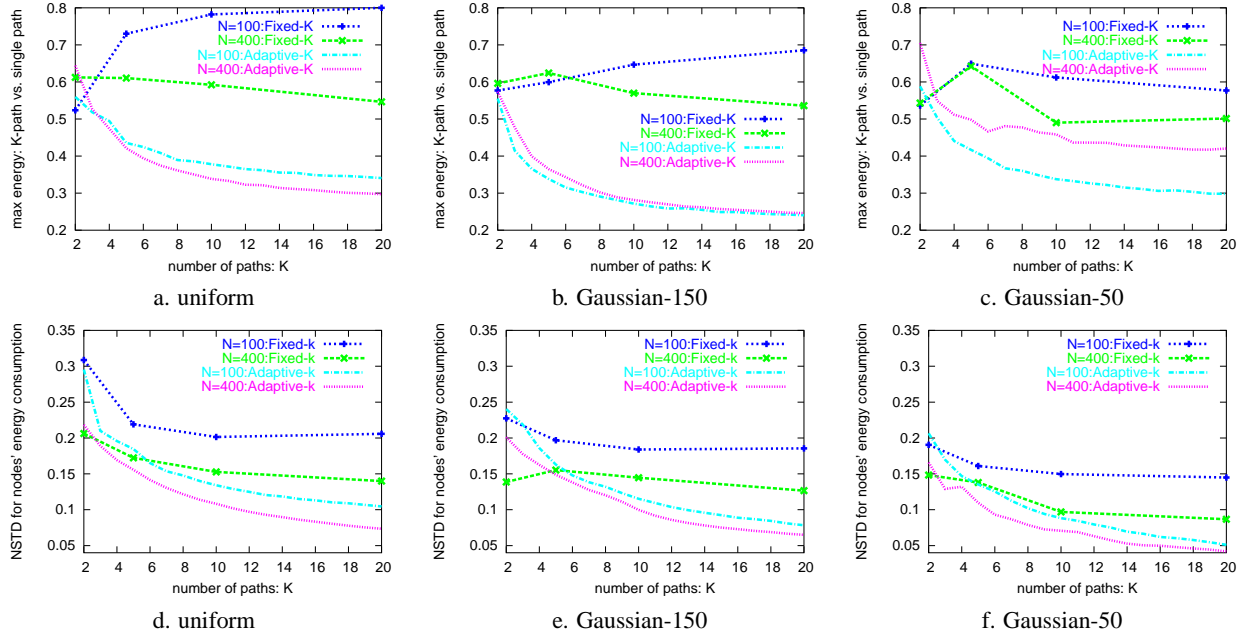
Here, the number of seed nodes for constructing one path may not equal  $\frac{n}{K}$ . A smaller number of seed nodes may lead to large number of iterations during path expansion, while a larger number of seed nodes could result in failure to construct a feasible path. In addition to the selection of seed nodes, during the further path expansion (Step 3), we also need to select the sensor nodes that consume the most energy (line 13 in Algorithm 1).

## 5 Simulation Results and Discussions

Levels	1	2	3	4	5	6
$P_i$	0.1	5	16	35	68	100
$R_i$ (meters)	1	20	40	60	80	100

**Table 2. The normalized power levels and corresponding transmission ranges for the sensor nodes used in the simulations.**

The performance of the proposed MPP heuristics are evaluated through extensive simulations. In addition to the fixed-K and adaptive-K MPP heuristic schemes, for comparison, the case where the mobile element follows a single path repeatedly is considered as the baseline. For the power levels of the sensor nodes, we assume that there are 6 levels. Moreover, based on our measured data of Tmote Sky



**Figure 3.** The performance of the proposed MPP heuristics versus the number of paths  $K$  to be planned; Here, the path limit ratio is 0.8.

sensors, the normalized power levels and the corresponding transmit ranges<sup>1</sup> are shown in Table 2.

In the simulations, we consider a square field of  $1000m \times 1000m$  and the base station is assumed to be in the middle of the field. There are 100 (or 400) sensor nodes scattered in the field with their locations following uniform or Gaussian distribution. For the Gaussian distribution, the mean for the  $x$  and  $y$  coordinations of sensors' location is 500 and we consider two different variances, 50 and 150, respectively. For each of these three distributions, we generate 100 data sets for the location of the sensor nodes and each point in the results is the average of over 100 data sets.

For the number of paths, we consider up to 20 paths with  $K = 2, 5, 10$  and 20 for the fixed-K scheme. For the first step in Algorithm 1, we use the Christofides MST heuristic [5] implemented using LEDA package [14]. Moreover, we define the maximum path length  $L^{max}$  as the length for the path that can pass by all the sensor nodes, where the path is also constructed from the MST heuristic. For the path length limit  $L$ , we consider the following ratio of  $\delta = \frac{L}{L^{max}}$ : 0.75, 0.8, 0.85, 0.9 and 0.95. For the case with  $\delta < 0.75$ , we found that the proposed heuristic schemes can hardly construct feasible paths for most of the data sets. In addition, for the adaptive-K scheme, the number of seed nodes for

constructing each path is 45% of the sensor nodes that consume the most energy when the mobile element follows the previous paths.

### 5.1 Effects of Number of Paths

In the first set of simulations, we examine how the number of paths will affect the performance of the proposed MPP heuristic schemes. For ease of representation, we use normalized energy consumption to show the improvement of the proposed MPP schemes over the one that exploits only a single path. That is, Figures 3abc show the normalized energy consumption for the most energy-hungry sensor node under the MPP heuristics over the one in the single path scheme, for the three different distributions of sensor nodes in the field of interest, respectively. Here, the path limit is set to be  $L = 0.8L^{max}$ .

From the figure, we can see that, regardless the number of paths constructed, the most energy-hungry sensor node under the fixed-K scheme consumes about 50% to 60% energy when compared to the one under the single path scheme for most of the cases (i.e., the lifetime of WSNs can be doubled under the fixed-K scheme). The reason is that, although the fixed-K scheme ensures that each sensor node serves as the seed node once and is on at least one of the path, the independent path construction for each path and the greedy approach adopted in the further path expansion

<sup>1</sup>Although Tmote Sky sensors have 32 different levels [16], the measurement of the transmission range for every level is extremely difficulty and we selected a few levels from our measurement.

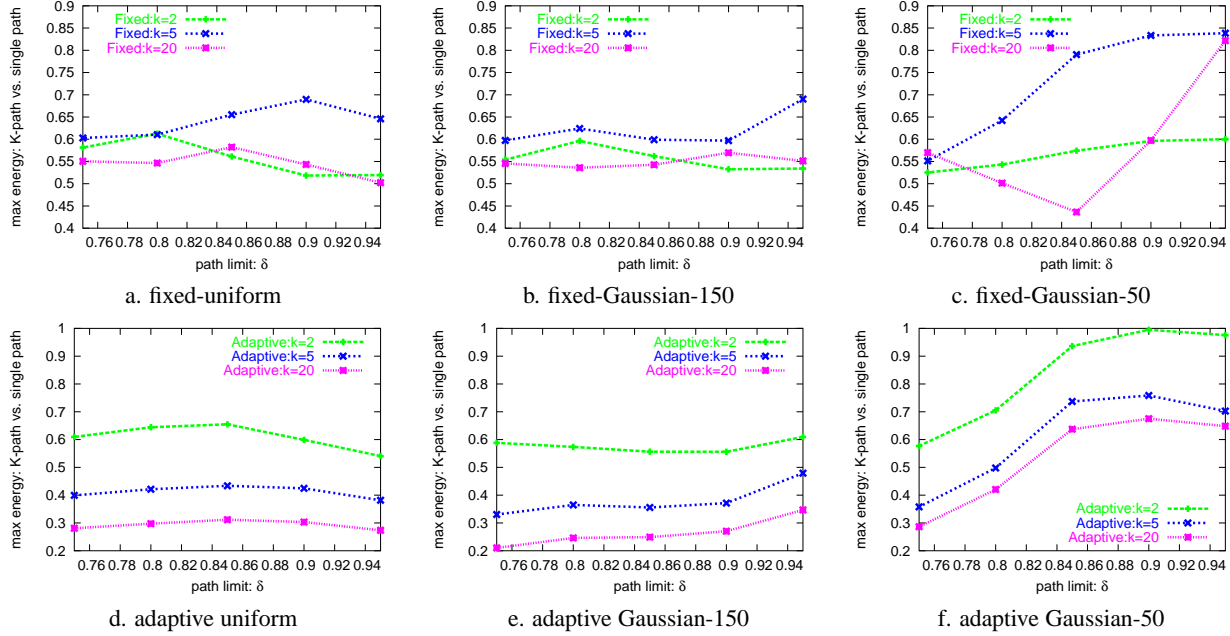


Figure 4. The performance of the MPP heuristic schemes versus the path length limit.

(Step 3 in Algorithm 1) cannot further reduce the energy consumed on the most energy-hungry sensor node. Moreover, for the case of 100 sensor nodes, the fixed-K scheme performs even worse when more paths are constructed. The reason is again because of the greedy approach adopted in the further path expansion, where it is possible for a sensor node being on the path that it serves as seed nodes but is far away from all other paths.

For the adaptive-K scheme, as the number of paths increases, the normalized energy consumption for the most energy-hungry sensor nodes generally decreases. That is, longer lifetime for the WSN can be achieved with more paths. However, the improvement becomes less significant as the number of paths is more than 10. When 20 paths are exploited, for the case of Gaussian distribution with 150 variance, the most energy-hungry sensor node consumes only 25% energy compared to that of the one under the single path scheme. That is, the lifetime of the WSN can be improved up to 4 times. In addition, since only 45% of the sensor nodes are selected as seed nodes when a new path is constructed, for the case of  $K = 2$ , 10% of the sensor nodes do not have the chance to serve as seed nodes and the adaptive-K scheme performs even worse than the fixed-K scheme. Therefore, for better performance of the MPP heuristics, the selection of seed nodes is crucial and each sensor node should serve as a seed node at least once when constructing the  $K$  paths.

Define the *normalized standard deviation (NSTD)* for the energy consumption of all sensor nodes as the stan-

dard deviation of the normalized energy consumption ratio  $\frac{E_i}{E^{max}}$  ( $i = 1, \dots, n$ ), where  $E^{max}$  is the energy consumption for the most energy-hungry sensor node for given  $K$  paths. Figures 3def show the NSTD of sensor nodes' energy consumption for the different cases under the proposed MPP heuristic schemes. Here, a smaller value means that the energy consumption for the sensor nodes is more balanced. From the results we can see that, in addition to achieving longer lifetime for the WSNs, the adaptive-K scheme in general obtains a better performance in terms of balancing the energy consumption across the sensor nodes. The exception is for  $K = 2$ , where the reason is the same as explained before when some sensor nodes did not get the chance to serve as seed nodes.

## 5.2 Effects of Path Length Limits

For different path length limit, Figure 4 shows the normalized energy consumption for the most energy-hungry sensor node under the MPP heuristic schemes when the one under the single path scheme is used as the baseline. From the results we can see that the performance of both fixed-K and adaptive-K schemes is rather stable for the different path length limits considered. Moreover, the results confirm that the performance of the fixed-K scheme does not depend on the number of paths, while the adaptive-K scheme performs better with more paths.

However, for the case where the sensor nodes are more clustered around the base station (i.e., Gaussian distribution

with variance of 50), both fixed- $K$  and adaptive- $K$  schemes result in large variations on their performance. The big variation of the fixed- $K$  scheme, especially for the case of  $K = 20$ , comes again from the greedy approach used in the further path expansion, which results in big difference on energy consumption for the sensor nodes. For the adaptive- $K$  scheme, the abnormality for the case of  $K = 2$  is due to again the fact that some sensor did not have chance to serve as seed nodes for the two paths constructed.

## 6 Related Work

Efficient data collection in wireless sensor networks (WSNs) has been studied extensively [1, 7]. To address the drawbacks of the multi-hop data forwarding schemes with a static base-station, where the sensor nodes close to the base station will deplete their energy quickly due to their high data transmission activities, mobile base stations have been explored to achieve balanced energy usage among sensor nodes [3, 4, 6, 8]. In addition, active mobile element has been exploited to visit the sensor nodes and collect data from them via single-hop communication. Shah *et al.* studied the performance of the mobile element to opportunistically collect data from a sparse WSN based on the random movement model [17]. For sensor nodes with limited buffer size, several heuristics have studied to control the mobile element to visit the sensor nodes before the buffer overflow and/or serve the varying data-rates [10, 18].

More recently, the hybrid approach that consider the combination of multi-hop forwarding and mobile elements has been proposed. Wang *et al.* show that the best scheme to extend the WSN's lifetime is to constrain the movement of the mobile element in the vicinity of the base station [22]. Considering the delay requirement of the data, Gu *et al.* studied schemes where urgent data are forwarded to the sensor nodes that are visited by the mobile element more frequently [10]. To reduce the length of the travel path for the mobile element, rendezvous points are used as regional collection points and the mobile element collects the data from the rendezvous points [23]. Sencar uses a mobile observer to collect data, where field of interest is divided into regions and the mobile element moves in straight lines in each region and multi-hop forwarding is used to relay packets from distant sensors to the sencar [12].

Mobile elements are also used to data collection, storage and retrieval in underwater sensor networks [20]. To further improve the performance, several schemes have been studied to employ multiple mobile elements to improve the efficiency of data collection (e.g., using load balancing technique) [4, 8, 11]. Different from most of the existing schemes with mobile elements and a single path, our work focuses on planning of multiple travel paths for the mobile element to extend the lifetime of WSNs.

## 7 Conclusions and Future Work

For data collection in wireless sensor networks (WSNs), mobile elements have been deployed to improve the energy efficiency by traversing the field of interest and collecting sensed data from nearby sensor nodes. However, most of the existing approaches using mobile elements for data collection in WSNs normally only plan a *single* path.

In this paper, we study the *multiple path planning (MPP)* problem for the mobile element. The basic idea is to construct multiple paths, which can be followed by the mobile element in turn during data collection in order to balance the energy consumption on individual sensor nodes, thus extending the WSN's lifetime. We show the intractability of the general MPP problem for constructing  $K$  paths and we study heuristic based solutions for constructing a path using *seed nodes*, which is a subset of the sensor nodes. Based on *when* and *how* the seed nodes are selected when constructing the paths, two MPP heuristics are proposed: *fixed- $K$*  and *adaptive- $K$*  schemes. The proposed heuristics are evaluated through extensive simulations. The results show that, the life of WSNs can almost be doubled with the fixed- $K$  scheme, even when  $K = 2$ . For the adaptive- $K$  scheme, the lifetime of WSNs generally increases when more paths are exploited, and up to 4 times can be achieved with 20 paths. Moreover, under the adaptive- $K$  scheme, the energy on the sensor nodes is consumed more evenly.

For our future work, we will consider cases where a WSN can operate until  $X\%$  of the sensor nodes die. Moreover, adaptive path scheduling for hybrid schemes with multi-hop data forwarding will be studied.

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