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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* 4 **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 [10] and ecology monitoring [16]). 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

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has the computational power to store and process all the collected data [1, 5]. 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 the neighbors 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, *mobile elements*, which can move around the deployed field and convey the data from each sensor node to the base station, have been exploited [14, 19, 22]. 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 [19]). 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 studied [9, 18, 19]. Here, the data is first aggregated locally using multi-hop schemes to some rendezvous points. Then, the mobile element visits these points to pick the data up [19].

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 [9, 19, 18, 19, 22]. However, such solutions with a single path may still 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.

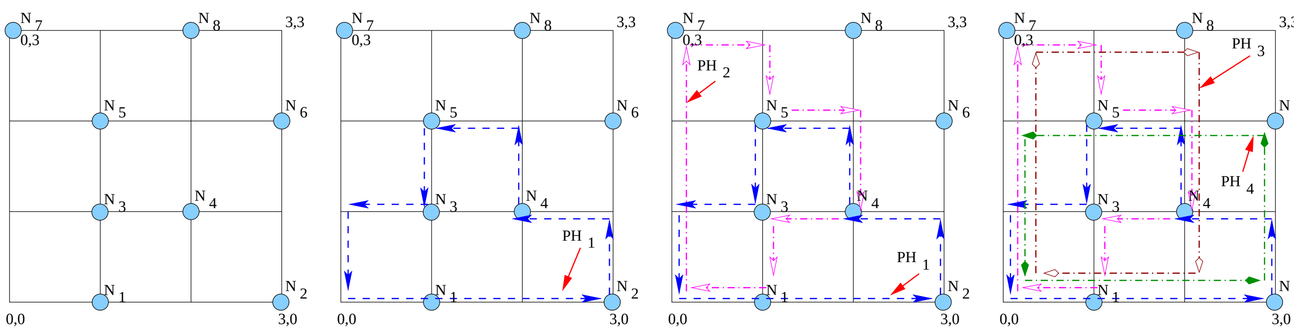
1.1 Closely Related Work

In order to address the drawbacks of the static base-station approach, there has been a flurry of work on employing a mobile element for data collection. The data mules [14] work exploits random movement of a mobile element to opportunistically collect data from a sparse WSN. Here, the nodes buffer all their data locally, and upload the data only when the mobile element arrives within direct communication distance. Zebranet [8] system uses tracking collars carried by animals for wildlife tracking. Data is forwarded in a peer-to-peer manner and redundant copies are stored in other nodes. Shared wireless infostation model [15] uses radio tagged whales as part of a biological information acquisition system. Mobility of the mobile element is not controlled in these approaches.

Mobile element scheduling (MES) work considers controlled mobility of the mobile element in order to reduce latency and/or serve the varying data-rates in the WSNs effectively [19]. The MES work shows that the problem of planning a path for the mobile element to visit the sensor nodes before their buffers overflow is NP-complete. Several heuristic based solutions are proposed to address this problem [19, 6, 21]. Sencar [9] uses a mobile observer to collect data. Area is divided into regions and the mobile element moves in straight lines in each region. Multi-hop forwarding is used to relay packets from distant sensors to sencar. Data salmon [4] constructs a spanning tree and moves the mobile base-station on this tree to optimize the cost of retrieval. 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 [20]. Mobile elements are also used to data collection, storage and retrieval in underwater sensor networks [17]. These work assume a single mobile element. Multiple mobile elements are also proposed to improve the performance using load balancing between the mobile elements [7].

Different from the existing single-path solutions, in this paper, for data collection in WSNs with a single mobile element that collects data *directly* from every sensor node, we study 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. Noting the intractability of the problem, two MPP heuristic schemes, *fixed-K* and *adaptive-K*, are proposed. The simulation results show the superior performance of the proposed multi-path schemes on extending the lifetime of WSNs compared to that of single-path solutions (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 concludes the paper and points out the directions for our future work.



(a) 4×4 field with 8 sensors (b) Single path (c) Two paths (d) Four paths

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

2 System Models and Assumptions

The WSN considered in this work consists of a set Φ 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 ($i = 1, \ldots, n$) 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 each sensor node 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, 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 [12]:

$$P(d) = \gamma + \alpha d^{\beta} \tag{1}$$

where γ and α are system dependent parameters and $2 \leq \beta \leq 4$. And, in general, γ 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 [13]). 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), ..., (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 $d^{max} = R_m$ (i.e., the maximum distance from the sensor nodes to the travel path of the mobile element). For instance, Tmote Sky sensor nodes can transmit up to 125 meters at its maximum transmission power level [13]. 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. When the mobile element follows a travel path PH during one round of data collection, the amount of energy consumed by the node N_i for transmitting its data to the mobile element will be $E_i = P_x \cdot t$, where $R_{x-1} < d_i \leq R_x$. That is, the energy consumption depends solely on d_i, the distance from the location of node N_i to the travel path PH.

Therefore, if the mobile element could *visit* the location 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. 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 4×4 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.

	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 $PS_3 = \{PH_1, PH_2, PH_3, PH_4\}$.

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 transmitting their data is shown in the second column (i.e., labeled as *path set* PS_1) in Table 1. Here, we can see that node N_7 consumes the maximum energy of 24 units, 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. 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:

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

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:

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

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 $PS = \{PH_1, \ldots, PH_K\}$ for the mobile element, so as to:

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

subject to

$$|PH_j| \leq L, \forall j \tag{5}$$

$$d_i^j \leq d^{max}, \forall i \forall j \tag{6}$$

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.

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 using K paths is NP-complete as well using restriction.

For $K = 1$ we call our problem *Sensor Power Problem* and state it as follows. Given n points $N_1 \ldots N_n$, what is the minimal power range a mobile element can use to communicate with all the sensors while traveling at most the length of L. We use the decision version of the sensor power problem to show NP-completeness and call it *Sensor Power Decision Problem* which is stated as follows. Given n points $N_1 \ldots N_n$ and a range ϵ, is ϵ range sufficient for the mobile element to communicate with all the sensors while traveling at most L? 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 $N_1 \ldots N_n$ with respective neighborhoods $\epsilon_1 \ldots \epsilon_n$, 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 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 Equations 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

For a given subset of seed sensor nodes $\Psi_j \subset \Phi$ ($j = 1, \cdots, K$), 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 [3]), 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 can transmit their data to the mobile element at the minimum power level P^{min}.

Then, in the second step, the 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}, no path expansion is needed. 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). 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.

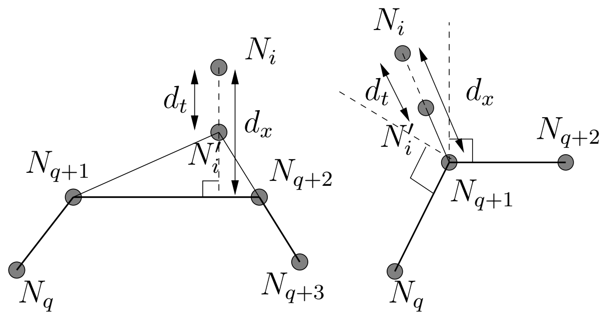
If a feasible path is obtained in the second step with the path length being less than L, the path will be further expanded in the last step. That is, following a certain strategy (which is different for the fixed-K and adaptive-K heuristics, as discussed below), some non-seed nodes that are not on the path will be selected (line 13) and the path is expanded to pass by them 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

Algorithm 1 : SinglePathConstruction

Input: location of all sensor nodes and base station, and the set Ψ_j of seed nodes;
Step 1: Get path PH_j from Ψ_j using TSP heuristics;
Step 2://extend path to ensure d^{max}
while ($\exists N_i \in \Phi - \Psi_j$ such that $d_i^j > d^{max}$) **do**
  //Here, d_i^j is the distance from N_i to PH_j;
  Expand path PH_j to ensure $d_i^j \leq d^{max}$;
end while
if (Length of path PH_j: $L_j > L$) **then**
  The construction of PH_j fails and exits;
end if
Step 3://further path extension to length limit L;
while Length of path PH_j: $L_j < L$ **do**
  N_m = PickNodeForFurtherExpansion();
  Calculate path increase Δ for PH_j to reach N_m;
  if ($\Delta <= L - L_j$) **then**
    Expand PH_j to reach N_m: $d_m^j = d^{min}$;
  else
    Expand PH_j with length increase as $L - L_j$;
  end if
end while

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.



(a) Node close to an edge (b) Node close to a vertex

Figure 2. Addition of a node to a path

Suppose that the path to be constructed is PH_j ($j = 1, \cdots, K$) 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}) and removing the edge from node N_{q+1} to node N_{q+2}. Here, the path length of PH_j will increase by $\Delta = |N_{q+1}, N'_i| + |N'_i, N_{q+2}| - |N_{q+1}, N_{q+2}|$.

As shown in Figure 2(b), for the second case, 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. That is, to guarantee that each sensor node is on *at least* one of the generated travel paths, the 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 sensor nodes that have the largest distance to the path will be selected (line 13 in Algorithm 1).

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 $j-1$ ($j = 2, \cdots, K$) paths are followed by the mobile element. For the first path, the seed nodes can be randomly selected.

For better performance, the sensor nodes that consume the highest amount of energy will be selected as seed nodes. That is, the construction of the j'th path will depend on all previous constructed paths. 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, 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.

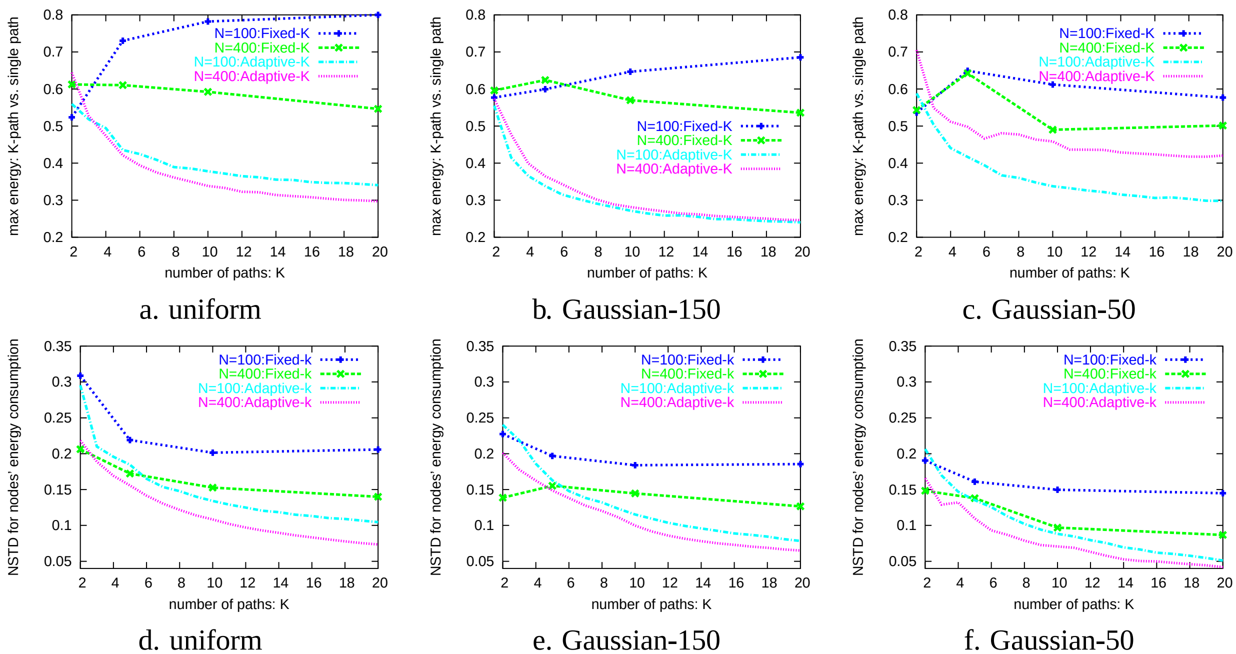


Figure 3. The performance of the proposed MPP heuristics versus the number of paths K to be planned; Here, the path limit ratio is 0.8.

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[1]. Moreover, based on our measured data of Tmote Sky sensors, the normalized power levels and the corresponding transmit ranges are shown in Table 2.

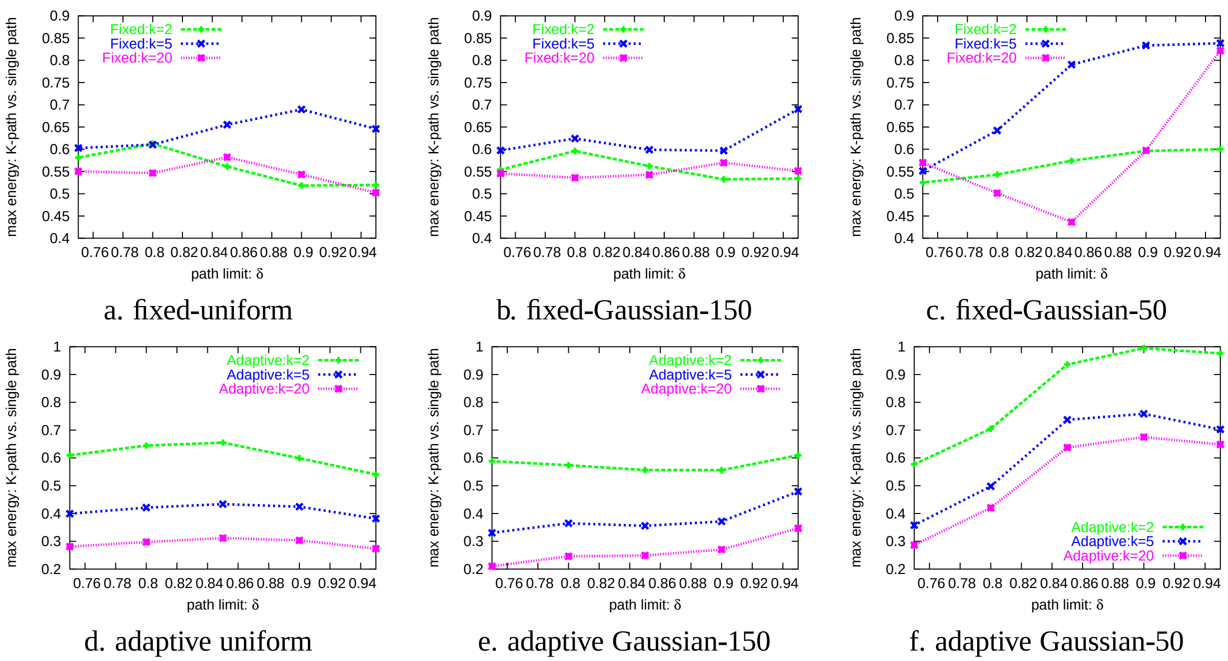
In the simulations, we consider a square field of $1000m \times 1000m$ and the base station is assumed to be in the middle of the field. There are 100 (or 400) sensor nodes scattered in the field with their

[1] Although Tmote Sky sensors have 32 different levels [13], the measurement of the transmission range for every level is extremely difficulty and we selected a few levels from our measurement.

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 [3] implemented using LEDA package [11]. 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[2] of $\delta = \frac{L}{L^{max}}$: $0.75, 0.8, 0.85, 0.9$ and 0.95. 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



a. fixed-uniform
b. fixed-Gaussian-150
c. fixed-Gaussian-50
d. adaptive uniform
e. adaptive Gaussian-150
f. adaptive Gaussian-50

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

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

[2] We found that, when the ratio is less than 0.75, no feasible path can be constructed for most of the data sets.

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 (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% compared to 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 the 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 the seed nodes at least once when constructing the K paths.

Define the *normalized standard deviation (NSTD)* for the energy consumption of all sensor nodes as the standard deviation of the normalized energy consumption ratio $\frac{E_i}{E^{max}}(i = 1, \cdots, n)$, 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 $K = 20$, possibly comes from again 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 $K = 2$ has the same reason as before.

6 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 the lifetime of WSNs can last until multiple nodes die (e.g, a WSN can operate until 10% of the sensor nodes die). Moreover, adaptive path scheduling for hybrid schemes with multi-hop data forwarding will be studied.

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