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Mobile Element Path Planning for Time-Constrained Data Gathering in Wireless Sensor Networks

Nunna Gopi Krishna
M.Tech (DSCE),
Al Habeeb College of Engineering & Technology,
Hyderabad.

Syed Samiuddin, M.Tech
Associate Professor & HOD,
Department of ECE,
Al Habeeb College of Engineering & Technology,
Hyderabad.

Abstract:

We consider the problem of gathering data from a sensor network using mobile elements. In particular, we consider the case where the data are produced by measurements and need to be delivered to a predefined sink within a given time interval from the time the measurement takes place. Mobile elements travel the network in predefined paths, collect the data from the nodes, and deliver them to the sink. Each node must be visited by a mobile element that must then reach the sink within the given time constraint. The goal is to plan the paths for the mobile elements that minimize the total length travelled.

Several variations of this problem have been considered in existing literature. We propose an algorithmic solution that builds nodedisjoint tours that always include the sink, cover the network, and optimize the total length travelled. We provide an integer linear programming formulation for the problem, and propose two novel heuristics for building the tours. We evaluate the performance of our algorithm by comparing it to the optimal solution as well as to an alternative heuristic, commonly used in related time-window vehicle routing problems, and demonstrate the superior performance of our approach.

Keywords:

wireless sensor network; mobile data gathering.

I. INTRODUCTION:

Path planning is a fundamental problem that has numerous applications in many areas, including but not limited to wireless sensor networks, travelling salesman problems, and vehicle routing. In wireless sensor networks, for example, mobile elements can be used for data gathering in order to avoid the more energy-consuming multi-hop forwarding.

However, using a mobile element that follows a long tour through the network to collect the data from all sensors may introduce unacceptable delays in the delivery of the data to the sink. Hence, planning the path of the mobile element(s) becomes an important part of improving the energy consumption in the network and prolonging its lifetime. For many sensor applications, it is natural to assume wherethe data generated in a sensor node need to be delivered within a certain maximum time interval to the sink. Henceforth, we refer to these maximum latency requirements as transit timeconstraints. Transit time constraints can arise from a variety of practical considerations, such as a need to guarantee the "freshness" of physical measurements at the point of processing (sink). Alternatively, the limited size of memory/buffer space at the sensor nodes themselves may put a constraint on the minimum frequency that the data must be collected by the mobile elements, so as to avoid overflowing.Assuming that the mobile elements conduct their data gathering tours with a regular periodicity, such a frequency constraint directly translates to a constraint on the maximum duration of the tour.

In a given network consisting of data-producing nodes along with associated time delivery constraints, a single mobile element may not be able to cover the gathering task. Recently, variations of the problem led to several approaches proposed in the literature, including using multiple mobile elements and partitioning the network among them [11,12], and combiningdata gathering by mobile elements with wireless multi-hop forwarding [22-26].The problem tackled in this study can be described as follows. Given a set of data-producing nodes, their locations, transit time constraints, and the location of a sink node where all the data must be gathered, the goal is to design a set of tours for (one or more) mobile elements, such that: (1) all nodes arevisited by exactly one mobile element, (2) all tours include thesink node, (3) all delivery deadlines are met, and (4) the totallength (or travelling time) of all the tours is minimized.

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For simplicity, in this paper we assume that the sensor nodes are on a plane and the mobile elements can move freely between any two nodes in a straight line; thus, the travel time of the mobile element is directly proportional to the Euclidean distance. However, our algorithms can be readily applied in networks where the travel time between nodes is governed by any other distance metric as well. The tour planning process is complicated by the fact that each node (sensor) may have a different transit time constraint. We refer to this problem as Time-constrained Mobile Element Scheduling (TMES).

II. PROBLEM DEFINITION:

We define the Time-constrained Mobile Element Scheduling problem, or TMES, as follows. Let Vbe a set of vertices, where each vertex corresponds to a node in the sensor network, and a distinguished vertex vs ε Vis the sink node. We assume that the nodes correspond to points in the Euclidean plane and that the mobile elements can move freely between any pair of nodes in a straight line; in other words, the possible movements of the mobile elements correspond to a complete graph G=(V,E), where E=VxVWe use d(u,v) to denote the Euclidean distance between vertices u,v εV We assume that all mobile elements move at a constant unit speed; consequently,d(u,v) can be equivalently interpreted as the time it takes a mobile element to travel between the two vertices; we use the two interpretations interchangeably in the rest of the paper. A tour is defined as an ordered sequence of vertices that starts and finishes at the same vertex, and is not self-intersecting (i.e. no vertex other than the first and last one is repeated in the sequence). The length, or travelling time, of a tour T=(Vk,V1,…,Vk) is the sum of the travelling times between all adjacent vertices in the tour, i.e d(T)=d(Vk,V1)+sum(d(Vi,Vi+1).

Each vertex v belongs to V is associated with a constraint Pv, which is the maximum period of time allowed between successive visits of a mobile element to the respective sensor. We assume that Pv>=2d(Vs,V) for any v belongs to V; otherwise, the problem as stated below cannot have a feasible solution. The objective of the TMES problem is to find a set of tours such that (1) each vertex (except the sink) belongs to exactly one tour, (2) the sink node Vsis the starting and finishing vertex of all tours, (3) if a tour includes vertex then the travelling time (or length) of the tour is less than Pv , and (4) thev sum of all tours' lengths is minimized.

III. RELATED WORK:

The use of mobile elements in data gathering has been studied in the literature in many different variations and for a diverse array of applications. Juang et al [14] and Small and Haas [15] consider applications in wildlife monitoring, using radio-equipped zebras and whales as mobile elements. These animal-based elements move randomly in the network terrain and exchange messages opportunistically. Zhao and Amar [10] present a scheme that uses mobile elements (ferries) to route the sensors' data in a sparse ad hoc network, and attempts to determine the path of the mobile elements that will minimize the average delay based on a defined traffic metric.

The mobile element scheduling problem (MES) is considered by Somasundara et al [12] as well as by Gu etal [16] and is closely related to the problem we consider in this work. The MES problem schedules one or multiple paths for mobile elements such that each sensor is visited before its buffer is full. A major difference between MES and our problem TMES is that, in MES, the mobile elements areassumed to act as sinks; thus, they can remain in the networkall the time, and there is no requirement for mobile elements to visit a sink node. Furthermore, the proposed solutions for the MES problem build the paths dynamically, namely: given thecurrent location of the mobile element and the buffer state of the sensors in the network at that particular time, the next step of the tour is decided. Conversely, in the problem we are Considering here, the mobile elements' tours are fixed and planned in advance so as to satisfy the given time constraints. These two variations of the problem are applicable to different scenarios; in particular, supporting the sink functionality in the MES scenario increases the cost of mobile elements, as well as the risk from any damage to them in a hostile environment.

IV. INTEGER LINEAR PROGRAM FORMULATION:

In this section, we present an ILP version of the TMES problem as follows. LetV={v1,v2,…,vn} be the set of nvertices or node locations and let d(u,v)denote the travelling time or distance between vertices u,v belongs to V. The transit constraints are P={Pv1,…,Pv2} , and let Pmax denote the largest transit constraint Pmax=max(Pv:vεV) We use Yuvas a 0-1 (indicator) variables for each pair of vertices u,vεVsuch that Yuv=1

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if there is a mobile element travelling from u to v, and 0 otherwise. Also, let Zu be an integer variable for each vertex uεV, taking only positive values, showing the order in which the vertices are visited in the resulting tours; note that this variable is well-defined since each vertex (except the sink) is visited by one and only one tour, and an optimal solution will always have a degree of freedom between following any tour in a clockwise or counter-clockwise manner. We denote the travelling time (length) of the clockwise and counter-clockwise sub-tour between a vertexv and the sink by αv and βv, respectively; thus, the total length of the tour that includes vertex v is αv+βv.Using the variables defined above, the TMES problem can be stated by the following ILP formulation:

$$\text{minimize} \quad \sum_{u,v \in V} y_{uv} \cdot d(u,v)$$

$$\text{subject to}$$

$$\begin{aligned}
\sum_{v \in V} y_{uv} &= 1 & \forall u \in V \quad (1)\\
\sum_{v \in V} y_{vu} - \sum_{u \in V} y_{uv} &= 0 & \forall u \in V \quad (2)\\
\alpha_u + \beta_u &\leq p_u & \forall u \in V \quad (3)\\
\alpha_u - \alpha_v + y_{uv}(p_{max} + d(u,v)) &\leq p_{max} & \forall u,v \in V \quad (4)\\
\beta_v - \beta_u + y_{uv}(p_{max} + d(u,v)) &\leq p_{max} & \forall u,v \in V \quad (5)\\
y_{1u} \cdot d(1,u) &\leq \alpha_u & \forall u \in V \quad (6)\\
y_{u1} \cdot d(u,1) &\leq \beta_u & \forall u \in V \quad (7)\\
z_u - z_v + nd(u,v) &\leq n-1 & \forall u \in V,\ v \in V\{v_s\} \quad (8)
\end{aligned}$$

Constraints (1) and (2) ensure that each vertex is assigned to exactly one tour. Constraints (3-5) ensure that the timeconstraints (Pv)are satisfied for each vertex. Specifically,constraint (3) ensures that travelling time of the clockwise and the counter-clockwise sub-tours between vertex uand the sink is less than or equal to the transit constraint for this vertex. Constraint (4) ensures that if a mobile element travels from vertex u to v in the clockwise sub-tour between any vertex and the sink, then the length of the clockwise sub-tour between vertex v and the sink is equal to .αu +d(u,v).Constraint (5) is similar to constraint (4) for the counter-clockwise sub-tour. Constraint (6) ensures that the clockwise sub-tour between the sink and the first vertex to be visited (u) is equal to αu, and constraint (7) does the same for the counter-clockwise sub-tour.Finally, constraint (8) prevent solutions that allow degenerate sub-tours, which are tours that are not connected to the origin (Vs). These constraints are based on the Miller-Tucker-Zemlin[20] sub-tour elimination constraints, which have been widely used in the literature for ILP formulations of both the TSP and the VRP problems.

V. ALGORTHIMIC APPROACH:

We proceed to propose two heuristic algorithms for solving the TMES problem, which can be seen to correspond to two natural approaches to the problem of constructing the required tours. The first approach starts from large tours that are efficient in terms of length but possibly violate the transit constraints, and then proceeds to cut segments from these tours to form smaller ones until all constraints are met. The second approach proceeds in the reverse direction: it starts by building short tours starting from the sink and then expands them as much as possible, always maintaining the property that no tour violates the time constraints of the vertices it visits. We refer to the former heuristic as the tour cutting (Tcut) heuristic, and the latter one as the tour packing (Tpac) heuristic.

A. The Tcut heuristic:

The tour cutting heuristic (Tcut) starts with a single TSP tour that covers all nodes (in our evaluations we used the Christofides algorithm [21] to compute the initial TSP tour, but any TSP solver can be used for this purpose). The algorithm then proceeds to recursively cut out pieces of the tour, as follows:

1. Let T be the tour so far. If T satisfies all of its nodes' time constraints, then stops and return T.
2. Otherwise, let v be the vertex with the smallest p_v (i.e. most stringent time constraint) in T; assign $t \leftarrow \langle v \rangle$;
3. For a vertex v that is a neighbor of either endpoint of t in T (i.e., such that either $\langle t, v \rangle$ or $\langle v, t \rangle$ is a sub-tour of T): if the length of the tour $\langle v_s, t, v, v_s \rangle$ or $\langle v_s, v, t, v_s \rangle$, respectively, does not violate the constraints of v and all the nodes in t, then set $t \leftarrow \langle t, v \rangle$ or $\langle v, t \rangle$, respectively;
4. Repeat step 3 until no more nodes can be added to t on either side;
5. Extract $\langle v_s, t, v_s \rangle$ as one of the tours in the solution; remove the nodes of t from T and recursively go back to step 1 for the remaining piece (or each of the disconnected two pieces) of T.

B. The Tpac heuristic:

The tour packing heuristic (Tpac) is a greedy algorithm that constructs a solution by iteratively adding one vertex to the solution at a time, in an order determined by a certain cost function defined below. More precisely, the algorithm starts from the sink node and, in each iteration, attempts to add a node to an existing tour as long as the time constraints remain satisfied for all vertices so far; when an existing tour cannot be extended any more, a new tour is initialized again from the sinknode.

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The choice of vertex to add in each step is made by evaluating a cost function for each node, which can be seen as a "fitness score" that measures whether the vertex would be a good fit for the current tour. This score depends on the time constraint of the node (normalized by the maximum constraint in the network) and the normalized distance of the node from the current tour. The distance of a node v from a given tour Tis defined as the distance of the node from the closest node in the tour, and denoted by d(v,T).

VI. NUMERICAL RESULTS:

In this section, we present two extensive sets of experiments to evaluate the performance of the algorithms presented above. The input instances are sets of nodes, randomly distributed over an area with a uniform density. The time constraints for all nodes are picked randomly from a uniform distribution between a lower and upper bound d(vT). The output solution for the TMES problem is a set of tours that cover all the nodes and respect all the constraints. Therefore,we are interested in evaluating (1) the number of tours returned by our heuristics, and (2) the total length of the tours. Clearly, if the transit constraints are very loose, a small number of tours will suffice to cover the network, and therefore the solution is closer to the single-tour (TSP) problem. As explained above, in such situations we expect the Tcut heuristic to perform better,since it is based on the solution of TSP and only requires a small number of adjustments to satisfy the nodes' time constraints. On the other hand, if the transit deadlines are very restrictive (short), then a large number of tours will be required, and therefore the tour packing heuristic should perform better, as it is not restricted by the optimal visiting sequence of TSP that may be far from the final solution. Therefore the parameters we consider in our experiments look at (1) varying the range of values from which the constraints are chosen, and (2) varying the proportion of sensors with tight as opposed to loose constraints within each instance.

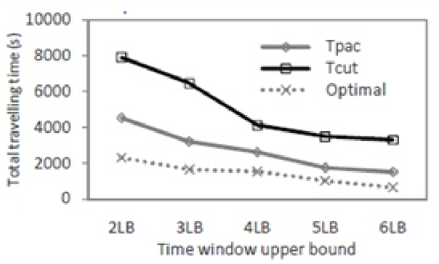

Figure 1(a). Time window upper bound against the total travelling time

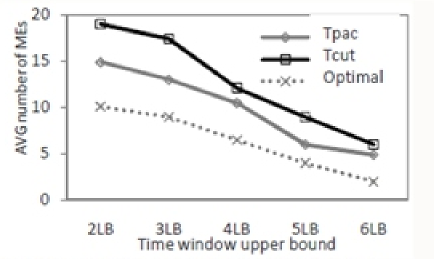

Figure 1(b). Time window upper bound against the average number of mobile elements

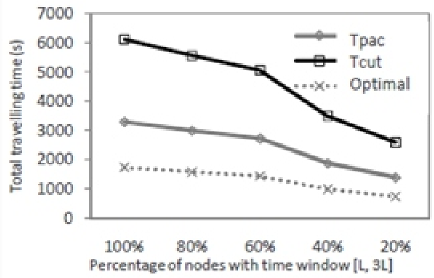

Figure 2(a). Percentage of nodes with time window [L,3L] against the total travelling time.

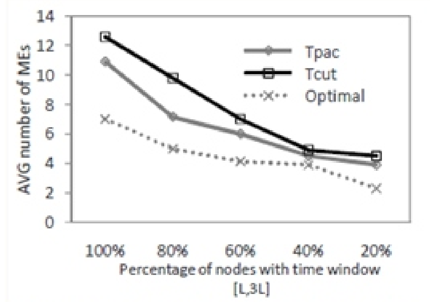

Figure 2(b). Percentage of nodes with time window [L,3L] against the average number of mobile elements.

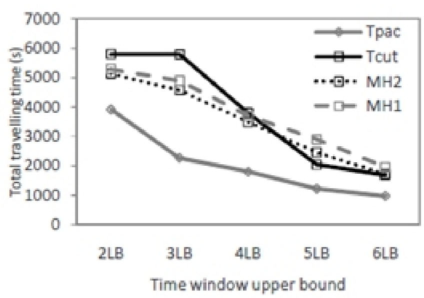

Figure 3(a). Time window upper bound against the total travelling time

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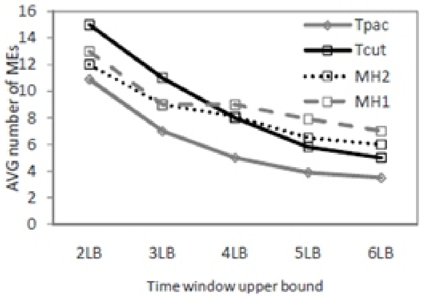

Figure 3(b). Time window upper bound against average number of mobile elements

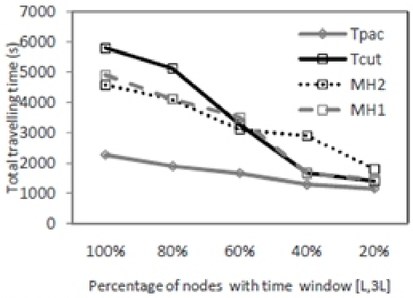

Figure 4(a). Percentage of nodes with time window [L,3L] against the total travelling time.

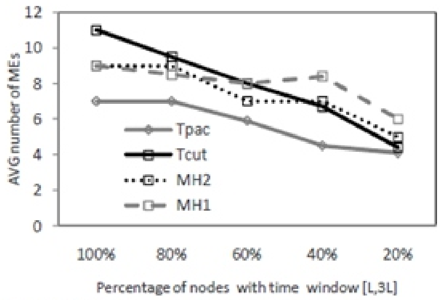

Figure 4(b). Percentage of nodes with time window [L, 3L] against average number of mobile elements

VII. CONCLUSION:

Our work provides an algorithmic heuristic solution for the transit constrained mobile element scheduling problem that clearly outperforms the previously proposed solutions for the scenarios considered in our experiments. Also we have presented a much more efficient integer linear program that can handle significantly larger input instances compared to the previously proposed formulation. An interesting future direction would be to investigate different variations of this problem where the elements have sink functionalities and can roam in network all the time. In addition, to cope with unexpected delays in the network, the heuristics can be modified by allowing the elements to wait at the nodes as long as the time constraints can be met.

It is alsointeresting to consider more optimized formulations for the ILP that will make it possible to solve optimally larger problem sizes and therefore provide a very good reference point forcomparison and evaluation of heuristics. These ILP formulations may be of independent interest in the area, as it is generally easy to add and modify objectives and constraints for variants of these problems. The presented heuristics assume that the network is an open field. However, in a real-world application, the network area may have obstacles. This situation can be modelled byassuming that the sink has a description of the entire area of the sensors as a graph that also lists the distances or more generally, the costs of moving between locations in the network. This description can easily incorporate the position of possible obstacles in the network or other irregularities.

Therefore it is possible to adjust our proposed algorithms to use the costs in the graph representation of the problem, instead of using the Euclidean distance of sensor locations. One of the requirements in our problem definition was that all tours include the sink node in the network. An interesting extension would be to relax this requirement, by assuming that tours that intersect can exchange data. In that case, we would only require that in the union of all tours, each connected component includes the sink. This would be a variation of the problem that would probably require new techniques for choosing the routing of each tour as well as the intersection points of the tours.

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