

To Fill or Not to Fill: The Gas Station Problem

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In this article we study several routing problems that generalize shortest paths and the traveling salesman problem. We consider a more general model that incorporates the actual cost in terms of gas prices. We have a vehicle with a given tank capacity. We assume that at each vertex gas may be purchased at a certain price. The objective is to find the cheapest route to go from s to t , or the cheapest tour visiting a given set of locations. We show that the problem of finding a cheapest plan to go from s to t can be solved in polynomial time. For most other versions, however, the problem is NP-complete and we develop polynomial-time approximation algorithms for these versions.

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1. INTRODUCTION

Optimization problems related to computing the shortest (or cheapest) tour visiting a set of locations, or that of computing the shortest path between a pair of locations, are pervasive in computer science and operations research. Typically, the measures that we optimize are in terms of distance traveled, or time spent (or in some cases, a combination of the two). There are literally thousands of papers dealing with problems related to shortest-path and tour problems.

In this article, we consider a more general model that incorporates the actual cost in terms of *gas prices*. We have a vehicle with a given tank capacity of U . In fact, we will assume that U is the distance the vehicle may travel on a full tank of gas (this can easily be obtained by taking the product of the tank size and the mileage per gas unit of the vehicle). Moreover, we may assume that we start with some given amount of gas μ ($\leq U$) in the tank. We assume that at each vertex v , gas may be purchased at a price

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of $c(v)$. This price is the cost of gas per mile. For example, if gas costs \$3.40 per gallon and the vehicle can travel 17 miles per gallon, then the cost per mile is 20 cents.

At each gas station we may fill up some amount of gas to “extend” the range of the vehicle by a certain amount. Moreover, since gas prices vary, the cost depends on where we purchase gas from.

In addition to fluctuating gas prices, there is significant variance in the price of gas between gas stations in different areas. For example, in the Washington D.C. area alone, the variance in gas prices between gas stations in different areas (on the same day) can be by as much as 20%. Due to different state taxes, gas prices in adjacent states also vary. Finally, one may ask: why do we expect such information to be available? In fact, there are a collection of Web sites¹ that currently list gas prices in an area specified by zip code. So it is reasonable to assume that information about gas prices is available. What we are interested in are algorithms that will let us compute solutions to some basic problems, given this information.

In this general framework, we are interested in a collection of basic questions.

- (1) *The gas station problem.* Given a start node s and a target node t , how do we go from s to t in the cheapest possible way if we start at s with μ_s amount of gas? In addition we consider the variation in which we are willing to stop to get gas at most Δ times.² Another generalization we study is the sequence gas station problem. Here, we want to find the cheapest route that visits a set of p locations in a specified order (for example, by a delivery vehicle).
- (2) *The fixed-path gas station problem.* An interesting special case is when we fix the path along which we would like to travel. Our goal is to find an optimal set of refill stops along the path.
- (3) *The uniform cost tour gas station problem.* Given a collection of cities T , and a set of gas stations S at which we are willing to purchase gas, find the shortest tour that visits T . We have to ensure that we never run out of gas. Clearly this problem generalizes the traveling salesman problem. The problem gets more interesting when $S \neq T$, and we address this case. This models the situation when a large transportation company has a deal with a certain gas company, and their vehicles may fill up gas at any station of this company at a prenegotiated price. Here we assume that gas prices are the same at each gas station. This could also model a situation where some gas stations with very high prices are simply dropped from consideration, and the set S is simply the set of gas stations that we are willing to use.
- (4) *The tour gas station problem.* This is the same as the previous problem, except that the prices at different stations can vary.

Of all the problems just mentioned, only the tour problems are *NP*-hard. For the first two we develop polynomial-time algorithms, and for the tour problems we develop approximation algorithms.

We would also like to note that our strategy yields a solution where the gas tank will be empty when one reaches a location where gas can be filled cheaply. In practice, this is not safe and one might run out of gas (for example, if one gets stuck in traffic). For that reason we suggest defining U to be smaller than the actual tank capacity so that we always have some “reserve” capacity.

¹<http://www.gasbuddy.com>, <http://www.aaa.com>.

²This restriction makes sense, because in some situations where the gas prices are decreasing as we approach our destination, the cheapest solution may involve an arbitrarily large number of stops, since we only fill up enough gas to make it to a cheapest station further down the path.

We now give a short summary of the results in the article.

- (1) *The gas station problem.* For the basic gas station problem, our algorithm runs in time $O(\Delta n^2 \log n)$ and computes an optimal solution. If we want to visit a sequence of p cities we can find an optimal solution in time $O(\Delta(np)^2 \log(np))$. In addition, we develop a second algorithm for the all-pairs version that runs in time $O(n^3 \Delta^2)$. This method is better than repeating the fixed destination algorithm n times when $\Delta < \log n$.
- (2) *The fixed-path gas station problem.* For the fixed-path version with an unbounded number of refill stops, we develop a fast $O(n \log n)$ -time algorithm.
- (3) *The uniform cost tour gas station problem.* Since this problem is *NP*-hard, we focus on polynomial-time approximation algorithms. We assume that every city has a gas station within a distance of $\alpha \frac{U}{2}$ for some $\alpha < 1$. This assumption is reasonable since in any case, every city has to have a gas station within distance $\frac{U}{2}$, otherwise there is no way to visit it. A similar assumption is made in the work on distance constrained vehicle routing problem [Li et al. 1992]. We develop an approximation algorithm with an approximation factor of $\frac{3}{2}(\frac{1+\alpha}{1-\alpha})$. We also consider a special case, namely when there is only one gas station. This is the same as having a central depot, and requiring the vehicle to return to the depot after traveling a maximum distance of U . For this special case, we develop an algorithm with factor $O(\ln \frac{1}{1-\alpha})$ and this improves the bound of $\frac{3}{2(1-\alpha)}$ given by Li et al. [1992] for the distance-constrained vehicle routing problem.
- (4) *The tour gas station problem.* For the tour problem with arbitrary gas prices, we can reduce this to the uniform cost tour gas station problem by paying a factor of β in the approximation guarantee. Here β is the ratio of maximum cost of gas to the minimum cost of gas (in practice likely to be around 1.2).

1.1. Related Work

The problems of computing shortest paths and the shortest TSP tour are clearly the most relevant ones here and are widely studied, and discussed in several books [Lawler et al. 1985; Papadimitriou and Steiglitz 1998].

One closely related problem is the orienteering problem [Arkin et al. 1998; Awerbuch et al. 1998; Golden et al. 1987; Blum et al. 2003]. In this problem the goal is to compute a path of a fixed length L that visits as many locations as possible, starting from a specified vertex. For this problem, a factor 3 approximation has been given recently by Bansal et al. [2004]. (In fact, they can fix the starting and ending vertices.) This algorithm is used as subroutine for developing a bicriteria bound for deadline TSP. By using the 3 approximation for the orienteering problem, we develop an $O(\log |T|)$ approximation for the single gas station tour problem. This is not surprising, since we would like to cover all the locations by finding walks of length at most U .

There has been some recent work by Nagarajan and Ravi [2006] on minimum vehicle routing that is closely related to the single gas station tour problem. In this problem, a designated root vertex (depot) and a deadline D are given and the goal is to use the minimum number of vehicles from the root so that each location is met by at least one of the vehicles, and each vehicle traverses length at most D . (In their definition, vehicles do not have to go back to the root.) They give a 4-approximation for the case where locations are in a tree and an $O(\log D)$ approximation for graphs with integer weights.

Another closely related piece of work is by Arkin et al. [2006] where tree and tour covers of bounded length are computed. What makes their problem easier is that there is no specified root node, or a set of gas stations one of which should be included in any

bounded length tree or tour. Several pieces of work deal with vehicle routing problems [Haimovich 1985, 1988; Frederickson et al. 1978] with multiple vehicles, where the objective is to bound the total cost of the solution, or to minimize the longest tour. However, these problems are significantly easier to develop approximation algorithms for.

Somewhat related to our gas station problem is the so-called gasoline puzzle. In this puzzle the objective is to drive around a closed loop. Along the way there are gas cans that we are supposed to use to fuel the car. Cans are placed at arbitrary location and contain varying amounts of gas, however, the total gas available in these cans is enough to go around the loop once. It is not difficult to show that there always exists a starting point on the loop such that if we start from there collecting gas as we go along, then we will be able to go around without running out of gas. The problem appears to have been first mentioned in a book by Lovász [1979]. Even though the puzzle has proved useful in solving other optimization problems [Charikar et al. 2002; Berger et al. 2008], it is not directly applicable to our setting.

2. THE GAS STATION PROBLEM

The input to our problem consists of a complete graph $G = (V, E)$ with edge lengths $d : E \rightarrow R^+$, gas costs $c : V \rightarrow R^+$ and a tank capacity U . (Equivalently, if we are not given a complete graph we can define d_{uv} to be the distance between u and v in G .) Our goal is to go from source s to destination t in the cheapest possible way using at most Δ stops to fill gas. For ease of exposition we concentrate on the case where we start from s with an empty tank. The case in which we start with μ_s units of gas can be reduced to the former as follows. Add a new node s' such that $d_{s's} = U - \mu_s$ and $c(s') = 0$. The problem of starting from s with μ_s units of gas and that of starting from s' with an empty tank using one additional stop are equivalent.

In this section we develop an $O(\Delta n^2 \log n)$ -time algorithm for the gas station problem. In addition, when $\Delta = n$ we show how to solve the problem in $O(n^3)$ time for general graphs, and $O(n \log n)$ time for the case where G is a fixed path.

One interesting generalization of the problem is the *sequence gas station problem* where we are given a sequence s_1, s_2, \dots, s_p of vertices that we must visit in the specified order. This variant can be reduced to the s - t version in an appropriately defined graph.

2.1. The Gas Station Problem Using Δ Stops

The basis of our algorithm is the following Dynamic Program (DP) formulation.

$$A(u, q, g) \doteq \begin{array}{l} \text{Minimum cost to go from } u \text{ to } t \text{ using } q \text{ refill stops,} \\ \text{starting with } g \text{ units of gas. We consider } u \text{ itself} \\ \text{to be one of the } q \text{ stops.} \end{array} \quad (1)$$

The main difficulty in dealing with the problem stems from the fact that, in principle, we need to consider every value of $g \in [0, U]$. One way to avoid this is to discretize the values g can take. Unfortunately this only yields a pseudo-polynomial-time algorithm. To get around this we need to take a closer look at the structure of the optimal solution.

LEMMA 2.1. *Let $s = u_1, u_2, \dots, u_l$ be the refill stops of an optimal solution using at most Δ stops. The following is an optimal strategy for deciding how much gas to fill at each stop: At u_i fill just enough to reach t with an empty tank; for $j < l$*

- (i) *If $c(u_j) < c(u_{j+1})$ then at u_j fill up the tank.*
- (ii) *If $c(u_j) \geq c(u_{j+1})$ then at u_j fill just enough gas to reach u_{j+1} .*

PROOF. If $c(u_j) < c(u_{j+1})$ and the optimal solution does not fill up at u_j then we can increase the amount filled at u_j and decrease the amount filled at u_{j+1} . This improves the cost of the solution, which contradicts the optimality assumption. Similarly, if

```

FILL-ROW( $u, q$ )
1   $R \leftarrow \{v \in V \mid d_{uv} \leq U\}$ 
2  for  $v \in R$  do
3      if  $c(v) \leq c(u)$ 
4          then  $\text{indep}(v) \leftarrow A[v, q-1, 0] + d_{uv}c(u)$ 
5          else  $\text{indep}(v) \leftarrow A[v, q-1, U - d_{uv}] + Uc(u)$ 
6  sort  $R$  in increasing  $\text{indep}(\cdot)$  value
7  let  $v \in R$  be first in sorted order
8  for  $g \in GV(u)$  in increasing value do
9      while  $g > d_{uv}$  do
10         let  $v \in R$  be next vertex in sorted order
11      $A[u, q, g] \leftarrow \text{indep}(v) - gc(u)$ 

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Fig. 1. An $O(n \log n)$ -time procedure for computing $A[u, q, *]$.

$c(u_j) \geq c(u_{j+1})$ then we can decrease the amount filled at u_j and increase the amount filled at u_{j+1} (without increasing the overall cost of the solution) until the condition is met. \square

Consider a refill stop $u \neq s$ in the optimal solution. Let w be the stop right before u . Lemma 2.1 implies that if $c(w) \geq c(u)$, we reach u with an empty tank, otherwise we reach u with $U - d_{wu}$ gas. Therefore, in our DP formulation we need to keep track of at most n different values of gas for u . Let $GV(u)$ be the set of such values, namely

$$GV(u) = \{U - d_{wu} \mid w \in V \text{ and } c(w) < c(u) \text{ and } d_{wu} \leq U\} \cup \{0\}.$$

The following recurrence allows us to compute $A(u, q, g)$ for any $g \in GV(u)$:

$$A(u, 1, g) = \begin{cases} (d_{ut} - g)c(u) & \text{if } g \leq d_{ut} \leq U \\ \infty & \text{otherwise} \end{cases} \quad (2)$$

$$A(u, q, g) = \min_{\substack{v \text{ s.t.} \\ d_{uv} \leq U}} \left\{ \begin{array}{ll} A(v, q-1, 0) + (d_{uv} - g)c(u) & : c(v) \leq c(u) \wedge g \leq d_{uv} \\ A(v, q-1, U - d_{uv}) + (U - g)c(u) & : c(v) > c(u) \end{array} \right\}$$

The cost of the optimal solution is $\min_{1 \leq l \leq \Delta} A(s, l, 0)$. The naive way of filling the table takes $O(\Delta n^3)$ time; however, this can be done more efficiently. Instead of spending $O(n)$ time computing a single entry of the table, we spend $O(\log n)$ amortized time per entry. More precisely, for fixed $u \in V$ and $1 < q \leq \Delta$ we design an algorithm that computes all entries of the form $A(u, q, *)$ in $O(n \log n)$ time. The pseudocode of this algorithm is given in Figure 1.

THEOREM 2.2. *There is an $O(\Delta n^2 \log n)$ -time algorithm for the gas station problem with Δ stops.*

PROOF. For fixed $u \in V$ and $1 < q \leq \Delta$ we show that the algorithm FILL-ROW correctly computes all entries of the form $A(u, q, *)$ in $O(n \log n)$ time using entries of the form $A(*, q-1, *)$. Since there are n possible choices of u and Δ possible choices of q , Theorem 2.2 follows immediately.

The DP recursion for $A(u, q, g)$ finds the minimum, over all v such that $d_{uv} \leq U$, of terms that corresponds to the cost of going from u to t through v . Split each of these terms into two parts based on whether they depend on g or not. Thus we have an independent part, which is either $A(v, q-1, 0) + d_{uv}c(u)$ or $A(v, q-1, U - d_{uv}) + Uc(u)$; and a dependent part, $-gc(u)$.

Our procedure begins by sorting the independent part of every term. Note that the minimum of these corresponds to the entry for $g = 0$. As we increase g , the terms decrease uniformly. Thus, to compute the table entry for $g > 0$ just subtract $gc(u)$ from the smallest independent part available. The only caveat is that the term corresponding to a vertex v such that $c(v) \leq c(u)$ should not be considered any more once $g > d_{uv}$, we say such a term *expires* after $g > d_{uv}$. Since the independent terms are sorted, once the smallest independent term expires we can walk down the sorted list to find the next vertex which has not yet expired. The procedure is dominated by the time spent sorting the independent terms which takes $O(n \log n)$ time. \square

2.2. Unbounded Number of Stops

We next consider the case when the number of stops is unbounded. Our algorithm is based on a similar DP formulation as the one used in the previous subsection. One minor modification is that since we do not care about the number of stops we can ignore the last component of the DP state and thus reduce the total number of states.

$$D(u, g) \doteq \text{Minimum cost to go from } u \text{ to } t, \text{ starting with } g \text{ units of gas} \quad (3)$$

Clearly, $D(t, 0) = 0$. For other vertices $u \neq t$ and $g \in GV(u)$, the optimal values should obey the following recurrence.

$$D(u, g) = \min_{\substack{v \text{ s.t.} \\ d_{uv} \leq U}} \left\{ \begin{array}{ll} D(v, 0) + (d_{uv} - g)c(u) & : c(v) \leq c(u) \wedge g \leq d_{uv} \\ D(v, U - d_{uv}) + (U - g)c(u) & : c(v) > c(u) \end{array} \right\} \quad (4)$$

Finding the values of D defined by the recurrence reduces to a shortest path computation in a new directed graph H with positive edge weights. The vertices of H are pairs (u, g) , where $u \in V$ and $g \in GV(u)$. The edges of H and their weight $w(\cdot)$ are defined by the DP recurrence (4); namely, for every $u, v \in V$ and $g \in GV(u)$ such that $d_{uv} \leq U$ we have $w((u, g), (v, 0)) = (d_{uv} - g)c(u)$ if $c(v) \leq c(u)$ and $g \leq d_{uv}$, or $w((u, g), (v, U - d_{uv})) = (U - g)c(u)$ if $c(v) > c(u)$. Clearly, the length of the shortest path from (u, g) to $(t, 0)$ in H equals $D(u, g)$ as the DP formulation for the shortest-path problem gives rise to the same recurrence (4).

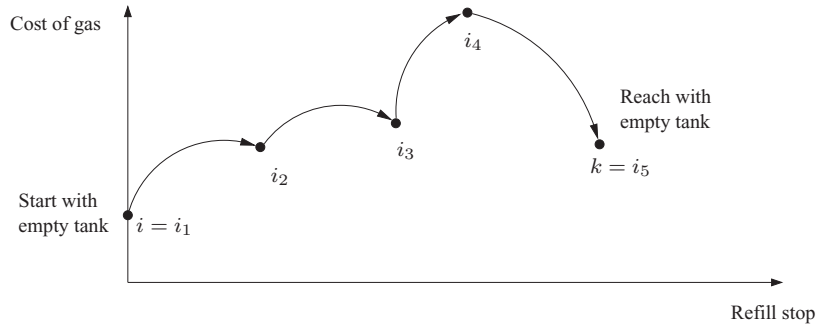
THEOREM 2.3. *The gas station problem with unbounded number of stops can be solved in $O(n^3)$ time.*

PROOF. Our objective is to find a shortest path from $(s, 0)$ to $(t, 0)$ in the graph H defined before. Note that H has at most n^2 vertices and at most n^3 edges. Using Dijkstra's algorithm [Cormen et al. 2001, Chapter 24] the theorem follows. \square

2.3. Faster Algorithm for the All-Pairs Version

Consider the case in which we wish to solve the problem for all starting nodes i , each having μ_i amount of gas in the tank initially. Using the method described in the previous section, we get a running time of $O(n^3 \Delta \log n)$ since we run the algorithm for each possible destination. We will show that for $\Delta < \log n$ we can improve this and get a bound of $O(n^3 \Delta^2)$.

As we did for the source-sink case, we first modify the instance so as to assume that we start with an empty tank. For each vertex i , add a new node i' such that $d_{i'i} = U - \mu_i$ and $c(i') = 0$. If we start at i with μ_i units of gas, it is the same as starting from i' where gas is free. We fill up the tank to capacity U , and then by the time we reach i we will have exactly μ_i units of gas in the tank. (Since gas is free at any node i' in any optimal solution we fill up the tank to capacity U). This will use one extra stop.

Fig. 2. Example to show $C(i, k, q)$ for $q = 4$.

In order to get the desired running time, we use a different DP formulation.

$$B(i, h, p) \doteq \text{Minimum cost to go from } i \text{ to } h \text{ (destination) with } p \text{ refill stops such that we start and end with an empty tank} \quad (5)$$

Since we start with an empty tank, we have to fill up gas at the starting point and this is included as one of the p refills allowed.

Our goal is to compute $B(i', h, \Delta + 1)$, the minimum cost to go from i' to h with at most Δ stops in-between, for all i' and h . Our DP recurrence for $B(i, h, p)$ will be based on the following observations.

- (1) If the gas price at the first stop after i , let us call this k , is cheaper than $c(i)$ then we will reach that station with an empty tank after filling d_{ik} units of gas at i (as long as $d_{ik} \leq U$).

$$B(i, h, p) = B(k, h, p - 1) + d_{ik}c(i)$$

- (2) If the first place where the cost of gas decreases from the previous stop is the $q + 1^{\text{st}}$ stop and the price is in increasing order in the first q stops then

$$B(i, h, p) = C(i, k, q) + B(k, h, p - q),$$

where the auxiliary term $C(i, k, q)$ is defined as the minimum cost of going from i to k with at most q refill stops, such that we start at i with an empty tank (filling gas at i counts as a stop) and finally reach k with an empty tank. In addition, the price of gas in intermediate stations is in increasing order except for the last stop.

We define $B(h, h, p) = 0$. For $i \neq h$ let $B(i, h, 1) = c(i)d_{ih}$ if $d_{ih} \leq U$, and $B(i, h, 1) = \infty$ otherwise. In general:

$$B(i, h, p) = \min \left\{ \min_{\substack{1 \leq k \leq n \\ 1 < q \leq p}} C(i, k, q) + B(k, h, p - q), \min_{\substack{1 \leq k \leq n \\ \text{s.t. } d_{ik} \leq U}} B(k, h, p - 1) + d_{ik}c(i) \right\}. \quad (6)$$

It only remains to show how to compute $C(i, k, q)$ for all relevant choices of i , k , and q . Suppose that in going from i to k we stop at $i_1 = i, \dots, i_q, i_{q+1} = k$ (see Figure 2). Note that $c(i_1) \leq c(i_2) \leq \dots \leq c(i_q)$, however $c(i_q) > c(i_{q+1})$. In fact, at i_1 we will get U amount of gas. When we reach i_j for $1 < j < q$, we will get $d_{i_{j-1}i_j}$ units of gas (the amount that we consumed since the previous fill-up) at a cost of $c(i_j)$ per unit of gas. The amount of gas we will get at i_q is just enough to reach k with an empty tank. Now we can see that the total cost is equal to $Uc(i_1) + d_{i_1i_2}c(i_2) + \dots + d_{i_{q-2}i_{q-1}}c(i_{q-1}) + (d_{i_{q-1}i_q} + d_{i_qk} - U)c(i_q)$. Note that the last term is nonnegative, since we could not reach k from i_{q-1} even with a full tank at i_{q-1} , without stopping to get a small amount of gas.

We compute $C(i, k, q)$ as follows. First note that if $d_{ik} \leq U$ then the answer is $d_{ik}c(i)$. Otherwise we build a directed graph $G' = (V \cup V_D, E \cup E_D)$, where V is the set of vertices in the original graph, and $V_D = \{i' | i \in V\}$.

For each $i \in V$ and $j \in V - i$ such that $d_{ij} \leq U$ and $c(i) \leq c(j)$, we add the edge (i, j) to E . The weight of this edge is $d_{ij}c(j)$.

For each $j \in V$ and $k' \in V_D \setminus \{j'\}$ such that $U < d_{jk} \leq 2U$, we add the edge $(j, k') \in E_D$. The weight of this edge is

$$\min \{(d_{jz} + d_{zk} - U)c(z) \mid c(j), c(k) < c(z) \text{ and } d_{jz}, d_{zk} \leq U\}.$$

Now we can express $C(i, k, q)$ as $Sp(i, k', q) + Uc(i)$ where $Sp(i, k', q)$ is the shortest path from i to k' in the graph G' using at most q edges.

To see why it is true, we can see that for any given order of stops between i and k (where the gas price is in increasing order in consecutive stops), the minimum cost is equal to the weight of the path in G' that starts from i , goes to the second stop in the given order (e.g., i_2), and then traverses the vertices of V in the same order and from the second last stop goes to k' . It is also possible that $q = 2$ and the path goes directly from $i = i_1$ to k in this case, and i_2 is the choice for z that achieves the minimum cost for the edge (i, k') .

For any given path P in G' between i and k' , if the weight of the path is W_P we can find a feasible plan for filling the tank at the stations so that the cost is equal to $W_P + Uc(i)$. It is enough to fill up the tank at the stations that are in the path, except the last one in which the tank is filled to only the required level to reach k . We can conclude that $C(i, k, q)$ is equal to $Sp(i, k', q) + Uc(i)$.

THEOREM 2.4. *There is an $O(n^3 \Delta^2)$ -time algorithm for the all-pairs gas station problem.*

PROOF. The running time for finding the shortest path in G' between all pairs of nodes with different number of stops (at most Δ) is $O(n^3 \Delta)$ by dynamic programming [Lawler 2001]. Thus, it makes $O(n^3 \Delta)$ time to compute $C(i, k, q)$ for all relevant i, k , and q .

Given these values, we can now compute $B(i, h, p)$ using (6). There are $n^2 \Delta$ states in the dynamic program and each one can be computed in time $O(n \Delta)$, which yields a running time of $O(n^3 \Delta^2)$. This computation dominates the overall running time and the theorem follows. \square

2.4. The Sequence Gas Station Problem

Suppose instead of a given source and destination, we are asked to find the cheapest way to start from a given location, visit a set of locations in a given order during the trip, and then reach the final destination. We define the problem in a formal way as follows.

Given an edge weighted graph $G = (V, E)$ and a list of vertices s_0, \dots, s_p , we wish to find the cheapest way to start from s_0 , visit s_1, \dots, s_{p-1} in this order and then reach s_p .

Note that we cannot reduce this problem to p separate source-destination subproblems and combine the solutions directly. To see why, consider the case where the gas price is very high at some station s_i and on the way from s_{i-1} to s_i there is a very cheap gas station near s_i . If we want to use the solution for the separate subproblems and then combine them, we will reach s_i with an empty tank so we have to fill the tank at s_i since we are out of gas; but the optimal solution is to reach s_i with some gas in the tank to make it possible to reach next station after s_i without filling the tank at s_i .

To solve this problem, we will make a new graph as follows: Make $p - 1$ new copies of the current graph G and call them G_1, \dots, G_{p-1} . G will become G_0 . Call v_i in G_j as $v_{i,j}$. Now connect G_i and G_{i+1} by merging $s_{i+1,i}$ and $s_{i+1,i+1}$ into one node. The solution

to the original problem is to find the cheapest way to go from $s_{1,0}$ to $s_{p,p-1}$ in the new graph. We can see that any path in this graph that goes from $s_{1,0}$ to $s_{p,p-1}$ will pass through $s_{i+1,i} \forall i, 0 \leq i \leq p-1$.

2.5. Fixed Path

Number the nodes along the path from 1 to n , so that we start at 1 and want to reach n . Without loss of generality assume we start with an empty tank. We present a fast, yet simple, exact algorithm for the case when there is no constraint on the number of refill stops.

For each gas station i , define $\text{prev}(i)$ as the station $j \leq i$ with the cheapest gas among those that satisfy $d_{ji} \leq U$. Similarly let $\text{next}(i)$ be the station $j > i$ with the cheapest gas such that $d_{ij} \leq U$. Ties are broken by favoring the station closest to n . We refer to these stations as the *previous* and *next station* of i .

Station i is said to be a *break point* if $\text{prev}(i) = i$. Identifying such stations is important because it allows us to decompose the problem into smaller subproblems that are easier to solve.

LEMMA 2.5. *There is an optimal solution that reaches every break point with an empty tank.*

PROOF. Fix an optimal solution following the two properties of Lemma 2.1. Let i be a break point and $j < i$ be the last station we stopped to get gas before reaching i . Since i is a break point, we have $c(i) \leq c(j)$. Therefore at j we fill just enough gas to reach i with an empty tank. \square

Our algorithm first computes previous and next stations for all i , identifies the break points, and then runs DRIVE-TO-NEXT to solve the subproblem to go from one break point to the next.

DRIVE-TO-NEXT(i, k)

- 1 Let x be i .
- 2 If $d_{xk} \leq U$ then just fill enough gas to go k .
- 3 Otherwise, fill up and drive to $\text{next}(x)$. Let x be $\text{next}(x)$, go to step 2.

THEOREM 2.6. *There is an $O(n \log n)$ -time algorithm for the fixed-path gas station problem with unbounded number of stops.*

PROOF. If we are given $\text{prev}(i)$ and $\text{next}(i)$ for every station i , then we can identify all the break points and run DRIVE-TO-NEXT in $O(n)$ time. We show how to compute the previous and next station for all i in $O(n \log n)$ time. To that end, we keep a priority queue holding a set of stations lying on a moving window of length U ; the priority of station i is $c(i)$. Starting from 1, that is from the stations $\{i : d_{1i} \leq U\}$, we slide the window toward n inserting and removing stations as we go along. Right after inserting station i into the queue, asking for the minimum in the queue gives us $\text{prev}(i)$. Similarly, right after removing i , asking for the minimum gives us $\text{next}(i)$. Since each insertion and deletion can be done in $O(\log n)$ time, the whole procedure takes $O(n \log n)$ time.

To show that the solution returned is optimal, by Lemma 2.5 we only need to argue that DRIVE-TO-NEXT is optimal for the subproblem of going from i to k starting and ending with an empty tank, given that there are no break points in between i and k . The key observation is that for every station x considered by the algorithm, if $d_{xk} > U$ then $c(x) \leq c(\text{next}(x))$. Since all stations in a range of U after x offer gas at cost at least $c(x)$,

an optimal solution fills up at x and drives up to the next cheapest station (namely, $\text{next}(x)$), precisely what the algorithm does. \square

Remark. even though DRIVE-TO-NEXT solves our special subproblem optimally, the strategy does not work in general. To see why, consider an instance where $c(i) > c(i+1)$ and $d_{1n} = U$. While the optimum stops on every station, DRIVE-TO-NEXT will tell us to go straight from 1 to n .

3. THE UNIFORM COST TOUR GAS STATION PROBLEM

In this section we study a variant of the gas station problem where we must visit a set of cities T in arbitrary order. We consider the case where gas costs the same at every gas station, but some cities may not have a gas station.

More formally, the input to our problem consists of a complete undirected graph $G = (V, E)$ with edge lengths $d : E \rightarrow R^+$, a set of cities $T \subseteq V$, a set of gas stations $S \subseteq V$, and tank capacity U for our vehicle. The objective is to find a minimum length tour that visits all cities in T , and possibly some gas stations in S . We are allowed to visit a location multiple times if necessary. We require any segment of the tour of length U to contain at least one gas station; this ensures that we never run out of gas. We call this the *uniform cost tour gas station problem*. We assume that we start with an empty tank at a gas station (in fact we can assume that this is a city that has a gas station).

We make the assumption that every city has a gas station at distance at most $\alpha \frac{U}{2}$. This assumption is reasonable, because if a city has no gas station within distance $\frac{U}{2}$, there is no way to visit it. We show a $\frac{3(1+\alpha)}{2(1-\alpha)}$ approximation for this problem. Note that when $\alpha = 0$, this gives the same bound as the Christofides method for the TSP.

The problem is *NP*-hard as it generalizes the well-known traveling salesman problem: just set the tank capacity to the largest distance between any two cities and let $T = S$. In fact, there is a closer connection between the two problems: If every city has a gas station, that is, $T \subseteq S$, we can reduce the gas station problem to the TSP. Consider a TSP instance on T under metric $\ell : T \times T \rightarrow R^+$, where ℓ_{xy} is the minimum cost of going between cities x and y starting with an empty tank (this can be computed by standard techniques). Since the cost of gas is the same everywhere, a TSP tour can be turned into a driving plan that visits all cities with the same cost and vice versa. Let OPT denote an optimal solution, and $c(OPT)$ its cost.

As mentioned earlier, we can use the algorithm for the uniform cost case to derive an approximation algorithm for the general case by paying a factor β in the approximation ratio. Here β is the ratio of the maximum price that an optimal solution pays for buying a unit of gas, to the minimum price it pays for buying a unit of gas (in practice this ranges from 1 to 1.2).

Unfortunately this reduction to the TSP breaks down when cities are not guaranteed to have a gas station. Consider going from x to y , where x does not have a gas station. The cost to go from x to y will depend on how much gas we have at x , which in turn depends on which city was visited before x and what route we took to get there.

An interesting case of the tour gas station problem is that of an instance with a single gas station. This is also known as the *distance constrained vehicle routing problem* and was studied by Li et al. [1992] who gave a $\frac{3}{2(1-\alpha)}$ approximation algorithm, where the distance from the gas station to the most distant city is $\alpha \frac{U}{2}$, for some $\alpha < 1$. We improve this by providing an $O(\log \frac{1}{1-\alpha})$ approximation algorithm. Without making any assumptions on α we show that a greedy algorithm that finds bounded length tours visiting the most cities at a time is a $O(\log |T|)$ -factor approximation.

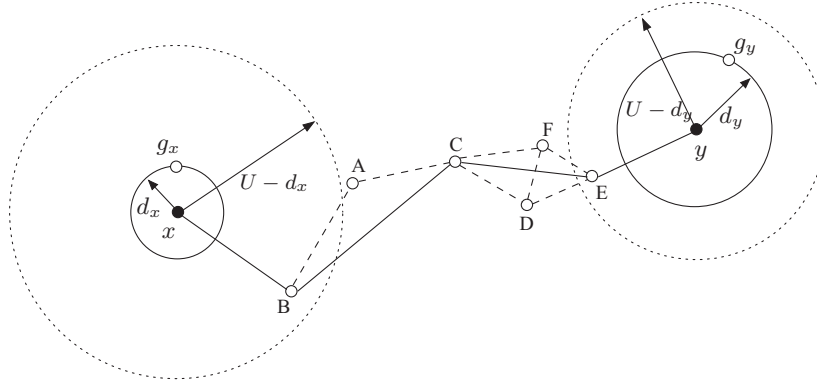


Fig. 3. Function ℓ_{xy} . The path shown is the shortest valid path from x to y . We use Euclidean distances in this example.

3.1. The Uniform Cost Tour Gas Station Problem

For each city $x \in T$ let $g_x \in S$ be the closest gas station to x , and let d_x be the distance from x to g_x . We assume that every city has a gas station at distance at most $\alpha \frac{U}{2}$; in other words, $d_x \leq \alpha \frac{U}{2}$ for all $x \in T$ for some $\alpha < 1$.

Recall that it is assumed that the price of the gas is the same at all the gas stations. We define a new distance function for the distance between each pair of cities. The distance ℓ is defined as follows: For each pair of cities x and y , ℓ_{xy} is the length of the shortest traversal to go from x to y starting with $U - d_x$ amount of gas and reaching y with d_y amount of gas. If $d_{xy} \leq U - d_x - d_y$ then we can go directly from x to y , and $\ell_{xy} = d_{xy}$. Otherwise, we can compute this as follows. Create a graph whose vertex set is S , the set of gas stations. To this graph add x and y . We now add edges from x to all gas stations within distance $U - d_x$ from x . Similarly we add edges from y to all gas stations within distance $U - d_y$ to y . Between all pairs of gas stations, we add an edge if the distance between the pair of gas stations is at most U . All edges have length equal to the distance between their endpoints. The length of the shortest path in this graph from x to y will be ℓ_{xy} . Note that the shortest path (in general) will start at x and then go through a series of gas stations before reaching y . This path yields a valid plan to drive from x to y without running out of gas, once we reach x with $U - d_x$ units of gas. When we reach y , we have enough gas to go to g_y . Also note that $\ell_{xy} = \ell_{yx}$ since the path is essentially “reversible.”

In Figure 3 we illustrate the definition of function ℓ_{xy} . We assume here that all distances are Euclidean. Note that from x , we can only go to B and not A since we start from x with $U - d_x$ units of gas. From B , we cannot go to D since the distance between B and D is more than U , even though the path through D to y would be shorter. From C we go to E since going through F will give a longer path, since from F we cannot go to y directly.

Note that the function ℓ may not satisfy triangle inequality. To see this, suppose we have three cities x, y, z . Let $d_{xy} = d_{yz} = \frac{U}{2}$. Let $d_x = d_y = d_z = \frac{U}{4}$ and $d_{xz} = U$. We first observe that $\ell_{xy} = \ell_{yz} = \frac{U}{2}$. However, if we compute ℓ_{xz} , we cannot go from x to z directly since we only have $\frac{3}{4}U$ units of gas when we start at x and need to reach z with $\frac{U}{4}$ units of gas. So we have to visit g_y along the way, and thus $\ell_{xz} = \frac{3}{2}U$.

The algorithm is as follows.

- (1) Create a new graph G' , with a vertex for each city. For each pair of cities x, y compute ℓ_{xy} as shown earlier.

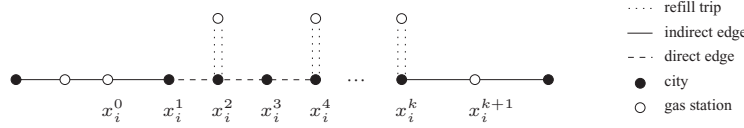


Fig. 4. Decomposition of the solution into strands.

- (2) Find the minimum spanning tree in (G', ℓ) . Also find a minimum weight perfect matching M on the odd degree vertices in the MST. Combine the MST and M to find an Euler tour \mathcal{T} .
- (3) Start traversing the Eulerian tour. Add refill trips whenever needed. (Details on this follow.)

THEOREM 3.1. *The algorithm described before has an approximation guarantee of $\frac{3}{2} \frac{(1+\alpha)}{(1-\alpha)}$.*

PROOF. It can be shown that the total length of the MST is less than the optimal solution cost. Suppose x_1, \dots, x_n is the order in which the optimal solution visits the cities. Clearly, the cost of going from x_i to x_{i+1} in the optimal solution is at least $\ell_{x_i x_{i+1}}$. Since the collection of edges (x_i, x_{i+1}) forms a spanning tree, we can conclude that the weight of the $\ell(\text{MST}) \leq c(\text{OPT})$. Next we show that the cost of M is at most $\frac{c(\text{OPT})}{2}$. Suppose the odd degree vertices are in the optimal solution in the order o_1, \dots, o_k . We can see that $\ell_{o_i, o_{i+1}}$ is at most equal to the distance we travel in the optimal solution to go from o_i to o_{i+1} . So the cost of minimum weighted matching on the odd degree vertices is at most $\frac{c(\text{OPT})}{2}$. So the total cost of the Eulerian tour \mathcal{T} is at most $\frac{3c(\text{OPT})}{2}$.

Now we need to transform the Eulerian tour into a feasible plan. First, every edge (x, y) in \mathcal{T} is replaced with the actual plan to drive from x to y that we found when computing ℓ_{xy} . If $d_{xy} \leq U - d_x - d_y$ the plan is simply to go straight from x to y , we call these *direct edges*. Otherwise the plan must involve stopping along the way in one or more gas stations, we call these *indirect edges*. Notice that the cost of this plan is exactly that of the Eulerian tour \mathcal{T} . Unfortunately, as we will see shortly this plan need not be feasible.

Define a strand to be a sequence of consecutive cities in the tour connected by direct edges. If a city is connected with two indirect edges, then it forms a strand by itself. Suppose the i^{th} strand has cities x_i^1, \dots, x_i^k . To this we add x_i^0 (x_i^{k+1}), the last (first) gas station in the indirect edge connecting x_i^1 (x_i^k) with the rest of the tour. Each strand now starts and ends with a gas station. We can view the tour as a decomposition into strands as shown in Figure 4. Note that if the distance between x_i^0 and x_i^{k+1} is more than U the overall plan is not feasible. To fix this we add for every city a refill trip to its closest gas station and then greedily try to remove them, while maintaining feasibility, until we get a minimal set of refill trips. Let us bound the extra cost these trips incur.

LEMMA 3.2. *Let L_i be the length of the i^{th} strand. Then the total distance traveled on the refill trips of cities in the strand is at most $\frac{2\alpha}{1-\alpha} L_i$.*

PROOF. Assume there are q_i refill trips in this strand. Label the cities with refill trips to their nearest gas stations $x_i^{j_1}, \dots, x_i^{j_{q_i}}$. Also label x_i^0 as $x_i^{j_0}$ and x_i^k as $x_i^{j_{q_i+1}}$. Note that $\ell(\mathcal{T}(x_i^{j_p}, x_i^{j_{p+2}})) \geq (1-\alpha)U$ (otherwise the refill trip at $x_i^{j_{p+1}}$ can be dropped). This gives us

$$2L_i > \sum_{0 \leq p \leq q_i-1} \ell(\mathcal{T}(x_i^{j_p}, x_i^{j_{p+2}})) \geq q_i(1-\alpha)U \implies q_i \leq \frac{2L_i}{(1-\alpha)U}.$$

The length of each refill trip is no more than αU . Therefore, the total length of the refill trips is at most $\alpha U q_i$, and the lemma follows. \square

Without loss of generality we can assume at least one of the cities in T has a gas station; otherwise, we can guess one station that the optimal solution uses and add it to T . This assumption is crucial because if we find a tour with only direct edges (there is a single strand) and the length of the strand is too short to warrant a refill trip, we want to make sure that we can fill gas in one of the cities.

Therefore, the cost of the solution is the total length of the strands (which is the length of the tour) plus the total cost of the refill trips

$$\ell(\mathcal{T}) + \sum_i \alpha U q_i \leq \left(1 + \frac{2\alpha}{1-\alpha}\right) \ell(\mathcal{T}) \leq \left(\frac{1+\alpha}{1-\alpha}\right) \frac{3}{2} c(\text{OPT}),$$

which yields the desired approximation ration. \square

3.2. The Tour Gas Station Problem

We show a reduction to the uniform cost tour problem. We can use the following scheme: sort all the gas prices in nondecreasing order $c_1 \leq c_2 \leq \dots \leq c_n$. Now guess a range of prices $[c_i \dots c_j]$ one is willing to pay, and let $\beta_{ij} = \frac{c_j}{c_i}$. Let S_{ij} include all the gas stations v such that $c_i \leq c(v) \leq c_j$. We can run the algorithm for the *uniform cost tour gas station problem* with set S_{ij} and cities T . This will yield a tour $\mathcal{T}^{[i,j]}$. We observe that the cost of the tour $\mathcal{T}^{[i,j]}$ is at most $O(\frac{\beta_{ij}}{1-\alpha})$ times the cost of an optimal solution, since its possible that we always pay a factor β_{ij} more than the optimal solution, at each station where we fill gas. Taking the best solution over all $O(n^2)$ possible choices gives a valid solution to the tour gas station problem.

3.3. Single Gas Station

In this version, there is a single gas station and our vehicle starts there. It must return to the gas station before it runs out of gas after traveling a distance of at most U from the previous fill-up. Fix constants $(\rho_1, \rho_2, \dots, \rho_l)$. Our algorithm first visits cities at distance $\rho_1 \frac{U}{2}$ from the gas station (we refer to these cities as C_0). Beyond $\rho_1 \frac{U}{2}$ we work in iterations. In the i th iteration we visit cities (C_i) that lie at distance in the range $(\frac{U}{2} \rho_i, \frac{U}{2} \rho_{i+1}]$ from the gas station. If we make $\frac{1-\rho_i}{1-\rho_{i+1}} = \gamma$ a constant, after $\lceil \log_\gamma \frac{1-\rho_1}{1-\alpha} \rceil$ iterations we will have visited all cities. We will argue that in each iteration we travel $O(c(\text{OPT}))$ distance, which gives us the desired result. The ρ_i values will be chosen to minimize the constants involved to get the following theorem.

THEOREM 3.3. *There is a $6.362 \ln \frac{1}{1-\alpha} - 1.534$ -factor approximation for the uniform cost tour gas station problem with a single station, for $\alpha \geq 0.5$.*

Remark. It is worth noting that for $\alpha \geq 0.5$ the preceding approximation ratio is always greater than 1.

PROOF. First we consider the cities C_0 at distance $\rho_1 \frac{U}{2}$ or less from the gas station. Find a TSP tour on the gas station and C_0 and chop it into segments of length $(1 - \rho_1)U$. The distance from the gas station to any location is at most $\rho_1 \frac{U}{2}$ and so the segments can be traversed with loops of length at most U . In fact we can start chopping the TSP tour at the gas station and make the first and the last segment be of length $(1 - \frac{\rho_1}{2})U$.

The total length of these tours will be

$$\text{cost}(C_0) \leq \left\lceil \frac{\text{cost}(\text{TSP}) - \rho_1 U}{(1 - \rho_1)U} \right\rceil U \leq \frac{\text{cost}(\text{TSP})}{(1 - \rho_1)} \leq \frac{3}{2(1 - \rho_1)} \cdot \text{OPT}.$$

The second inequality holds if we assume $\rho_1 \geq .5$. The third comes from using Christofides algorithm [Christofides 1976] to find the TSP tour and the fact that OPT is a valid TSP tour.

Notice that it does not work well when cities are far away from the gas station ($\alpha \approx 1$). In our scheme those far away cities will be visited in a different fashion. In the i th iteration we visit cities C_i at distance $(\rho_i \frac{U}{2}, \rho_{i+1} \frac{U}{2}]$ by finding a collection of paths of length at most $(1 - \rho_{i+1})U$ spanning C_i and then turning these segments into loops.

Suppose we knew that in the optimal solution there are k_i loops that span some city in C_i —this quantity can be guessed. First we run Kruskal's algorithm but stop once the number of components becomes k_i , let R_i be the resulting forest. Each tree is doubled to form a loop and then chopped into segments of length $(1 - \rho_{i+1})U$. Let k'_i be the number of such segments. The cost of the these loops is therefore

$$\text{cost}(C_i) \leq 2 \text{cost}(R_i) + k'_i \rho_{i+1} U.$$

LEMMA 3.4. *The number of segments k'_i is at most $(2\gamma + 1)k_i$.*

PROOF. The edges in R_i form a minimum weight forest with k_i components, we can relate this to the cost of OPT. Consider turning each loop in OPT into a path by keeping the stretch between the first and the last city in C_i . The set P of such paths is a forest with k_i components, therefore $\text{cost}(R_i) \leq \text{cost}(P) \leq (1 - \rho_i)U k_i$.

Using this we can bound the number of segments we get after doubling and chopping R_i .

$$k'_i \leq \left\lceil \frac{2 \text{cost}(R_i)}{(1 - \rho_{i+1})U} \right\rceil + k_i \leq \left\lceil \frac{2(1 - \rho_i)U k_i}{(1 - \rho_{i+1})U} \right\rceil + k_i \leq (2\gamma + 1)k_i \quad \square$$

We now bound the cost of visiting the cities in C_i .

$$\begin{aligned} \text{cost}(C_i) &\leq 2 \text{cost}(R_i) + k'_i \rho_{i+1} U \\ &\leq 2 \text{cost}(\text{OPT}) - 2k_i \rho_i U + (2\gamma + 1)k_i \rho_{i+1} U \\ &\leq 2 \text{cost}(\text{OPT}) + (2\gamma - 1)(\text{cost}(\text{OPT}) - k_i \rho_i U) - 2k_i \rho_i U + (2\gamma + 1)k_i \rho_{i+1} U \\ &\leq (2\gamma + 1) \text{cost}(\text{OPT}) + (2\gamma + 1)k_i (\rho_{i+1} - \rho_i)U \end{aligned}$$

Let k be the number of loops in the optimal solution whose length is greater than $\rho_1 U$, notice that loops spanning cities beyond $\rho_1 \frac{U}{2}$ must be at least this long, therefore $k \geq k_i$ for all i . Adding up over all iterations we get

$$\begin{aligned} \sum_{i=1}^l \text{cost}(C_i) &\leq (2\gamma + 1)(l \text{cost}(\text{OPT}) + k(\rho_l - \rho_1)U) \\ &\leq (2\gamma + 1) \left(l + \frac{1 - \rho_1}{\rho_1} \right) \text{cost}(\text{OPT}). \end{aligned}$$

After $l = \lceil \log_{\gamma} \frac{1 - \rho_1}{1 - \alpha} \rceil$ iterations we will have visited all cities at a cost of

$$\left\lceil \frac{3}{2(1 - \rho_1)} + (2\gamma + 1) \left(\log_{\gamma} \frac{1 - \rho_1}{1 - \alpha} + 1 + \frac{1}{\rho_1} - 1 \right) \right\rceil \text{cost}(\text{OPT}).$$

We can use numerical optimization to minimize the approximation ratio in the expression from above. Setting $\rho_1 = 0.7771$ and $\gamma = 3.1811$ give us Theorem 3.3. \square

3.4. A Greedy Algorithm

In this case we do not make any assumption on the maximum distance from a city to its closest gas station. We will use the *point-to-point orienteering path* as the basis of the greedy scheme. In the point-to-point orienteering problem, each vertex in the graph has a prize. The goal is to find a path P of maximum length d (predefined) between two given vertices s and t so that the total prize of P is maximized. A 3-approximation algorithm for this problem is described in Bansal et al. [2004]. The greedy algorithm works as follows: At the beginning the prize of all the cities are initialized to 1. As the algorithm proceeds whenever we visit a city in a tour, we reset its prize to 0. The greedy algorithm will repeatedly choose the point-to-point orienteering path that begins and ends at s with maximum length U , until the prize of all the vertices are reset to zero. Using an argument similar to that in set-cover it can be shown that both the total cost and the number of cycles given by this approach is at most $O(\log |T|)$ times the optimum cost.

THEOREM 3.5. *The greedy method gives an $O(\log |T|)$ approximation guarantee for both the total cost and the number of the cycles in the single gas station problem.*

PROOF. Observe that if an algorithm approximates the number of cycles in the optimal solution, it also approximates the total length of the tour over the optimal solution. For any given solution, we can merge each two cycles of length less than $\frac{U}{2}$ together. The new tour is still feasible and of length less or equal the initial tour. Thus, there exists a minimum-length solution in which the sum of the lengths of any two cycles is at least U . Consider the solution with minimum length and with the property that we can merge no more cycles. If the number of cycles in this tour is N_c and the total length traversed is L , by the previous argument we conclude that $L \geq \lceil \frac{J}{2} \rceil U$. Now, suppose we give an algorithm which covers all the points in αOPT_c cycles where OPT_c is the optimal number of cycles to cover all the points. We can conclude that the length of the tour is at most $2\alpha T$. From now on we try to find the approximation factor for the number of cycles in our solution. Suppose the optimal number of cycles is J . The total length of the tour will be at most $U \times J$. Let u_i and s_i denote the number of elements covered in round i and the total number of elements covered from the beginning until this round, respectively. Therefore, considering the way we choose the cycles we can assert that $u_1 \geq \frac{n}{3J}$ (where n is the number of cities), and also for each u_i $u_i \geq \frac{n-s_{i-1}}{3J}$ holds. The algorithm continues until $s_i \geq n$. We define s_i , by the following recursion.

$$s_i \geq \begin{cases} \frac{n}{3J} & i = 1 \\ s_{i-1} + \frac{n-s_{i-1}}{3J} & i > 1 \end{cases}$$

After solving the preceding recursion, we see that $s_i \geq n(1 - \frac{1}{3J})^i$. Our goal is to find the smallest i so that $s_i > n - 1$. Hence, if iterate for $i > J \cdot O(\log n)$, all the cities would be covered. So the greedy method will give us an $O(\log n)$ approximate solution for both length and number of cycles. \square

4. CONCLUSIONS

Current problems of interest are to explore improvements in the approximation factors for the special cases of Euclidean metrics, and planar graphs. In addition we would also like to develop faster algorithms for the single source and destination case, perhaps at the cost of sacrificing optimality of the solution.

REFERENCES

ARKIN, E. M., HASSIN, R., AND LEVIN, A. 2006. Approximations for minimum and min-max vehicle routing problems. *J. Algor.* 59, 1, 1–18.

- ARKIN, E. M., MITCHELL, J. S. B., AND NARASIMHAN, G. 1998. Resource-Constrained geometric network optimization. In *Proceedings of the 14th Annual Symposium on Computational Geometry (SoCG)*. 307–316.
- AWERBUCH, B., AZAR, Y., BLUM, A., AND VEMPALA, S. 1998. New approximation guarantees for minimum-weight k-trees and prize-collecting salesmen. *SIAM J. Comput.* 28, 1, 254–262.
- BANSAL, N., BLUM, A., CHAWLA, S., AND MEYERSON, A. 2004. Approximation algorithms for deadline-TSP and vehicle routing with time-windows. In *Proceedings of the 36th Annual ACM symposium on Theory of Computing (STOC)*. 166–174.
- BERGER, A., BONIFACI, V., GRANDONI, F., AND SCHÄFER, G. 2008. Budgeted matching and budgeted matroid intersection via the gasoline puzzle. In *Proceedings of the 13th Integer Programming and Combinatorial Optimization Conference*. 273–287.
- BLUM, A., CHAWLA, S., KARGER, D. R., LANE, T., MEYERSON, A., AND MINKOFF, M. 2003. Approximation algorithms for orienteering and discounted-reward TSP. In *Proceedings of the 44th Annual IEEE Symposium on Foundations of Computer Science (FOCS)*. 46.
- CHARIKAR, M., KHULLER, S., AND RAGHAVACHARI, B. 2002. Algorithms for capacitated vehicle routing. *SIAM J. Comput.* 3, 665 – 682.
- CHRISTOFIDES, N. 1976. Worst-case analysis of a new heuristic for the traveling salesman problem. Tech. rep., Graduate School of Industrial Administration, Carnegie-Mellon University.
- CORMEN, T. H., LEISERSON, C. E., RIVEST, R. L., AND STEIN, C. 2001. *Introduction to Algorithms*. M.I.T. Press and McGraw-Hill.
- FREDERICKSON, G. N., HECHT, M. S., AND KIM, C. E. 1978. Approximation algorithms for some routing problems. *SIAM J. Comput.* 7, 2, 178–193.
- GOLDEN, B. L., LEVY, L., AND VOHRA, R. 1987. The orienteering problem. *Naval Res. Logist.* 34, 307–318.
- LAWLER, E. L. 2001. *Combinatorial Optimization: Networks and Matroids*. Dover Publications.
- LAWLER, E. L., LENSTRA, J. K., KAN, A. H. G. R., AND SHMOYS, D. B. 1985. *The Traveling Salesman Problem: A Guided Tour of Combinatorial Optimization*. John Wiley & Sons.
- LI, C.-L., SIMCHI-LEVI, D., AND DESROCHERS, M. 1992. On the distance constrained vehicle routing problem. *Oper. Res.* 40, 4, 790–799.
- LOVÁSZ, L. 1979. *Combinatorial Problems and Exercises*. North-Holland.
- HAIMOVICH, M. A. R. K. 1985. Bounds and heuristics for capacitated routing problems. *Math. Oper. Res.* 10, 4, 527–542.
- HAIMOVICH, M. A. G. RINNOOY KAN, L. S. 1988. Analysis of heuristics for vehicle routing problems. In *Vehicle Routing: Methods and Studies*, 47–61.
- NAGARAJAN, V. AND RAVI, R. 2006. Minimum vehicle routing with a common deadline. In *Proceedings of the 9th International Workshop on Approximation Algorithms for Combinatorial Optimization Problems (APPROX)*. 212–223.
- PAPADIMITRIOU, C. H. AND STEIGLITZ, K. 1998. *Combinatorial Optimization*. Dover Publications, Inc.

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