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Household-Level Economies of Scale in Transportation

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One of the fundamental concerns in the analysis of logistical systems is the trade-off between localized, independent provision of goods and services versus provision along a centralized infrastructure such as a backbone network. One phenomenon in which this trade-off has recently been made manifest is the transition of businesses from traditional brick-and-mortar stores to retail sales facilitated via e-commerce, such as grocery delivery services. Conventional wisdom would dictate that such services ought to be more efficient—say from the perspective of the overall carbon footprint—because of **the economy of scale achieved by aggregating demand through a delivery van**, as opposed to the many separate trips that customers would otherwise take using their own means of transport.

In this paper, we quantify the changes in overall efficiency due to such services by looking at “household-level” **economies of scale in transportation**; a person might perform many errands in a day (such as going to the bank, grocery store, and post office), and that person has many choices of locations at which to perform these tasks (e.g., a typical metropolitan region has many banks, grocery stores, and post offices). Thus, the total driving distance (and therefore the overall carbon footprint) that that person traverses is the solution to a *generalized travelling salesman problem* (GTSP) in which they select both the best locations to visit and the sequence in which to visit them. We perform a probabilistic analysis of the GTSP under the assumption that all relevant locations are independently and identically distributed uniformly in a region and then determine the amount of adoption of such services that is necessary, under our model, in order for the overall carbon footprint of the region to decrease.

Keywords: continuous location; facilities/equipment planning; stochastic networks/graphs; travelling salesman.

Subject classifications: facilities/equipment planning; location: continuous; networks/graphs: stochastic, traveling salesman.

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1. Introduction

In designing a logistical system, a key decision that frequently arises is whether to use a decentralized, independent scheme to allocate goods and services, or whether a centralized infrastructure such as a backbone network is preferable. On the one hand, service executed at a local level features the obvious benefits of proximity and specialization, inasmuch as people and communities obtain things from locations that are close to them. Conversely, by aggregating network flows via a backbone network, individuals and communities are able to reap the benefits of economies of scale, economies of agglomeration, and economies of density.

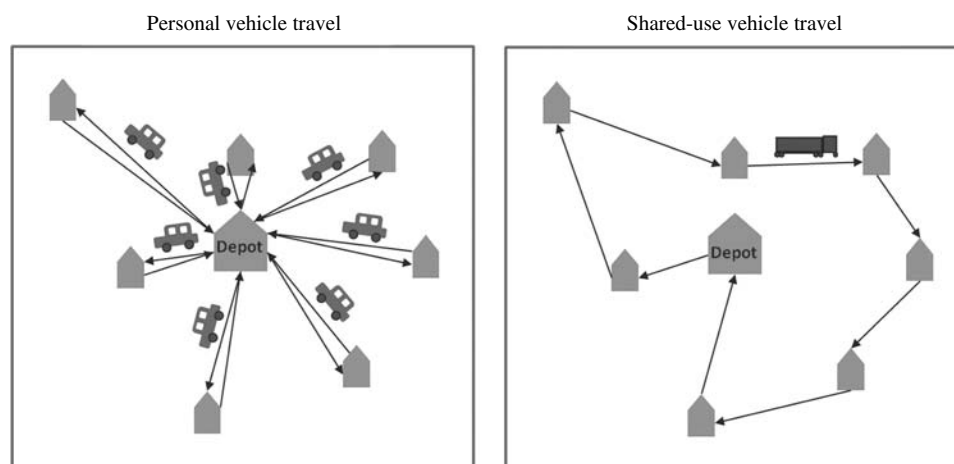
One phenomenon in which this trade-off has recently been made manifest is the transition of businesses from

traditional brick-and-mortar stores to retail sales facilitated via e-commerce (Anderson et al. 2003, Lee and Whang 2001, Mokhtarian 2004); particular recent examples include Google Shopping Express, Amazon Prime, Instacart, and Walmart To Go (Bensinger 2013, Bowman 2014, Harris and Cook 2007, Press 2011), among many others. As discussed in Somerville (2013) for the case of grocery delivery:

There’s still a lot of debate over what works and what doesn’t. Is it a good idea to have a warehouse for food storage, or ask the customers to pick up their food? How much should delivery cost? How often and where should online grocery companies deliver?

In the past, the costs associated with delivery service have been so big—huge warehouses and refrigerators, gas-guzzling trucks traveling door to door...that the math has never worked out[.]

Figure 1. The image is reproduced from Figure 1 of Wygonik and Goodchild (2012), which compares the cost of direct trips to and from a central location (at left) with travelling salesman tours that visit multiple locations (right).



A major complication in problems of this kind is the difficulty of creating a model that is mathematically tractable enough to give useful insights as well as faithful to the original phenomenon being modelled. The specific topic that we emphasize in this paper is the analysis of *multistop trips* made by households: on a given day, a person will often visit multiple locations on one outing (such as running errands on the way to or from one's place of work), and each of these locations will usually have *alternatives* (e.g., there are usually multiple choices of which grocer or post office to use). Thus, the calculation of the “cost” of a multistop trip is more complicated than a mere travelling salesman tour or a sequence of direct trips to and from the various destinations and the household. For example, one might be willing to travel a long distance to visit a bank that is farther away than the nearest available branch if it is located more closely to other businesses that they will also visit (say, by virtue of being located in a central business district or shopping center).

In the current literature, this complication is handled by either simplifying the problem at hand or by introducing additional assumptions into the problem structure. For example, Wygonik and Goodchild (2012) perform a detailed computational study that estimates the changes in net CO₂ emissions that result by introducing grocery delivery services in Seattle, Washington. As suggested in Figure 1 of that paper (which we reproduce here in Figure 1 as well), the authors do not consider the possibility of multistop trips and compare the cost of a direct trip between one's house and a store to the marginal cost incurred by adding oneself to a travelling salesman tour that services many households. As another example, McKinnon and Woodburn (2009, p. 23) acknowledge the importance of multistop trips (which they call “trip chaining”) in calculating carbon footprints, and assume constant values for trip lengths, such as 12.8 miles for an average shopping trip by car and a constant number of stops:

Shopping can be part of a wider combined trip and involve only a minor detour. We assume that where a shopper

undertakes trip chaining, the shopping component of the trip makes up a quarter of the overall total mileage.

A third example can be found in (Suh et al. 2012, p. 9484), who consider a closely related problem in which a customer receiving a package can specify *multiple* locations at which the delivery service may drop off the package (e.g., “please drop off my package at my home, my work, my gym, or my friend's house”). The analysis therein is based on Monte Carlo simulation and is highly sensitive to problem specifics, and the issue of trip chaining at the household level is addressed by assigning a fixed amount of trip chaining to estimate marginal costs (the authors also cite Berube et al. 2010, who make a similar assumption):

Generally, social network members will not participate or choose the burden of pickup if they have to go to a pickup point solely for the purpose of making a pickup for another person. Pickup trips for social network actors can be regarded as a chain event and [are] a determining variable. We assumed a 100% trip chain to additional mileage for pickup in both PLS and SPLS—in other words, the entire detour distance for pickup is attributed to the package. By contrast, previous research has applied a 0% trip chain effect for pickup (Berube et al. 2010).

The objective of this paper is to apply tools from geometric probability theory to derive a more nuanced model of the costs of multistop trips taken by a household as a function of the number of destinations that one must visit and the number of alternatives of each of these that is available. We then apply this analysis to predict the change in carbon footprint as households in a geographic region make increased use of delivery services versus trips to brick-and-mortar stores.

1.1. Related Work

This paper is primarily concerned with continuous approximation models for transportation problems and is therefore in the company of Burns et al. (1985), Campbell (1992),

Huang et al. (2013), Jabali et al. (2012), Novaes et al. (2000), Ouyang (2007), for example. We are particularly interested in the *asymptotic* behavior of a certain Euclidean optimization problem, the *generalized travelling salesman problem* (GTSP), and as such our analysis is closely related to such papers as Beardwood et al. (1959), Bertsimas and Simchi-Levi (1996), Haimovich and Kan (1985), Redmond and Yukich (1994), Steele (1981). One particularly related result can be found in Aldous and Krikun (2006), who study the asymptotic behavior of the “TSP on sparse subsets,” which is similar to our GTSP.

The GTSP is a reasonably well-known combinatorial problem and has been studied for almost 50 years (Srivastava et al. 1969). The primary focus of study on this problem has been on the rapid solution of particular problem instances in a combinatorial setting (Ben-Arieh et al. 2003, Laporte et al. 1996, Noon and Bean 1991, Shi et al. 2007, Yang et al. 2008), whereas our work is focused more on limiting behavior. For our purposes, the GTSP arises organically as a way of studying the impact of multistop trips, or “trip chaining.” The seminal paper, Adler and Ben-Akiva (1979), studies this phenomenon from a theoretical perspective by describing a particular utility function at the household level that is justified with empirical travel data. A subsequent paper, Kitamura (1984), develops a model of destination choice that employs the “prospective utility” of a destination zone as its “attraction measure.” The paper by Hensher and Reyes (2000) builds a variety of logit models in order to study the potential barrier that trip chaining creates in attracting car users to switch to public transport.

The intent of our work is to better understand the trade-off between centralized and decentralized distribution schemes. Our work could be said to follow naturally from McKinnon and Woodburn (2009), Suh et al. (2012), Wygonik and Goodchild (2012), for example, and would also fit in the company of Carlsson and Jia (2013), Cachon (2014), Daganzo (2005), all of who study this same trade-off in one form or another.

1.2. Notational Conventions

In this paper we will consider a planar region \mathcal{R} with area A , which is usually assumed without loss of generality to be the unit square. We assume that \mathcal{R} has a population of N people, who perform n tasks each day, and there are k locations at which each task can be performed (in Section 3.2, we further allow k itself to vary for each task). The cost per mile of delivery trucks along the backbone network is given by ϕ and the cost per mile of passenger vehicles is given by ψ . We will also make use of some standard conventions in asymptotic analysis:

- We say that $f(x) \in \mathcal{O}(g(x))$ if there exists a constant c and a value x_0 such that $f(x) \leq c \cdot g(x)$ for all $x \geq x_0$.
- We say that $f(x) \in \Omega(g(x))$ if there exists a constant c and a value x_0 such that $f(x) \geq c \cdot g(x)$ for all $x \geq x_0$.

- We say that $f(x) \in \Theta(g(x))$ if $f(x) \in \mathcal{O}(g(x))$ and $f(x) \in \Omega(g(x))$.
- We say that $f(x) \sim g(x)$ if $\lim_{x \rightarrow \infty} f(x)/g(x) = 1$.

When necessary, we will clarify this notation in some particular cases because we are interested in limiting behavior that concerns two values, the number of locations n and the number of choices k , and such notation is known to introduce complicated ambiguities (Demaine et al. 2001, Howell 2008).

2. Summary of Key Facts and Findings from Related Work

This brief section introduces two previous geometric results that are closely related to the problem that we will study in the following section.

LEMMA 1. For any set of n' points $x_1, \dots, x_{n'}$ contained in a square of area A' , the length of the optimal TSP tour through $x_1, \dots, x_{n'}$, denoted $\text{TSP}(x_1, \dots, x_{n'})$, satisfies $\text{TSP}(x_1, \dots, x_{n'}) \leq \sqrt{2A'n'} + (7/4)\sqrt{A'} < \alpha_1 \sqrt{A'n'}$, where $\alpha_1 = 2.7$.

PROOF. See Few (1955) and Karloff (1989). \square

This result can be stated more strongly in a probabilistic fashion as in the celebrated *Beardwood-Halton-Hammersley (BHH) Theorem*:

THEOREM 1. Suppose that $\{X_1, X_2, \dots\}$ is a sequence of random points i.i.d. according to the uniform distribution defined on a compact planar region \mathcal{R} with area A . Then with probability one,

$$\lim_{N \rightarrow \infty} \frac{\text{TSP}(X_1, \dots, X_N)}{\sqrt{AN}} = \beta,$$

where β is a constant.

PROOF. See, for example, Beardwood et al. (1959), Redmond and Yukich (1994), and Steele (1987). \square

It is additionally known that $0.6250 \leq \beta \leq 0.9204$ and conjectured that $\beta \approx 0.7124$; see Applegate et al. (2010) and Finch (2003).

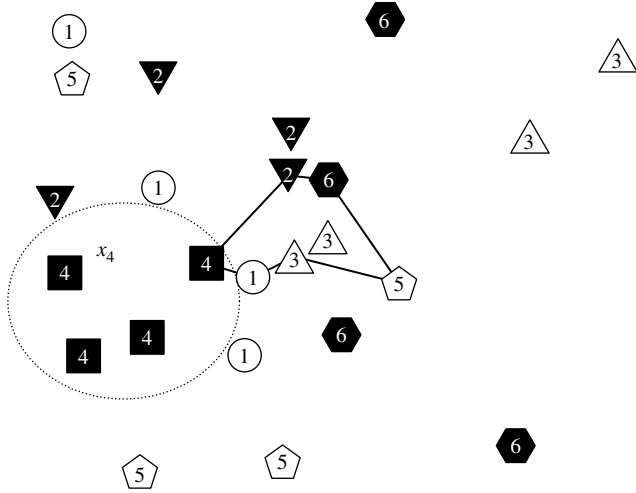
3. Analysis of the Generalized TSP Tour

The main combinatorial object that we will use to model household trips is the *GTSP tour*, defined as follows:

DEFINITION 1. Given n sets of points $\mathcal{X}_1, \dots, \mathcal{X}_n$ in the plane, the *GTSP tour* $\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)$ is the shortest cycle that contains one element from each point set \mathcal{X}_i .

See Figure 2 for an example. Clearly, when each point set is a singleton (i.e., $\mathcal{X}_i = \{x_i\}$ for all i), we see that $\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n) = \text{TSP}(x_1, \dots, x_n)$. We will commit a minor abuse of notation throughout this paper by using the term $\text{GTSP}(\cdot)$ to refer both to the tour itself and to its length.

Figure 2. A GTSP tour of six sets of points $\mathcal{X}_1, \dots, \mathcal{X}_6$, with \mathcal{X}_4 outlined for purposes of clarity. The optimal tour contains one element from each such set (and is the shortest such tour to do so).



The GTSP is, of course, a generalization of the TSP, which has been analyzed extensively from a geometric probabilistic perspective (Redmond and Yukich 1994, Steele 1981). However, many of these results for the TSP cannot be generalized in a straightforward way to the GTSP. To give one example, page 30 of Steele (1987) establishes a simple nearest-neighbor argument that explains why $\mathbf{E}(\text{TSP}(X_1, \dots, X_n)) \in \Omega(\sqrt{n})$ for independent, uniformly distributed X_i in the unit square: for any point X_i , it can be shown that $\mathbf{E}(\min_{j: j \neq i} \|X_i - X_j\|) \in \Omega(1/\sqrt{n})$, from which the desired result follows by summing over all n points. This does not carry over to the GTSP because we have $|\mathcal{X}_1| + \dots + |\mathcal{X}_n|$ points in total and we are summing over only n of them. It is also worth noting that there are two kinds of limits of interest to us, namely, the case where $n \rightarrow \infty$ and the case where $|\mathcal{X}_i| \rightarrow \infty$ for all i , and the latter does not appear to have much connection to previous work on the TSP. Our first result describes the limiting behavior where $n \rightarrow \infty$.

3.1. Analysis of the Case $n \rightarrow \infty$

The following theorem describes the behavior of the GTSP when we fix $|\mathcal{X}_i| = k$ for all i and we let $n \rightarrow \infty$:

THEOREM 2. *Let $\mathcal{X}_1, \dots, \mathcal{X}_n$ denote n sets of points, each having cardinality k , and suppose that all nk points are distributed independently and uniformly at random in a region \mathcal{R} having area A . Then the expected length of a GTSP tour of $\mathcal{X}_1, \dots, \mathcal{X}_n$ satisfies*

$$\mathbf{E}(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)) \in \Theta(\sqrt{An/k})$$

as $n \rightarrow \infty$ with k fixed. In particular, there exist constants $\alpha_1 < 2.7$ and $\alpha_2 > 0.0681$ such that, for any k , there exists a threshold \bar{n} such that $\mathbf{E}(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)) \leq \alpha_1 \sqrt{An/k}$ and $\mathbf{E}(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)) \geq \alpha_2 \sqrt{An/k}$ whenever $n \geq \bar{n}$.

The upper bound that $\mathbf{E}(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)) \leq \alpha_1 \sqrt{An/k}$ is a fairly straightforward generalization of the result from Few (1955) and we prove it presently; we will prove the lower bound that $\mathbf{E}(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)) \geq \alpha_2 \sqrt{An/k}$ afterward because we will require an additional combinatorial lemma.

PROOF OF THE UPPER BOUND. Assume without loss of generality that $A = 1$, and make an additional further assumption that \mathcal{R} is the unit square (generalizing the argument to arbitrary regions \mathcal{R} is a routine task that we omit for brevity): let m be an even integer and consider the path \mathcal{P} obtained by traversing the width of \mathcal{R} horizontally a total of m times, starting at the upper leftmost corner of \mathcal{R} and moving downward by an amount $1/(m-1)$, as shown in Figure 3(a); it is obvious that the length of \mathcal{P} is simply $m+2$. Given a collection of point sets $\mathcal{X}_1, \dots, \mathcal{X}_n$ in \mathcal{R} , we can perturb \mathcal{P} to form a new path \mathcal{P}' that visits one point from each point set \mathcal{X}_i by simply inserting a pair of vertical line segments between \mathcal{P} and the nearest point (measured only in the vertical direction) in each \mathcal{X}_i , as shown in Figure 3(a). Of course, the vertical distance between \mathcal{P} and any arbitrary point $x \in \mathcal{X}_i$ simply follows a uniform distribution between 0 and $1/(2(m-1))$, and therefore we see that the vertical distance d between \mathcal{P} and its nearest neighbor in \mathcal{X}_i (again, in the vertical sense) satisfies

$$\mathbf{E}(d) = \frac{1/(2(m-1))}{k+1}.$$

Our objective is therefore to select a value m so as to minimize the total length of \mathcal{P} plus these additional n displacements, i.e., to minimize

$$m+2+2n \cdot \frac{1/(2(m-1))}{k+1},$$

where we have an additional multiplier “2” since each vertical displacement consists of an outbound and inbound trip. As n becomes large, we see that the optimal m satisfies

$$m^* \sim \sqrt{\frac{n}{k+1}},$$

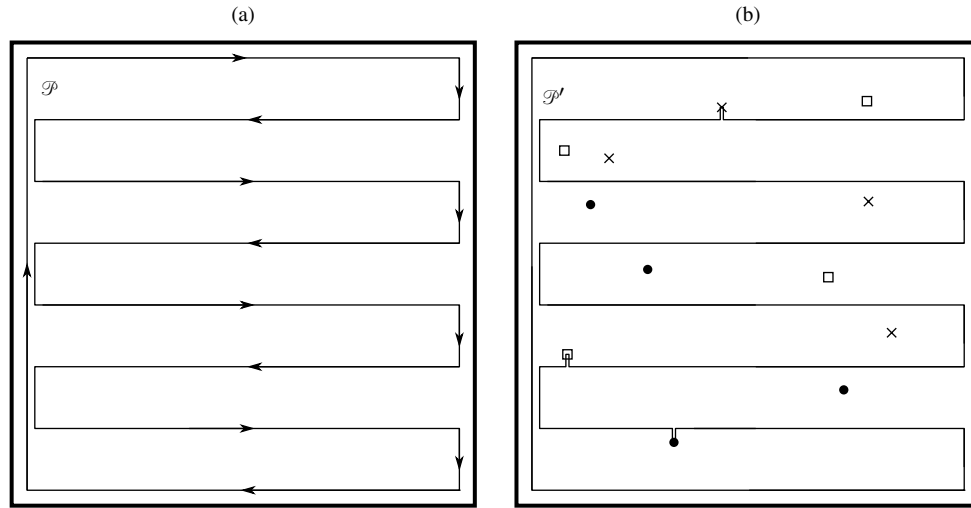
which results in a total length that satisfies

$$\text{length}(\mathcal{P}') \sim \frac{2\sqrt{n}}{\sqrt{k+1}} < 2\sqrt{\frac{n}{k}},$$

which proves that $\mathbf{E}(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)) \leq \alpha_1 \sqrt{An/k}$. \square

To prove the lower bound that $\mathbf{E}(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)) \geq \alpha_2 \sqrt{An/k}$, we must first introduce a combinatorial lemma:

Figure 3. In (3(a)), we show the path \mathcal{P} , which traverses the region \mathcal{R} horizontally a total of $m = 8$ times. In (3(b)), we show the perturbed path \mathcal{P}' , where we have $n = 3$ point sets \mathcal{X}_i consisting of $k = 4$ points each.



LEMMA 2. Let $\mathcal{L} \subset \mathbb{Z}^2$ denote an $m \times m$ square integer lattice in the plane, let $n \geq 2$ be an integer, and let $l > 0$. Let \mathcal{P} denote the set of all paths of the form $\{x_1, \dots, x_n\}$, with $x_i \in \mathcal{L}$ for each i , and whose length does not exceed l . Then

$$|\mathcal{P}| \leq m^2 \cdot \binom{l+n-1}{n-1} \cdot \left(\frac{8l}{n-1}\right)^{n-1}.$$

PROOF. Note that we have allowed “replacement” in the construction of \mathcal{P} , i.e., we are also considering paths in which $x_i = x_j$ for some (i, j) pairs. We note that any element $\mathcal{P} \in \mathcal{P}$ can be uniquely described by specifying the triplet $(x, \mathbf{d}, \mathbf{q})$ defined as follows:

- The point $x \in \mathcal{L}$ is simply the first member of \mathcal{P} .
- The n -tuple $\mathbf{d} = \{d_1, \dots, d_n\}$ represents the distance travelled from each point to the next, measured in the l_∞ norm. In other words, for a path $\{x_1, \dots, x_n\}$, we have $d_i = \|x_{i+1} - x_i\|_\infty$. Note that d_n is not defined according to this definition; we therefore define $d_n := l - \sum_{i=1}^{n-1} d_i$, so that $\sum_{i=1}^n d_i = l$ for all valid \mathbf{d} . Obviously, we have $0 \leq d_i \leq l$ for all i .

- The $(n-1)$ -tuple $\mathbf{q} = \{q_1, \dots, q_{n-1}\}$ represents the “angles” between pairs of points. Specifically, given a point x_i and a corresponding distance d_i , we see that there are at most $8d_i$ possible places where x_{i+1} could be located (since x_{i+1} must lie on the boundary of a square of side length $2d_i$ centered at x_i). The element q_i specifies which of these is the correct location of x_{i+1} .

An example of this is shown in Figure 4. We will bound $|\mathcal{P}|$ from above by looking at the set of all triplets $(x, \mathbf{d}, \mathbf{q})$ such that $x \in \mathcal{L}$, $\sum_{i=1}^n d_i = l$, and $q_i \leq 8d_i$ for all i . Assume without loss of generality that l is an integer, and let \mathcal{D} denote the set of all permissible n -tuples \mathbf{d} . By construction, of course, \mathcal{D} is simply the set of all integer n -tuples $\{d_1, \dots, d_n\}$ such that $d_i \geq 0$ and $\sum_{i=1}^n d_i = l$. Given any $\mathbf{d} \in \mathcal{D}$, let \mathbf{d}' denote the n -tuple defined by setting $d'_i = d_i + 1$ for all i . We then see that $\sum_{i=1}^n d'_i = l + n$ and that

$1 \leq d'_i \leq l + n$ for all i . As Figure 5 suggests, each \mathbf{d}' corresponds to a selection of $n-1$ elements out of $l+n-1$ possibilities. Thus, we see that

$$|\mathcal{D}| \leq \binom{l+n-1}{n-1}.$$

It is simpler to bound the set \mathcal{Q} of all valid $(n-1)$ -tuples \mathbf{q} . For any fixed \mathbf{d} , the number of possible choices of \mathbf{q} is at most $8^{n-1} \prod_{i=1}^{n-1} d_i$. By the AM-GM inequality, using the fact that $\sum_{i=1}^{n-1} d_i \leq l$, we see that

$$8^{n-1} \prod_{i=1}^{n-1} d_i \leq 8^{n-1} \left(\sum_{i=1}^{n-1} \frac{d_i}{n-1}\right)^{n-1} = \left(\frac{8l}{n-1}\right)^{n-1}$$

and thus

$$|\mathcal{Q}| \leq \left(\frac{8l}{n-1}\right)^{n-1}.$$

Finally, since there are m^2 choices of the initial point x in the triplet $(x_1, \mathbf{d}, \mathbf{q})$, we conclude that \mathcal{P} satisfies

$$|\mathcal{P}| \leq m^2 \cdot \binom{l+n-1}{n-1} \cdot \left(\frac{8l}{n-1}\right)^{n-1}$$

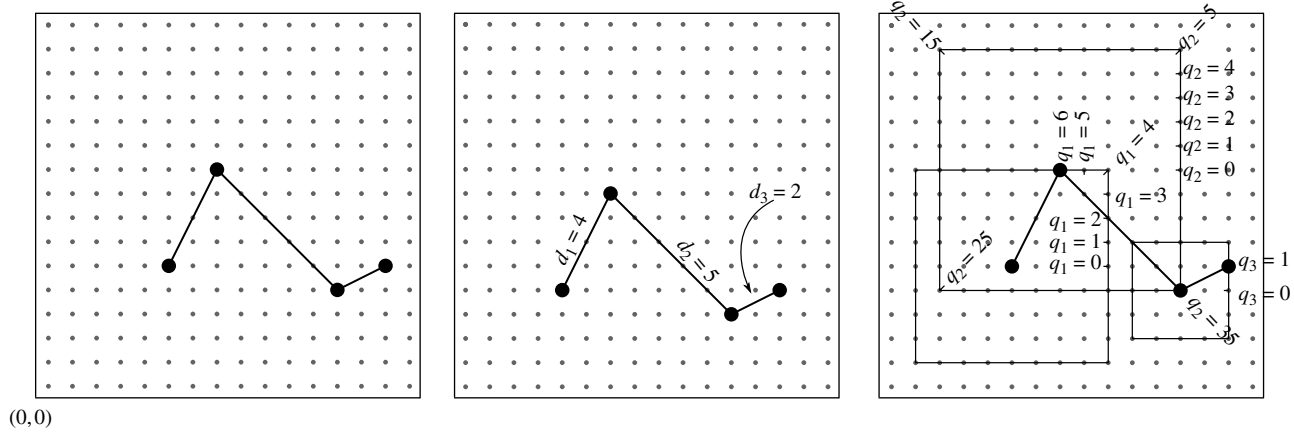
as desired. \square

We are now ready to prove the lower bound of Theorem 2:

PROOF OF THE LOWER BOUND OF THEOREM 2. We will again assume that the service region \mathcal{R} is the unit square, and we will then let \mathcal{L} denote a lattice within \mathcal{R} of the form

$$\left\{0, \frac{1}{m}, \frac{2}{m}, \dots, \frac{m-1}{m}, 1\right\} \times \left\{0, \frac{1}{m}, \frac{2}{m}, \dots, \frac{m-1}{m}, 1\right\}.$$

It is immediately clear that for any path $\mathcal{P} := \{x_1, \dots, x_n\} \subset \mathcal{R}$, there exists a path in \mathcal{L} obtained by rounding the

Figure 4. The path has a length of approximately 13.8, and therefore is a member of \mathcal{P} if we have l equal to (say) 15.

Notes. We will construct its triplet $(x, \mathbf{d}, \mathbf{q})$ as follows: obviously, we have $x = (5, 5)$ (the first element of the path), as indicated in 4(a). Figure 4(b) shows that the l_∞ distances between the four points are $d_1 = 4$, $d_2 = 5$, and $d_3 = 2$, respectively, which would then imply that $d_4 = l - (d_1 + d_2 + d_3) = 4$. Finally, the construction of \mathbf{q} is shown in 4(c): given a point x_i on the path and a distance d_i , there are $8d_i$ possible places where the consecutive point x_{i+1} could be located. The path shown has $q_1 = 6$, $q_2 = 35$, and $q_3 = 1$.

terms of \mathcal{P} to their nearest neighbor in \mathcal{L} whose length is within n/m of the original path. Thus, it will suffice to prove the lower bound of Theorem 2 for the special case where all of the elements of the sets \mathcal{X}_i lie in elements of \mathcal{L} , and study the limiting behavior as $m \rightarrow \infty$.

We first see that there are at most k^n total distinct subsets of the form $\{x_1, \dots, x_n\}$, with $x_i \in \mathcal{X}_i$ for each i . For each of these subsets, there are $n!$ different orderings, and we therefore conclude that there are at most $n! \cdot k^n$ valid paths that visit one point from each of the subsets \mathcal{X}_i . By applying the union bound, we see that

$$\begin{aligned} \Pr(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n) \leq \alpha_2 \sqrt{n/k}) \\ = \Pr(\text{one of the } n! \cdot k^n \text{ valid paths has length} \leq \alpha_2 \sqrt{n/k}) \\ \leq n! \cdot k^n \Pr(\text{length}(\mathcal{P}) \leq \alpha_2 \sqrt{n/k}), \end{aligned}$$

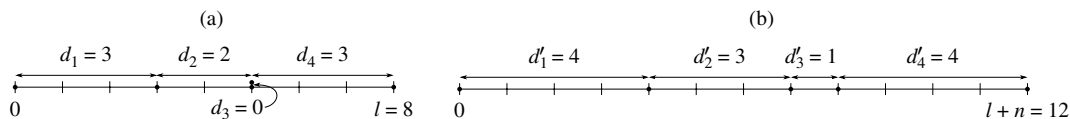
where \mathcal{P} is the path obtained by selecting the first element from each set \mathcal{X}_i and visiting these elements in a sequence chosen uniformly at random. By construction, we see that \mathcal{P} is simply a path that is sampled uniformly at random from the collection of *all* possible paths between n points taken from \mathcal{L} . Of course, we can see immediately that there are exactly m^{2n} of these. By scaling the lattice of Lemma 2

by a factor of $1/m$ (i.e., our lattice \mathcal{L}), we see that there are at most

$$\begin{aligned} m^2 \cdot \binom{m\alpha_2 \sqrt{n/k} + n - 1}{n - 1} \cdot \left(\frac{8m\alpha_2 \sqrt{n/k}}{n - 1} \right)^{n-1} \\ \leq m^2 \cdot \frac{(m\alpha_2 \sqrt{n/k} + n - 1)^{n-1}}{(n - 1)!} \cdot \left(\frac{8m\alpha_2 \sqrt{n/k}}{n - 1} \right)^{n-1} \end{aligned}$$

paths of length $\alpha_2 \sqrt{n/k}$ through our lattice \mathcal{L} and therefore

$$\begin{aligned} \limsup_{m \rightarrow \infty} \Pr(\text{length}(\mathcal{P}) \leq \alpha_2 \sqrt{n/k}) \\ \leq \limsup_{m \rightarrow \infty} \left(m^2 \cdot \frac{(m\alpha_2 \sqrt{n/k} + n - 1)^{n-1}}{(n - 1)!} \cdot \left(\frac{8m\alpha_2 \sqrt{n/k}}{n - 1} \right)^{n-1} \right) \cdot (m^{2n})^{-1} \\ = (8\alpha_2^2)^{n-1} \cdot \frac{n^{n-1}}{(n - 1)! \cdot (n - 1)^{n-1} \cdot k^{n-1}} \\ \Rightarrow \Pr(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n) \leq \alpha_2 \sqrt{n/k}) \\ \leq n! \cdot k^n \cdot (8\alpha_2^2)^{n-1} \cdot \frac{n^{n-1}}{(n - 1)! \cdot (n - 1)^{n-1} \cdot k^{n-1}} \\ = k \cdot (8\alpha_2^2)^{n-1} \cdot \frac{n^n}{(n - 1)^{n-1}}. \end{aligned}$$

Figure 5. The figures correspond to the case where $n = 4$ and $l = 8$.

Notes. As 5(a) shows, any n -tuple \mathbf{d} can be uniquely represented by simply placing n points on the number line from 0 to l , where the first point is placed a distance d_1 from the origin and each subsequent point i is placed a distance d_i to the right of its predecessor. Since d_4 is defined so that the entries of \mathbf{d} sum to l , the last such point that is placed must be precisely at a distance l from the origin. The placement shown corresponds to the case $\mathbf{d} = (3, 2, 0, 3)$. In 5(b), we show the same point placement for the n -tuple \mathbf{d}' , which is obtained by adding 1 to each of the entries of \mathbf{d} . It is obvious that any such n -tuple \mathbf{d}' can be uniquely constructed by selecting $n - 1 = 3$ points from the $l + n - 1 = 11$ valid locations of points in 5(b) and computing the sequential distances between those points; the diagram corresponds to the case $\mathbf{d}' = (4, 3, 1, 4)$.

The above quantity approaches 0 as $n \rightarrow \infty$ because $8\alpha_2^2 < 1$. Thus,

$$\begin{aligned} \mathbf{E}(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)) &\geq \left(1 - k \cdot (8\alpha_2^2)^{n-1} \cdot \frac{n^n}{(n-1)^{n-1}}\right) \alpha_2 \sqrt{n/k} \\ &= \alpha_2 \sqrt{n/k} - \sqrt{k} \cdot 8^{n-1} \alpha_2^{2n-1} \cdot \frac{n^{n+1/2}}{(n-1)^{n-1}} \\ &\sim \alpha_2 \sqrt{n/k} \text{ as } n \rightarrow \infty, \end{aligned}$$

which proves the desired lower bound as desired. \square

The proof above completes our analysis of the GTSP for the case where the number of point sets, n , becomes large, and the cardinalities $|\mathcal{X}_i|$ are all fixed and equal to some value k . The next section describes the case where n is fixed and the cardinalities $|\mathcal{X}_i|$ become large.

3.2. Analysis of the Case $|\mathcal{X}_i| \rightarrow \infty$

This section studies the limiting behavior of the GTSP when we assume that the number of sets, n , is fixed, and the cardinalities of each set \mathcal{X}_i become large. To describe these n cardinalities in terms of a single parameter, we assume that $|\mathcal{X}_i| = k_i = tq_i$, where $\mathbf{q} > \mathbf{0}$ is a vector that sums to one, and we let the single parameter t approach infinity.

THEOREM 3. *Let $\mathcal{X}_1, \dots, \mathcal{X}_n$ denote n sets of points, each having cardinality $k_i > 0$, and suppose that all $\sum_{i=1}^n k_i$ points are distributed independently and uniformly at random in a region \mathcal{R} having area A . Further assume that $k_i = tq_i$ for all i (where \mathbf{q} is a probability vector), and let $k_G = (\prod_{i=1}^n k_i)^{1/n} = t(\prod_{i=1}^n q_i)^{1/n}$ be the geometric mean of the k_i 's. Then the expected length of a GTSP tour of $\mathcal{X}_1, \dots, \mathcal{X}_n$ satisfies*

$$\mathbf{E}(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)) \in \Theta\left(\sqrt{\frac{An}{k_G}}\right)$$

and

$$\mathbf{E}(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)) \in \Omega\left(\sqrt{\frac{An}{k_G^{n/(n-1)}}}\right)$$

as $t \rightarrow \infty$ with n and \mathbf{q} fixed. In particular, there exist constants $\alpha_1 < 2.7$ and $\alpha_2 > 0.0681$ such that, for any $n \geq 2$, there exists a threshold \bar{k} such that

$$\mathbf{E}(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)) \leq \alpha_1 \sqrt{\frac{An}{k_G}} \quad (1)$$

and

$$\mathbf{E}(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)) \geq \alpha_2 \sqrt{\frac{An}{k_G^{n/(n-1)}}} \quad (2)$$

whenever $k_G \geq \bar{k}$. In addition, the upper bound (1) can be tightened as follows:

$$\begin{aligned} \mathbf{E}(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)) &\leq \alpha_1 \sqrt{\frac{An}{k_G^{n/(n-1)}}} \cdot (n^2 \log k_G + \log n)^{1/(2(n-1))} \quad (3) \end{aligned}$$

whenever $k_G \geq \bar{k}$.

PROOF. As in the proof of Theorem 2, we will assume that the service region \mathcal{R} is the unit square. The proof of the upper bound (1) proceeds as follows: since we are examining the limiting behavior of $\mathbf{E}(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n))$ for large k_G , we can divide the region \mathcal{R} into k_G squares $\square_1, \dots, \square_{k_G}$ of area $1/k_G$. By Lemma 1, we see that if one of the k_G squares \square_i happens to contain an element from each of the n point sets $\mathcal{X}_1, \dots, \mathcal{X}_n$, then $\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n) \leq \alpha_1 \sqrt{n/k_G}$. If none of the squares have this property, then as a crude upper bound we simply use $\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n) \leq \alpha_1 \sqrt{n}$, so that

$$\mathbf{E}(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)) \leq p\alpha_1 \sqrt{n/k_G} + (1-p)\alpha_1 \sqrt{n},$$

where p is the probability that one of the k_G squares contains an element from each \mathcal{X}_i . Thus, our goal is now to show that $p \rightarrow 1$ at a sufficiently rapid rate as $k_G \rightarrow \infty$.

Our proof now requires a *Poissonization* argument (Steele (1987)): for each of the k_G boxes \square_i , let Y_1^i, \dots, Y_n^i denote n point sets uniformly and independently distributed within \square_i , where $|Y_j^i|$ follows a Poisson distribution with mean $\lambda_j := k_j/k_G = q_j/(\prod_{i=1}^n q_i)^{1/n}$. If we define point sets $\mathcal{Y}_1, \dots, \mathcal{Y}_n$ by setting

$$\mathcal{Y}_j = \bigcup_{i=1}^{k_G} Y_j^i,$$

then it is immediately obvious that $\mathbf{E}(|\mathcal{Y}_j|) = k_j$ for all j ; it is also easy to verify that the distribution of the point sets $\mathcal{X}_1, \dots, \mathcal{X}_n$ is the same as the distribution of the point sets $\mathcal{Y}_1, \dots, \mathcal{Y}_n$, conditioned on the event that $|\mathcal{Y}_j| = k_j$ for all j (see page 100 of Mitzenmacher and Upfal 2005, for example). For a particular box \square_i , the probability that \square_i contains at least one element from each of the sets \mathcal{Y}_j is

$$\begin{aligned} \Pr(\square_i \text{ contains at least one from each } \mathcal{Y}_j) &= \Pr(|Y_1^i| \geq 1) \cdot \dots \cdot \Pr(|Y_n^i| \geq 1) \\ &= \prod_{j=1}^n (1 - e^{-\lambda_j}) \end{aligned}$$

and therefore,

$$\begin{aligned} \Pr(\underbrace{\text{none of the boxes } \square_i \text{ contains at least one from each } \mathcal{Y}_j}_{=:E}) &= \left[1 - \prod_{j=1}^n (1 - e^{-\lambda_j})\right]^{k_G}. \end{aligned}$$

By the law of total probability, we have

$$\begin{aligned} \Pr(E) &= \sum_{k'_1=0}^{\infty} \dots \sum_{k'_n=0}^{\infty} \Pr(E \mid |\mathcal{Y}_1| = k'_1 \cap \dots \cap |\mathcal{Y}_n| = k'_n) \\ &\quad \cdot \Pr(|\mathcal{Y}_1| = k'_1 \cap \dots \cap |\mathcal{Y}_n| = k'_n) \end{aligned}$$

and therefore in particular,

$$\Pr(E) \geq \Pr(E \mid |\mathcal{Y}_1| = k_1 \cap \dots \cap |\mathcal{Y}_n| = k_n) \\ \cdot \Pr(|\mathcal{Y}_1| = k_1 \cap \dots \cap |\mathcal{Y}_n| = k_n).$$

We next observe that

$$\Pr(|\mathcal{Y}_1| = k_1 \cap \dots \cap |\mathcal{Y}_n| = k_n) = \prod_{j=1}^n \Pr(|\mathcal{Y}_j| = k_j) \\ = \prod_{j=1}^n \frac{k_j^{k_j}}{k_j!} e^{-k_j} \\ > \frac{1}{e^n \sqrt{k_1 \dots k_n}},$$

where the last inequality holds because $k'! < e\sqrt{k'}(k'/e)^{k'}$ for all positive integers k' (see Lemma 5.8 of Mitzenmacher and Upfal (2005)). We therefore conclude that

$$\left[1 - \prod_{j=1}^n (1 - e^{-\lambda_j})\right]^{k_G} \\ = \Pr(E) > \underbrace{\Pr(E \mid |\mathcal{Y}_1| = k_1 \cap \dots \cap |\mathcal{Y}_n| = k_n)}_{1-p} \frac{1}{e^n \sqrt{k_1 \dots k_n}},$$

or in other words,

$$1 - p < \left[1 - \prod_{j=1}^n (1 - e^{-\lambda_j})\right]^{k_G} e^n \sqrt{k_1 \dots k_n}. \quad (4)$$

It then follows that

$$\mathbf{E}(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)) \leq p \alpha_1 \sqrt{\frac{n}{k_G}} + (1-p) \alpha_1 \sqrt{n} \\ \leq \alpha_1 \sqrt{\frac{n}{k_G}} + \alpha_1 \sqrt{n} \left[1 - \prod_{j=1}^n (1 - e^{-\lambda_j})\right]^{k_G} e^n \sqrt{k_1 \dots k_n}.$$

Our proof is therefore complete if we can show that, for any fixed n , we have

$$\frac{\alpha_1 \sqrt{n/k_G} + \alpha_1 \sqrt{n} [1 - \prod_{j=1}^n (1 - e^{-\lambda_j})]^{k_G} e^n \sqrt{k_1 \dots k_n}}{\alpha_1 \sqrt{n/k_G}} \rightarrow 1$$

or equivalently that

$$\left[1 - \prod_{j=1}^n (1 - e^{-\lambda_j})\right]^{k_G} e^n k_G^{(n+1)/2} \rightarrow 0$$

as $k_G \rightarrow \infty$. Taking natural logarithms, this is equivalent to proving that

$$k_G \log \left(1 - \prod_{j=1}^n (1 - e^{-\lambda_j})\right) + n + \frac{n+1}{2} \log k_G \rightarrow -\infty$$

as $k_G \rightarrow \infty$. Since $0 < e^{-\lambda_j} < 1$ for all j , we have $0 < 1 - \prod_{j=1}^n (1 - e^{-\lambda_j}) < 1$, which guarantees that the inner term of the logarithm above is always negative. The limit

above therefore holds, which completes the proof of the upper bound (1).

To prove the tighter upper bound (3), the argument is nearly the same, except that we instead divide the region \mathcal{R} into $b(k_G)$ squares $\square_1, \dots, \square_{b(k_G)}$ of area $1/b(k_G)$, where we set

$$b(k_G) = \frac{k_G^{n/(n-1)}}{(n^2 \log k_G + \log n)^{1/(n-1)}}.$$

In the interest of brevity, we will simply write b instead of $b(k_G)$. Applying precisely the same reasoning as before, the counterpart to inequality (4) is now

$$p > 1 - \left[1 - \prod_{j=1}^n (1 - e^{-k_j/b})\right]^b e^n \sqrt{k_1 \dots k_n},$$

so that

$$\mathbf{E}(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)) \\ \leq \alpha_1 \sqrt{n/b} + \alpha_1 \sqrt{n} \left[1 - \prod_{j=1}^n (1 - e^{-k_j/b})\right]^b e^n \sqrt{k_1 \dots k_n}.$$

Our proof is therefore complete if we can show that, for any fixed n , we have

$$\frac{\alpha_1 \sqrt{n/b} + \alpha_1 \sqrt{n} [1 - \prod_{j=1}^n (1 - e^{-k_j/b})]^b e^n \sqrt{k_1 \dots k_n}}{\alpha_1 \sqrt{n/b}} \rightarrow 1$$

or equivalently that

$$\left[1 - \prod_{j=1}^n (1 - e^{-k_j/b})\right]^b e^n \sqrt{k_1 \dots k_n} \sqrt{b} \rightarrow 0$$

as $k_G \rightarrow \infty$. This is straightforward and shown in Section EC.1 of the online supplement (available as supplemental material at <http://dx.doi.org/10.1287/opre.2016.1533>).

To prove the lower bound (2), we apply Lemma 2 again: as in the proof of Theorem 2, we let \mathcal{L} denote a lattice within \mathcal{R} of the form

$$\left\{0, \frac{1}{m}, \frac{2}{m}, \dots, \frac{m-1}{m}, 1\right\} \times \left\{0, \frac{1}{m}, \frac{2}{m}, \dots, \frac{m-1}{m}, 1\right\}$$

and we assume that all of the elements of the sets \mathcal{X}_i lie in elements of \mathcal{L} (recall that we are assuming that m is arbitrarily large). By scaling the lattice of Lemma 2 by a factor of $1/m$ (i.e., our lattice \mathcal{L}), we see that the number of paths in \mathcal{L} whose length does not exceed length l is at most

$$m^2 \cdot \binom{ml+n-1}{n-1} \cdot \left(\frac{8ml}{n-1}\right)^{n-1} \\ \leq m^2 \cdot \frac{(ml+n-1)^{n-1}}{(n-1)!} \cdot \left(\frac{8ml}{n-1}\right)^{n-1}$$

for all $l > 0$. Thus, if \mathcal{P} is the path obtained by selecting the first element from each set \mathcal{X}_i and visiting these elements in a sequence chosen uniformly at random, we see that

$$\begin{aligned} & \limsup_{m \rightarrow \infty} \Pr(\text{length}(\mathcal{P}) \leq l) \\ & \leq \limsup_{m \rightarrow \infty} \frac{m^2 \frac{(ml+n-1)^{n-1}}{(n-1)!} \cdot \frac{(8ml)}{(n-1)^{n-1}}}{m^{2n}} \\ & = \frac{8^{n-1} l^{2n-2}}{(n-1)!(n-1)^{n-1}}. \end{aligned}$$

The number of all possible GTSP tours through $\mathcal{X}_1, \dots, \mathcal{X}_n$ is at most $n! \prod_{i=1}^n k_i = n! \cdot k_G^n$, and therefore, it follows from the union bound that

$$\begin{aligned} \Pr(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n) \leq l) & \leq n! \cdot k_G^n \cdot \frac{8^{n-1} l^{2n-2}}{(n-1)!(n-1)^{n-1}} \\ & = n \cdot k_G^n \cdot \frac{8^{n-1} l^{2n-2}}{(n-1)^{n-1}}. \end{aligned}$$

We now set $l = c\sqrt{n/k_G^{n/(n-1)}}$ with $c = \sqrt{6}/24$ to obtain

$$\begin{aligned} & \mathbf{E}(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)) \\ & \geq \left(1 - \Pr\left(\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n) \leq c\sqrt{\frac{n}{k_G^{n/(n-1)}}}\right)\right) \\ & \quad \cdot c\sqrt{\frac{n}{k_G^{n/(n-1)}}} \\ & \geq c \left(1 - (8c^2)^{n-1} \cdot \frac{n^n}{(n-1)^{n-1}}\right) \sqrt{\frac{n}{k_G^{n/(n-1)}}} \\ & \geq 0.0681 \sqrt{\frac{n}{k_G^{n/(n-1)}}} \end{aligned}$$

for $n \geq 2$ as desired, which completes the proof. \square

REMARK 1. The problem described in Theorem 2 is closely related to the BHH Theorem (i.e., Theorem 1), which corresponds to the special instance of our problem where $k = 1$. For the purpose of studying the household-level economies of scale obtained by multistop trips, we assert that Theorem 3 is more relevant. This is because a typical person rarely visits more than, say, 10 destinations in a given day, whereas there are likely to be much more than 10 banks, grocery stores, and so forth in a given metropolitan region. By performing numerical simulations based on Laporte and Semet (1999) for small n and assuming that $|\mathcal{X}_i| = k$ is the same across all point sets \mathcal{X}_i , we adopt the approximation

$$\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n) \approx \alpha \sqrt{\frac{n}{k^{n/(n-1)}}},$$

where $\alpha = 0.29$.

3.3. Clustering

Our analysis of the GTSP has assumed that all of the demand points are independently and uniformly distributed in the unit square. Of course, there are many reasons why these assumptions might not hold, such as the presence of spatial competition or economies of density. Fortunately, many phenomena of this kind can already be addressed using our existing models by appropriately selecting the cardinalities $|\mathcal{X}_i|$: one example of this is the classical Hotelling model (Hotelling 1929), which predicts that competing stores will often locate themselves immediately next to one another. Thus, although there might be a total of k_i stores of type i in \mathcal{R} , the total number of *distinct locations* of these stores would be $k'_i < k_i$, and it would be more realistic to assume that $|\mathcal{X}_i| = k'_i$ instead. Another example is the existence of shopping malls; here, suppose that tasks $1, \dots, i^*$ can be performed at shopping malls (with $i^* \leq n$, obviously), and that \mathcal{X} denotes the set of shopping malls in \mathcal{R} . One can then compare the cost of a tour that does not use a mall, $\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)$, with the cost of a tour that uses a mall, $\text{GTSP}(\mathcal{X}, \mathcal{X}_{i^*+1}, \dots, \mathcal{X}_n)$. Which of the two of these is shorter depends on i^* and the cardinality of $|\mathcal{X}|$.

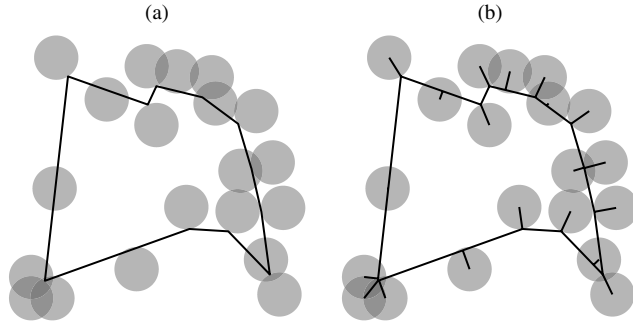
If it is truly necessary to explicitly enforce clustering of each point set \mathcal{X}_i (such as a garment district or an enclave such as a Chinatown or Little Italy), then an alternate model is required. One possibility is the *TSP with neighborhoods* (Dumitrescu and Mitchell 2003), which is a special case of the GTSP in which each point set \mathcal{X}_i is a ball \mathcal{B}_i of radius r (as opposed to being a finite set of points) that is centered at a point x_i , and the goal is to find the shortest tour that touches every ball; see Figure 6(a) for an example. We will derive asymptotic expressions for the TSP with neighborhoods with the help of Lemma 3:

LEMMA 3. Let $\mathcal{B}_1, \dots, \mathcal{B}_n$ be a collection of balls of radius r , centered at points x_1, \dots, x_n , all of which are contained in the unit square. We have

$$\begin{aligned} \text{TSP}(x_1, \dots, x_n) - 2nr & \leq \text{GTSP}(\mathcal{B}_1, \dots, \mathcal{B}_n) \\ & \leq \min\{\text{TSP}(x_1, \dots, x_n), \lceil 1/(2r) \rceil + 3\}. \end{aligned}$$

PROOF. The leftmost inequality holds because one can always make a tour that touches x_1, \dots, x_n by augmenting the tour $\text{GTSP}(\mathcal{B}_1, \dots, \mathcal{B}_n)$ with n line segments of length at most r , as shown in Figure 6(b). The fact that $\text{GTSP}(\mathcal{B}_1, \dots, \mathcal{B}_n) \leq \text{TSP}(x_1, \dots, x_n)$ is obvious. The fact that $\text{GTSP}(\mathcal{B}_1, \dots, \mathcal{B}_n) \leq \lceil 1/(2r) \rceil + 3$ is due to essentially the same idea as that expressed in Figure 3(a); if we construct a tour that traverses the width of \mathcal{R} horizontally a total of $\lceil 1/(2r) \rceil$ times (with the “+3” term added because we also travel one unit down and one unit up as before and because, if $\lceil 1/(2r) \rceil$ is odd, then we must make one additional horizontal traversal), then we must touch each ball at some point. \square

Figure 6. Figure 6(a) shows a tour of $n = 20$ neighborhoods; the optimal tour intersects each ball and is the shortest such tour to do so. Figure 6(b) shows that one can always augment an optimal tour in such a way as to touch the centers of each ball.



Using the fact that $\text{TSP}(x_1, \dots, x_n) \sim \beta\sqrt{n}$ for uniformly distributed points x_i , we can write an approximation of Lemma 3 for large n as

$$\beta\sqrt{n} - 2nr \lesssim \text{GTSP}(\mathcal{B}_1, \dots, \mathcal{B}_n) \lesssim \min\left\{\beta\sqrt{n}, \left\lceil \frac{1}{2r} \right\rceil + 3\right\},$$

where the notation “ \lesssim ” reflects the lower-order terms that we are dropping by introducing the square-root approximation. There are two aspects of the inequalities above that need correction: the first is that we can tighten the left-hand inequality by using the fact that $\beta\sqrt{n'} - 2n'r \lesssim \text{GTSP}(\mathcal{B}_1, \dots, \mathcal{B}_n)$ for all $n' \leq n$. The lower bound is maximized when $n' = \beta^2/(16r^2)$, at which the bound evaluates to $\beta\sqrt{n'} - 2n'r = \beta^2/(8r)$. Thus, a tighter lower bound is to use $\beta\sqrt{n} - 2nr$ if $n < \beta^2/(16r^2)$ and to use $\beta^2/(8r)$ otherwise. The second correction is that we should not require that r be constant, because this would result in both inequalities becoming constant as $n \rightarrow \infty$. Thus, we represent r as a sequence indexed by n , $\{r_n\}$, with the assumption that $r_n \rightarrow 0$ as $n \rightarrow \infty$. In summary, our new bounds are

$$\left. \begin{array}{ll} \beta\sqrt{n} - 2nr_n & \text{if } n < \frac{\beta^2}{16r_n^2} \\ \frac{\beta^2}{8r_n} & \text{otherwise} \end{array} \right\} \lesssim \text{GTSP}(\mathcal{B}_1, \dots, \mathcal{B}_n) \lesssim \min\left\{\beta\sqrt{n}, \frac{1}{2r_n}\right\},$$

and it is straightforward to verify that the left- and right-hand sides of the inequalities above are always within a factor of $4/\beta^2$ of one another.

4. Models

This section considers several models of increasing complexity. In each model, we assume that each person has n

“tasks” that they must complete each day (such as going to work, the grocer, and so forth), and each of these tasks can be performed at k different locations. Thus, it would be sensible to postulate that the distance travelled by each person in the region would be given by the expression $\text{GTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)$, where the point sets \mathcal{X}_j each denote the locations at which these tasks can be performed. By the analysis in Remark 1, we would approximate this with the expression $\alpha\sqrt{n/k^{n/(n-1)}}$. However, some potential error may result because this expression does not take into account the additional distance incurred by leaving and returning to each person’s house, which we assume is distributed uniformly at random in the region. Ideally, we would like to approximate this with the expression $\text{GTSP}(\{x_i\}, \mathcal{X}_1, \dots, \mathcal{X}_n)$, where x_i denotes person i ’s home location, and we will do so in Section 6. For now, we simply remark that this expression is somewhat unwieldy because it involves computing a GTSP tour of sets of different magnitudes and thus involves a comparison of “inbound-and-outbound” costs of starting and ending a trip as well as the “peddling” cost of moving between destinations on this trip (see Langevin et al. 1996 for a detailed overview). Since the purpose of this study is to examine the benefits of multistop trips at the household level, we instead opt to approximate each person’s distance travelled (from their house to their n destinations) as $\alpha\sqrt{n/k^{n/(n-1)}}$ as justified in Remark 1.

4.1. A Simple Example: Luddites and Shut-Ins

The scenario we describe in this section is too simple to be of practical use, but is helpful as a “minimum working example” that explains what factors affect the carbon footprint in a region most significantly. Suppose that our city is a square region \mathcal{R} of area 1 and has a population N . Each person has n locations to visit daily ($n-1$ errands plus their home) and each errand has k possible locations where that errand can be performed (e.g., there are k grocery stores and k banks in the region). Each of the N people in the region corresponds to a point sampled independently and uniformly at random in \mathcal{R} , and each person belongs to one of two classes, either “luddites” or “shut-ins,” distinguished as follows:

- A *luddite* performs all of their tasks by themselves and drives to each of the n locations.
- A *shut-in* shops for everything online and remains stationary while packages are delivered to them.

Let the fraction of shut-ins in the city be p , implying that pN people are to be served by a delivery truck. This truck performs a travelling salesman tour of pN points, whose length is approximately $\beta\sqrt{pN}$ (for large N) by Theorem 1, with $\beta \approx 0.7124$. Therefore, the total carbon footprint due to these shut-ins is $\phi\beta\sqrt{pN}$, where ϕ represents the amount of emissions produced per mile driven by a delivery truck.

A luddite visits n places each day (their house, plus their $n-1$ tasks) and has k choices for each place to

visit. From Theorem 3 and Remark 1, as well as the introductory paragraph to this section, we adopt the expression $\alpha\sqrt{n/k^{n/(n-1)}}$ to model the distance traversed by each luddite, where $\alpha = 0.29$ is the proportionality constant of Remark 1. There are $(1-p)N$ such people, and their total carbon footprint is therefore $\psi(1-p)N\alpha\sqrt{n/k^{n/(n-1)}}$, where ψ represents the amount of emissions produced per mile driven by a passenger car. The total carbon footprint of the region, regarded as a function of p , is then given by

$$f(p) := \phi\beta\sqrt{pN} + \psi(1-p)N\alpha\sqrt{n/k^{n/(n-1)}}, \quad (5)$$

which is concave in p . Note that when $p = 0$ (i.e., there are no shut-ins and everyone does their own driving), the carbon footprint is $\psi N\alpha\sqrt{n/k^{n/(n-1)}}$. We also note that

$$f(p)|_{p=(\phi^2\beta^2k^{n/(n-1)})/(\psi^2\alpha^2nN)} = f(p)|_{p=0} = \psi N\alpha\sqrt{n/k^{n/(n-1)}},$$

which (coupled with the concavity of $f(\cdot)$) tells us that we must have $p \geq (\phi^2\beta^2k^{n/(n-1)})/(\psi^2\alpha^2nN) =: p_0$ in order for the carbon footprint to be reduced as a result of using delivery services. It is also worth pointing out that $f(\cdot)$ is maximized when $p = p_0/4$, and attains a maximum value of

$$\begin{aligned} & \phi\beta\sqrt{pN} + \psi(1-p)N\alpha\sqrt{n/k^{n/(n-1)}}|_{p=p_0/4} \\ &= \frac{\phi^2\beta^2\sqrt{k^{n/(n-1)}} + 4\psi^2\alpha^2nN/\sqrt{k^{n/(n-1)}}}{4\psi\alpha\sqrt{n}}. \end{aligned}$$

4.2. Marginal Costs

The preceding model describes an extreme case in which each person in \mathcal{R} either makes no use whatsoever of delivery services or uses delivery services exclusively. One middle ground that is also worth studying is the case where people belong to two classes as before, but the two classes differ by only one task:

- A *luddite* performs all of their tasks by themselves and drives to each of the n locations (this is the same as in the preceding model).
- An *early adopter* visits $n-1$ locations and uses a delivery service for the remaining task.

A model of this kind is useful when one wants to understand the benefits of implementing a new delivery service for a specific good, such as groceries; one example of this can be found in Wygonik and Goodchild (2012), who discuss the consequences of introducing grocery delivery services in Seattle, Washington. A more nationalized phenomenon would be the recent introduction of “last-mile” services such as Google Shopping Express (Bowman 2014), which offers same-day deliveries facilitated by a specialized fleet of vehicles. If we let p denote the fraction of early adopters in \mathcal{R} , we then see that the total carbon footprint in the region is given by

$$\begin{aligned} f(p) := & \underbrace{\phi\beta\sqrt{pN} + \psi p N \alpha \sqrt{(n-1)/k^{n/(n-1)}}}_{\text{early adopters}} \\ & + \underbrace{\psi(1-p)N\alpha\sqrt{n/k^{n/(n-1)}}}_{\text{luddites}} \end{aligned}$$

$$\begin{aligned} &= \phi\beta\sqrt{pN} + \frac{\psi N \alpha}{\sqrt{k^{n/(n-1)}}} [\sqrt{n} - p(\sqrt{n} - \sqrt{n-1})] \\ &\approx \phi\beta\sqrt{pN} + \frac{\psi N \alpha}{\sqrt{k^{n/(n-1)}}} \left[\sqrt{n} - \frac{p}{2\sqrt{n}} \right], \end{aligned}$$

where all terms (except for p) are the same as in (5), and we have used the series approximation $\sqrt{n} - \sqrt{n-1} = 1/(2\sqrt{n}) + \mathcal{O}(n^{-3/2})$ in the last line. In the same manner as in the preceding section, we note that when $p = 0$, the carbon footprint is $\psi N\alpha\sqrt{n/k^{n/(n-1)}}$, and also that

$$f(p)|_{p=(4\phi^2\beta^2nk^{n/(n-1)})/(\psi^2\alpha^2N)} = f(p)|_{p=0} = \psi N\alpha\sqrt{n/k^{n/(n-1)}},$$

which tells us that we must have $p \geq (4\phi^2\beta^2nk^{n/(n-1)})/(\psi^2\alpha^2N)$ in order for the carbon footprint to be reduced as a result of using delivery services. Note that this threshold is greater than that of the preceding section (which had a threshold of $(\phi^2\beta^2k^{n/(n-1)})/(\psi^2\alpha^2nN)$) by a factor of $4n^2$; this is simply a mathematical manifestation of the intuition that larger values of n (i.e., more trip chaining at the household level) lead to significantly greater economies of scale at the household level. This in turn implies that delivery services must be adopted at a larger rate in order for the carbon footprint to decrease.

4.3. Multiple Delivery Services

The model in Section 4.1 assumes that a single delivery truck serves all of the pN luddites. It is not hard to model the case where there are multiple such services; the main difference is that there is a loss in efficiency because competing delivery services do not consolidate their routes together, thus reducing the benefits of economies of scale. Suppose that there are m delivery services in the region, and that service i delivers goods to a fraction of δ_i of the shut-ins in the region, visiting $\delta_i p N$ customers in total (this model assumes that each shut-in is uniquely associated with one delivery service). Therefore, applying Theorem 1, we see that the work done by service i can be approximated as $\beta\sqrt{\delta_i p N}$, and therefore the total carbon footprint due to shut-ins is $\phi\beta\sqrt{pN} \sum_{i=1}^m \sqrt{\delta_i}$. Obviously, since $\sum_{i=1}^m \sqrt{\delta_i} \geq 1$ always holds, we see that the carbon footprint within the region will only increase as a result of employing multiple delivery services (provided that these services do not cooperate to share their loads efficiently). The total carbon footprint of the region is then given by

$$\begin{aligned} f(p) := & \phi\beta\sqrt{pN} \sum_{i=1}^m \sqrt{\delta_i} + \psi(1-p)N\alpha\sqrt{n/k^{n/(n-1)}} \\ &= \bar{\phi}\beta\sqrt{pN} + \psi(1-p)N\alpha\sqrt{n/k^{n/(n-1)}}, \end{aligned}$$

where we define $\bar{\phi} := \phi \sum_{i=1}^m \sqrt{\delta_i}$, which reduces to the same problem as (5).

4.4. A Probabilistic Model

The model in this section improves on that of 4.1 by modelling customer behavior in a smoother way than the luddite/shut-in dichotomy. Rather than assigning a set fraction of the population to be shut-ins, we assume that each customer uses a delivery service to do each of their n daily tasks with probability q . Thus, the number of locations that the person actually visits is a binomial random variable, X , with parameters n and q , and the expected amount of driving for that person is $\mathbf{E}(\alpha\sqrt{X/k^{n/(n-1)}}) = (\alpha/\sqrt{k^{n/(n-1)}})\mathbf{E}(\sqrt{X})$.

If a person chooses to perform a task online, then a delivery truck will visit their house. Note that the only circumstance under which a delivery truck does not visit their house is if that person chooses to complete *all* n activities by driving to n different locations. Thus, the probability that a person is visited by a delivery truck is given by $p := 1 - q^n$, and we see that the number of houses that the truck visits is a binomial random variable Y with parameters N and p , and the expected distance that the delivery truck travels is $\beta\mathbf{E}(\sqrt{Y})$. The total carbon footprint in the region is therefore

$$f(p) := \phi\beta\mathbf{E}(\sqrt{Y}) + \psi\frac{\alpha N}{\sqrt{k^{n/(n-1)}}}\mathbf{E}(\sqrt{X}), \quad (6)$$

where $X \sim B(n, q)$ and $Y \sim B(N, p)$. To simplify the above expression, the following lemma is useful:

LEMMA 4. *Let $X \sim B(n, p)$ be a binomially distributed random variable. Then as $p \rightarrow 0$ with n fixed, we have $\mathbf{E}(\sqrt{X}) \sim np$, and as $p \rightarrow 1$ with n fixed, we have $\mathbf{E}(\sqrt{X}) \sim \sqrt{np}$.*

PROOF. See Section EC.2 of the online supplement. \square

The preceding lemma allows us to conclude that, for values of p near 0 (which implies that q is close to 1, i.e., very little delivery is used), we can approximate (6) by

$$\begin{aligned} f(p) &\approx \phi\beta Np + \psi\alpha N\sqrt{\frac{nq}{k^{n/(n-1)}}} \\ &= N\left[\phi\beta p + \psi\alpha\sqrt{\frac{n(1-p)^{1/n}}{k^{n/(n-1)}}}\right]. \end{aligned}$$

Note that according to this approximation, we have

$$\left.\frac{df}{dp}\right|_{p=0} \approx N\left(\phi\beta - \frac{\psi\alpha}{2\sqrt{nk^{n/(n-1)}}}\right),$$

which we expect to be positive since $\phi\beta$ and $\psi\alpha$ ought to be approximately the same order of magnitude. This tells us that initially, as people in \mathcal{R} begin to make more use of delivery services, the total carbon footprint in the region increases.

5. A Numerical Example

In this section, we give a simple example of an instance of the model in Section 4.2 using estimates of the relevant input parameters. This model seems to be the most timely, as evidenced by the prevalence of last-mile delivery services such as Google Shopping Express, Amazon Prime, Instacart, and Walmart To Go (Bensinger 2013, Bowman 2014, Harris and Cook 2007, Press 2011). Table 1 shows our estimates for parameters ϕ , ψ , α , and β , which we do not expect (for the most part) to vary on the region being served. To estimate k for various regions, we used census data obtained from U.S. Census Bureau (2012) that gives the number of grocery stores in various metropolitan regions; these numbers (as well as N , the populations of these regions) are shown in Table 2. Figure 7 shows plots of the total emissions, $f(p)$, for four metropolitan areas. From Table 2, we see that the critical thresholds p^* are quite high, and in many instances, the household-level economies of scale are high enough that even a 100% usage of delivery services is less efficient than leaving drivers to their own devices (this corresponds to the entries in the table that are marked “>1”). The alternative analysis in the next section is somewhat more optimistic.

6. Incorporating Inbound-and-Outbound Costs

As described in the beginning of Section 4, the models we have described thus far have not paid special attention to the “inbound-and-outbound” costs associated with leaving and returning to one’s home. This section describes a result that is related to Theorems 2 and 3 in which we take a GTSP tour of n point sets, $\mathcal{X}_1, \dots, \mathcal{X}_n$, in addition to a fixed point x_0 (which represents a person’s home). Note that the limiting behavior for fixed k and $n \rightarrow \infty$ is the same as in Theorem 2 because we are merely inserting one additional point, and therefore it will suffice to consider only the limiting behavior for the case where n is fixed and $k \rightarrow \infty$:

THEOREM 4. *Let $\mathcal{X}_1, \dots, \mathcal{X}_n$ denote n sets of points, each having cardinality k , and suppose that all nk points are distributed independently and uniformly at random in a region \mathcal{R} having area A . Let x_0 be a point in the*

Table 1. Input parameter estimates for our numerical example.

Parameter	Estimate	Source
ϕ	1,303 $\frac{\text{grams CO}_2}{\text{mile}}$	Kodjak (2004)
ψ	350 $\frac{\text{grams CO}_2}{\text{mile}}$	Administration (2011)
α	0.29	Numerical simulations based on Laporte and Semet (1999)
β	0.7124	Applegate et al. (2010)

Table 2. The number of grocery stores k , the populations N , and the critical thresholds p^* at which emissions decrease because of adoption of delivery services.

Region	k	N	$p^* = (4\phi^2\beta^2nk^{n/(n-1)})/(\psi^2\alpha^2N)$				
			$n = 3$	$n = 4$	$n = 5$	$n = 6$	$n = 7$
Los Angeles-Long Beach-Anaheim, CA Metro Area	3,358	13,052,921	>1	>1	>1	>1	>1
Chicago-Naperville-Elgin, IL-IN-WI Metro Area	2,889	9,522,434	>1	>1	>1	>1	>1
Indianapolis-Carmel-Anderson, IN Metro Area	295	1,928,982	>1	>1	>1	0.95	0.92
Salt Lake City, UT Metro Area	192	1,123,712	>1	>1	>1	0.98	0.96
Tulsa, OK Metro Area	136	951,880	>1	0.98	0.81	0.76	0.75
Albuquerque, NM Metro Area	119	901,700	>1	0.86	0.72	0.68	0.68
El Paso, TX Metro Area	138	830,735	>1	>1	0.95	0.89	0.88
McAllen-Edinburg-Mission, TX Metro Area	132	806,552	>1	>1	0.92	0.87	0.86
Little Rock-North Little Rock-Conway, AR Metro Area	124	717,666	>1	>1	0.96	0.90	0.90
Colorado Springs, CO Metro Area	83	668,353	>1	0.72	0.62	0.60	0.60
Boise City, ID Metro Area	73	637,896	0.98	0.64	0.55	0.54	0.54
Provo-Orem, UT Metro Area	50	550,845	0.64	0.44	0.40	0.39	0.40
Killeen-Temple, TX Metro Area	84	420,375	>1	>1	>1	0.97	0.97
Green Bay, WI Metro Area	43	311,098	0.90	0.64	0.59	0.58	0.60
Clarksburg, WV Micro Area	25	94,310	>1	>1	0.99	>1	>1
Elmira, NY Metro Area	24	88,911	>1	>1	0.99	>1	>1
DuBois, PA Micro Area	22	81,184	>1	>1	0.98	>1	>1

Notes. The first and second columns are obtained from U.S. Census Bureau (2012). Here the cells marked “>1” indicate that, even at 100% adoption of delivery services, the carbon footprint of the region is still larger than the case where $p = 0$, i.e., no delivery services are used.

interior of \mathcal{R} . Then the expected length of a GTSP tour of $\{x_0\}, \mathcal{X}_1, \dots, \mathcal{X}_n$ satisfies

$$\mathbf{E}(\text{GTSP}(\{x_0\}, \mathcal{X}_1, \dots, \mathcal{X}_n)) \in \mathcal{O}(\sqrt{An/k} \cdot \sqrt{\log k})$$

and

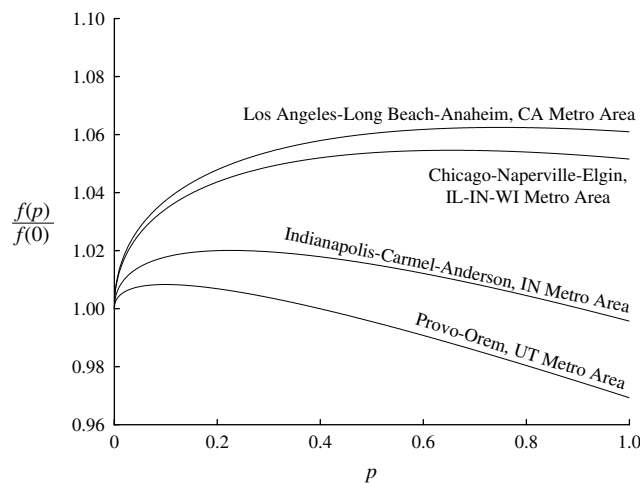
$$\mathbf{E}(\text{GTSP}(\{x_0\}, \mathcal{X}_1, \dots, \mathcal{X}_n)) \in \Omega(\sqrt{An/k})$$

as $k \rightarrow \infty$ with n fixed. Specifically, there exists a constant $\alpha_3 > 0.136$ such that the following statements hold:

1. For any n , there exists a threshold k_0 such that

$$\mathbf{E}(\text{GTSP}(\{x_0\}, \mathcal{X}_1, \dots, \mathcal{X}_n)) \leq \alpha_1 \sqrt{An/k} \cdot \sqrt{\log k}$$

Figure 7. A plot of the change in total carbon footprint for four different cities, for the model described in model in Section 4.2.



Note. Here we assume that $n = 6$. The value $f(0)$ simply represents the total emissions when no delivery services are used, and therefore when $f(p)/f(0) < 1$ we find that delivery services result in a net improvement.

whenever $k \geq k_0$, where $\alpha_1 = 2.7$ is the constant from Lemma 1.

2. For any n , there exists a threshold k_0 such that

$$\mathbf{E}(\text{GTSP}(\{x_0\}, \mathcal{X}_1, \dots, \mathcal{X}_n)) \geq \alpha_3 \sqrt{\frac{An}{k}}$$

whenever $k \geq k_0$.

PROOF. Assume as in the previous proofs that \mathcal{R} is the unit square. To prove Claim 1, consider a square \square_0 of area $a := \log k / (2k)$ centered at the point x_0 , and suppose that k is sufficiently large (i.e., that a is sufficiently small) that \square_0 is entirely contained within \mathcal{R} . Let p denote the probability that \square_0 contains at least one element from each point set \mathcal{X}_i , in which case we clearly have $\text{GTSP}(\{x_0\}, \mathcal{X}_1, \dots, \mathcal{X}_n) \leq \alpha_1 \sqrt{a(n+1)}$ from Lemma 1. Since $p = (1 - (1-a)^k)^n$, we therefore see that as $k \rightarrow \infty$, we have

$$\begin{aligned} \mathbf{E}(\text{GTSP}(\{x_0\}, \mathcal{X}_1, \dots, \mathcal{X}_n)) &\leq p\alpha_1 \sqrt{a(n+1)} + (1-p)\alpha_1 \sqrt{n+1} \\ &= \frac{\alpha_1}{2} \sqrt{\frac{n+1}{k}} \cdot \left(\left[1 - k^{-k} \left(k - \frac{1}{2} \log k \right)^k \right]^n \right. \\ &\quad \left. \cdot (\sqrt{2 \log k} - 2\sqrt{k}) + 2\sqrt{k} \right) \\ &\sim \frac{\alpha_1}{2} \sqrt{\frac{n+1}{k}} \cdot [(1 - n\sqrt{1/k})(\sqrt{2 \log k} - 2\sqrt{k}) + 2\sqrt{k}] \\ &\leq \frac{\sqrt{2}\alpha_1}{2} \sqrt{\frac{n+1}{k}} \cdot \sqrt{\log k} \leq \alpha_1 \sqrt{n/k} \cdot \sqrt{\log k} \end{aligned}$$

as desired.

To prove the second claim, we find it useful to revisit Lemma 2, and we again let \mathcal{L} denote a lattice within \mathcal{R} of the form

$$\left\{0, \frac{1}{m}, \frac{2}{m}, \dots, \frac{m-1}{m}, 1\right\} \times \left\{0, \frac{1}{m}, \frac{2}{m}, \dots, \frac{m-1}{m}, 1\right\}.$$

We first see that there are at most k^n total distinct subsets of the form $\{x_0, x_1, \dots, x_n\}$, with $x_i \in \mathcal{X}_i$ for each $i \geq 1$. For each of these subsets, there are $n!$ different orderings, and we therefore conclude that there are at most $n! \cdot k^n$ valid paths that originate at x_0 and visit one point from each of the subsets \mathcal{X}_i . By applying the union bound, we see that for any l ,

$$\begin{aligned} \Pr(\text{GTSP}(x_0, \mathcal{X}_1, \dots, \mathcal{X}_n) \leq l) \\ &= \Pr(\text{one of the } n! \cdot k^n \text{ valid paths has length} \leq l) \\ &\leq n! \cdot k^n \Pr(\text{length}(\mathcal{P}) \leq l), \end{aligned}$$

where \mathcal{P} is the path obtained by selecting the first element from each set \mathcal{X}_i and visiting these elements in a sequence chosen uniformly at random. By construction, we see that \mathcal{P} is simply a path that is sampled uniformly at random from \mathcal{P} , the collection of all possible paths originating at x_0 that visit n additional points taken from the lattice \mathcal{L} . Of course, we can again see that $|\mathcal{P}| = m^{2n}$. By scaling the lattice of Lemma 2 by a factor of $1/m$ in the vertical and horizontal directions, there are at most

$$\binom{ml+n}{n} \cdot \left(\frac{8ml}{n}\right)^n \leq \frac{(ml+n)^n}{n!} \cdot \left(\frac{8ml}{n}\right)^n$$

paths in \mathcal{P} whose length is at most l . Thus,

$$\begin{aligned} \limsup_{m \rightarrow \infty} \Pr(\text{length}(\mathcal{P}) \leq l) \\ &\leq \limsup_{m \rightarrow \infty} \frac{((ml+n)^n/n!) \cdot ((8ml)/n)^n}{m^{2n}} \\ &= \frac{l^{2n} 8^n n^{-n}}{n!} \\ &\Rightarrow \Pr(\text{GTSP}(\{x_0\}, \mathcal{X}_1, \dots, \mathcal{X}_n) \leq l) \leq k^n l^{2n} 8^n n^{-n} \end{aligned}$$

for all l . We now set $l = c\sqrt{n/k}$, with $c = \sqrt{6}/12$, obtaining

$$\begin{aligned} \mathbf{E}(\text{GTSP}(\{x_0\}, \mathcal{X}_1, \dots, \mathcal{X}_n)) \\ &\geq (1 - k^n l^{2n} 8^n n^{-n})l \\ &= \frac{1}{12} \cdot \frac{\sqrt{6n}(1 - 3^{-n})}{\sqrt{k}} > 0.136\sqrt{n/k}, \end{aligned}$$

which completes the proof. \square

REMARK 2. By performing numerical simulations for small n and large k in the same way as in Remark 1, we adopt the approximation

$$\text{GTSP}(\{x_0\}, \mathcal{X}_1, \dots, \mathcal{X}_n) \approx \alpha' \sqrt{n/k},$$

where $\alpha' = 0.47$.

6.1. Revised Simulations

In this section we present a revised numerical simulation that is entirely analogous to that of Section 5, only we now incorporate inbound-and-outbound costs as in Theorem 4. Thus, whereas we previously had a critical threshold of

$$p^* = \frac{4\phi^2 \beta^2 n k^{n/(n-1)}}{\psi^2 \alpha^2 N},$$

we now see by a straightforward analysis that under the revised model, the critical threshold is instead

$$p^* = \frac{4\phi^2 \beta^2 n k}{\psi^2 (\alpha')^2 N}.$$

These thresholds are shown in Table 3. These are somewhat more encouraging than those of Section 5, although we still see that a significant amount of adoption of delivery services is required. A recent survey (Supermarket News 2013) of 22,000 homes suggests that approximately 13% of shoppers have purchased groceries online in the last 30 days, which happens to be close to the average of the entries of Table 3. This would suggest that, at present, the benefits to carbon footprints due to delivery services are just beginning to be realized, if at all.

7. Conclusions

We have conducted an asymptotic analysis of the GTSP tour of n sets of k points each in the unit square, $\text{EGTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n)$, as $k \rightarrow \infty$ and as $n \rightarrow \infty$. For the case where k is fixed and $n \rightarrow \infty$, our analysis that $\text{EGTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n) \in \Theta(\sqrt{n/k})$ and that $\text{EGTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n) \in \Omega(\sqrt{n/k})$ is tight inasmuch as the lower and upper bounds have the same order. For the case where n is fixed and $|\mathcal{X}_i| \rightarrow \infty$ for all i , our upper and lower bounds differ by a term of order $(n^2 \log k_G + \log n)^{1/(2(n-1))}$, where k_G is the geometric mean of the $|\mathcal{X}_i|$'s. We conjecture that, in this case, one actually has

$$\text{EGTSP}(\mathcal{X}_1, \dots, \mathcal{X}_n) \in \Theta\left(\sqrt{\frac{An}{k_G^{n/(n-1)}}}\right),$$

although this will clearly require further analysis. We have also analyzed the GTSP for the case where one also has a singleton x_0 , that is, $\text{EGTSP}(\{x_0\}, \mathcal{X}_1, \dots, \mathcal{X}_n)$, and $|\mathcal{X}_i| = k$ for all i ; in this case we have upper and lower bounds that differ by a term of order $\sqrt{\log k}$.

Numerical analyses of the preceding models, when applied to the problem of estimating the change in carbon footprint that results from using delivery services, suggest that a considerable amount of adoption of delivery services is necessary before one begins to see a decrease in carbon footprint. The reason for this is simply that the economy of scale that is realized by delivery services requires a significant initial level of adoption in order to compete with the household-level economy of scale that the customers already possess, given their wide choice of locations to visit and the number of daily locations they visit.

Table 3. The number of grocery stores k , the populations N , and the critical thresholds p^* at which emissions decrease as adoption of delivery services increases under the revised model.

Region	k	N	$p^* = (4\phi^2\beta^2nk)/(\psi^2(\alpha')^2N)$				
			$n = 2$	$n = 3$	$n = 4$	$n = 5$	$n = 6$
Los Angeles-Long Beach-Anaheim, CA Metro Area	3,358	13,052,921	0.10	0.14	0.17	0.20	0.23
Chicago-Naperville-Elgin, IL-IN-WI Metro Area	2,889	9,522,434	0.12	0.16	0.20	0.24	0.28
Indianapolis-Carmel-Anderson, IN Metro Area	295	1,928,982	0.06	0.08	0.10	0.12	0.14
Salt Lake City, UT Metro Area	192	1,123,712	0.07	0.09	0.11	0.14	0.16
Tulsa, OK Metro Area	136	951,880	0.06	0.08	0.10	0.11	0.13
Albuquerque, NM Metro Area	119	901,700	0.06	0.07	0.09	0.11	0.12
El Paso, TX Metro Area	138	830,735	0.07	0.09	0.11	0.13	0.15
McAllen-Edinburg-Mission, TX Metro Area	132	806,552	0.07	0.09	0.11	0.13	0.15
Little Rock-North Little Rock-Conway, AR Metro Area	124	717,666	0.07	0.09	0.12	0.14	0.16
Colorado Springs, CO Metro Area	83	668,353	0.05	0.07	0.08	0.10	0.12
Boise City, ID Metro Area	73	637,896	0.05	0.06	0.08	0.09	0.11
Provo-Orem, UT Metro Area	50	550,845	0.04	0.05	0.06	0.07	0.09
Killeen-Temple, TX Metro Area	84	420,375	0.08	0.11	0.13	0.16	0.18
Green Bay, WI Metro Area	43	311,098	0.06	0.08	0.09	0.11	0.13
Clarksburg, WV Micro Area	25	94,310	0.11	0.14	0.17	0.21	0.24
Elmira, NY Metro Area	24	88,911	0.11	0.14	0.18	0.21	0.25
DuBois, PA Micro Area	22	81,184	0.11	0.14	0.18	0.21	0.25

Note. The first and second columns are obtained from U.S. Census Bureau (2012).

Supplemental Material

Supplemental material to this paper is available at <http://dx.doi.org/10.1287/opre.2016.1533>.

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