AN EMPIRICAL STUDY OF THE DEVIATION BETWEEN ACTUAL AND
SHORTEST-TRAVEL-TIME PATHS

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Few empirical studies of revealed route characteristics have been reported in the literature. This study challenges the widely applied shortest-path assumption by evaluating routes followed by residents of the Minneapolis–St. Paul metropolitan area, as measured by the GPS Component of the 2010 Twin Cities Travel Behavior Inventory conducted by the Metropolitan Council. It finds that most travelers used paths longer than the shortest path. This is in part a function of trip distance, trip circuity, number of turns, and age of the driver. Some reasons for these findings are conjectured.

Keywords: Empirical study, Actual paths, Shortest travel time paths
INTRODUCTION

Few empirical studies of revealed route characteristics have been reported in the literature. Previous research by the authors [29] found fewer than 40% of commuters took the shortest paths, though 90% of subjects took routes which were within 5 minutes of the shortest paths. Other researchers have found similar results [1,15,18]. The reasons for this are several, but the simplest explanation is that people care about things in addition to and other than average travel time.

Previous research finds travelers care about monetary cost [3], avoiding stops [27], travel time reliability [2], aesthetics [26]. Travelers might misperceive travel times [17]. They also might not want to engage in route search, and instead want to remain on habitual routes.

Mismeasurement of the shortest path is also as a possibility, though this has been disproved as the dominant reason.

This study tests the widely applied shortest travel time path assumption by evaluating routes followed by residents of the Minneapolis-St. Paul metropolitan area, as measured by the GPS Component of the 2010 Twin Cities Travel Behavior Inventory. Some of the deviation between actual and shortest travel time path is explained using a regression model, with network structure and socio-demographic factors as independent variables.

This paper addresses data, methodology, analysis of between travelers differences, models, and results. This paper then discusses causes for the observations that people do not choose the shortest path.

DATA

Several sources of data were used for this study, including travel data, travel speeds, and base network data. All of these sources discussed in greater detail in the following sections.

Travel data

The first data source is from the Travel Behavior Inventory (TBI), conducted by the Metropolitan Council for the Twin Cities (Minneapolis-St. Paul region) in 2010 and 2011. A GPS Component of the survey was used in this analysis; the GPS data were collected from a subset of individual subjects from 250 households. These household were issued GPS units to carry for a seven-day period. In addition, the same subjects also completed a travel survey on one weekday. This is detailed in the TBI report for Metropolitan Council [16], and the data are available at the Transportation Secure Data Center.

Valid GPS data were collected from 278 persons from the 250 households surveyed as part of the TBI. Trip exclusions are shown in Table 1. The small sample collected for this study avoided “false positives,” as the commute trips identification constraint condition was strict. However, this constraint may have excluded real work trips in which:

- There are errors in the longitude and latitude of some origins or destinations because of the accuracy of GPS devices (if one of the errors is greater than 500 meters, then it would not be considered a commute trip);
- The location of home and work differs significantly from the parking location, and a break was detected in the GPS data at the point of parking; and
- The GPS tracks started in the middle of a trip because users may have forgotten to turn the GPS on at the origin, or the GPS signal may not have been located until the trip was underway.
If these issues occurred near origin or destination, then this trip were not identified as commute trips, which inflates the numbers of Home to Other (H2O), Other to Home (O2H), and Other to Other (O2O) trips.

<table>
<thead>
<tr>
<th>Steps</th>
<th>Numbers</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Origin trips</td>
<td>16,902</td>
<td>• The identification was based on time gap between two successive GPS points;</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• If the dates of two GPS points were different and were not at midnight, the latter point was considered as origin of the next trip;</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• If the dates of two GPS points were the same, then time of them was checked;</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• If time gap was greater than a threshold (300 seconds), they were also assigned as different trips.</td>
</tr>
<tr>
<td>1</td>
<td>12,572</td>
<td>• Remove trips in which all the number in speed column is zero.</td>
</tr>
<tr>
<td>2</td>
<td>8,461</td>
<td>• Remove trips where trip duration was less than 5 minutes.</td>
</tr>
<tr>
<td>3</td>
<td>4,895</td>
<td>• Because in some trips the speed is ‘2’ or ‘0’ with no other numbers, remove the trips with average speed less than 2.</td>
</tr>
<tr>
<td>H2W, Auto</td>
<td>142</td>
<td>• Use the method in the paper to find identify trips.</td>
</tr>
<tr>
<td>H2W, Auto</td>
<td>124</td>
<td>• Destinations of two of the trips are not in the Twin Cities GIS network, so were excluded.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Some of the trips involved indirect travel from home to work; indirect trips were exclude from the H2W category, and were instead included in H2O.</td>
</tr>
</tbody>
</table>

**Travel Sppeeds**

The second data source is the TomTom road speed network data for 2010, which was acquired by the Metropolitan Council for the TBI [6]. To understand these data better, travel times for the first two data sources were compared. Since the two data sources are mapped to different networks, these sources had to be harmonized.

As shown in Figure 1, TomTom data are largely consistent with GPS data for the same links, though TomTom’s times are a bit lower (speeds higher) on average. Potential causes for this discrepancy include differences in definition, sampling, and the treatment of traffic signals, and the possibility that some subjects made small stops that were not identified as distinct trips. A nontrivial number of TBI GPS links had travel times significantly higher than TomTom data. The TomTom methodology for averaging link travel times (and the number of observations used to construct those averages) is proprietary. As a result, the GPS data may have included short stops (engine running) or weather conditions that were not accounted for as part of this study; similar trips may have been filtered out by TomTom.
FIGURE 1 Travel Time Comparison on Links between TomTom GPS and TBI GPS Data
(on average, TomTom travel times are lower than observed in the TBI)

METHODOLOGY
During the GPS data processing phase for the TBI, three steps were considered: 1) trips identification; 2) mode classification; and 3) trip purpose identification.

Trip Identification
Trips were tracked by GPS devices by finding origin and destination points for each trip. The identification was based on the time gap between two successive GPS points. If the dates of two GPS points were different and were not at midnight, then the latter point was considered as the origin of next trip. If the dates of two GPS points were the same, then the times of successive GPS points were compared. If the time gap (start of GPS data [possible trip] n+1 – end of GPS data [possible trip] n) was greater than a 300-second (5-minute) threshold, then they were also considered different trips; however, if the points were within 300 seconds, then they were considered part of the same trip. GPS points at the start or end of trips that showed no spatial movement, such points or trips, were removed.

Mode Classification
Mode classification is an important assessment in the use of GPS data. For this study, as set of mode identification rules were developed based on the literature [5, 10, 28] and expert assessment (these rules are shown in Table 2). Note that these rules are not complete in the sense that they do not guarantee that a segment will be classified into a mode. Instead, these rules aim to identify trips unambiguously by mode; ambiguous trips may have no identified mode.

Visual inspection of the individual trip records suggested that they plausibly reflect the actual modes taken; however, a fast bike and a slow car remain indistinguishable using this method. From the perspective of this study, focusing on automobile users, the most important task was to avoid “false positives” (nonauto trips showing up as auto), rather than worrying about “false negatives” (auto trips excluded from the sample set). Other studies may have different objectives with regard to modal classification, and typically identifying transit is more difficult.
TABLE 2 Trip Classification Rules

<table>
<thead>
<tr>
<th>Mode</th>
<th>Criteria</th>
</tr>
</thead>
</table>
| Walk   | • Maximum speed of all points ≤ 20km/h  
         • Duration > 60s  
         • Percentile of speed of all points ≤ 10km/h  
         • Average speed of all points ≤ 6km/h |
| Rail   | • Distance from first point of speed accelerates to 10km/h to the nearest rail station < 150m  
         • Distance from last point that speed is greater than 10km/h to the nearest rail station < 150m  
         • Average speed of all points > 10km/h |
| BUS    | • Distance from first point of speed accelerates to 10km/h to the nearest bus stop < 50m  
         • Distance from last point that speed is greater than 10km/h to the nearest bus stop < 50m  
         • Average speed of all points > 10km/h |
| Bicycle| • 85th percentile of speed of all points ≥ 10km/h and < 20km/h  
         • Max speed of all points ≤ 30km/h |
| Car    | • The remaining trip segments with average speed of all points > 10km/h |

Trip Purpose Identification

Trip purposes are identified based on the relative location of the GPS trip origin and destination (start and stop point) and the subject’s known home and work location, as detailed in Table 3. In order to identify whether a trip is traveling from the origin to the destination directly without multiple purposes, the trip angles were calculated at 5 and 10 minutes after leaving and before arriving, respectively. A schematic diagram is given in Figure 2.

If the angles at 5 and 10 minutes are both greater than 90 degrees, a trip was considered to have other stops on the way to the destination (e.g., dropping children off at school on the way to work). Among the trips that meet the trip angles requirement, the length of dwell time or duration of vehicle deviating from street center lines for more than 20 meters is examined. In previous studies, the length of dwell time varies from 45 seconds to 300 seconds (e.g., 45s by ). Because a typical cycle length at signal-control intersections is 90s for one direction and it is possible to wait more than 1 cycle length during peak periods. 120s of dwell time was chosen in this paper. Again, avoiding false positives (misidentifying nonwork trips as work trips) was more of a concern than the converse, since introducing nonwork trips into the sample were expected to create more bias than excluding random work trips.

TABLE 3 Definitions of Trips Based on Relative Location of Trip Origin and Known Home and Work Locations

<table>
<thead>
<tr>
<th>Destination</th>
<th>Origin</th>
<th>worker</th>
<th>non-worker</th>
</tr>
</thead>
<tbody>
<tr>
<td>H ≤ 500m</td>
<td>worker</td>
<td>H2H</td>
<td>-</td>
</tr>
<tr>
<td>H &gt; 500m</td>
<td>worker</td>
<td>H2O</td>
<td>H2H</td>
</tr>
<tr>
<td>W ≤ 500m</td>
<td>worker</td>
<td>W2H</td>
<td>W2H</td>
</tr>
<tr>
<td>H + W &gt; 500m</td>
<td>worker</td>
<td>O2H</td>
<td>O2H</td>
</tr>
<tr>
<td>W ≤ 500m</td>
<td>non-worker</td>
<td>H2W</td>
<td>-</td>
</tr>
<tr>
<td>H + W &gt; 500m</td>
<td>non-worker</td>
<td>W2W</td>
<td>-</td>
</tr>
<tr>
<td>H ≤ 500m</td>
<td>non-worker</td>
<td>H2O</td>
<td>H2H</td>
</tr>
<tr>
<td>H &gt; 500m</td>
<td>non-worker</td>
<td>W2O</td>
<td>O2H</td>
</tr>
<tr>
<td>H ≤ 500m</td>
<td>non-worker</td>
<td>O2O</td>
<td>O2O</td>
</tr>
</tbody>
</table>
After being divided into trips, modes, and trip purposes, auto commute trips were identified. As shown in Table 4, the GPS data contains 124 home-based drive commute trips belonging to 58 travelers from 51 households. No W2W trips were identified, so those have been excluded. Several round trips from home without stops (H2H) trips were identified. Persons with no work address were identified as nonworkers. Trips to destinations other than the main work address were classified as nonwork (Other) trips, even if the function of the trip was for work, as that could not be determined from the GPS data.

TABLE 4 Number of Trips, by Travel Mode and Trip Purpose

<table>
<thead>
<tr>
<th></th>
<th>H2W</th>
<th>H2O</th>
<th>O2H</th>
<th>W2H</th>
<th>W2O</th>
<th>O2W</th>
<th>O2O</th>
<th>H2H</th>
<th>Total</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Walk</td>
<td>1</td>
<td>24</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>17</td>
<td>67</td>
<td>26</td>
<td>138</td>
</tr>
<tr>
<td>Train</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Bus</td>
<td>8</td>
<td>26</td>
<td>104</td>
<td>14</td>
<td>14</td>
<td>110</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>288</td>
</tr>
<tr>
<td>Bike</td>
<td>0</td>
<td>13</td>
<td>104</td>
<td>14</td>
<td>14</td>
<td>110</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>63</td>
</tr>
<tr>
<td>Drive</td>
<td>142</td>
<td>969</td>
<td>982</td>
<td>90</td>
<td>68</td>
<td>85</td>
<td>1073</td>
<td>10</td>
<td>3419</td>
<td>100.00</td>
</tr>
<tr>
<td>Not identified</td>
<td>25</td>
<td>260</td>
<td>313</td>
<td>12</td>
<td>15</td>
<td>53</td>
<td>308</td>
<td>0</td>
<td>986</td>
<td>20.14</td>
</tr>
<tr>
<td>Total</td>
<td>176</td>
<td>1292</td>
<td>1410</td>
<td>118</td>
<td>95</td>
<td>173</td>
<td>1595</td>
<td>36</td>
<td>4895</td>
<td>100.00</td>
</tr>
<tr>
<td>Percentage</td>
<td>3.60</td>
<td>26.39</td>
<td>28.80</td>
<td>2.41</td>
<td>1.94</td>
<td>3.53</td>
<td>32.58</td>
<td>0.74</td>
<td>100.00</td>
<td></td>
</tr>
</tbody>
</table>

Auto commute GPS data were then matched to TLG Twin Cities network. This method snapped all points to the nearest (by distance) link, ensuring:

- The link was a through link with no broken ends except for origin and destination links;
- The link was in the same travel direction as the GPS data; and
- There were no cycles (routes using the same link multiple times) in the network route.

The shortest-distance route was then developed on the TLG network, while the shortest-time route was computed using the TomTom network. TomTom speed data includes seven periods in a 24-hour day:

- Early Morning (AM1).
- Late Morning (AM2).
- Midday (MD).
Link travel speed was selected based on the trip period’s start time in GPS data. This was then compared to the total distance between the actual route and the shortest-distance route as well as the shortest-time route. The total travel time between the actual route and shortest-time route was also compared. The total overlap distance was calculated using the actual route, the TomTom shortest-travel-time-path route, and the shortest-distance route. An example of one subject’s shortest-travel-time path (using TomTom data), shortest-distance path, and actual path is shown in Figure 3.

Besides finding the general difference between the actual path and the shortest-time route, the trip circuity and the number of turns were also compared. (The circuity is the ratio of network to Euclidean, or straight-line, distance.) Through this process, the relationship between time difference and circuity, and the difference between time and the number of turns on the actual route, is found.

**DESCRIPTIVE RESULTS (BETWEEN TRAVELERS)**

Figure 4(a) compares (in percentage terms) actual GPS travel times with estimated TomTom times on the shortest path. As can be seen, almost all trips had travel times longer than the TomTom shortest path (a few are shorter because the TomTom network does not have speeds on some local roads). This is in part because end-of-trip details (e.g., parking) are not a part of the TomTom network. More than half the trips were longer (30% or more) than the estimated shortest-travel-time path.

Figure 4(b) displays the absolute difference in minutes. More than half of all auto commute trips in the sample are more than 5 minutes longer than the shortest path. The highest travel time differences occur for trips with low overlap. For trips with a high overlap rate, the time
differences are not as large, but are still far from zero. However, when compared to the
shortest-distance route (Figure 5(a)), the percentage of overlap between the actual route and the
shortest-time route (Figure 5(b)) is higher. However, only about one quarter (35 out of 124) chose
a route that has a high degree of overlap (>90%) with the shortest-travel-time route.

Figure 6(a) and Figure 6(b) demonstrate that when the circuitry of the actual route
increases, the difference in times decreases; as the number of turns rises, the difference shrinks.
The average difference for males is nominally higher than females (male:273s; female:254s), and the standard deviation for males is also higher than for females (male:402s; female:382s). These differences do not appear to be significant.

FIGURE 4 Travel Time Comparison (percentages) (a) & Travel Time Difference (minutes)
(b) Between TBI GPS Time ($t_{GPS}$) on Actual Routess and TomTom GPS Time ($t_{sp}$) on
Shortest-Time Route

FIGURE 5 Percentage of Overlap: (a) Difference Between Actual Route and Shortest
Distance Route, (b) Difference Between Actual Route and Shortest Travel Time Route

FIGURE 6 The Relationship Between Time Difference and Circuitry of Actual Route (a), and
Number of Turns on the Actual Route (b).

MODELS
As part of this study, models were built to reveal the relationship between the ratio of observed
GPS time to the estimated shortest path time from TomTom data and circuitry to the number of
turns for actual route as well as sociodemographic characteristics. As a first step, a simple Ordinary Least Squares (OLS) linear regression was constructed for each attribute.

Equation 1: OLS Linear Regression
\[ Y = aX + b \]
These models then revealed how attributes affect the time difference between GPS time \((t_{GPS})\) on the actual route and TomTom time on the shortest-time route \((t_{sp})\). Figure 4 through Figure 6 displays these results. A multivariate linear regression model was then built.

Generally, the ratio of observed to shortest-path travel time \((\tau)\) is expected to be a function of network characteristics \((N)\) and individual characteristics \((S)\).

Equation 2: Ratio of Observed to Shortest-Path Travel Time, Specified as General Function of Network Structure and Individual Characteristics
\[ \tau = f(N, S) \]
The variables of interest can then be further specified:

Equation 3: Ratio of Observed to Shortest-Path Travel Time, Dependent on Network Distance, Circuity, Number of Turns, and the Age and Gender of the Traveler
\[ \tau = f(D_{sp}, C_{GP}, T_{GPS}, A_t) \]
Where:
- \(\tau = t_{GPS}/t_{sp}\)
- \(D = \text{Distance}\)
- \(C = \text{Circuity} = D_{\text{network}}/D_{\text{Euclidean}}\)
- \(T = \text{Number of turns}\)
- \(A_t = \text{Age of the individual traveler}\)

Undoubtedly, other variables may play in this, including the location of traffic signals or crash data, but they were not available or tested in this analysis. These results are presented in the next section.

REGRESSION MODEL RESULTS (BETWEEN TRAVELERS)
The final regression results are shown in Table 4-6. The dependent variable is the ratio of the time \((\tau)\) on the chosen path \((t_{GPS})\) from the TBI and the estimate of the travel time on the shortest path \((t_{sp})\) from TomTom data.

This ratio decreases with distance. Longer trips are more likely than short trips to follow the shortest path. Longer trips may also need to be more efficient because of their length (and associated time budgets).

All else being equal, it is to be expected that more circuity would add to total travel time on the shortest path. However, longer-distance trips are less circuitous, both because the network structure enables movement to routes higher in the hierarchy of roads, which are traversed for long distances, and because short trips often have to travel on curvilinear subdivision streets (especially in the postwar suburbs) [9]. In addition, people select for less circuitous routes when choosing where to live relative to their work location (or vice versa) [12]. In this study, more circuitous routes were found to be associated with lower travel time ratios. This is a complex result without an easy intuitive explanation.

In regard to ratios, the proportion by which the actual travel time exceeds the shortest-path time drops as the circuity increases. While this is not at all surprising for the
denominator (shortest-path time), it is more surprising for the numerator (actual [GPS] time). It is possible that individuals who live in places that have more circuitous networks have fewer choices in routes, and thus fewer opportunities to reasonably deviate from the shortest route (thus lowering the ratio). Clearly, as with all results, additional research may provide additional answers.

Routes with more turns (TGPS) have a significantly higher time ratio. The variable for turns on the shortest-path route (Tsp) was statistically insignificant, and dropped from the final regression. Other model variables (including variables for both network and household structure) were tested in various combinations and were not statistically significant.

Overall, the model explains approximately 15% of the variance in the time ratio. Though the variables are statistically significant, the small size of this sample, combined with the fact that it is for only one metropolitan area, necessitate additional research before strong conclusions can be drawn about the explanatory—much less causal—factors explaining why people do not choose the shortest path. The Discussion section offers some conjectures.

### TABLE 5 Explaining $\tau$, the Ratio of GPS Travel Time to Shortest-Path Travel Time

| Independent Variables | Coef. | Std. Err. | t | P>|t| |
|------------------------|-------|-----------|---|-----|
| Distance               | -0.0000185 | 6.67e-06 | -2.78 | 0.006 |
| Circuity-GPS           | -0.6569722 | 0.3180107 | -2.07 | 0.041 |
| Circuity-sp            | -0.8381146 | 0.4148644 | -2.02 | 0.046 |
| Turns-GPS              | 0.0597149 | 0.0232824 | 2.56 | 0.012 |
| Age                    | -0.0096658 | 0.0049401 | -1.96 | 0.053 |
| Constant               | 3.684621 | 0.621362 | 5.93 | 0.000 |
| Adjusted $R^2$         | 0.1457 |
| Sample Size (N)        | 124 |

### DISCUSSION

Using empirical data from a GPS-based study of approximately 250 households, and focusing on auto commuters in that dataset, this study tests a crucial assumption in transportation planning practice, embedded in the principle of user equilibrium due to Wardrop [23], that travelers choose the shortest-travel-time path. The research has found that most travelers do not choose the shortest-travel-time-path, and the overlap between their actual path and the analyst’s best estimate of the shortest path is well below 100%. The following represents an attempt to understand why people are not taking the shortest path:

**Selflessness.** Wardrop’s principle [23] assumes that people are selfish, but perhaps they are selfless. It is assumed that individuals aim to minimize their own travel time rather than the travel time of society as a whole. However, people cannot know what decision will minimize society’s travel time because of computational and informational issues, as discussed later. However, if individuals had that information, then perhaps they might selflessly choose a different route. In the absence of such information, individuals are (at best) only guessing whether what they are doing is in the best interest of society as a whole, even if their choice involves some self-sacrifice. (This assumes that individuals are still making their trips. In the case of roadway congestion, it would be better for everyone else—from a travel time perspective—to avoid the trip altogether.)

**Rationality.** Wardrop’s principle assumes that people are rational, but maybe people are not rational, or at least not rational all the time. This is true in the sense that people react emotionally and intuitively, employing what Nobel Prize winner Daniel Kahneman [11] calls System 1 in Thinking Fast and Slow, based on heuristic rules. Individuals do not have time for rational assessment. In another sense, for a repeated decision (like commuting back and forth to
work), it costs a significant amount of travel time—a scarce resource—to systematically behave irrationally. Therefore, it is assumed that people are behaving rationally (engaging Kahneman’s System 2) when they can. The idea of bounded rationality, developed by Herbert Simon [20], has been applied to route choice problems by many researchers, see e.g. [7,8,14]. Models with bounded rationality can be built, with such models assuming or estimating the bounds to this rationality due to information, cognitive limits, and time available to make a decision.

**Perception.** Individuals may select the shortest travel time on their route, but they may misperceive the travel time on the network due to perception or cognition limits. On a 24-minute trip, few travelers will know the travel time to the nearest 30 seconds or minute. In surveys, reported travel times are typically rounded to 5 minutes; on occasion, surveys round to the nearest 15 minutes. As a result, if people are only perceiving time in 5- or 15-minute chunks, saving 1 or 2 minutes will not be perceived as important [17].

**Computation.** Travelers cannot accurately add travel times across different road segments, and they cannot systematically compare the travel times over alternative routes even if they had a complete dataset due to computational constraints.

**Information.** People do not remember or store information related to complete maps of the roadway network. People often possess good mental maps of the local street network near their home, workplace, and frequently visited locations, but if they live far from where they work, then they tend not to know the detailed roadway network in-between. There are limits to people’s ability to navigate. The cognitive or mental maps of most individuals are far from complete. Most people only have the experience of the routes they have actually used. Individuals can test other routes to gain experience/knowledge, but individuals (unlike GPS systems) do not innately possess this information.

**Valuation.** Perhaps people are minimizing the weighted sum of travel time, where time spent in different conditions is valued differently. It is known from the transit literature, for instances, that time spent waiting for a bus is much more onerous than time spent aboard a vehicle in motion making progress toward its destination; this effect is pronounced if the arrival time of the bus is uncertain [24,27].

**Objective.** Wardrop’s model assumes that people care only about minimizing travel time. People may be rational, but they may prioritize other trip characteristics instead of or in addition to travel time. There is evidence from other transportation choices that people, in general, are not minimizing travel time [21]. When a person chooses a place to live, that individual is not choosing to minimize her commute time to work. In fact, some studies have considered a hypothetical relocation of everybody’s place of residence, whereby each person’s house was equivalent to the structure in which they currently reside, but was “moved” to be as close to their workplace as possible (given everyone else was similarly moved). As a result, average commute times fell from approximately 24 minutes to 8 or 10 minutes. There is a significant amount of “excess travel” from a strict travel time-minimizing perspective [21]. There are many reasons for excess travel, but the most obvious reason is that it is not “excess” from the point of view from people traveling. People are making home-location decisions for a variety of reasons: the journey to work is not the only consideration. (However, travel time must be a consideration for some individuals, otherwise cities would not exist.) It is possible that people, when choosing a home location, might underestimate the amount of time that will be spent traveling, and thus underestimate the frustration associated with long commutes, and are thus unhappier than expected [22]. A major source of time estimation error arises because most people search for homes on the weekend, but tend to commute on weekdays.
Search cost. How long does it take to figure out the travel time on alternative routes? Is a traveler willing to spend 10 minutes exploring the network in order to save 30 seconds of travel time every day for the rest of her career? From a purely rational perspective, such a search may be worthwhile because the payback period is only 20 days. However, people often discount the possibility of saving time, worrying that a shortcut will be longer; individuals may also fear getting lost. Fear of the unfamiliar is a major deterrent to exploration [25].

Route quality. Many factors describe the quality or condition of a route and its environment. Is it potholed or newly paved? Does it run through a pleasant or unpleasant neighborhood? Evidence from previous studies shows that some people prefer a longer route if it is an attractive boulevard or parkway rather than a drive through a freeway trench [26]. This study was unable to assess the aesthetics of alternative routes.

Reliability. The likelihood of arriving on time, and not just the expected travel time, affects willingness to select a route. There is the old parable of the man who drowned in an average of one inch of water. Similarly, it might not matter to a traveler that the average travel time is 20 minutes if one day a week (but never knowing in advance which day) that traveler can expect a travel time of 60 minutes. Travelers do not want to leave 40 minutes earlier to avoid the occasional bad outcome, and they may be willing to take a slower but more reliable route. Travelers may even have a mixed strategy, or portfolio, combining different routes in order to achieve a personally satisfactory tradeoff between expected time and reliability [13]. In practice, this means that some people might take surface streets (which are generally slower, but more reliable) instead of freeways (which are faster, but subject to more catastrophic breakdowns of traffic flow) [2]. In principle, with multiday GPS data, this question can be assessed more deeply. Unfortunately, the one-week timeframe and small sample size do not permit drawing conclusions about reliability from this dataset.

Pleasure of travel. Maybe people are rational, but perhaps they prefer traveling to being at work or home, and so choose longer routes to prolong the experience. Many people want to commute; Redmond and Mokhtarian [19] find a positive value to some amount of commuting, and that the preferred commute length is not typically zero. However, it appears that many commutes are longer than the desired amount. For some people, the longer route, which provides some psychological buffer between the stresses of work and the stresses of home, is desired.

CONCLUSIONS AND FUTURE RESEARCH
This study analyzed GPS data from the Minneapolis-St. Paul region. In general, it found that travelers do not take the shortest path, and many travelers use different routes between the same home and work location each day. Several reasons for these findings were explored, and multiple factors—such as network structure—affect people’s choice of routes, perhaps through their perception of time, or through the cognitive burden (mental transaction costs) associated with route complexity.

This study also revealed many follow-on topics that could be the subject of a deeper investigation than could be provided with this study and its limited sample. Further investigation into whether sociodemographic and economic factors explain route choice is warranted. Intrahousehold models of travel demand may explain route choices, particularly to the extent that there are embedded pick-up and drop-off passenger trips that do not leave an obvious GPS signal (e.g., the engine is running, and the passenger exits the vehicle quickly). Such an analysis may require further validation against trip-diary data, or new survey techniques using better observational methods, in order to better understand people’s activities. This research focused on work trips because of their regularity; however, most trips are not work trips, and further research...
should examine the factors affecting route choice for nonwork trips. More examination of preferences for route types is warranted, and this is easier to discover in more controlled experiments [3, 26]. In addition, the use of radio, Internet, in-vehicle GPS navigation systems, or other forms of traveler information is likely to continue to shape traveler route choices in coming years. Finally, the advent of automated vehicles may change this problem radically from one of traveler choice to one of understanding the logic of the embedded algorithms of the in-vehicle navigation systems.

In short, given that the shortest-path assumption explains so little of actual route choice, it is the authors’ conclusion that applied route choice models should be reformulated with more realistic behavioral assumptions. The academic literature has discussed this problem for decades, but the magnitude of the problem has not been quantified until recently with the advent of GPS data. New multiday GPS data enable new approaches to this problem.

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