A Freight Tour Synthesis Model—An Efficient Use of Urban Freight Data

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The authors would like to acknowledge the support from the Volvo Research and Educational Foundations (VREF) that funded the Urban Freight Platform (UFP) and the Center of Excellence for Sustainable Urban Freight Systems (CoE-SUFS) through its Future Urban Transport research program.
Introduction

• The boost of technology led to large amounts of data
• Some examples of use of big data for transportation
  – 13 mile fast lane on Highway 1 from Tel Aviv to Ben Gurion Airport (Israel). Tolls increase when congestion is high
  – Crow-sourced traffic information of Google Maps/Waze
  – Variable message signs: monitoring parking spaces and inform users, inform users about travel times
  – Tracking freight flows and analysis using GPS data, ATRI

In transportation, big data is used mainly for traffic management
Freight Demand Modeling

• Traffic data is not being used to answer…
  — when is it cost efficient to build a new road
  — how will an increase in density or a new development increase freight traffic
  — what could be the benefits from consolidation or off-hour deliveries

• Using data for planning requires analytical freight demand models
Freight Demand Modeling

Traditional demand models

Freight Trip Generation → OD Matrix → Travel patterns

Large scale survey

Planning scenario

Future traffic

Travel patterns

Synthesis models

Freight Trip Generation

Current traffic

Traffic assignment models

The boost of ITS and big data dictates more synthesis models
Freight Tour Synthesis Model

• Premises for the time-dependent freight tour synthesis (FTS) model:
  i. Freight is a consequence of demand for goods from retailers, restaurants, cafés, bars, hospitals, schools…
  ii. Urban freight is distributed in tours
  iii. Cost depend on both travel time and service time
  iv. Flow traversing some links can be used as control variables
Freight Tour Synthesis Model

Notation:
- ➡ Loaded vehicle-trip
- ➞ Empty vehicle-trip
- ➞ Commodity flow
- ▲ Consumer (receiver)
Freight Tour Synthesis Model

- Data requirements:
  - Spatial distribution of freight agents and their economic characteristics
  - Freight trip generation data
  - Logistics component: freight vehicles tours data
  - Network topology
  - Traffic data: number of vehicles in a link, weight, time at loading zone,…
Spatial distribution and freight trip generation
Logistics: GPS tracks

Network topology and traffic data


Source: http://www.bgu.ac.il/~bargera/tntp/Austin/Austin%20Flow%20Map%201%2012-15-08.jpg
**Freight Tour Synthesis Model**

**Logistics component**
- Network Topology and Characteristics
  - Tour Sequence Generation
    - Tour Incidence Matrices

**Freight Demand**
- Economic Information
  - Freight Trip Generation

**Traffic component**
- Link Traffic Counts
  - Traffic Assignment

**Inputs**

**Intermediary components**

**Main Component**

**Outputs**

**Entropy-based Optimization Algorithm**

- Tour flows
Case Study: Denver Region

- Transportation Analysis Zones (TAZ): 483
- Average TAZ Demand: 490 trips/day
- Average TAZ visited/tour: 3.6
- Cost on network: 154,960 hours/day
- Avg. speed: 18.23 to 71.36 mph
- Service Time: 10-390 mins and median 21 mins

Trip length distribution

\[ y = 0.1897e^{-0.204x} \]

\[ R^2 = 0.89 \]

- Actual Flows TLD
- Estimated Flows TD-FTS-3-A
- Estimated Flows TD-FTS-3-B

Percent of Total Flow vs. Tour Impedance (minutes)
## Results: Performance Metrics

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<td></td>
<td>AM 1</td>
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<tr>
<td>DCGM</td>
<td>112.6%</td>
<td>DCGM</td>
<td>78.6%</td>
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<td>S-EM</td>
<td>44.3%</td>
<td>TD-EM</td>
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### OD Flows

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### Mean Average Percentage Errors:

- **Gravity Model (DCGM):** 113-119%
- **Static Entropy Maximization (S-EM):** 43.8-44.3%
- **Freight Tour Synthesis (FTS):** 22-43%
FTS Industry sectors flows

**Wholesale**

Estimated Daily Flows DMA: $y = 0.99x$  
$R^2 = 0.75$

**Retail**

Estimated Daily Flows DMA: $y = 0.85x$  
$R^2 = 0.67$

**Manufacturing**

Estimated Daily Flows DMA: $y = 0.96x$  
$R^2 = 0.96$

**Services**

Estimated Daily Flows DMA: $y = 0.93x$  
$R^2 = 0.86$
Conclusions

• Most big data for urban freight are traffic and vehicle data
• To use big data for planning and to enhance decision making, we need more Freight synthesis models
• Freight synthesis models must incorporate features of freight
  — Tour-based distribution
  — Temporal aspect
  — Different industries different patterns
• FTS reduces significantly costs of freight modeling, outperforms other aggregate methods, and are very adaptable

Existing technology is in place to generate enough data, but there is a need for models that synthesize demand based on these big data
Thanks Questions?

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References

Appendix
PROGRAM TD-FTS2

Minimize \( e(x) = \sum_{a=1}^{A} \sum_{k=1}^{K} \left( v_{ak}^{k} - \sum_{d=1}^{K} \sum_{m=1}^{M} \sum_{y=1}^{Y} P_{m}^{d} \delta_{am}^{kd} x_{m,y}^{d} \right)^{2} \)

Minimize \( z(x) = \sum_{d=1}^{K} \sum_{m=1}^{M} \sum_{y=1}^{Y} \left( \left( x_{m,y}^{d} + \frac{1}{2} \right) \left( \ln \left( x_{m,y}^{d} + \frac{1}{2} \right) - 1 \right) \right) \)

Subject to:

\[
\sum_{d=1}^{K} \sum_{m=1}^{M} \gamma_{jm} x_{m}^{d} = D_{j}^{y} \quad \forall j \in N, y \in Y
\]

\[
\sum_{d=1}^{K} \sum_{m=1}^{M} \sum_{y=1}^{Y} c_{m} x_{m,y}^{d} = C
\]

\( x_{m,y}^{d} \geq 0, \quad \forall m \in M, d \in K, y \in Y \)
FTS performance per interval

AM 1: 12:00 am to 3:59 am
- $y = 0.90x$
- $R^2 = 0.92$

AM 2: 4:00 am to 7:59 am
- $y = 0.94x$
- $R^2 = 0.96$

AM 3: 8:00 am to 11:59 am
- $y = 0.81x$
- $R^2 = 0.96$

AM 4: 12:00 pm to 3:59 pm
- $y = 0.95x$
- $R^2 = 0.97$

AM 5: 4:00 pm to 7:59 pm
- $y = 0.90x$
- $R^2 = 0.94$

PM 3: 8:00 pm to 11:59 pm
- $y = 0.94x$
- $R^2 = 0.97$

Estimated TD Tour Flows vs. Actual TD Tour Flows for different time intervals.
Logistics: freight vehicle tours

Source: (Holguín Veras et al., 2012)