Methodology for Tour-Based Truck Demand Modeling

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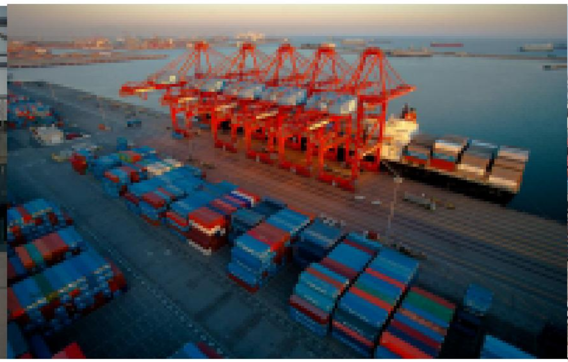
Relevant Project (Oct. 2011 – Jun. 2013) : California Statewide Freight Forecasting Model Development



Introduction: California Statewide Freight Forecasting Modeling

- $ 1.4 Million Caltrans Project
  - A core "state of practice" commodity-based four step model, and various "enhancements"
    - Approximately 2 year timeline (Oct. 2011 – Jun. 2013)
    - Model scope identified during $ 0.1 Million scoping study conducted in 2009-2010.

- Policy-sensitive model to forecast commodity flows and commercial vehicle flows within California addressing:

  - GHG (Greenhouse Gas) reduction strategies such as Carbon pricing
    - Freight transportation CO2 emissions accounted for 7.4% of total US emissions in 2009

  - Socioeconomic conditions
  - Land use policies related to freight
  - Multimodal infrastructure investments

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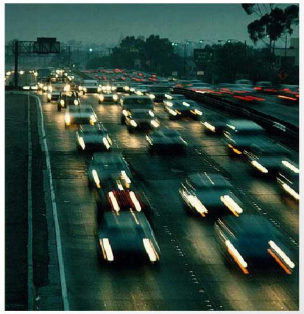
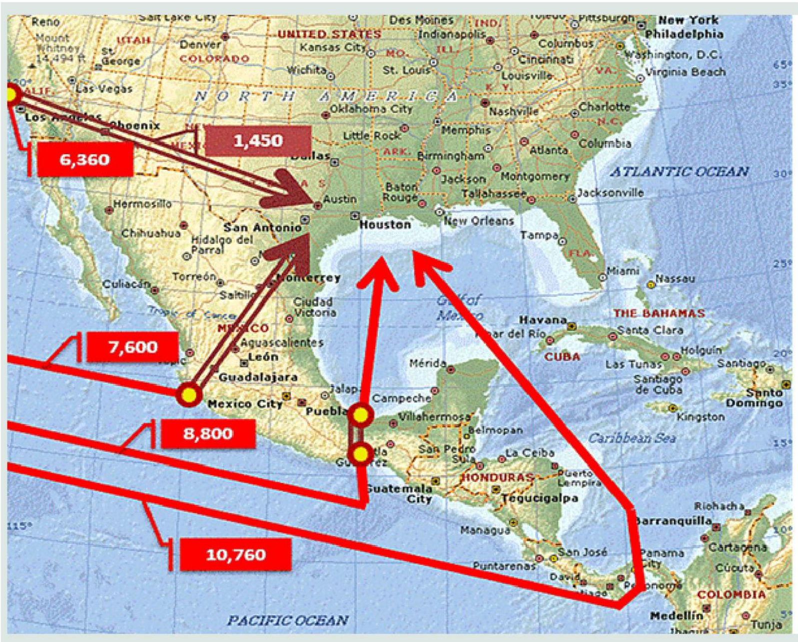


An example Scenario I

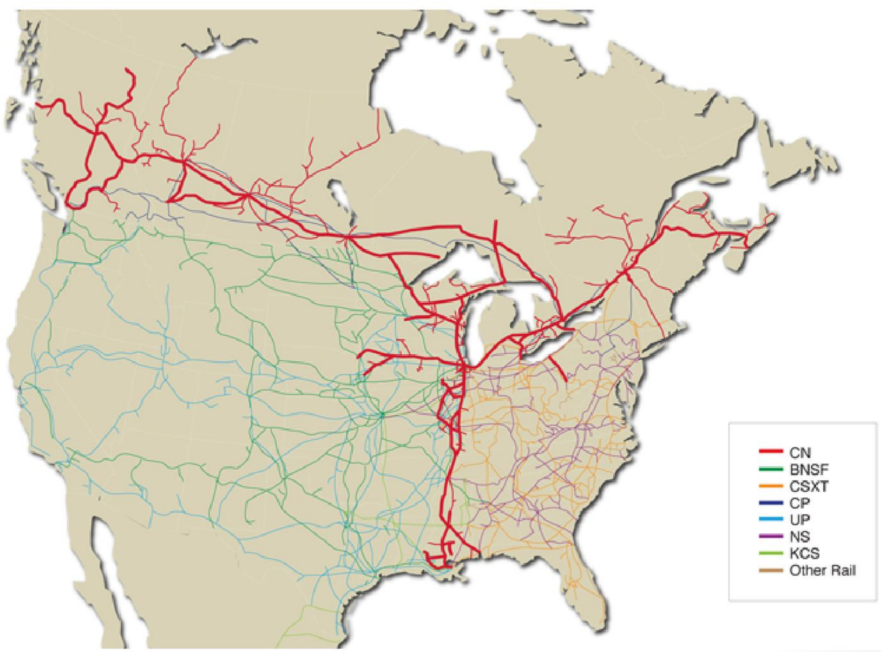
: California Statewide Freight Forecasting Modeling

- Panama Canal is widened in 2014.



Source: http://www.asafashar.com/images.html (Ph.D. Asaf Ashar)

- Canadian National Railway



Source: http://www.cn.ca/ (CN)

An example Scenario II

: California Statewide Freight Forecasting Modeling

- Carbon Pricing

"How would truck/rail mode share change
if a carbon tax of $20/ton was levied
on transportation fuels?"

Source: Kickoff Meeting for California Statewide
Freight Forecast Model Development

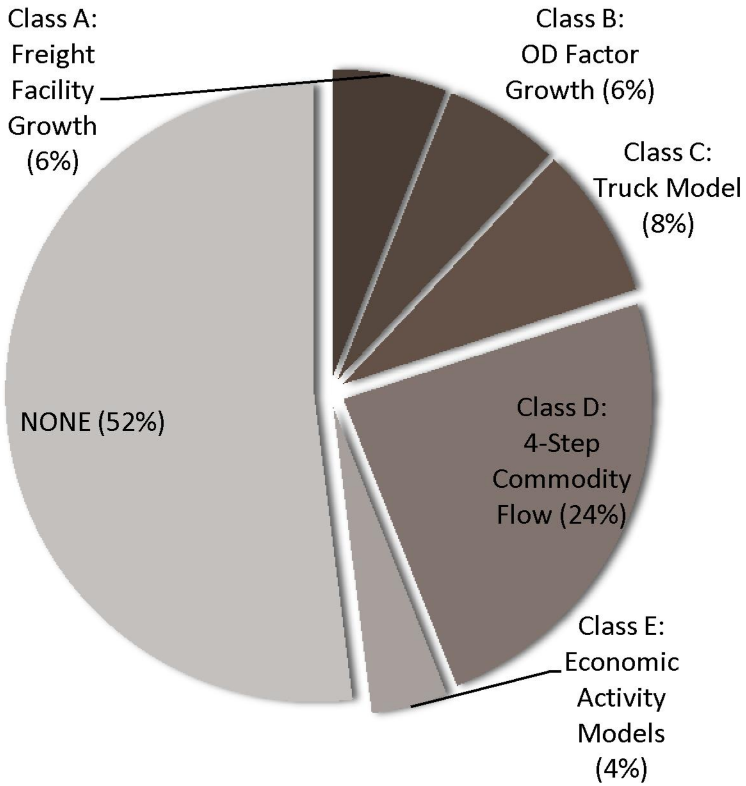
- Capacity Changes/Improvement

Source: http://www.polb.com/ (Port of Long Beach)

Freight Forecasting Modeling

: Existing Models and Recent Research Trends

- Breakdown of Statewide Freight Model

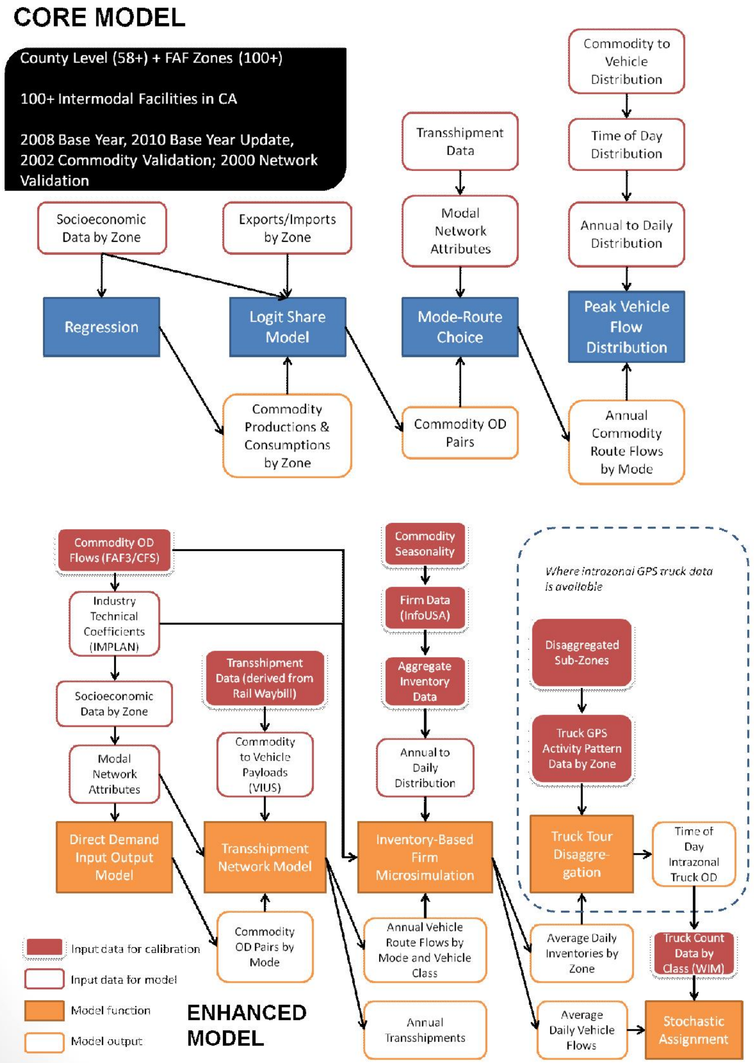


*Class F, G: Logistics (F) and Truck Activity (G) Models (0%)

Chow et al. (2010)

- **Recent Research Trend:**
  - Economic Input-output models (PECAS (Hunt & Abraham, 2003); Ham, Kim & Boyce, 2005; TransNIEMO (Gordo et al., 2010)
  - Disaggregate Shipper/Firm Behavior (de Jong & Ben-Akiva, 2007; Doonnelly, 2009; Samimi et al., 2010)
  - Urban truck tour microsimulation (Hunt & Stefan, 2007)
  - Aggregate truck tour distributions (Wang & Holguín-Veras, 2009; You, 2012)
  - Truck Activity-Based Model (You, 2012)

Proposed Freight Forecasting Model



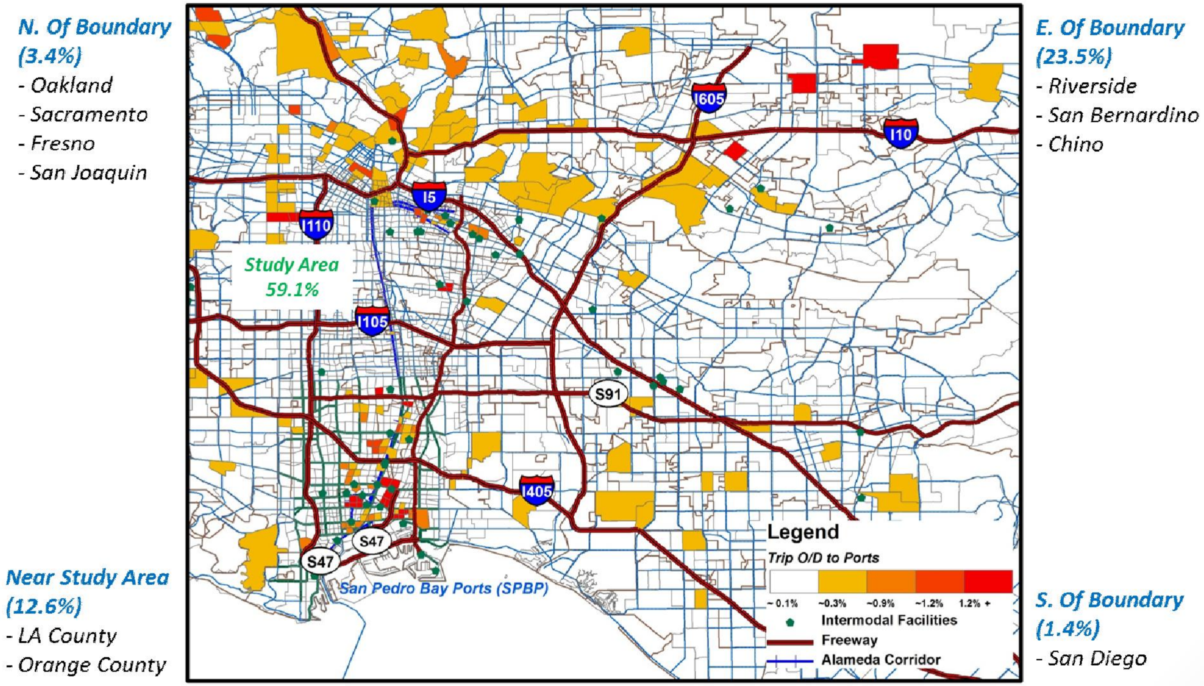
- Summary of Progress
  - % of work complete: 15%
  - Completed Enhancement Modules
    - Transshipment Network Model
      : Chow and Ritchie (TRB, 2012)
    - Truck Tour Disaggregation
      : You (Dissertation, 2012)
- Website
  - http://freight.its.uci.edu/
  - http://freight.its.uci.edu/calfred/

Source: Kickoff Meeting for California Statewide Freight Forecast Model Development (Ph.D. Joseph Chow)

Methodology for Tour-Based Truck Demand Modeling

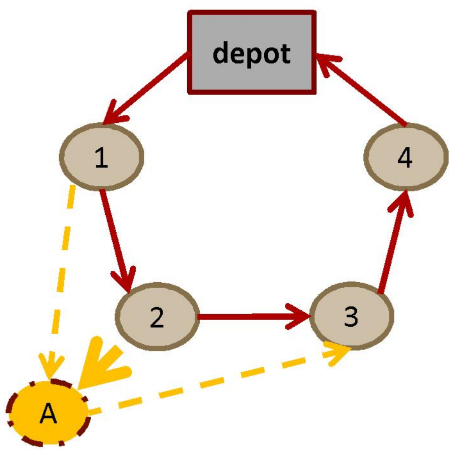
Background: Clean Truck Program (CTP)

- Part of California's Goods Movement Emissions Reduction Program
- Under the CTP, from January 1, 2010, the SPBP banned trucks with 1993 and older engines, in addition to almost all 1994-2003 trucks
- All CTP truck owners must tag their vehicle with a RFID for replacement funds must allow a GPS device to be installed.
- CTP trucks' movements: 1 year (2010) GPS data from 540 Trucks

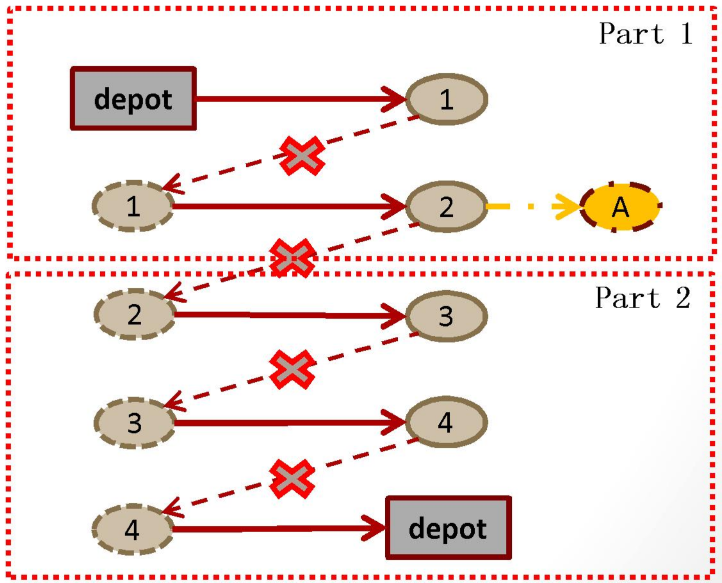


Motivation
: Needs for Innovative Freight Transportation Model

- Freight Transportation Modeling
  - Mostly trip based model (demand) used
  - Does not address extensive trip chaining behavior in freight truck movement; *Hensher and Figliozzi (2007)*
  - Move toward to innovative freight model including tour based model



<Tour based trajectories>



<Trip based trajectories>

Organization of Presentation Outline

Tour Behavior of Clean Trucks

- A Comprehensive Framework for GPS Processing
- Drayage Truck Tour Information
- Drayage Truck Tour Behavior and Characteristics

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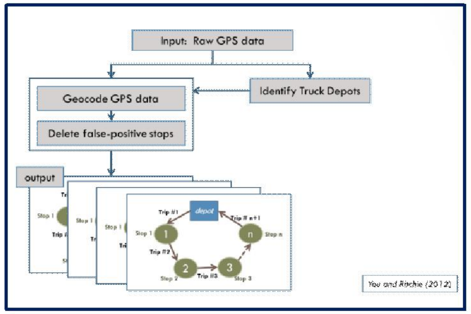
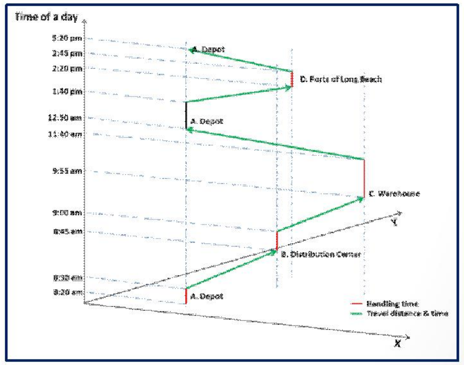
Tour-Based Modeling using Clean Truck GPS data

- Disaggregate Approach
- Inverse Sequential Selective Vehicle routing Problem (InvSSVRP)

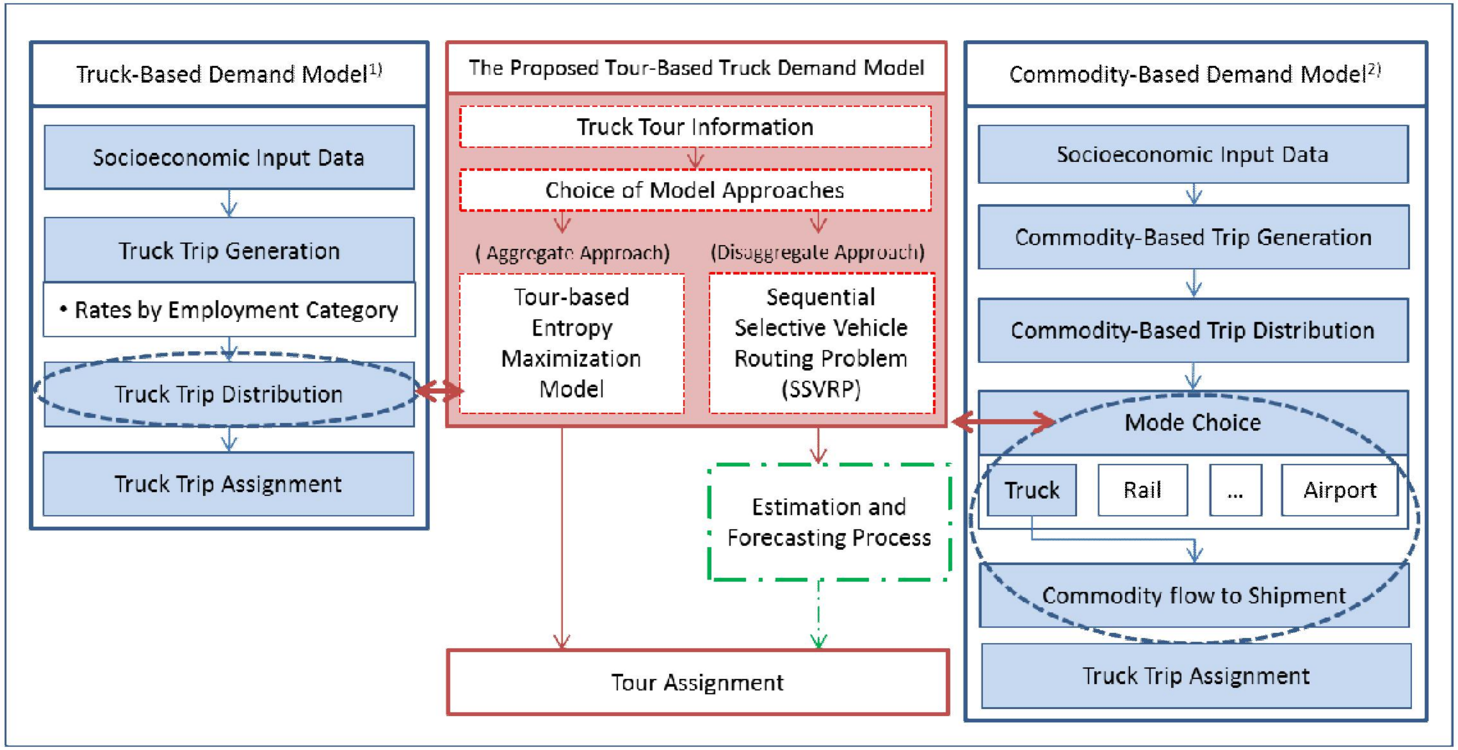
↓

Potential Application





Compatibility of the Proposed Models



1) A Conventional Framework for Truck-Based Demand Model used in SCAG (Southern California Association of Governments

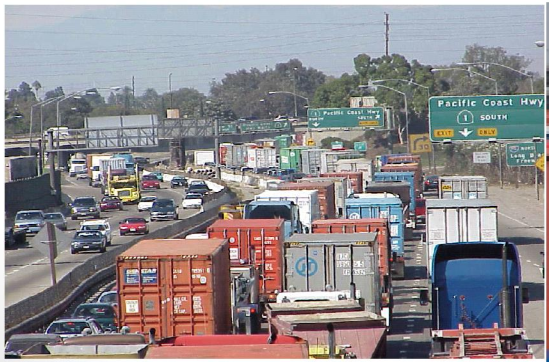
2) A Conventional Framework for Commodity-Based Model used in CalTrans (California Department of Transportation)

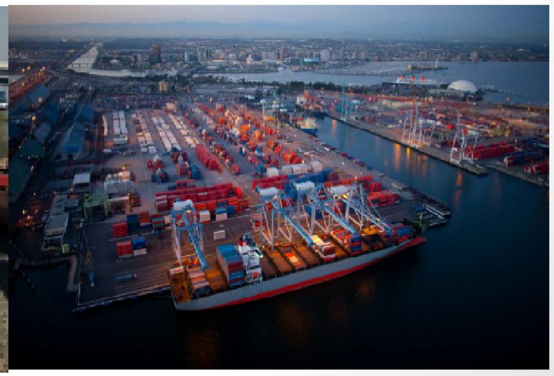
The proposed tour-based truck demand models

Conventional freight forecasting models

Potential Application for future research

Tour Behavior of Clean Trucks

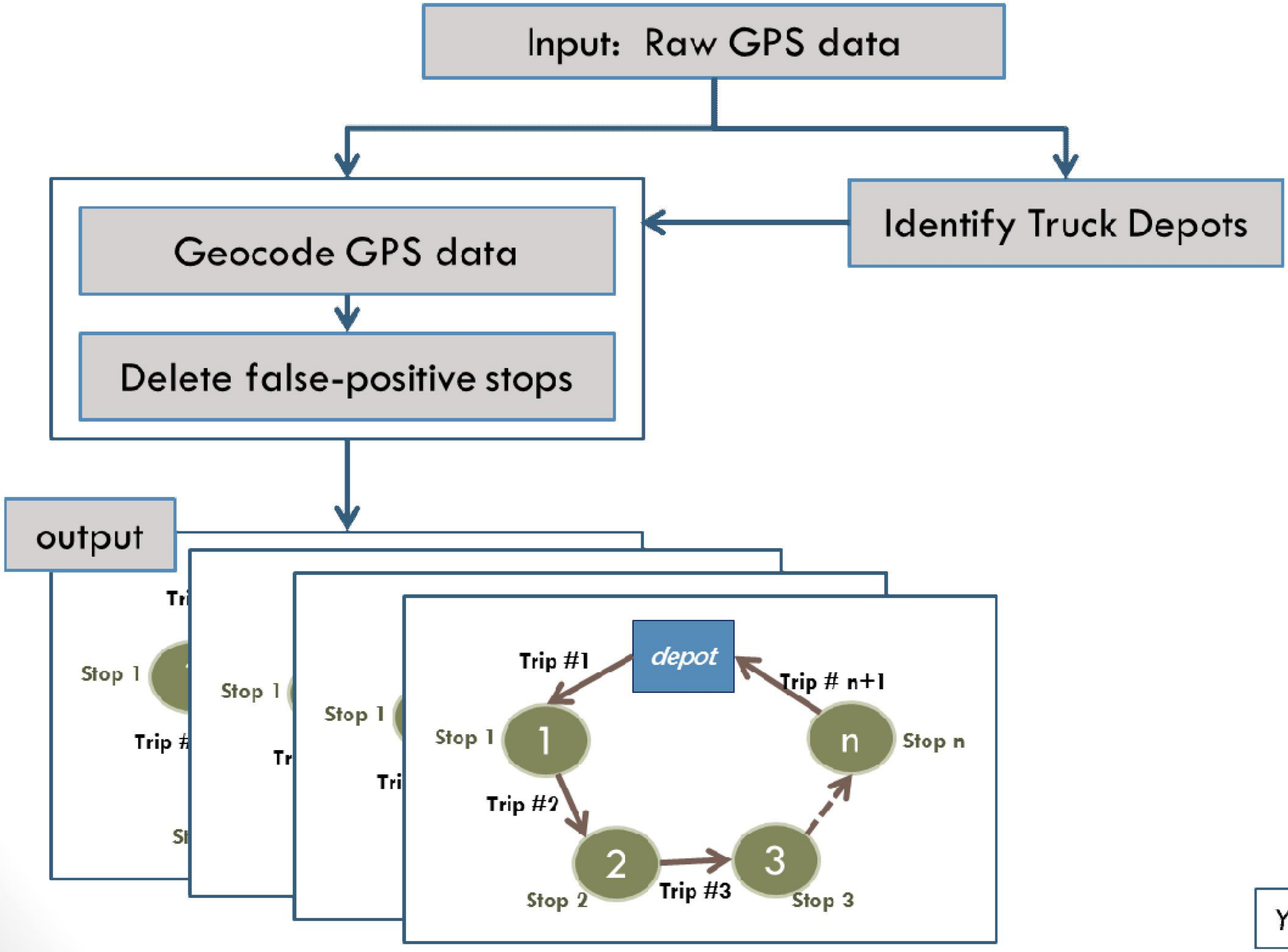




Literature Review

- Efforts to complement conventional surveys with GPS data
  - Survey data: expensive, time consuming and low response rates
  - GPS data
    - Capability of capturing truck trajectories over many years
    - Truck Performance Measurement using GPS data
      - Greaves and Figliozzi, 2008; Du and Aultman-Hall, 2007; Schussler and Axhausen, 2009; Battelle, 1999; McCormack and Hallenbeck, 2006; Ma et al, 2011; Zhao et al, 2011.
    - Truck GPS Data for Freight Forecasting
      - Developing Trip Generation Data (Bassok et al, 2011)
      - Identifying Trip Destination (Sharman and Roorda, 2011)
      - ***However, few studies have been tried to extract tour information from GPS data.***

Tour Information from GPS Data



You and Ritchie (2012)

A Framework of GPS Data Processing

Truck Trip/Tour Identification

Step 1: Select all potential O-D stops *

Step 2: Identify Truck Depots by selecting the greatest major cluster of the last stops of the day *

Step 3: Geocode O-D stops and truck depots
- Match each record with TACs (Traffic Analysis Cells)
- Criteria 1: spatial allowance * → Compatible Clustering Merging Method

Step 4: Identify Closed/Open tours
- Identify tours corresponding to trips and truck depots
- Criteria 2: Maximum Stop Duration * → 80 % percentile of the observed data

Step 5: Delete false-positive stops
- Stops on roads and irrelevant freight facilities
- Criteria 3: Minimum Stop Duration *

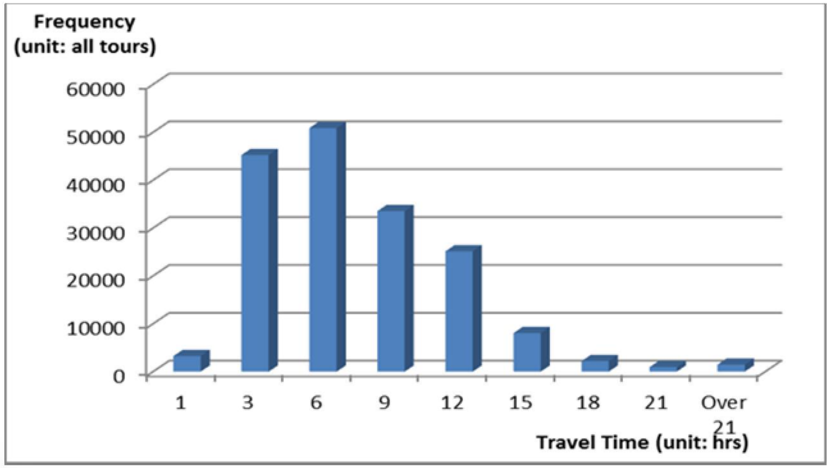
Step 6: Condense pairs of intra zonal trips caused by transaction and queuing

Step 7: Impose new tours with three hour stop duration before the peak hours (3:00 a.m. -6:00 p.m.)

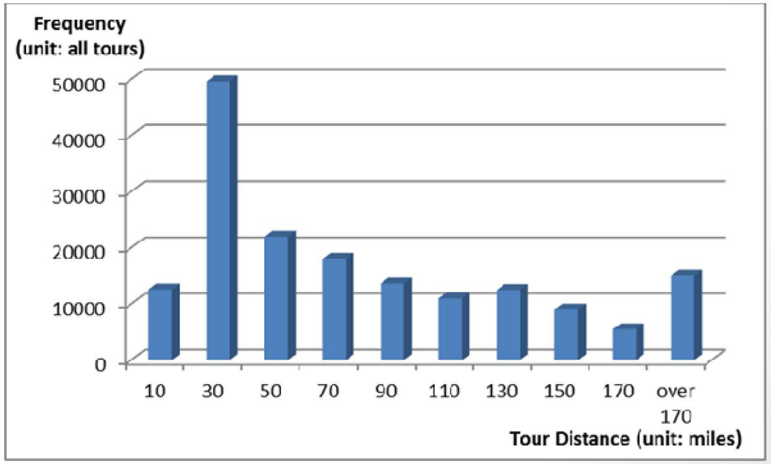
Step 8: Delete Abnormal pairs of Tours/Trips*

Tour Results I

- Observed Trip Chain Behavior
  - The CTP trucks operated an average of 1.7 tours per day which was higher number than those of other commercial vehicles.
  - Approximately 3.1 visited per tour (equivalent to 6.2 trips per day): lower number than other commercial vehicles due to use of drayage trucks which were often involved in lengthy loading/unloading of containers in and out of SPBP and at each stop.



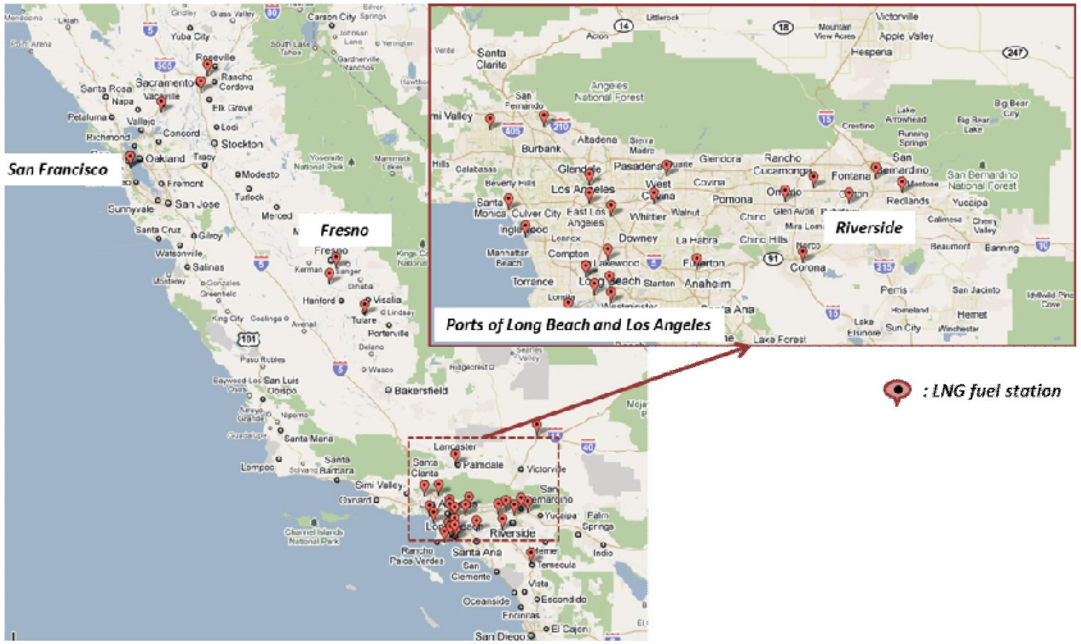
< Distribution of Tour Travel Time>



< Distribution of Tour Distance>

Tour Results II

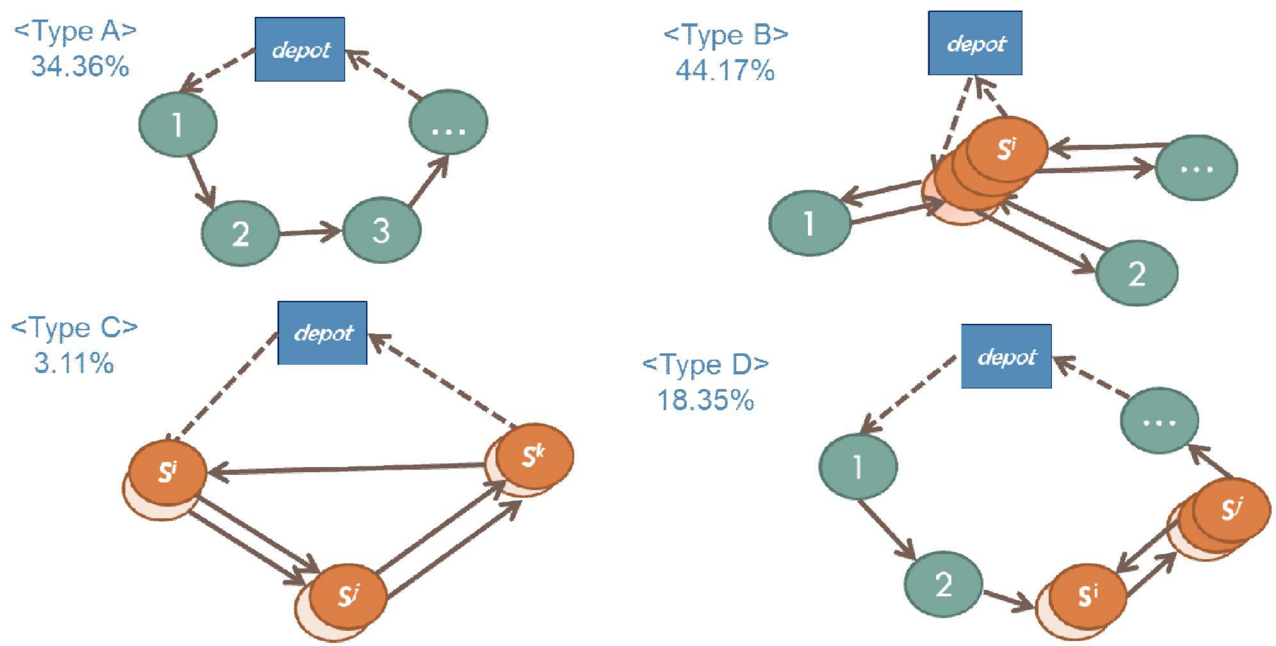
- Observed Tour Characteristics by Fuel Type
  - Tour Travel Time: Diesel truck > LNG truck
  - Tour Distance: Diesel Truck > LNG truck
  - Diesel trucks: more fuel stations available & less frequent fueling required



<LNG Fuel Station>

Tour Results III

- Four types of tours were identified; three tour types (B, C, and D) exhibited repetitive trip patterns.



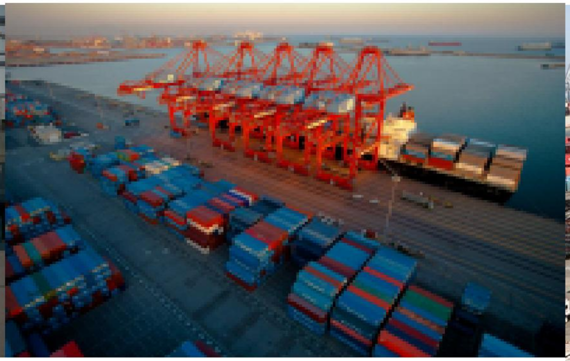
* S^i, S^j, and S^K : a location indicator for the ports of Long Beach and Los Angeles, near-dock, and off-dock intermodal facilities ($i \neq j \neq k$)

Intermediate Conclusion I

- Introduced an effective analytical framework to process GPS data
  - Under the analytical framework, we could interpret complex port related freight movements and
  - provide tour characteristics by several environmental factors.
- The CTP drayage trucks' tour behaviors are distinct in several ways.
  - Relatively small number of visits per tour because of lengthy loading/unloading of containers
  - Four tour types including repetitive patterns

→ *With these insights into clean trucks at the SPBP, it is clear that a tour-based model is needed.*

Truck Tour Modeling using the Sequential Selective Vehicle Routing Problem



Disaggregate Tour-Based Approach

- Most of these approaches at the disaggregate level by solving a vehicle routing problem* or by using the probabilities generated by a set of discrete choice models**
  - * Wisetjindawat et al., 2007; Donnelly, 2007.
  - ** Stefan et al., 2005; Gliebe et al., 2007; Hunt and Stefan, 2007.

- Discrete Choice Model
  - Requires tremendous data to build and calibrate.
  - Dose not make optimal choices with simultaneous utility maximization under the complex choice situations

- Vehicle Routing Problem
  - The capability of the inverse problem to calibrate the objective coefficients and arrival time constraints allows to use VRPs for model forecasting.

Inverse Optimization Problem

- A theory that seeks out a set of model parameters such that observed decision variables are optimal (Tarnatola, 2005)
- Effectively formulated for an linear programming and network flow problem (Burton and Toint, 1992; Ahuja and Orlin, 2001) and mixed integer linear programming problem (Wang, 2009)
- Solved Household activity pattern problem using Inverse Optimization approach (Chow and Recker, 2012)

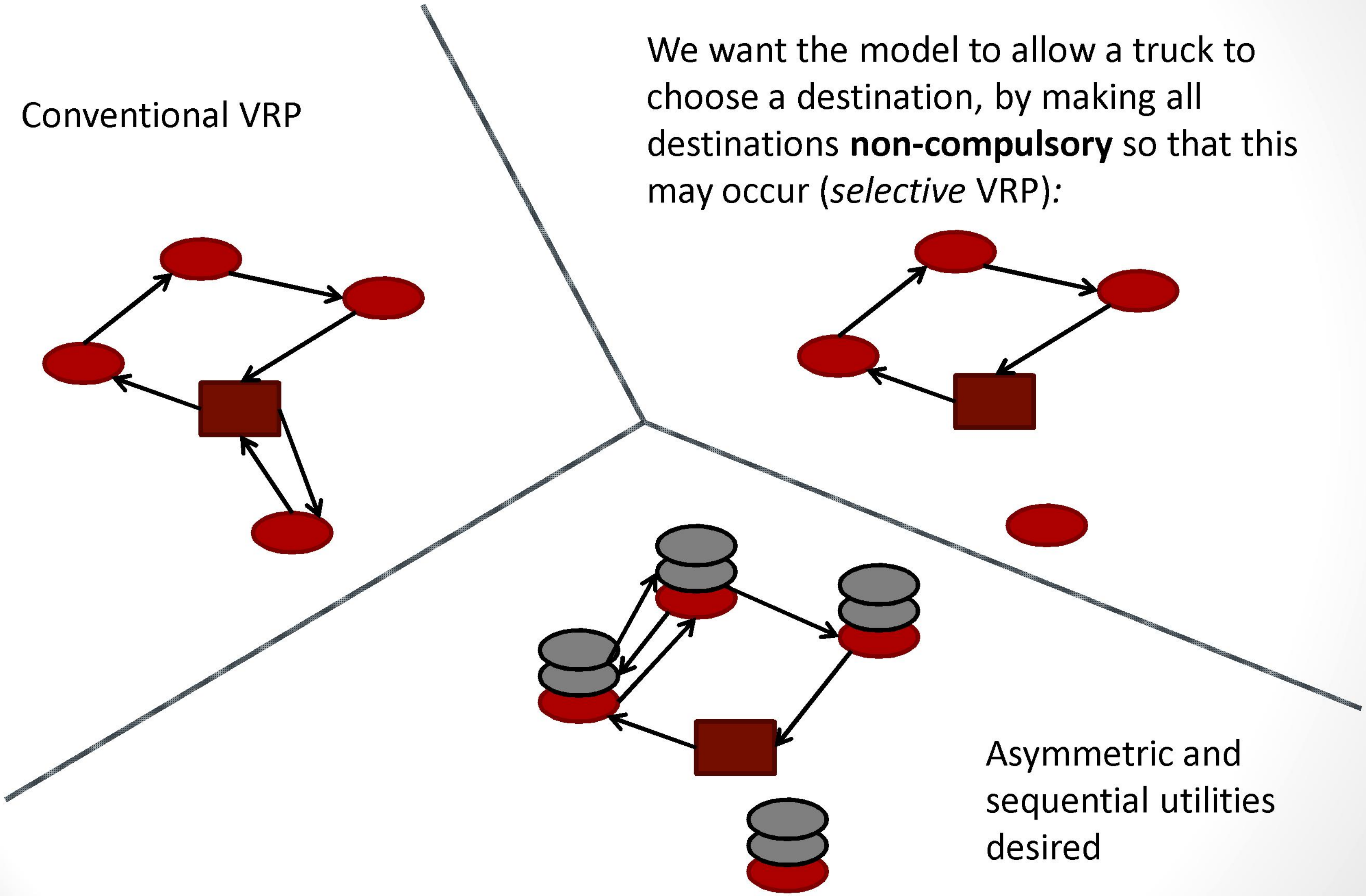
HAPP Estimation and Forecasting Process

- Proposed an estimation and forecasting framework using Household Activity Pattern Problem (HAPP) by *Chow and Recker (2012)*
- Emphasized the necessity of justifying the selection rule with logical and statistical consistence.
- Proposed Method of Successive Average (MSA) for obtaining invariant common prior to infer traveler behavior from ‘n’ observation to population.

Sequential Selective Vehicle Routing Problem I

Conventional VRP

We want the model to allow a truck to choose a destination, by making all destinations **non-compulsory** so that this may occur (*selective* VRP)*:*



Asymmetric and sequential utilities desired

Source: Kickoff Meeting for California Statewide Freight Forecast Model Development

Sequential Selective Vehicle Routing Problem II

- Provides a utility-maximizing decision-making optimization framework under spatial-temporal constraints to explain observed truck patterns as activity participation analogous to household activity patterns.
- A normative model that can be calibrated with GPS data
- By solving *the Inverse selective vehicle routing problem*,
  - Determine set of coefficient for utilities and travel disutilities for a given firm such that the observed pattern using GPS data are optimal.

- Multi-Objective Selective Vehicle Routing Problem

$$\boldsymbol{Minimize\ Z = \sum_{i=0}^{J} \beta_i Z_i(X, \Psi, T)}$$

  - Multiple-objective function can be expanded to J objective functions
  - By setting $\beta_i = 0$, the corresponding function can be disregarded.

Sequential Selective Vehicle Routing Problem III

- Arrival Station 1 : from Depot
- Arrival Station 2: Not from Depot

Sequence expanded for multiple visits

R=0	Sequence				
node	1	2	3	4	5
Depot0	0	0	0	0	0
Depot1	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0
5	0	0	0	0	0
S*	1	1	0	0	0
Depot2	0	0	0	0	0

R=1	Sequence				
node	1	2	3	4	5
Depot0	0	0	0	0	0
Depot1	0	0	0	0	0
1	1	1	0	0	0
2	1	0	0	0	0
3	1	0	0	0	0
4	1	0	0	0	0
5	1	0	0	0	0
S*	0	0	1	1	0
Depot2	1	1	0	0	0

Selected nodes for maximizing utilities

Formulation I: Selective Sequential Vehicle Routing Problem

- Multi-Objective Function
  - Z_0: maximizing the number of visits at the location (w) within the sequence (s)

$$\mathbf{Z_0} = -\sum_{u \in P}\sum_{s \in S}\sum_{r \in \{1,2\}} \boldsymbol{\Psi}_{\mathbf{usr}}$$

  - Z_1: minimizing the total travel time

$$\mathbf{Z_1} = \sum_{u \in P}\sum_{w \in P}\sum_{v \in V}\sum_{q \in S}\sum_{s \in S} \mathbf{t_{uw} X^{v}_{u_q w_s}} + \sum_{w \in P}\sum_{v \in V}\sum_{s \in S} \mathbf{t_{0w} X^{v}_{0_1 w_s}} + \sum_{u \in P}\sum_{v \in V}\sum_{s \in S} \mathbf{t_{u,n+2} X^{v}_{u_s, n+2_1}}$$

  - Z_2: minimizing the total emissions (PM: Particulate Matter)

$$Z_2 = \sum_{u \in P}\sum_{w \in P}\sum_{v \in V}\sum_{q \in S}\sum_{s \in S} e_{uw} c_{uw} X^{v}_{u_q w_s} + \sum_{w \in P}\sum_{v \in V}\sum_{s \in S} e_{0w} c_{0w} X^{v}_{0_1 w_s}$$
$$+ \sum_{u \in P}\sum_{v \in V}\sum_{s \in S} e_{u,n+2} c_{u,n+2} X^{v}_{u_s, n+2_1}$$

Formulation II: Selective Sequential Vehicle Routing Problem

- Z_3: minimizing the total truck operation hours

$$\mathbf{Z_3} = \sum_{\mathbf{v} \in \mathbf{V}} (\mathbf{T}^{\mathbf{v}}_{\mathbf{n+2}} - \mathbf{T}^{\mathbf{v}}_{\mathbf{0}})$$

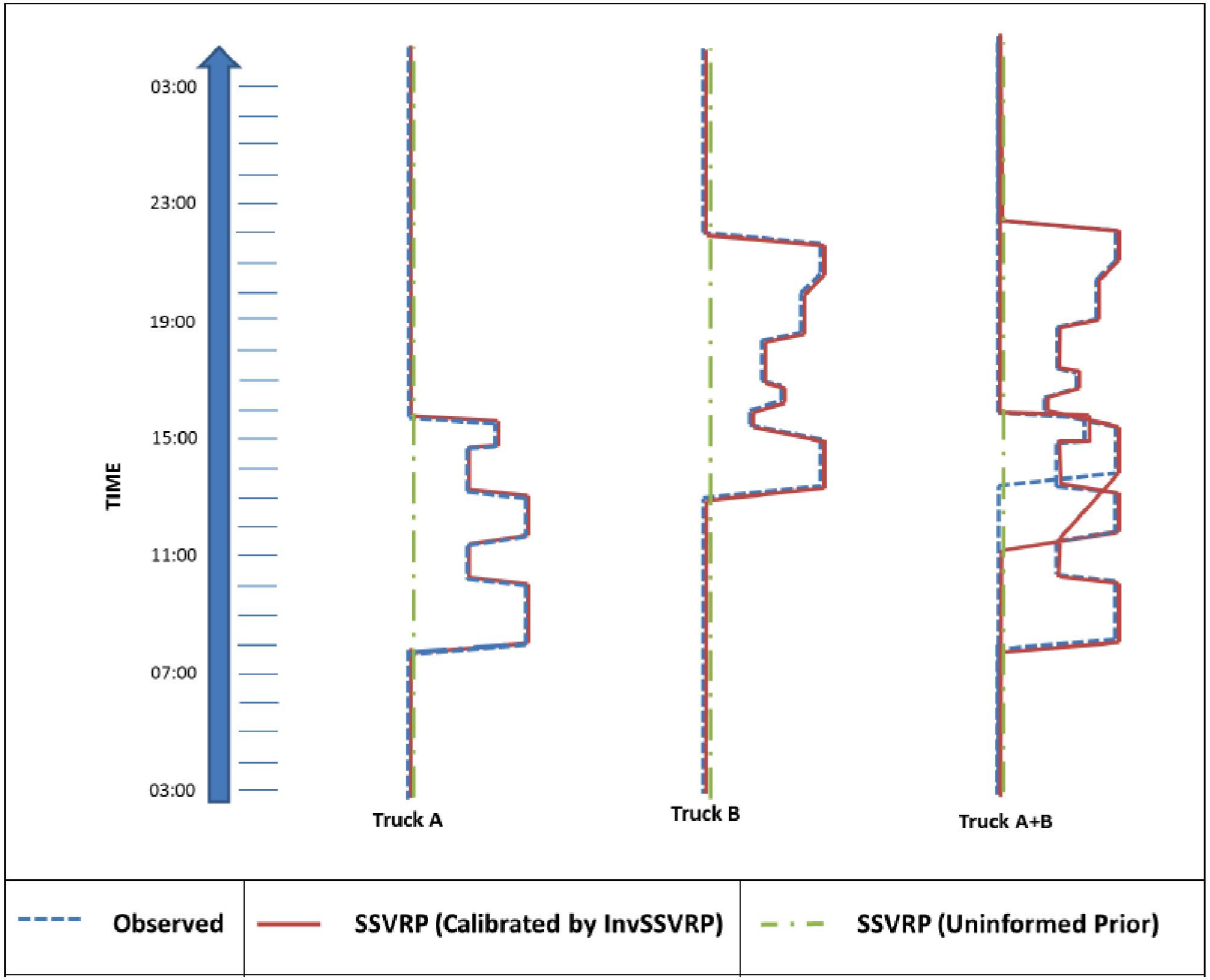
- Z_4 and Z_5 : minimizing early arrival times and late arrival times

$$\boldsymbol{Z_4} = \sum_{s \in S} \boldsymbol{d^{-}_{us} Z_{4,us}}$$

$$\boldsymbol{Z_5} = \sum_{s \in S} \boldsymbol{d^{+}_{us} Z_{5,us}}$$

- Constraint Groups
  - Constraints 1: Truck visiting utilities
  - Constraints 2: Node-Sequence
  - Constraints 3: Flow Conservation
  - Constraints 4: Arrival Time
  - Constraints 5: Non-negativity and binary variables

Numerical Test: SSVRP with Calibrated by InvSSVRP



Applying MSA for a Common Prior Calculation

< InvSSVRP Results using MSA-based Common Prior versus Uninformed Prior >

	Utility to visit*	Travel Time	Emissions	Operation Hours	Early Arrival	Late Arrival
Common Prior from MSA (P*)	-0.9802	0.0010	0	0.0096	2.40	6.19
Mean InvSSVRP (P*)	-0.9998	0.0251	0	0.0418	2.40	6.19
Standard Deviation (P*)	0.0020	0.0658	0	0.0681	N/A	N/A
Uniformed Common Prior (P0)	-1	1	1	1	2.40	6.19
Mean InvSSVRP (P0)	-0.9998	0.0348	0.0099	0.0513	2.40	6.19
Standard Deviation (P0)	0.0020	0.1170	0.0995	0.1170	N/A	N/A

*: Common prior for the utility to visit have one for each of the node-sequences and the results are all same after rounding in our case study.

< Goodness of Fit Measures with Common Prior from MSA >

	SSVRP (Uninformed Prior) [a)]	SSVRP (Calibrated by InvSSVRP) [b)]	ρ^2**
SSE* of Visiting Node-Sequence (X)	1936	26	0.9866
SSE of Arrival Times (T)	4.6509e+07	1.3211e+07	0.7159

*: Squared Standard Error
**: 1 - (b/a)

Contribution and Future Research



Contributions

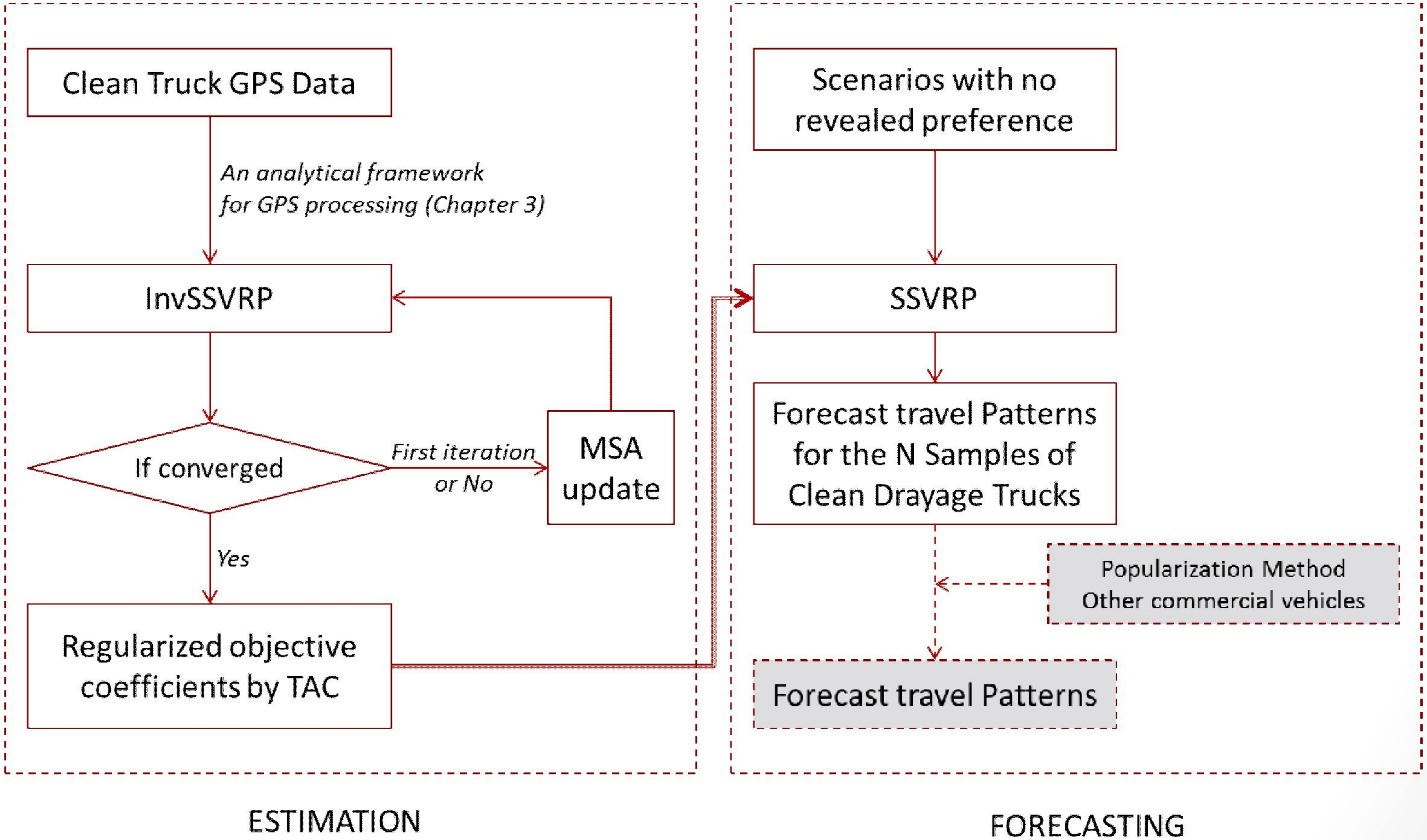
- Proposed *a comprehensive analytical framework for processing the GPS data* to both interpret the trip chaining of the clean drayage trucks and to prepared sufficient tour data for clean truck modeling at the SPBP.
  - Identified all drayage trucks into *the four tour types* and three of them contain repetitive trip patterns in a tour.
  - Presented *tour characteristics by several environmental factors.*
- For the disaggregate level, the InvSSVRP provides a potential for forecasting model under the optimization framework by finding proper objective coefficients and standardizing them.
  - Activity-based modeling considering freight transportation using GPS data

Future Research I

- Our GPS data are collected from the clean drayage trucks only.
  - *GPS data from other commercial vehicles (e.g. ATRI GPS data)* collected by many different vendors would make this dissertation expand to not only the clean drayage trucks but also overall freight movements.
  - It would help to identify how clean drayage truck behavior differs from *other commercial vehicles* represented by diesel truck heavily emitted air pollutions.
- Incorporating *heuristic algorithms* with our InvSSVRP and SSVRP would possibly suggest implementing them at regional level or state level.

Future Research II

- Potential Application for Forecasting Model



< SSVRP Estimation and Forecasting Processing>

Thank you…



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