VEHICLE ROUTING PROBLEMS IN CONGESTED URBAN AREAS

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Outline

- The Vehicle Routing Problem (VRP)
- VRP in Urban Areas
- Data Issues
- Stochastic and Time dependent
- Emissions
- Current and Future Research

Classical VRP

VRP

- A fleet of vehicles
- Each vehicle has a finite, known, capacity
- A set of customers
- Each customer has a finite, known, demand
- Minimize routing costs while satisfying constraints (capacity, demands)

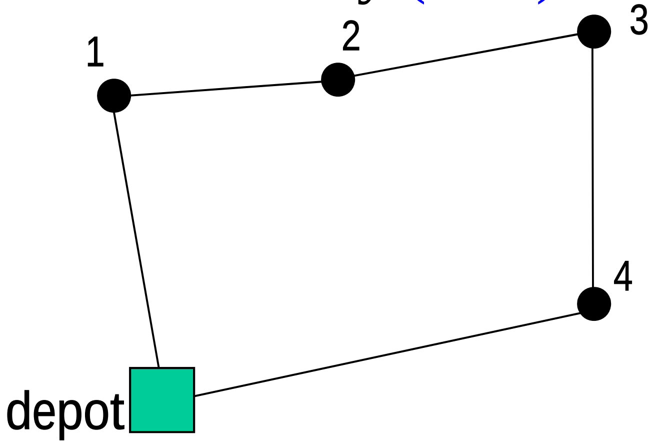
Distribution Costs

- **VARIABLE**
  – Distance Related
    - Fuel, maintenance, etc.
  – Time Related
    - Driver salary, overtime, late delivery penalties.

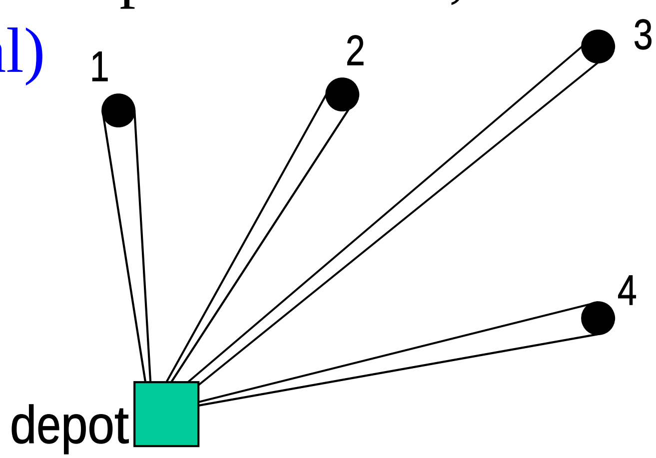
- **FIX**
  – Fleet Size
    - Capital cost, insurance, licenses, etc.

Extreme Cases

One truck only (TSP)

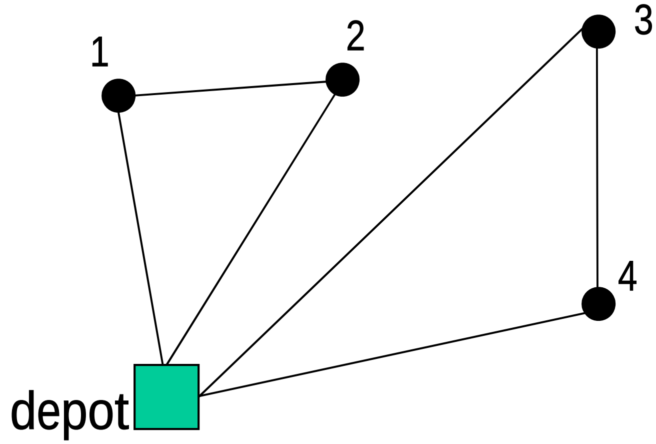


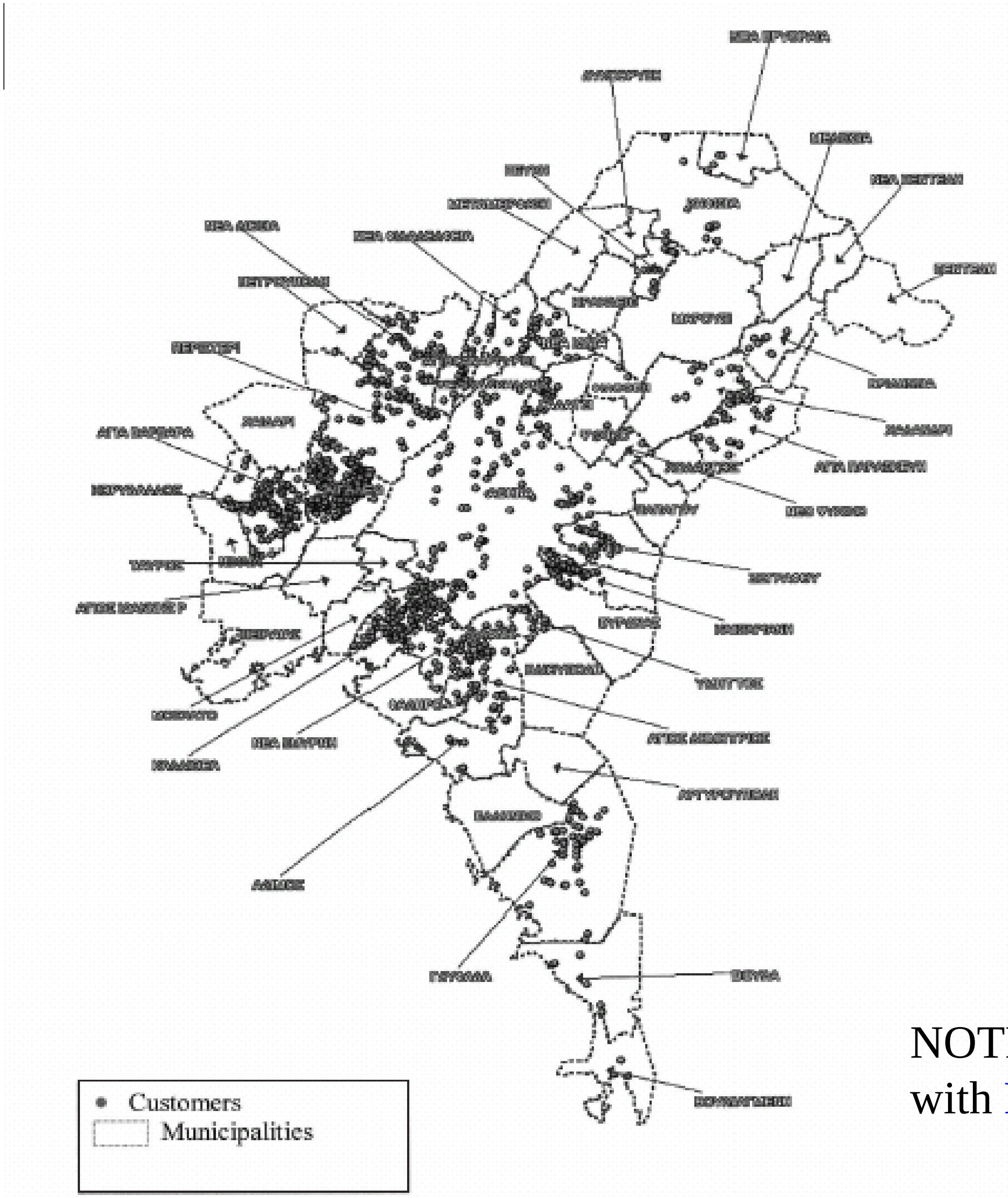
One truck per customer, 4 trucks (trivial)



Usual Case

More than one but less than 4





A real world example

Map of a delivery company customers.

The distributor supplies goods to a large number of supermarkets throughout Athens.

The number of customers is 1943.

(Ioannou et al., 2001)

NOTE CLUSTERS AND AREAS with RANDOM CUSTOMERS

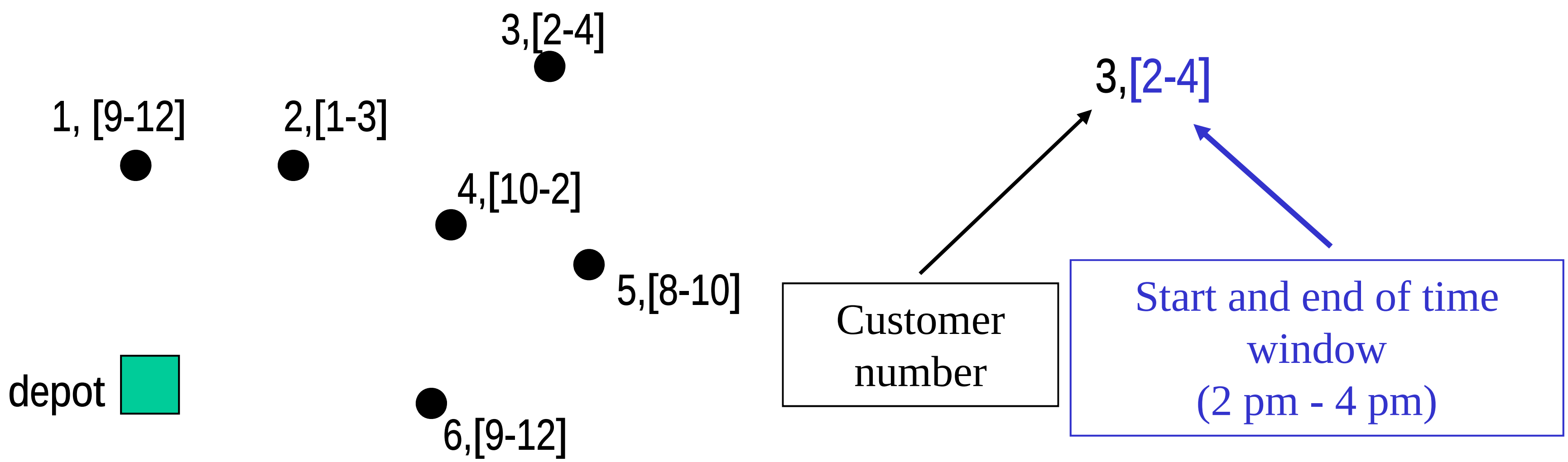
Routing is not a trivial problem…

- In general, “n” customers and “m” trucks needed
- Assume, n=50, where time and capacity constraints are sufficient to restrain possible routes up to 10 customers
- Then, the number of possible routes with m=50 and no more than 10 customers per routes is:

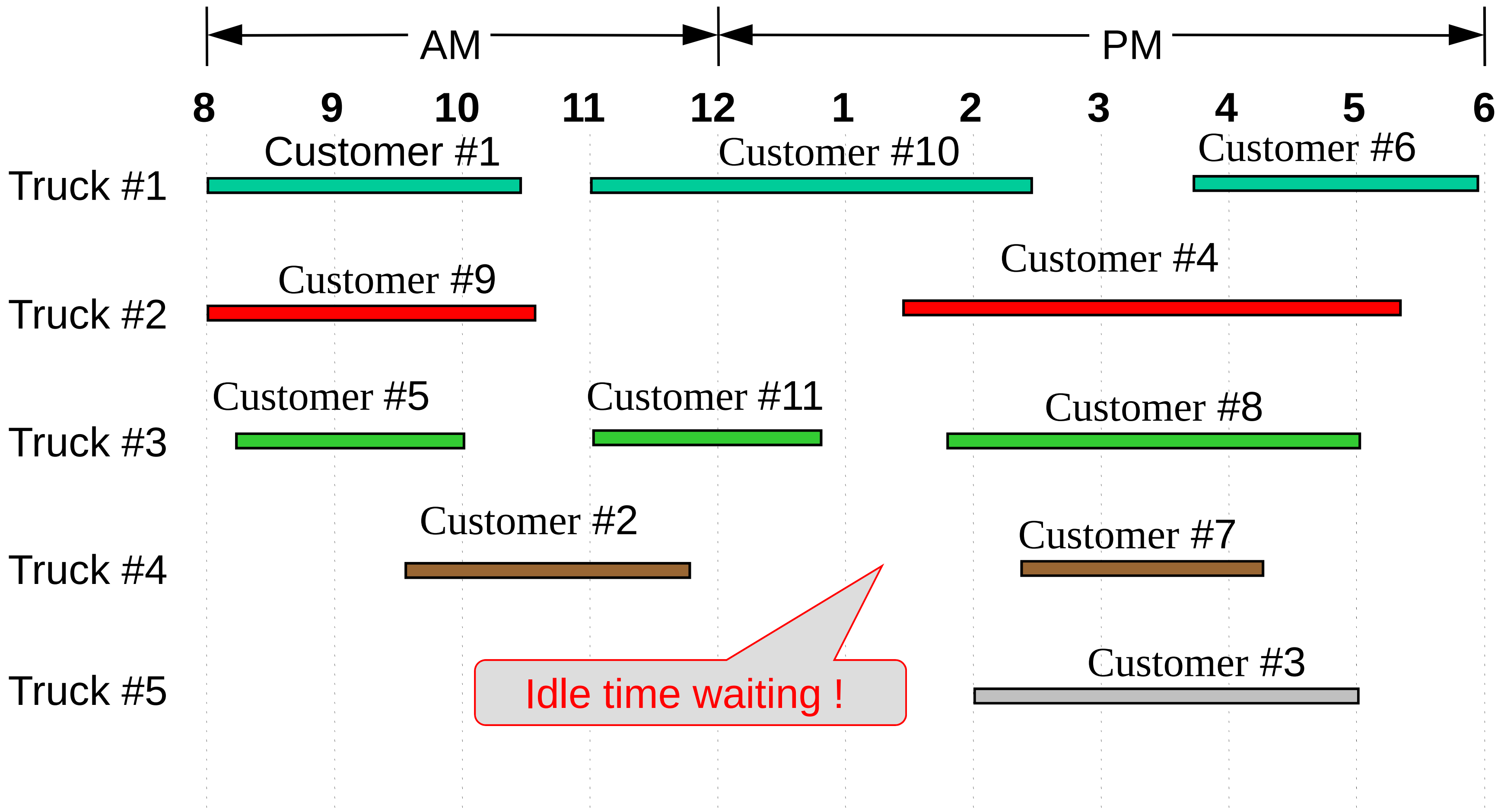
$$\sum_{n=1}^{10}\left[\frac{50!}{(50-n)!}\right] \approx 3.8\text{x}10^{16}$$

Time Windows

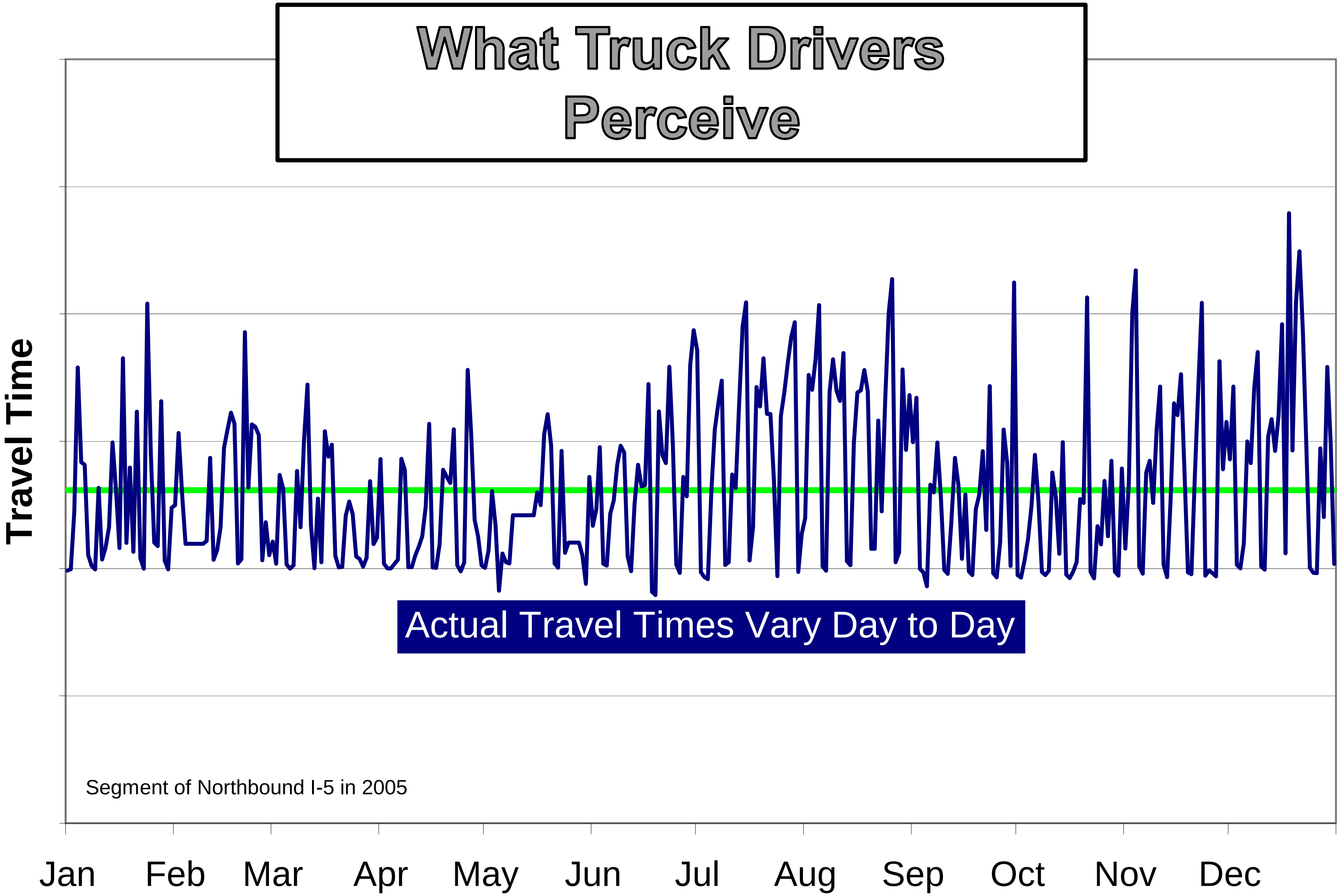
- Problems with time windows involve routing <u>and scheduling</u>



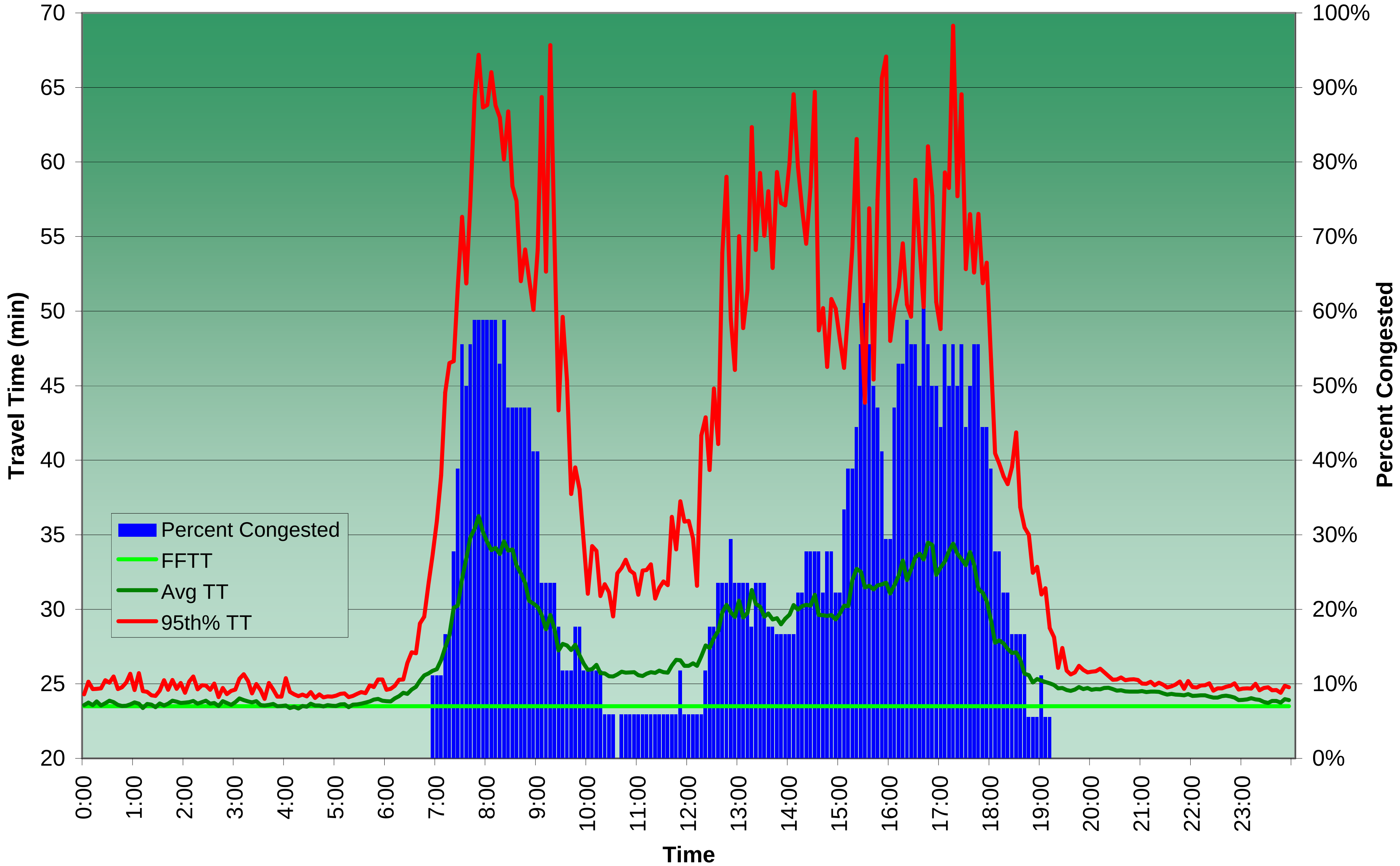
Scheduling


AM
PM
8
9
10
11
12
1
2
3
4
5
6
Truck #1
Customer #1
Customer #10
Customer #6
Truck #2
Customer #9
Customer #4
Truck #3
Customer #5
Customer #11
Customer #8
Truck #4
Customer #2
Customer #7
Truck #5
Idle time waiting !
Customer #3

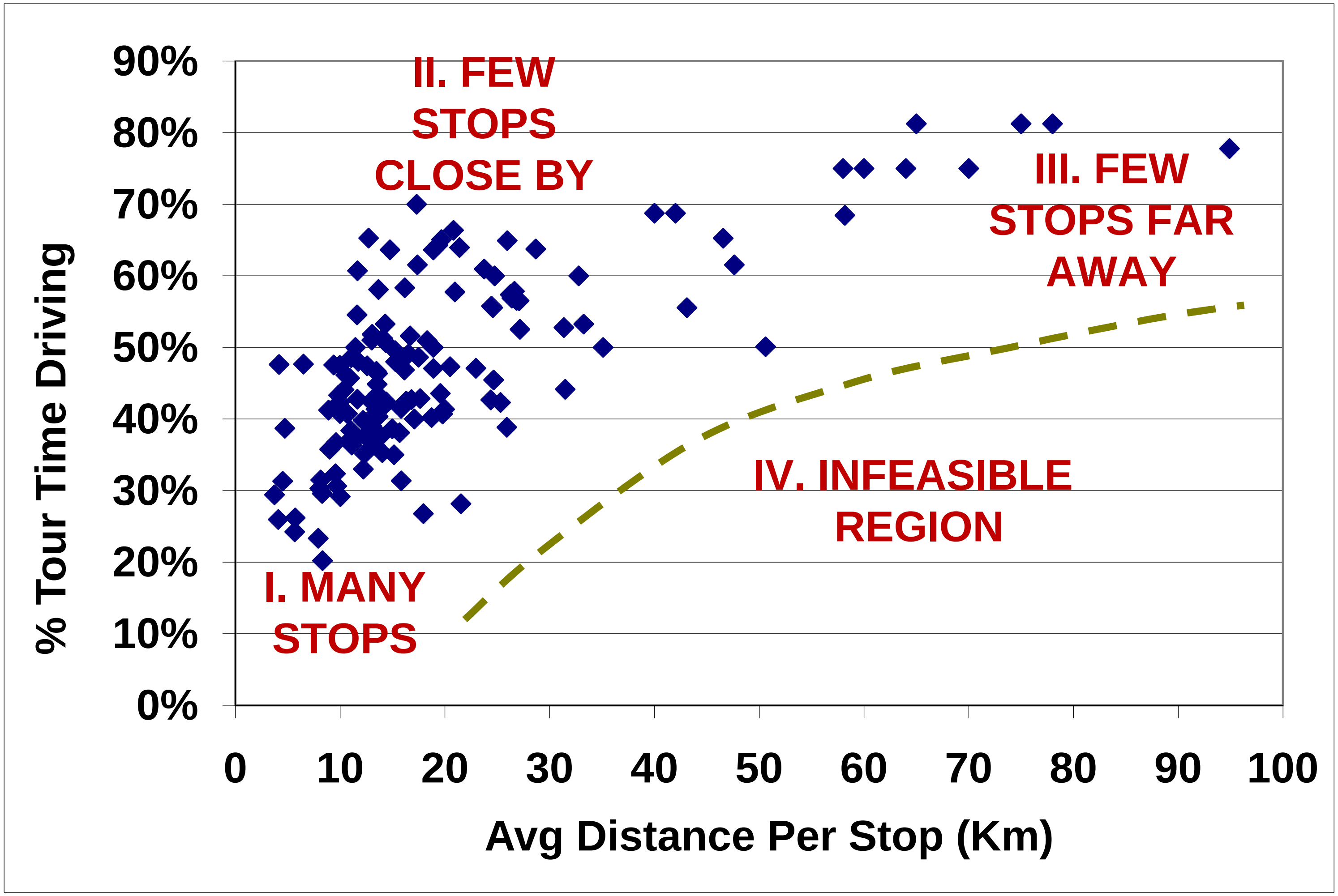
VRP in Urban Areas


What Truck Drivers Perceive
Travel Time
Actual Travel Times Vary Day to Day
Segment of Northbound I-5 in 2005
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec

Estimated Monthly Travel Time I-5 N September 2006



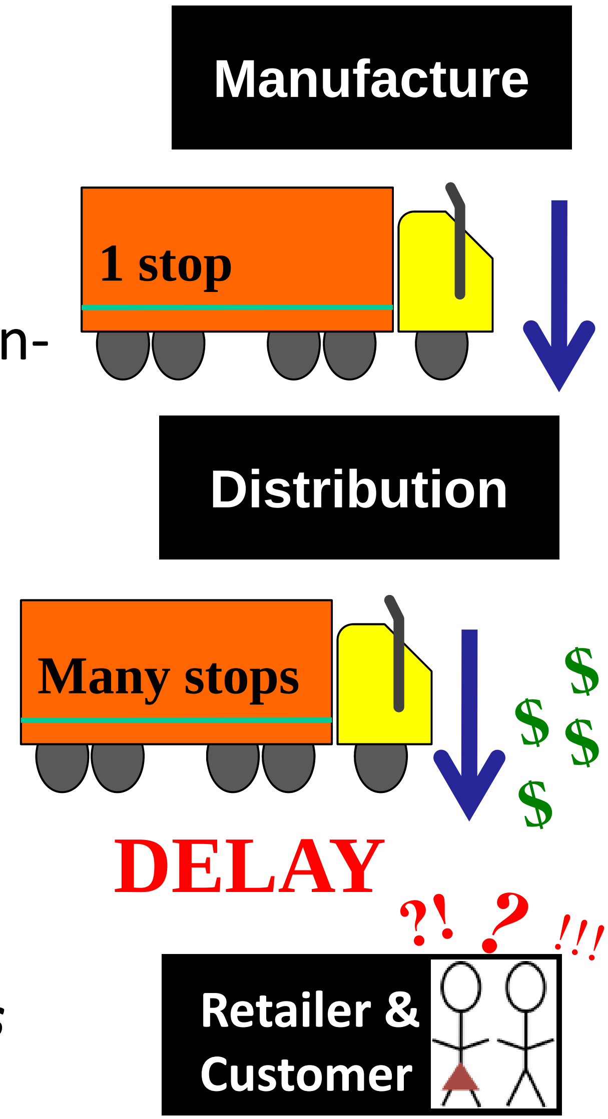
Tour Classification & Sensitivity to Congestion



Two factors that can be used to monitor/track congestion

Wider implications: supply chains

- **Increased Delays and Congestion in Urban Areas**
- **Delay and Congestion Impacts…**
  - Businesses rely on timely deliveries (just-in-time)
  - Customer satisfaction is important
  - Deliver by a deadline (8am, 11am, 1pm, etc.)
  - Penalties for late deliveries



OBJECTIVE: Develop a solution method for stochastic time-dependent VRP in urban areas

Tour Classification & Sensitivity to Congestion

		Distance to Depot		
		Short	Medium	Long
Service Time or Constrains	Low	**Low**	**High**	**Approaching Infeasibility**
	High	**Medium**	**Approaching Infeasibility**	***Use 3PL New Depot***

From analytical insights and numerical studies: congestion quickly reduces the threshold values of "Long"

Data Issues

How do we calculate travel time distributions?

- Freeways: loop detectors…
- Arterials: GPS, bluetooh, etc..
- BUT, we need point to point travel times… for any two points in an urban area
  - Along paths with many links
  - Each link is a piece of freeway, arterial, local street, etc..

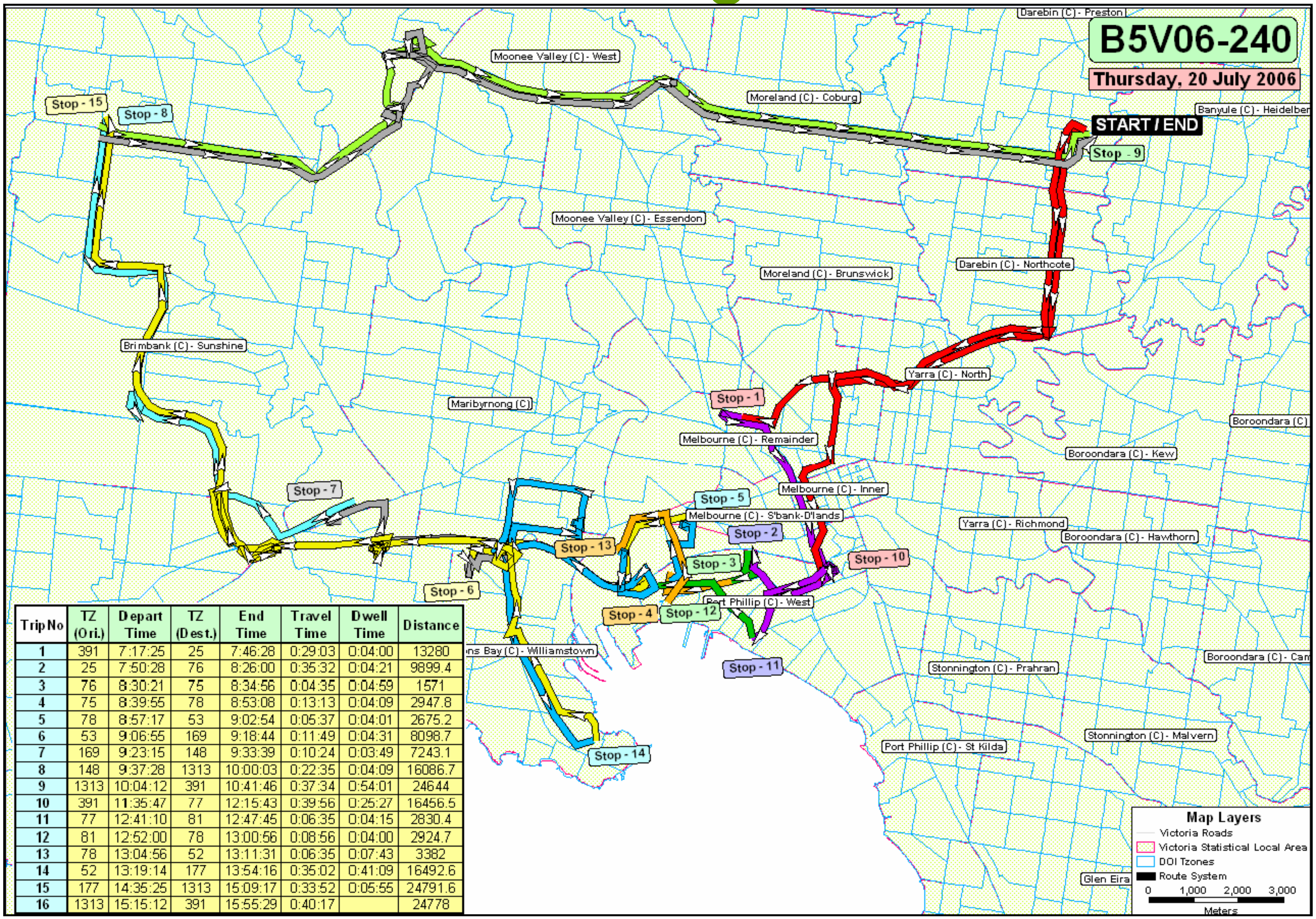
The Greater Melbourne Region

Data Quality Assessment (Before Processing)

30 trucks, one week of GPS data in Melbourne, Australia. Automated routines to process 'raw' GPS data into trips (detailed in the paper).

	Good Records	Bad/Missing Records*	Total Records
Morning ( )	1,843,050	96,726	1,939,776
	95%	5%	
Afternoon ( )	1,643,729	100,800	1,744,529
	94%	6%	
Night ( )	1,498,446	54,553	1,552,999
	96%	4%	
Total	4,985,225	252,079	5,237,304
	95%	5%	

Results of the Processing Routines



Trip No	TZ (Ori.)	Depart Time	TZ (Dest.)	End Time	Travel Time	Dwell Time	Distance
1	391	7:17:25	25	7:46:28	0:29:03	0:04:00	13280
2	25	7:50:28	76	8:26:00	0:35:32	0:04:21	9899.4
3	76	8:30:21	75	8:34:56	0:04:35	0:04:59	1571
4	75	8:39:55	78	8:53:08	0:13:13	0:04:09	2947.8
5	78	8:57:17	53	9:02:54	0:05:37	0:04:01	2675.2
6	53	9:06:55	169	9:18:44	0:11:49	0:04:31	8098.7
7	169	9:23:15	148	9:33:39	0:10:24	0:03:49	7243.1
8	148	9:37:28	1313	10:00:03	0:22:35	0:04:09	16086.7
9	1313	10:04:12	391	10:41:46	0:37:34	0:54:01	24644
10	391	11:35:47	77	12:15:43	0:39:56	0:25:27	16456.5
11	77	12:41:10	81	12:47:45	0:06:35	0:04:15	2830.4
12	81	12:52:00	78	13:00:56	0:08:56	0:04:00	2924.7
13	78	13:04:56	52	13:11:31	0:06:35	0:07:43	3382
14	52	13:19:14	177	13:54:16	0:35:02	0:41:09	16492.6
15	177	14:35:25	1313	15:09:17	0:33:52	0:05:55	24791.6
16	1313	15:15:12	391	15:55:29	0:40:17		24778

Sample Size Issues (1)

- Sample size undoubtedly affects the level of detail or granularity achievable in the congestion analysis.

- Despite the use of several months of complete routing data, congestion analysis proved to be a difficult task

- Seven factors that complicate the travel reliability analysis for the company are mentioned…

Sample Size Issues (2)

1. The sheer number of possible origin destination (OD) pairs. For 190 customers, the possible number of network paths is 17,955.
2. Time of day breakdown, distinguishing between peak and non-peak periods.
3. Departure time vs. arrival time: long trips may fall in both rush and non-peak periods.
4. Directional effects (e.g. to CBD or away from CBD)
5. No information available about potential travel times in alternative routes.
6. At the tour level, variation of customer demands precludes the direct comparison of tours travel times.
7. Some correlations in travel times can also be found…

How to deal with travel data collection:
interfacing with the Google Maps API

1 Select Customers

Click on the screen to select customers. The first selection is the depot.

Start with clicking on map

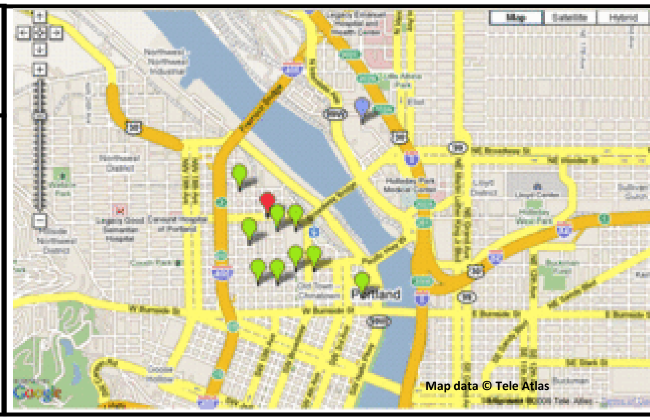
Filename: Browse.. Submit
Output to text Output to js

ID	Y-coor	X-coor
1	45.502	-122.610
2	45.495	-122.608
3	45.497	-122.622
4	45.507	-122.618
5	45.500	-122.617
6	45.501	-122.607
7	45.501	-122.618
8	45.496	-122.618
9	45.499	-122.611
10	45.506	-122.614
11	45.503	-122.615
12	45.526	-122.679
13	45.522	-122.676
14	45.517	-122.683
15	45.525	-122.686
16	45.527	-122.684
17	45.525	-122.682
18	45.521	-122.689
19	45.518	-122.678
20	45.521	-122.682
21	45.520	-122.688

Output Customer coordinates

2 O-D Matrices

Calculate travel time and distance origin-destination matrices.



Customer ID: 5 Submit

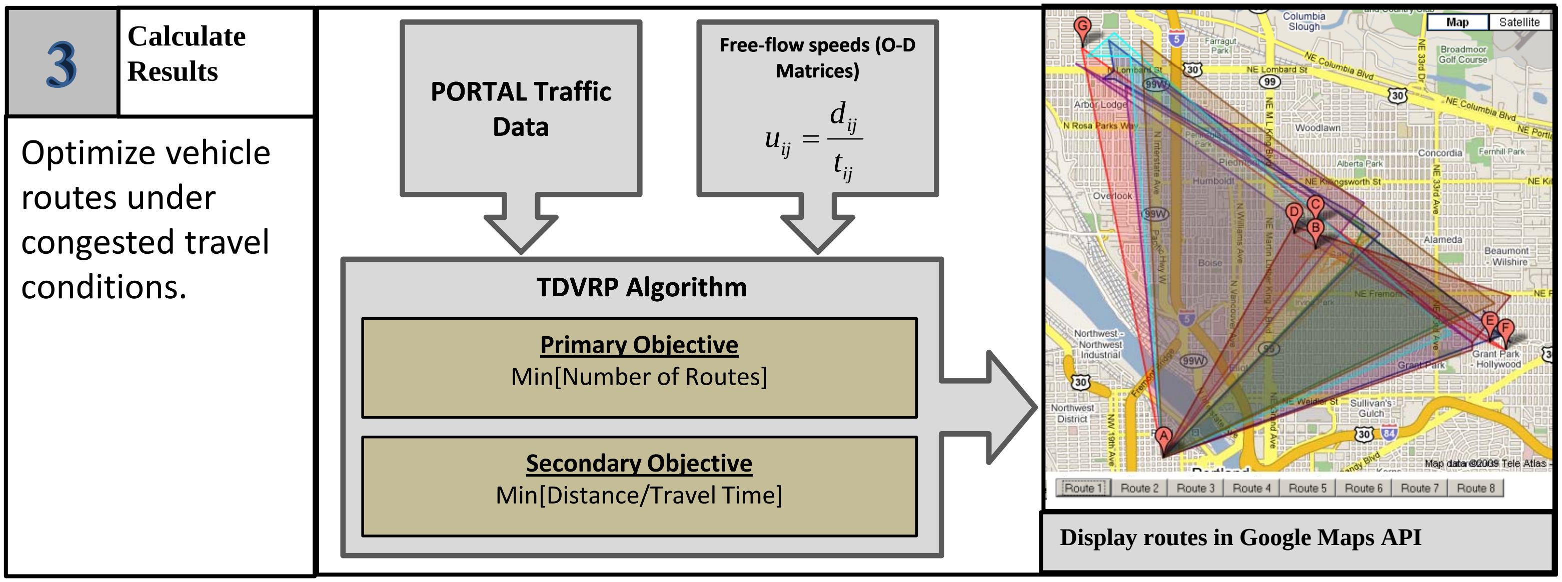
Distance Table (ID, meters)
0 1594 1996 1797 2274 1738 2193 2348 2059 1726 1697
1 0 402 700 680 404 677 1449 465 828 680
2 402 0 622 387 327 542 1399 542 778 907
3 672 622 0 426 496 397 777 1165 156 603
4 748 671 393 0 573 156 1012 1210 549 996

Output Distance O-D Matrix d_{ij}

Time Table (ID, seconds)
0 163 239 216 300 218 280 356 238 218 231
1 0 76 111 138 57 146 263 76 125 121
2 86 0 137 86 72 120 335 138 189 208
3 129 137 0 100 98 88 215 216 52 167
4 163 143 86 0 114 34 275 259 138 226

Output Travel Time O-D Matrix t_{ij}

Reduced computational complexity:
Implementing the Google Maps API



Incorporate bottleneck and congestion data using functions:

- Modify "uncongested speeds", use time-spaced dependent formulas
- Reduced computational overhead:
  - storage/retrieval of travel time matrices and data
  - feasibility checks and computations

Modeling: stochastic and time dependent

Problem Definition

- The objective function:
  - minimization of the number of routes when the optimal number of routes is unknown,
  - a secondary objective is the minimization of the maximum probability of deadline violation, total time, or distance.
- Types of decision variables:
  - a binary decision variable that indicates whether a vehicle travels between any pair of customers in a given vehicle,
  - a real decision variable for each customer service start time, and
  - a binary variable associated to using a given path (in a real network)

***** Customer locations change daily (little repetition)**

Constraints

- The probability of violating a deadline cannot exceed a given value (per customer),
- Vehicle capacity,
- All customers must be served, if a vehicle arrives at a customer it must also depart from that customer, routes must start and end at the depot, each vehicle leaves from and returns to the depot exactly once, and
- Service times must satisfy time window start and ending times and service start time must allow for travel time between customers.

Solution Approach

(a) Transform into an "equivalent deterministic problem"

- Use time-dependent "buffer" times for congestion
- Incorporate into a Time-dependent VRP and solve

(b) Stochastic component: computing probabilities of violating a deadline: use "real network data" ***`

(c) Iterate

***** Customer locations change daily (little repetition)**

Why iterations? correlations in Travel Time

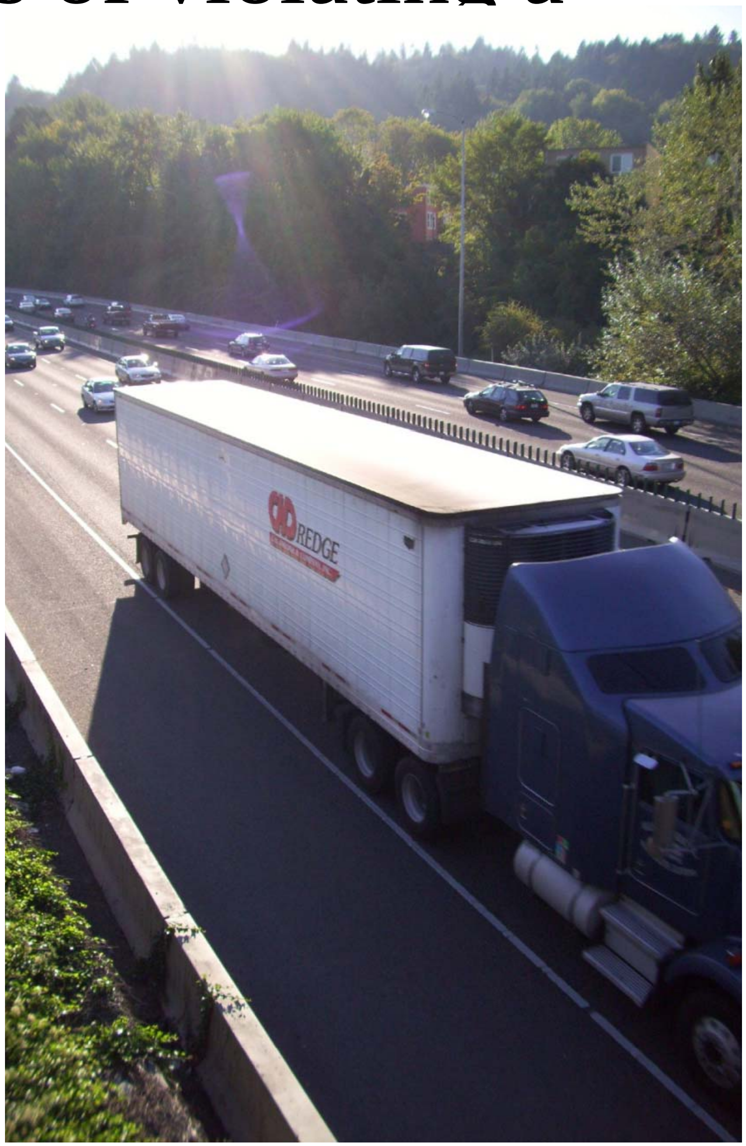
- The data also demonstrated a positive correlation between travel times.
- Given the tour sequence:
  - depot→customer A→customer B
  - if a higher than average travel time takes place for the link depot→customer A, then a higher than average travel time between customer A and customer B is likely
  - Correlations can be important in multi-stop tours (cumulative effect of delays and size of buffer needed)

(a) TDVRP Solution Algorithms

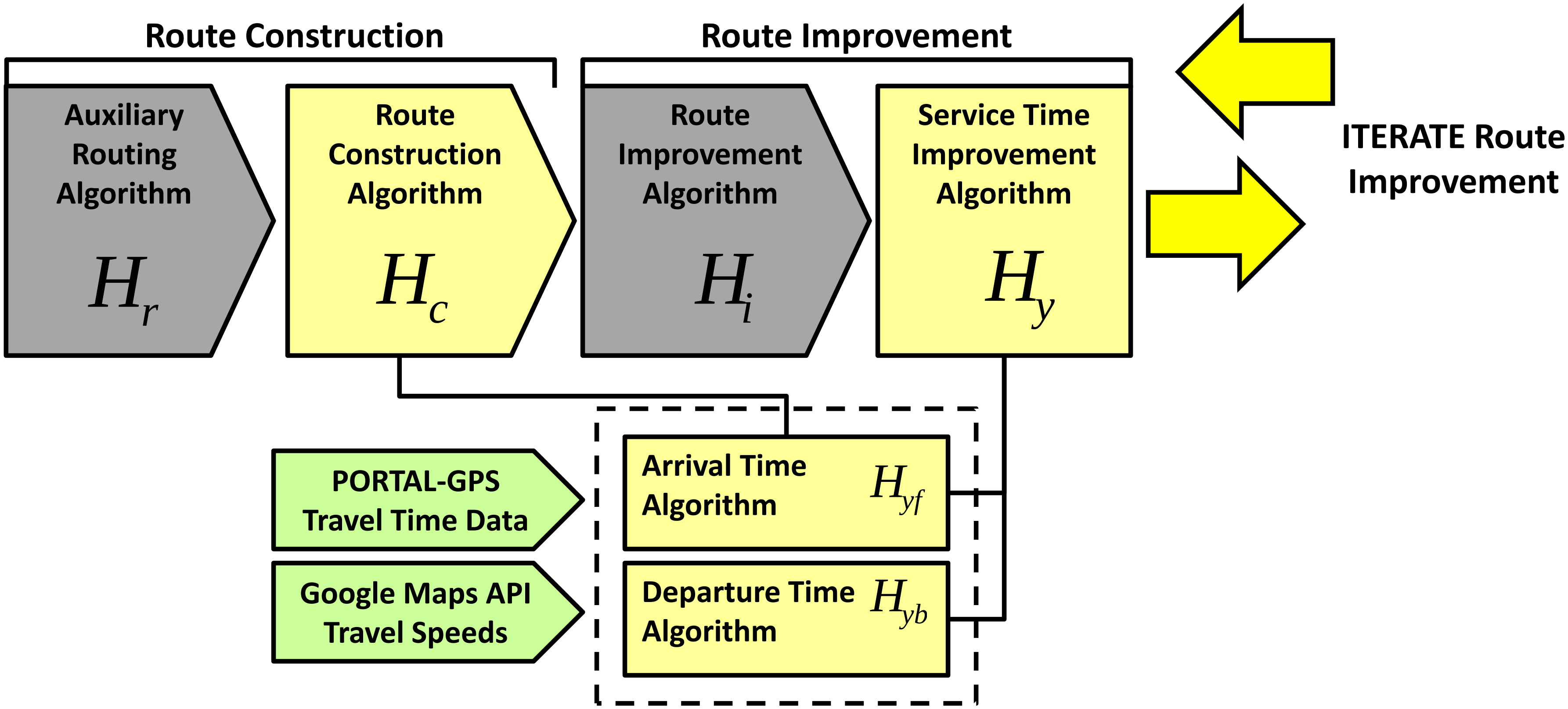
- The solution method is divided into five algorithms:
  1. Using historical data, calculate travel times and add a time dependent "buffer"
     - Historical data (recurrent congestion)
  2. An auxiliary route building heuristic, is repeatedly called during the execution of the construction heuristic
  3. A route construction algorithm that calls the route building heuristic
  4. A route improvement algorithm that calls the route construction heuristic
  5. A service time improvement algorithm that aims at reducing costs by changing service start times for a given set of routes produced by algorithms 2, 3, and 4

(b) Computing probabilities of violating a deadline

- Using *real* data
- Recurring & Non-Recurring Congestion
  - Recurring: day-to-day caused by fluctuating demand/changes in geometry
  - Non-Recurring: unexpected event (e.i.; incident, weather)
- Access to:
  - Loop Sensor data from Oregon DOT
  - GPS truck travel data

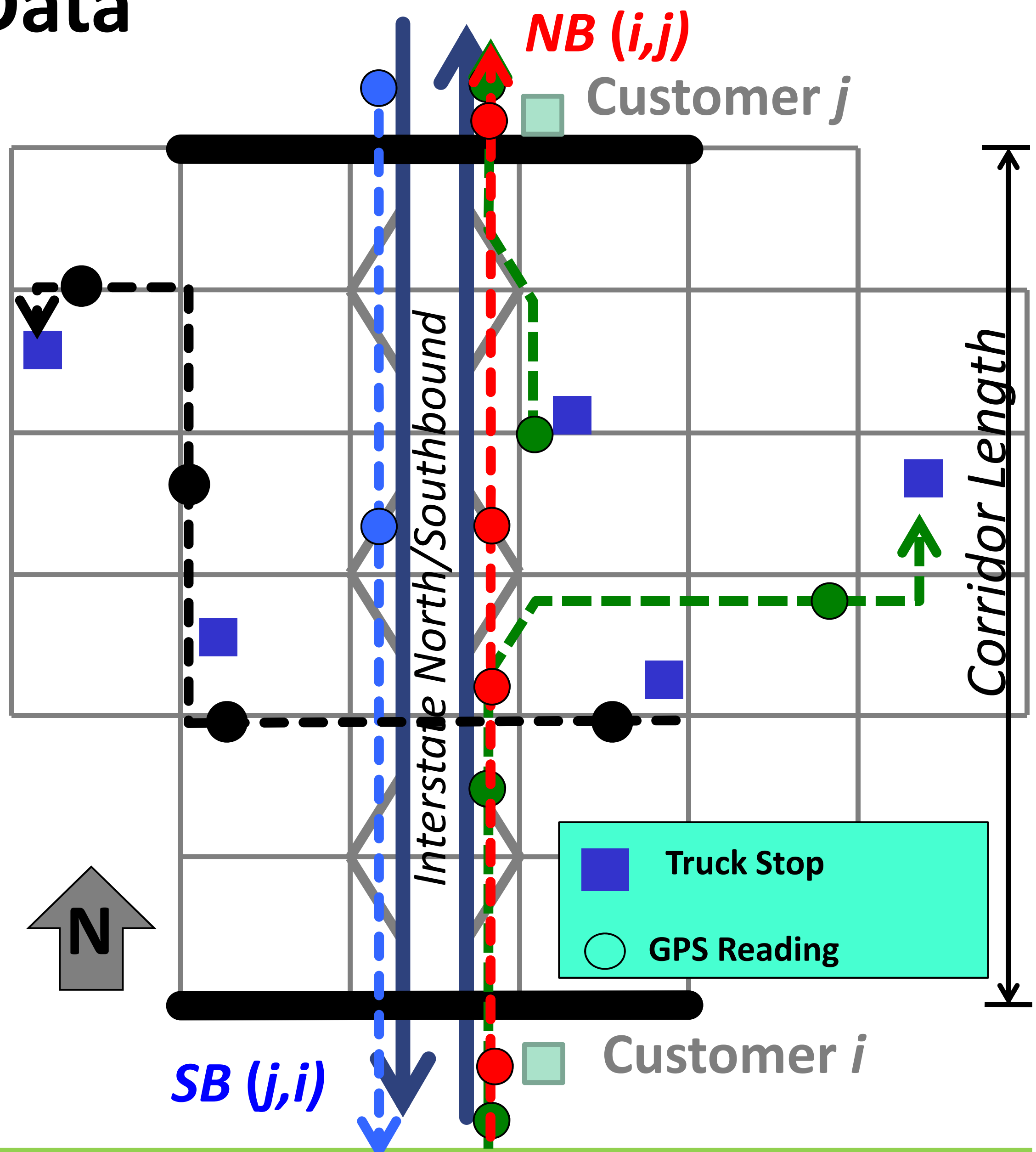


- **Calculate vehicle travel times under congested travel conditions**
- **Free-flow travel times from API modified using GPS/PORTAL travel time data to simulate congested conditions and travel time uncertainty**



Description of GPS Data

- Determine Shortest Path (*i,j*)
- GPS Truck Types
  - **Through**
  - **Partial Through**
  - **Partial Local**
  - **Local**

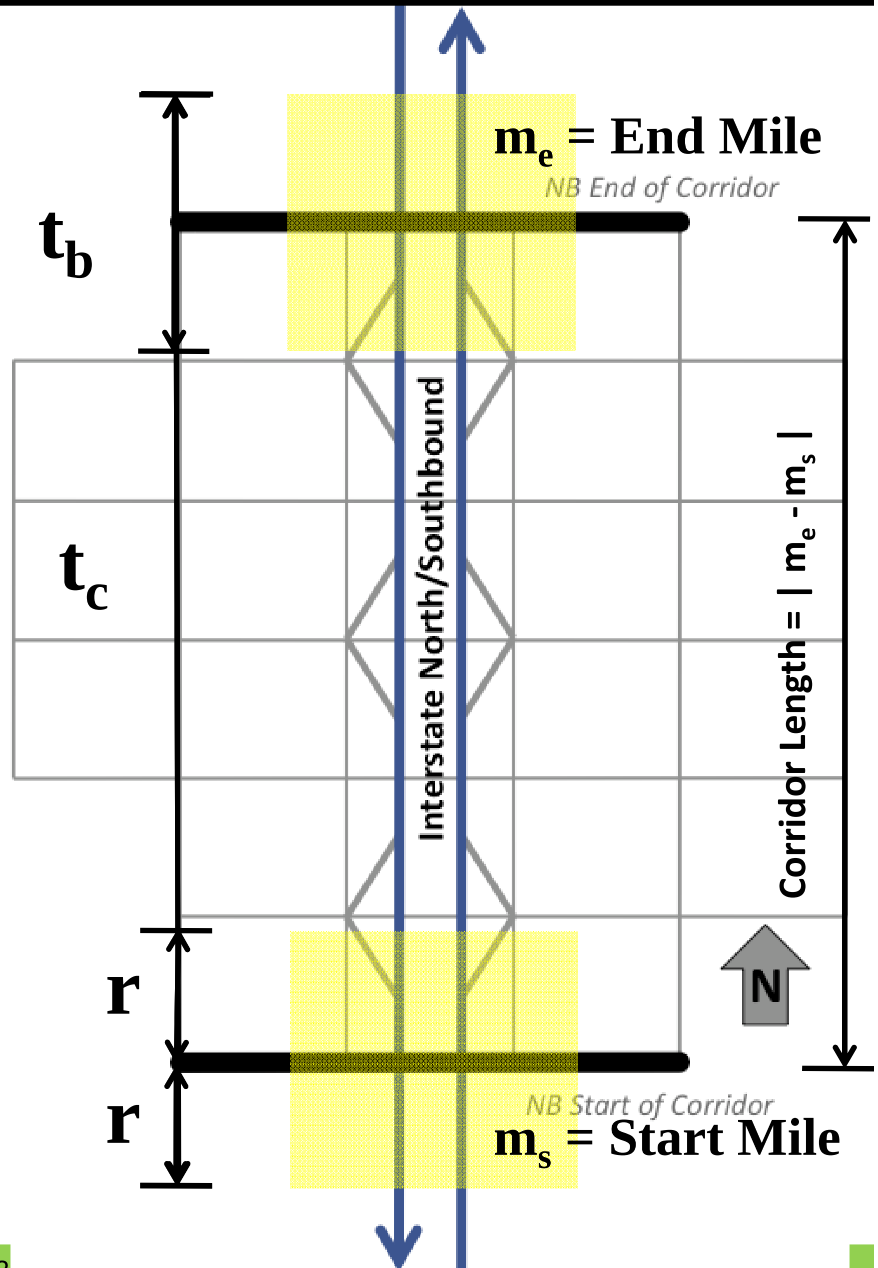


- Develop Filter to ID

Overlapping Trucks
Same or similar time of day !

Methodology

- **Purpose of Filter: To Identify Overlapping GPS readings**
- **Two Step Process:**
  - Filter Process 1: Matching GPS Readings to Identify Potential Trucks
  - Filter Process 2: Compare to PORTAL (sensor data) speeds if possible
  - Integrates available data/records using an algorithm



Filter Parameters

m_s = Start Milepost
m_e = Start/End Milepost
r = Buffer radius
t_b = Threshold time ending
t_c = Threshold time start

- (b) Evaluate probability of a deadline violation
  - Use average times and standard deviations of travel times to estimate probabilities of late arrivals
  - Montecarlo sampling can be used too
  - "Learn" value of adequate buffer times per *time of the day*
- (c) Iterate
  - Improve routes using new knowledge
  - Start improving routes where there are *severe violations* or *too much slack*

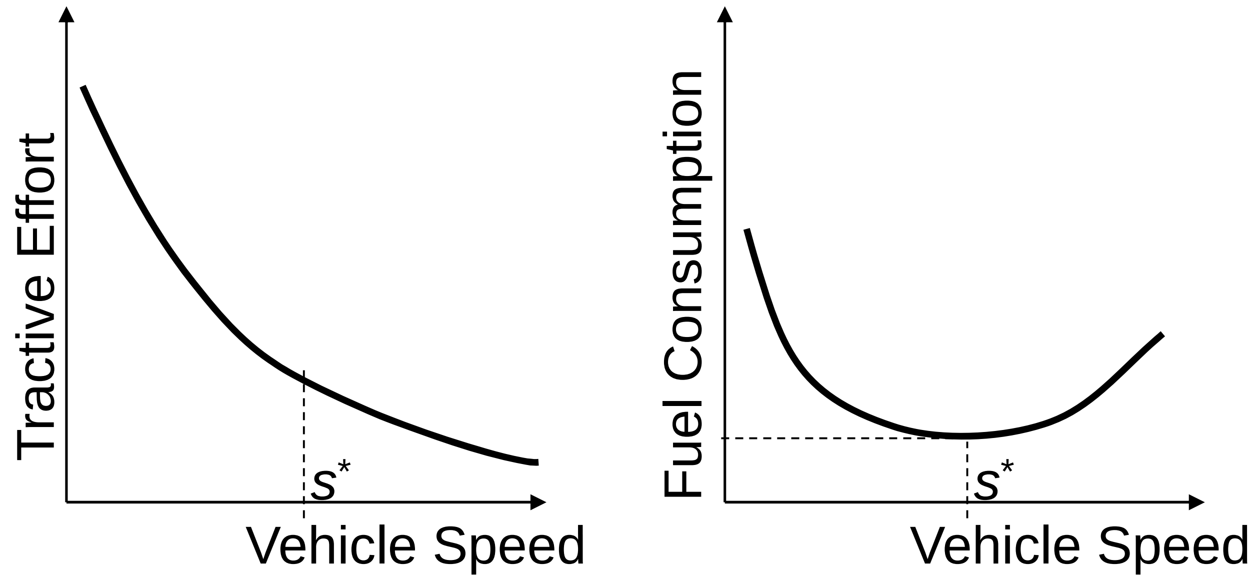
Evaluation of results

- Improved estimation of the probability of violating deadlines
- Reduction in violations
- We can simulate:
  - probability of violating deadlines with new and old method
  - Changes in fleet size, distance traveled, etc.

- Evaluation not trivial in practice (changes in customer locations)

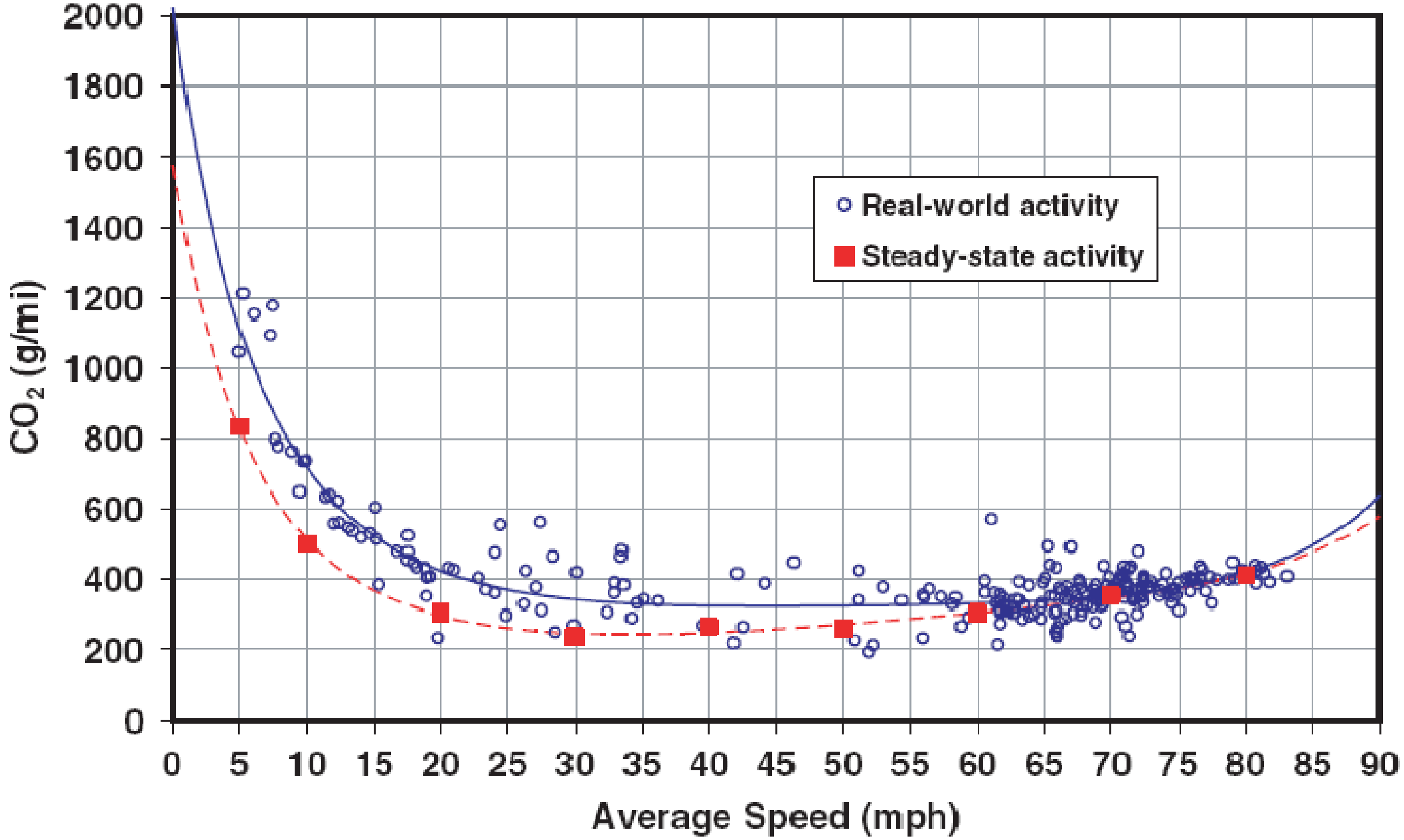
Emissions and Energy Minimization

Motivation



- **Increased Delays and Congestion in Urban Areas**
- **Delay and Congestion Impacts…**
  - Emissions
  - Energy Consumption

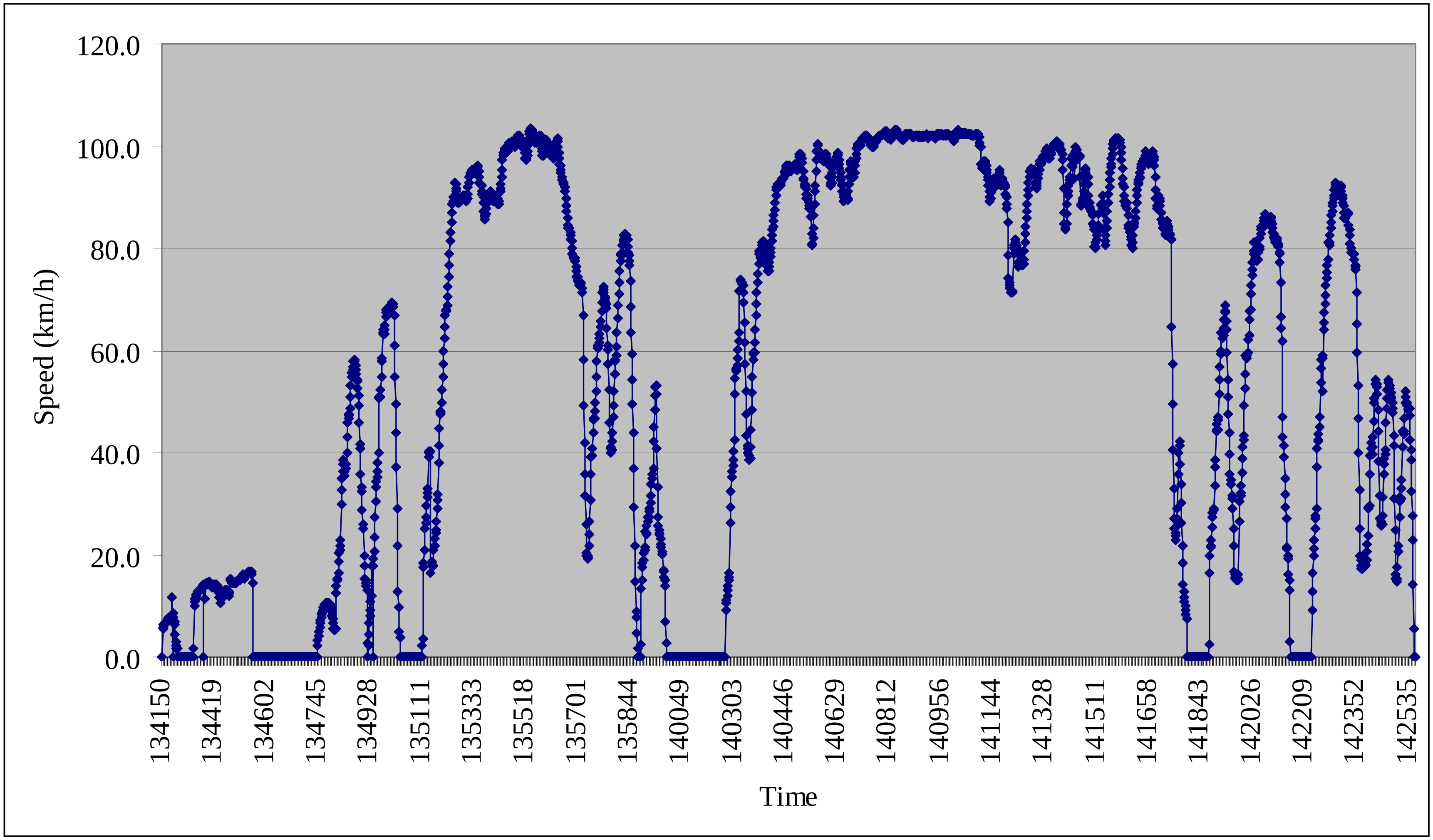
Motivation



CO_2 emissions as a function of average speed

(Barth and Boriboonsomsin, 2008)

Speed-Time Profiles for Input to Fuel Consumption and Emissions Models



Linking Engine Efforts and Emissions

The power P consumed at a speed v is obtained from

$$P = ms(ds/dt) + \frac{1}{2}\rho c_D A_f s^3 + Gmgs + f_{rl}mgs$$

Where:

$m =$ vehicle mass,

$\rho =$ air density,

$c_D =$ drag coefficient,

$A_f =$ vehicle frontal section,

$s =$ vehicle travel speed,

$g =$ acceleration of gravity,

$W = mg =$ total vehicle weight,

$G =$ grade, and

$f_{rl} =$ a coefficient of rolling resistance.

Four resistances:

- **acceleration**
- **aerodynamic**
- **grade**
- **rolling**

Motivation

- **Increased Delays and Congestion in Urban Areas**
- **Delay and Congestion Impacts…**
  - Emissions
  - Energy Consumption

OBJECTIVE:

- **Develop a solution method to incorporate *emissions* and *energy* consumption in Vehicle Routing Problems**

- **Introduce realistic yet manageable formulations**

Problem Definition

- The objective function:

  (a) minimization of the number of routes when the optimal number of routes is unknown, a secondary objective is the minimization of emissions, energy, distance, and travel time costs

  (b) minimization of the weighted cost of routes plus emissions, energy, distance, and travel time costs (when the number of routes is unknown)

Problem Definition

- Types of decision variables
  - a binary decision variable that indicates whether a vehicle travels between any pair of customers in a given vehicle,
  - a real decision variable for each customer service start time, and
  - a real decision variable associated with *chosen* travel speed
- Constraints:
  - Typical: capacity, time windows, 1 vehicle-1 customer, 1 depot, etc.
  - **Additional: keep track of weight after serving each customer and departure time**

Formulation

(a) Total Cost Minimization EEVRP

minimize

$$\sum_{k\in K}\sum_{j\in C} c_k x_{0j}^k + c_d \sum_{k\in K}\sum_{(i,j)\in V} d_{ij} x_{ij}^k + c_t \sum_{k\in K}\sum_{j\in C} (y_{n+1}^k - y_0^k) x_{0j}^k +$$
$$+\sum_{k\in K}\sum_{(i,j)\in V} x_{ij}^k (c_e + c_f^{'}) v_{ij} (y_i^k + g_i)$$

Minimize costs associated to number of routes, distance, duration, energy, and emissions

Some Additional Constraints *beyond* TD-VRP-TW

$$b_i = \sum_{j\in V}\sum_{k\in K} (y_i^k + g_i) x_{ij}^k$$

Departure time

$$w_j^k = \sum_{i\in V} q_j x_{ji}^k + \sum_{i\in V} w_i^k x_{ij}^k, \ \forall k \in K, \forall j \in C$$

Keep track of weight

$$v_{ij}(b_i) = cs(g_i) + d_{ij} w_i^k (\alpha_{ij} + \alpha_w) + \sum_{l=0}^{l=p} (\alpha_0 + \alpha_1 (z_{ij}^l)^2 + \frac{\alpha_2}{z_{ij}^l}) d_{ij}^l$$

Cost per link *ij* is a function of speed

Complexity beyond usual TD-VRP…

- the sequence of customers visited impacts departure times and vehicle weight;
- departure time is a function of the amount of waiting at a customer location;
- the impact of vehicle weight and travel speeds on emissions/energy consumption;
- The asymmetry and non-linearity of the problem in terms of speeds and directions of travel; and
- Strict hard time window and capacity constraints.

Evaluation of results

- Improved estimation of emissions (CO_2) and energy consumption
- Significant reduction in emission levels in simulated experiments
- Tractable formulation and solution algorithm

General conclusions…

- Integration of algorithms and real data
- Based on a modular and hierarchical algorithmic approach
  - Efficient, simple, and flexible algorithm to deal with stochastic time dependent travel times and emissions
- Provides good quality solutions and reasonable running times
  - Tradeoffs precomputing “a priori” and dynamic updates
  - Customer locations: fixed vs. stochastic

Acknowledgment to graduate research assistants

- ***Ryan Conrad***
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- ***Shreemoyee Sarkar***
- ***Nikki Wheeler***

Current Research

ADDITIONAL RESEARCH AREAS PROJECTS

- Operation and Control of Transit Fleet (TriMet – OTREC)
- State Freight Modeling (ODOT)
- Emissions and Traffic (Miller)
- Green Fleet Replacement Models (OTREC-ODOT)
- Climate Change and Transportation (Region X FHWA – OTREC)
- Sensors, Visualization, and Traffic (NSF - CS and CEE)

Related Papers

- Figliozzi, M., Emissions Minimization Vehicle Routing Problem, Forthcoming 2010, Transportation Research Record.
- Figliozzi, M., An Iterative Route Construction and Improvement Algorithm for the Vehicle Routing Problem with Soft-time Windows. Transportation Research, part C, 2009.
- Conrad, R., Figliozzi, M. Algorithms to Quantify the Impacts of Congestion on Time-Dependent Real-World Urban Freight Distribution Networks, Forthcoming 2010, Transportation Research Record.
- Wheeler, N., Figliozzi, M., Analysis of the Impacts of Congestion on Freight Movements in the Portland Metropolitan Area: A methodology to analyze and estimate the impacts of recurring and non-recurring congestion on commercial vehicles combining GPS, traffic sensor, and incident data, Proceeding National Urban Freight Conference, Long Beach, CA, October 2010.
- Figliozzi, M., A Route Improvement Algorithm for the Vehicle Routing Problem with Time Dependent Travel Times. Proceedings 88th Transportation Research Board Annual Meeting, Washington DC, January 2009
- Figliozzi, M.A., The Impacts of Congestion on Commercial Vehicle Tours Characteristics and Costs. Forthcoming 2009 Transportation Research Part E –Transport and Logistics.
- Figliozzi, M.A., Planning Approximations to the average length of vehicle routing problems with time window constraints. Transportation Research Part B - Methodological, 2009, 43(4): p. 438-447.
- Greaves, S. and M. Figliozzi, Urban Commercial Vehicle Tour Data Collection Using Passive GPS Technology: Issues And Potential Applications. Transportation Research Record 2049, 2008: p. 158-166.
- Figliozzi, M.A., Planning Approximations to the average length of vehicle routing problems with time window constraints. *Transportation Research Part B - Methodological*, 2009, 43(4): p. 438-447.
- Figliozzi, M.A., H.S. Mahmassani, and P. Jaillet, Pricing in Dynamic Vehicle Routing Problems. Transportation Science, 2007. 41(3): p. 302.

– Papers can also be downloaded from: http://web.cecs.pdx.edu/~maf

THANK YOU

For papers, more information, please contact me at:

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