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:

\[ \sum_{n=1}^{10} \left[ \frac{50!}{(50-n)!} \right] \approx 3.8 \times 10^{16} \]
Time Windows

- Problems with time windows involve routing and scheduling

Start and end of time window (2 pm - 4 pm)
Scheduling

Truck #1
- Customer #1
- Customer #9

Truck #2
- Customer #5

Truck #3
- Customer #11

Truck #4
- Customer #2

Truck #5
- Customer #3

Idle time waiting!

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VRP in Urban Areas
Actual Travel Times Vary Day to Day

Segment of Northbound I-5 in 2005
Tour Classification & Sensitivity to Congestion

Two factors that can be used to monitor/track congestion:

- Average distance per stop (Km)
- Percentage of tour time driving
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

<table>
<thead>
<tr>
<th>Service Time or Constrains</th>
<th>Short</th>
<th>Medium</th>
<th>Long</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Low</td>
<td>High</td>
<td>Approaching Infeasibility</td>
</tr>
<tr>
<td>High</td>
<td>Medium</td>
<td>Approaching Infeasibility</td>
<td>Use 3PL New Depot</td>
</tr>
</tbody>
</table>

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).

<table>
<thead>
<tr>
<th></th>
<th>Good Records</th>
<th>Bad/Missing Records*</th>
<th>Total Records</th>
</tr>
</thead>
<tbody>
<tr>
<td>Morning ( )</td>
<td>1,843,050</td>
<td>96,726</td>
<td>1,939,776</td>
</tr>
<tr>
<td></td>
<td>95%</td>
<td>5%</td>
<td></td>
</tr>
<tr>
<td>Afternoon ( )</td>
<td>1,643,729</td>
<td>100,800</td>
<td>1,744,529</td>
</tr>
<tr>
<td></td>
<td>94%</td>
<td>6%</td>
<td></td>
</tr>
<tr>
<td>Night ( )</td>
<td>1,498,446</td>
<td>54,553</td>
<td>1,552,999</td>
</tr>
<tr>
<td></td>
<td>96%</td>
<td>4%</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>4,985,225</td>
<td>252,079</td>
<td>5,237,304</td>
</tr>
<tr>
<td></td>
<td>95%</td>
<td>5%</td>
<td></td>
</tr>
</tbody>
</table>
Results of the Processing Routines

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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.

2. O-D Matrices
   Calculate travel time and distance origin-destination matrices.

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Reduced computational complexity: Implementing the Google Maps API

3 Calculate Results

Optimize vehicle routes under congested travel conditions.

PORTAL Traffic Data

Free-flow speeds (O-D Matrices)

\[ u_{ij} = \frac{d_{ij}}{t_{ij}} \]

TDVRP Algorithm

Primary Objective
Min[Number of Routes]

Secondary Objective
Min[Distance/Travel Time]

Display routes in 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

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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

\( m_e = \) End Mile
\( m_s = \) Start Mile
\( \text{Corridor Length} = |m_e - m_s| \)
• (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

\[ \text{CO}_2 \] 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

$$P = ms\left(\frac{ds}{dt}\right) + \frac{1}{2} \rho c_D A_f s^3 + G m g s + f_r m g s$$

Where:

- $m = \text{vehicle mass}$,
- $\rho = \text{air density}$,
- $c_D = \text{drag coefficient}$,
- $A_f = \text{vehicle frontal section}$,
- $s = \text{vehicle travel speed}$,
- $g = \text{acceleration of gravity}$.

$W = mg = \text{total vehicle weight}$,
- $G = \text{grade}$, and
- $f_r = \text{a coefficient of rolling resistance}$.

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 EEEVRP

\[
\text{minimize} \quad \sum_{k \in K} \sum_{j \in C} c_{k} x_{0j}^{k} + c_{d} \sum_{k \in K} \sum_{(i,j) \in \mathcal{E}} d_{ij} x_{ij}^{k} + c_{t} \sum_{k \in K} \sum_{j \in C} (y_{n+1}^{k} - y_{0}^{k}) x_{0j}^{k} + \\
+ \sum_{k \in K} \sum_{(i,j) \in \mathcal{E}} x_{ij}^{k} (c_{e} + c_{f}') v_{ij} (y_{i}^{k} + g_{i})
\]

Some Additional Constraints beyond TD-VRP-TW

\[
b_{i} = \sum_{j \in \mathcal{V}} \sum_{k \in K} (y_{i}^{k} + g_{i}) x_{ij}^{k}
\]

\[
w_{j}^{k} = \sum_{i \in \mathcal{V}} q_{j} x_{ji}^{k} + \sum_{i \in \mathcal{V}} w_{i}^{k} x_{ij}^{k}, \quad \forall k \in K, \forall j \in C
\]

\[
v_{ij}(b_{i}) = cs(g_{i}) + d_{ij} w_{i}^{k} (\alpha_{i} + \alpha_{w}) + \sum_{l=0}^{l=p} (\alpha_{0} + \alpha_{1} (z_{ij}^{l})^{2} + \alpha_{2} z_{ij}^{l}) d_{ij}^{l}
\]

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

Departure time

Keep track of weight

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
- Myeonwoo Lim
- 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


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

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