Solving the Empty Container Problem using Double-Container Trucks under Stochastic Demand

Presenter: Siyuan Yao

Prof. Maged Dessouky  Dr. Santiago Carvajal
Content

• Background

• Literature Review

• Model and Approach

• Vehicle Routing Problem

• Experimental Analysis

• Conclusion
• **Background**

**Ports of Los Angeles and Long Beach Cargo Forecasting**

- In 2018 there were about 9 million Twenty Foot Equivalent Units shipped via the Port of Los Angeles.
- Inbound & outbound TEUs are not balanced
- Unnecessary truck traffic near the port area.

![Inbound & Outbound TEU Forecasting](https://www.trucks.com/2019/02/12/atri-worst-highway-bottlenecks-driving-trucking-speeds-down/)

<table>
<thead>
<tr>
<th>Year</th>
<th>Inbound Loads</th>
<th>Outbound Loads</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>2010</td>
<td>10</td>
<td>7</td>
</tr>
<tr>
<td>2015</td>
<td>15</td>
<td>10</td>
</tr>
<tr>
<td>2020</td>
<td>20</td>
<td>15</td>
</tr>
<tr>
<td>2025</td>
<td>25</td>
<td>20</td>
</tr>
<tr>
<td>2030</td>
<td>30</td>
<td>25</td>
</tr>
</tbody>
</table>
• **Background**

**Current Container Movement**

**Container Movement with “Street Exchanges”**

The biggest challenge for the Street Exchange is the coordination problem between companies.
• Background

Double Container Movement (Dessouky & Carvajal, 2017)

Container Movements Using Double Container Trailers (DCAM)

Benefits of using double-container trailers
• Reduce the total number of trips
• Reduce the total number of trailers
• Increase the possible routes between all the locations

Single Container Trailer
1. One Loaded Container
2. One Empty Container

Double-Container Trailer
1. Two Loaded Containers
2. Two Empty Containers
3. One Loaded and One Empty Container
• Literature Review

The Empty Container Problem

1. Deterministic Model:

2. Stochastic World:

3. Empty Container Policies and Implementation:

4. Perspective of a Single Company:

The Vehicle Routing Problem

1. VRP in the Empty Container Problem
   Zhang et al. (2009), Tan et al. (2006), Sterzik and Kopfer (2013)

2. Generalization of the VRP
• **Model and Approach**

**Stochastic Double Container Assignment Model (DCSAM)**

• Today’s demand is deterministic
• Future demand follows a Markov Chain in which each state has some probability distribution
• Assume transitional probabilities and pdf of demands can be obtained by historical data
• Assume $S$ different scenarios each with probability $\theta_s$ of occurring
• Let $\bar{d}_{i,t,s}$ be the mean number of containers demanded at location $i$ by time $t$ under scenario $s$
• Let $\mu_s$ be the mean number of containers that arrive at the port under scenario $s$
• Let $\varphi$ be the penalty incurred for not fulfilling a unit of demand
• Let $z_{i,t,s}$ be the unmet demand for location $i$ at time $t$ for scenario $s$
• A double container truck can only pick up when it is empty
• Model and Approach

General Model Information

• Location Class:
  1. Importers
  2. Exporters
  3. Depots
  4. Port

• Demand and Supply:

<table>
<thead>
<tr>
<th></th>
<th>Importers</th>
<th>Exporters</th>
<th>The Port</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demand</td>
<td>Import Containers</td>
<td>Empty Containers</td>
<td>Export Containers</td>
</tr>
<tr>
<td>Supply</td>
<td>Empty Containers</td>
<td>Export Containers</td>
<td>Import Containers</td>
</tr>
</tbody>
</table>

• Model runs in a two-day horizon but only the first day’s vehicle movement will be implemented.

• Time is discretized.
Model and Approach

General Model Information (cont.)

• The objective is to minimize the transportation costs.
• Variables are container movements and truck movements.
• Constraint groups:
  1. Capacity
  2. Demand
  3. Container Flow Consistency
  4. Container Balance
  5. VRP Scheduling

All the constraints need to be satisfied at every time discretization point for today and tomorrow.
• Model and Approach

Vehicle Routing Problem

By solving the LP relaxation model, we can generate the container assignment solution with the initial solution in the following way:

1. Initial Workload Construction
   • With the solution generated in the DCSAM, we can compute the workload at each location at every time point

2. Initial VRP solution Construction
   • In each iteration, we introduce one new vehicle into the system
   • The new vehicle will search feasible workloads from the beginning of the day till the end of the day.
   • Keep adding vehicles until all the workloads been assigned.

The initial VRP solution would be a list of vehicles with corresponding job(s), i.e.

Vehicle i: \{job_{i1}, job_{i2}, job_{i3}\}
• Model and Approach

Vehicle Routing Problem

After we have the initial VRP solution, we now introduce our modified ALNS to find out the VRP solution, by repeating the following procedure:

1. Pick out those vehicles with only one pickup in the whole day.

   Vehicle 1 $\{job_{11}, job_{12}, job_{13}\}$
   Vehicle 2 $\{job_{21}, job_{22}, job_{23}\}$
   : $\vdots$
   Vehicle k $\{job_{k1}, job_{k2}\}$
   : $\vdots$
   Vehicle p-3 $\{job_{(p-3)1}, job_{(p-3)2}\}$
   Vehicle p-2 $\{job_{(p-2)1}\}$
   Vehicle p-1 $\{job_{(p-1)1}\}$
   Vehicle p $\{job_{p1}\}$

   Remaining job: $\{job_{(p-2)1}, job_{(p-1)1}, job_{p1}\}$
Model and Approach

Vehicle Routing Problem

2. Randomly choose several workloads from the remaining vehicles.

Vehicle 1 \{job_{11}, job_{12}, job_{13}\}
Vehicle 2 \{job_{21}, job_{22}, job_{23}\}
\vdots
Vehicle k \{job_{k1}, job_{k2}\}
\vdots
Vehicle p-3 \{job_{(p-3)1}, job_{(p-3)2}\}

Remaining job: \{job_{(p-2)1}, job_{(p-1)1}, job_{p1}, job_{13}, job_{k2}\}
• Model and Approach

Vehicle Routing Problem

3. Insert job back into remaining vehicles, until no remaining job can be assigned to the remaining vehicles.

Vehicle 1 \{job_{11}, job_{12}\}
Vehicle 2 \{job_{21}, job_{22}, job_{23}\}
: 
Vehicle k \{job_{k1}\}
: 
: 
Vehicle p-3 \{job_{(p-3)1}, job_{(p-3)2}\}

Remaining job:
\{ job_{(p-2)1}, 
  job_{(p-1)1}, 
  job_{p1}, 
  job_{p1}, 
  job_{13}, 
  job_{k2} \} 

4. Assign job to new vehicle until no remaining job left.
## Experimental Analysis

### Parameter Setting

<table>
<thead>
<tr>
<th>Parameter name</th>
<th>Parameter value</th>
</tr>
</thead>
<tbody>
<tr>
<td># of importers (I)</td>
<td>5</td>
</tr>
<tr>
<td># of exporters (E)</td>
<td>3</td>
</tr>
<tr>
<td># of depots (D)</td>
<td>2</td>
</tr>
<tr>
<td>Loading and unloading time of containers</td>
<td>1 hour</td>
</tr>
<tr>
<td>Truck turnover time at port</td>
<td>2 hours</td>
</tr>
<tr>
<td>Daily time horizon</td>
<td>12 hours</td>
</tr>
<tr>
<td>Time discretization size</td>
<td>1 hour</td>
</tr>
<tr>
<td>Location capacity</td>
<td>10</td>
</tr>
<tr>
<td>Time horizon</td>
<td>10 days</td>
</tr>
<tr>
<td>Number of scenarios</td>
<td>3</td>
</tr>
<tr>
<td>Number of ALNS iterations (Ψ)</td>
<td>700</td>
</tr>
<tr>
<td>Number of jobs to remove at each iteration (Δ)</td>
<td>10</td>
</tr>
<tr>
<td>Number of trucks to be removed at each iteration (ζ)</td>
<td>2</td>
</tr>
</tbody>
</table>

1. No ship arriving or leaving
2. Ship arriving
3. Ship departing

Tomorrow’s state depends on yesterday and today’s states.
• Experimental Analysis

Parameter Setting (cont.)

Transitional probability distribution

\[
\begin{bmatrix}
0.1 & 0.45 & 0.45 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0.7 & 0.05 & 0.25 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0.7 & 0.25 & 0.05 \\
0.05 & 0 & 0.95 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.9 & 0.09 & 0.01 \\
0.05 & 0.95 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0
\end{bmatrix}
\]

Demand distribution

\[
\begin{array}{c|c|c|c}
\text{Location} & \text{State 1} & \text{State 2} & \text{State 3} \\
\hline
\text{Importer} & (38,42) & (43,47) & (33,37) \\
\text{Exporter} & (28,32) & (23,27) & (33,37) \\
\text{Port} & (195,205) & (185,195) & (205,215) \\
\end{array}
\]

\[
\begin{array}{c|c|c|c}
\text{Location} & \text{State 1} & \text{State 2} & \text{State 3} \\
\hline
\text{Importer} & (36,44) & (41,49) & (31,39) \\
\text{Exporter} & (26,34) & (21,29) & (31,39) \\
\text{Port} & (190,210) & (180,200) & (200,220) \\
\end{array}
\]

\[
\begin{array}{c|c|c|c}
\text{Location} & \text{State 1} & \text{State 2} & \text{State 3} \\
\hline
\text{Importer} & (34,46) & (39,51) & (29,41) \\
\text{Exporter} & (24,36) & (19,31) & (29,41) \\
\text{Port} & (185,215) & (175,205) & (195,225) \\
\end{array}
\]
• Experimental Analysis

Experimental Results

We compare both of these models against a solution knowing perfect information for the 10 days and the container assignments are solved collectively for these 10 days. Each experiment was run for 10 trials.

<table>
<thead>
<tr>
<th>Demand Distribution</th>
<th>Transition Probability Distribution 1</th>
<th>Transition Probability Distribution 2</th>
<th>Transition Probability Distribution 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DCSAM</td>
<td>DCAM</td>
<td>DCSAM</td>
</tr>
<tr>
<td>1</td>
<td>1.04</td>
<td>1.10</td>
<td>1.05</td>
</tr>
<tr>
<td>2</td>
<td>1.07</td>
<td>1.14</td>
<td>1.09</td>
</tr>
<tr>
<td>3</td>
<td>1.10</td>
<td>1.16</td>
<td>1.12</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Demand Distribution</th>
<th>Transitional Probability Distribution 1</th>
<th>Transitional Probability Distribution 2</th>
<th>Transitional Probability Distribution 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DCSAM</td>
<td>DCAM</td>
<td>DCSAM</td>
</tr>
<tr>
<td>1</td>
<td>0.015</td>
<td>0.019</td>
<td>0.023</td>
</tr>
<tr>
<td>2</td>
<td>0.017</td>
<td>0.011</td>
<td>0.045</td>
</tr>
<tr>
<td>3</td>
<td>0.025</td>
<td>0.024</td>
<td>0.065</td>
</tr>
</tbody>
</table>
DCASM performs around 4% to 6% better than the DCAM model because DCASM considers more of the future information than DCAM. If we can predict tomorrow’s state and demand more accurate, the model can perform even better.
Thank you for listening!