Solving the Empty Container Problem

using Double-Container Trucks under Stochastic Demand

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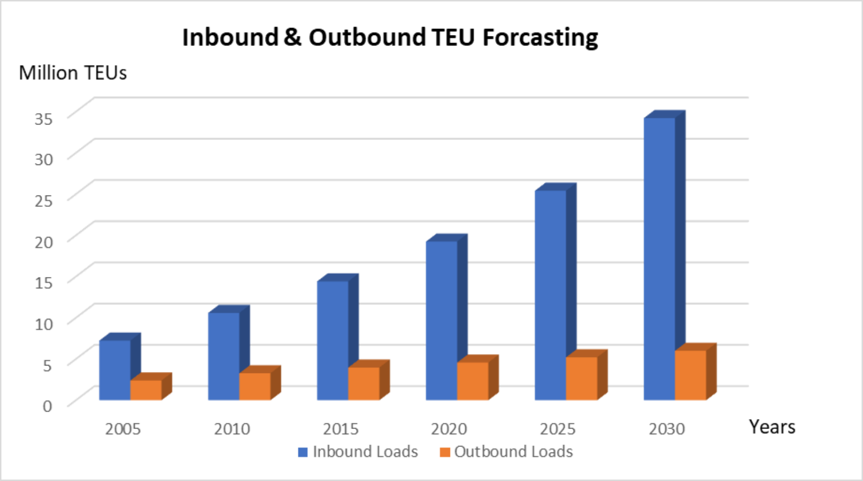
Content

Ports of Los Angeles and Long Beach Cargo Forecasting

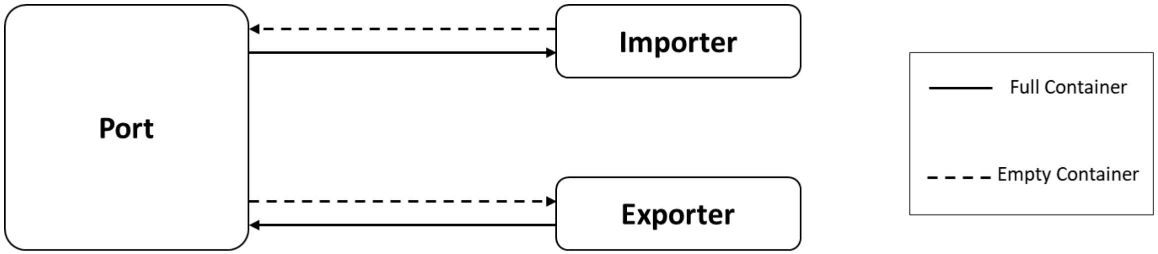
- In 2018 there were about 9 million Twenty Foot Equivalent Units shipped via the Port of Los Angeles.
- Inbound & outbound TEUs are not balanced
- Unnecessary truck traffic near the port area.



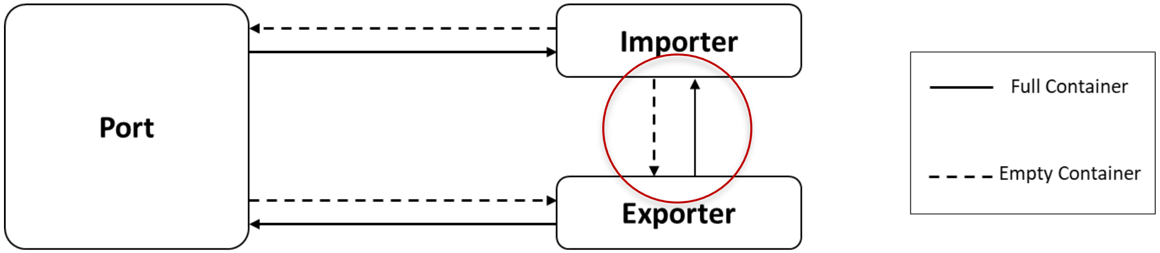
Picture retrived from:
https://www.trucks.com/2019/02/12/atri-worst-highway-bottlenecks-driving-trucking-speeds-down/

• Background

Current Container Movement



Container Movement with “Street Exchanges”



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

Double Container Movement (Dessouky & Carvajal, 2017)

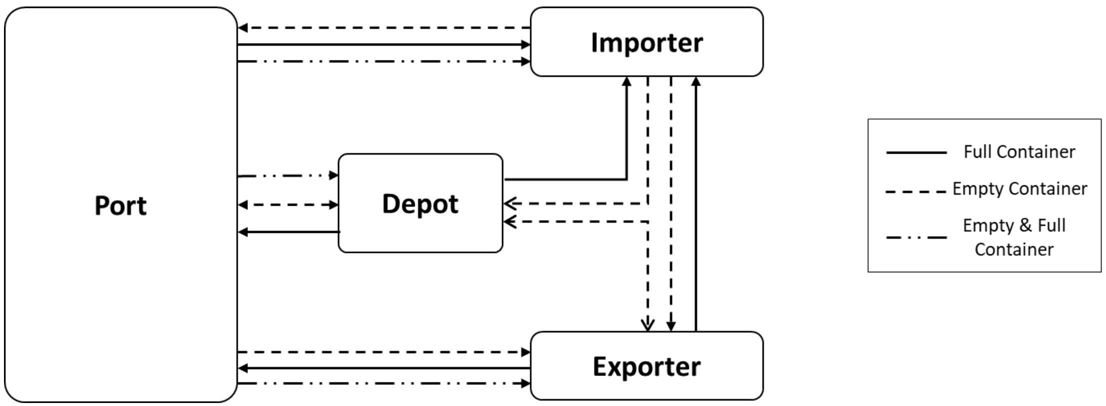
Container Movements Using Double Container Trailers (DCAM)

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



The Empty Container Problem

1. Deterministic Model:
   Dejax and Crainic (1987), Bourbeau et al. (2000) , Jula et al. (2006), Chang et al. (2008), Lam et al (2007)
2. Stochastic World:
   Bandeira et al (2009), Erera et al. (2009), Braekers et al (2013), Chang et al (2008)
3. Empty Container Policies and Implementation:
   Tioga Group (2002), Dam Le (2003), Islam et al. (2010), Choong at al. (2002)
4. Perspective of a Single Company:
   Shen and Khoong (1995), Li et al (2014), Choong (2000)

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
   Ropke and Pisinger (2006), Coehlo et al. (2016), Christofides (1985), Archetti et al. (2001), Bazgan et al. (2005)

- **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 θ_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 μ_s be the mean number of containers that arrive at the port under scenario s
- Let φ 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

General Model Information

- Location Class:
  1. Importers
  2. Exporters
  3. Depots
  4. Port
- Demand and Supply:

	Importers	Exporters	The Port
Demand	Import Containers	Empty Containers	Export Containers
Supply	Empty Containers	Export Containers	Import Containers

- Model runs in a two-day horizon but only the first day's vehicle movement will be implemented.
- Time is discretized.

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.

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 : $\{job_{i1}, job_{i2}, job_{i3}\}$

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

Vehicle Routing Problem

2. Randomly choose several workloads from the remaining vehicles.

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

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

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:

$\{ \quad job_{(p-2)1},$

$job_{(p-1)1},$

$job_{p1},$

$job_{13},$

$job_{k2} \quad \}$

4. Assign job to new vehicle until no remaining job left.

- **Experimental Analysis**

Parameter Setting

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

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

$$\begin{array}{c} [11]\\ [12]\\ [13]\\ [21]\\ [22]\\ [23]\\ [31]\\ [32]\\ [33] \end{array} \begin{bmatrix} 0.1 & 0.45 & 0.45 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.7 & 0.05 & 0.25 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.7 & 0.25 & 0.05 \\ 0.05 & 0 & 0.95 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.9 & 0.09 & 0.01 \\ 0.05 & 0.95 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.9 & 0.01 & 0.09 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

$$\begin{array}{c} [11]\\ [12]\\ [13]\\ [21]\\ [22]\\ [23]\\ [31]\\ [32]\\ [33] \end{array} \begin{bmatrix} 0.2 & 0.4 & 0.4 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.6 & 0.1 & 0.3 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.6 & 0.3 & 0.1 \\ 0.1 & 0 & 0.9 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.8 & 0.15 & 0.05 \\ 0.1 & 0.9 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.8 & 0.05 & 0.15 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

$$\begin{array}{c} [11]\\ [12]\\ [13]\\ [21]\\ [22]\\ [23]\\ [31]\\ [32]\\ [33] \end{array} \begin{bmatrix} 0.3 & 0.35 & 0.35 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.5 & 0.15 & 0.35 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.5 & 0.35 & 0.15 \\ 0.2 & 0 & 0.8 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.7 & 0.2 & 0.1 \\ 0.2 & 0.8 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.7 & 0.1 & 0.2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}$$

Demand distribution

Location	State 1	State 2	State 3
Importer	(38,42)	(43,47)	(33,37)
Exporter	(28,32)	(23,27)	(33,37)
Port	(195,205)	(185,195)	(205,215)

Location	State 1	State 2	State 3
Importer	(36,44)	(41,49)	(31,39)
Exporter	(26,34)	(21,29)	(31,39)
Port	(190,210)	(180,200)	(200,220)

Location	State 1	State 2	State 3
Importer	(34,46)	(39,51)	(29,41)
Exporter	(24,36)	(19,31)	(29,41)
Port	(185,215)	(175,205)	(195,225)

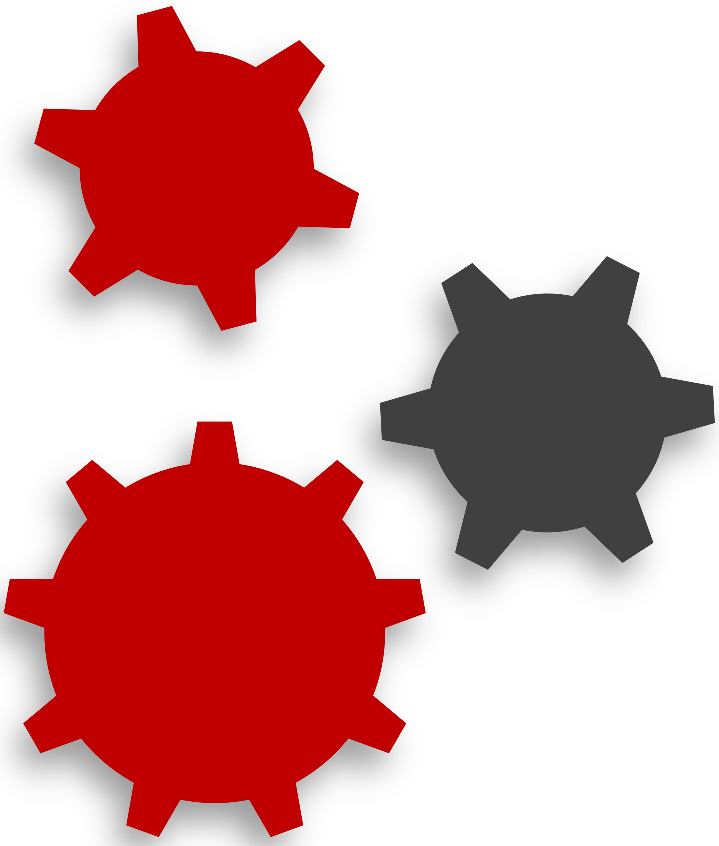
Experimental Results

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.

		Transition Probability Distribution 1		Transitional Probability Distribution 2		Transitional Probability Distribution 3	
		DCSAM	DCAM	DCSAM	DCAM	DCSAM	DCAM
Demand Distribution	1	1.04	1.10	1.05	1.11	1.07	1.13
	2	1.07	1.14	1.09	1.16	1.11	1.15
	3	1.10	1.16	1.12	1.18	1.14	1.19

		Transitional Probability Distribution 1		Transitional Probability Distribution 2		Transitional Probability Distribution 3	
		DCSAM	DCAM	DCSAM	DCAM	DCSAM	DCAM
Demand Distribution	1	0.015	0.019	0.023	0.024	0.019	0.025
	2	0.017	0.011	0.045	0.030	0.036	0.019
	3	0.025	0.024	0.065	0.036	0.029	0.045

- **Conclusion**



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!