Same-Day Delivery: Tactical Design

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Motivation

Same Day Delivery in Manhattan

Order online by 11am. Get it by 7pm.
Outline

Introduction

Tactical Model

Tactical Design Examples

Computational Validation

Conclusions
E-Retail
Since TRISTAN IX

Amazon Retail Ecommerce Sales
US, 2016-2019

Source: eMarketer, June 2018

www.eMarketer.com
Same-Day Delivery

- Same-day delivery (SDD) crucial for e-retail to compete with brick-and-mortar. But...
  - Extremely costly “last mile”.
  - Lower order numbers, fewer economies of scale.
  - Fewer than 1/4 of customers willing to pay, and then only small amount (McKinsey).
  - Flat fees (e.g. Amazon Prime) may help amortize costs.
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- *Simultaneous* order acceptance, picking, packing and last-mile distribution.
  - **This talk:** Delivery by end of day/common order deadline.
Same-Day Delivery

- Operational Models
  - Azi/Gendreau/Potvin (12,14), Campbell/Savelsbergh (05), Klapp/Erera/T. (18a,b,19), Ulmer (17a,b), Ulmer/Thomas (18), Ulmer/Thomas/Mattfeld (18), Voccia/Campbell/Thomas (17), ...
  - Can be used for tactical analysis, but complex and not transparent.
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- Our Goal: Simple, “higher-level” model capturing typical system behavior.
  - What does the “average” SDD operating day look like?
Tactical Dispatching Model

- Single depot with vehicle fleet serving fixed region.
- Orders appear at constant unit rate from 0 to \( N \).
- All orders must be served, dispatches complete by \( T > N \).
- Objective: Minimize total dispatching time.
A dispatch to serve $n$ orders takes $f(n)$ time, where

$$f(0) = 0, \quad f \text{ is increasing, concave, can “keep up”}.$$
Tactical Dispatching Model

Dispatch time

- A dispatch to serve \( n \) orders takes \( f(n) \) time, where
  
  \[ f(0) = 0, \quad f \text{ is increasing, concave, can “keep up”}. \]

- Motivation: \( f(n) = a + bn + c\sqrt{n} \) for \( n > 0 \), where
  - \( c\sqrt{n} \) is a BHH (59) routing time approximation,
  - assuming order locations are randomly distributed.
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- Continuous approximations widely used in logistics (Franceschetti/Jabali/Laporte 17), including urban logistics (Carlsson/Song 18, Figliozzi 07, van Heeswijk/Mes/Schutten 17).
Tactical Dispatching Model

Dispatch time

- For example, for
  1. unit square service region, center depot,
  2. Manhattan distances,
  3. 30 customer locations sampled uniformly,

we estimate TSP length as $1.04\sqrt{n}$.

- Asymptotic constant in this case estimated at $\approx 0.89$ (Johnson/McGeoch/Rothberg 96).
Tactical Dispatching Model

Dispatch time

• Realistic situation:
  1. 8 mile by 8 mile service region (center depot)
  2. 25 mph average vehicle speed, Manhattan distances
  3. an order every 6 minutes
  4. 5-minute dispatch setup, 2-minute delivery per order

• We convert this to

\[
f(n) = 5/6 + 1/3n + 3.3\sqrt{n} \quad (\times \; 6 \; \text{minutes}).
\]
Optimal Structure

Concavity abhors balance

Dispatches should be as unbalanced as possible:

- This looks nice,
Optimal Structure
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- but this is better,
Optimal Structure
Concavity abhors balance

Dispatches should be as unbalanced as possible:

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- but this is better,

- and so is this!
Consequences and Intuition

1. Decreasing dispatch lengths as day progresses.
   
   • Matches empirical observations in operational models (KET 18a,b).
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2. Dispatching (and each vehicle) start inactive, then become active and remain so for rest of day.
   - Useful for shift scheduling.
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3. A dispatch takes all currently unserved orders.
   - Vehicles can be “pre-loaded”.
   - Not necessarily true with geographic order discrimination.
Many Vehicles
Optimal policy

- Each vehicle
  1. takes all available orders,
  2. leaves such that its dispatch ends at $T$.

- Compute by solving equations of the form
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  $$t_1 + f(t_1) = T,$$
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Optimal policy

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\[ t_1 + f(t_1) = T, \quad t_2 + f(t_2 - t_1) = T, \]
\[ t_3 + f(N - t_2) = T, \ldots \]
One Vehicle
Optimal policy

1. Each dispatch takes all available orders.
2. No waiting between dispatches.
3. Last dispatch returns at $T$.

* Minimum dispatch quantity for all dispatches except possibly last one.
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- Try solving progressively higher-order equations:

\[
\begin{align*}
t_1 + f(N - t_1) &= T, & \text{(one dispatch)} \\
t_1 + f(t_1) + f(N - t_1) &= T, & \text{(two)} \\
t_1 + f(t_1) + f(f(t_1)) + f(N - t_1 - f(t_1)) &= T, & \ldots \text{(three)}
\end{align*}
\]
Tactical Design
Fleet sizing

1. $8 \times 8$ mile region, uniformly random locations.
2. An order every 8 minutes for 10 hours, 12-hour day.
3. Manhattan norm, 25 mph, 1 minute service per order.
Tactical Design

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- Many Vehicles: Two dispatches, 64 and 11 orders.
- Single Vehicle: Two dispatches, 55 and 20 orders.
  - Dispatch time increase of only 4%!
Tactical Design

Choosing order cutoff $N$

- If revenue is linear in orders served, how long do we accept orders?
  - Assume fleet can be as large as necessary.

![Diagram showing time intervals $t_1$, $t_2$, and $t_3$ leading to $T$.]
Tactical Design

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- Optimal to maximally utilize dispatched vehicles:

  One vehicle: Can prove similar result for one, two dispatches.
Tactical Design

Other potential applications:

1. Service region partitioning.
   
   • Small areas served by single vehicle, or large area served by many?
Tactical Design

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2. Combining SDD and overnight deliveries.
   - Starting the day with orders accumulated.
Tactical Design

Other potential applications:

1. Service region partitioning.
   • Small areas served by single vehicle, or large area served by many?

2. Combining SDD and overnight deliveries.
   • Starting the day with orders accumulated.

3. Length of work day, size of service region, ...
Computational Validation

1. $8 \times 8$ mile service region (center depot)
2. 25 mph average vehicle speed, Manhattan distances
3. an order every 6 minutes, 12-hour day ($T = 120$)
4. 5-minute setup, 2 minutes per order
Computational Validation

1. $8 \times 8$ mile service region (center depot)
2. 25 mph average vehicle speed, Manhattan distances
3. an order every 6 minutes, 12-hour day ($T = 120$)
4. 5-minute setup, 2 minutes per order

- Choose $N = 105$ to fully utilize three vehicles ($69, 25, 11$).
- Model predicts 554 total minutes of dispatching time.
Computational Validation

Operational benchmark

- Poisson arrivals (6-min. rate), uniformly random locations.
- Compute TSP for all accumulated orders, dispatch when
  \[ \text{setup} + \text{service time} + \text{TSP} = \text{remaining time}. \]
- Repeat three times (update cutoff operationally).
Computational Validation
Operational benchmark

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- Compute TSP for all accumulated orders, dispatch when \( \text{setup + service time + TSP} = \text{remaining time} \).
- Repeat three times (update cutoff operationally).

![Histogram of simulated total orders served](chart)

- 1,000 simulations
- 103.4 avg. orders served (predicted 105)
- 550 avg. minutes (predicted 554)
Conclusions

- Expect unbalanced dispatches in SDD.
  - Decreasing dispatch lengths.
  - Divide day into inactive/active parts.

- Use policy structure for tactical design.
  - Fleet sizing, cutoff time, partitioning, ...
  - Accurate operational predictions (within 1%-1.5%).
Conclusions

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  - Fleet sizing, cutoff time, partitioning, ...
  - Accurate operational predictions (within 1%-1.5%).

- Ongoing and future work:
  - Finite fleet of two or more.
  - Choosing service area, varying over day.

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