Same-Day Delivery: Tactical Design

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Motivation?
Motivation

Same Day Delivery in Manhattan

Order online by 11am. Get it by 7pm.
E-Retail

• E-retail is a large and growing sector of retail and overall economy.
  • About or above 10% of all US retail since 2013 (Forrester Research).
  • Average annual online spending to reach $2,000 per buyer in 2018 (Forrester Research).
  • Amazon alone accounts for almost half of US e-retail (eMarketer).
  • Amazon now second to Walmart in terms of global employment numbers (566K vs. 2.3M); both very active in e-retail (Fortune).

• No longer the future – this is the present.
E-Retail

Amazon Retail Ecommerce Sales
US, 2016-2019

Source: eMarketer, June 2018

www.emarketer.com
Same-Day Delivery

• Intense competition in e-retail, constant need for innovation – the customer wants it NOW.

• Same-day delivery (SDD) further erodes brick-and-mortar advantage. But...
Same-Day Delivery

- Intense competition in e-retail, constant need for innovation – the customer wants it NOW.

- Same-day delivery (SDD) further erodes brick-and-mortar advantage. 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.
Same-Day Delivery

What’s new?

- Traditional delivery: order acceptance, picking and packing *before* last-mile distribution.

- Overnight/next-day delivery, two-day delivery, cheaper/free regular delivery.
Same-Day Delivery

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• Traditional delivery: order acceptance, picking and packing before last-mile distribution.
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• Same-day delivery: simultaneous order acceptance, picking, packing and last-mile distribution.
  • This talk: Delivery by end of day/common order deadline.
  • Food/grocery delivery: order-specific delivery times, 30 minutes to two hours (Amazon Restaurants, GrubHub, Uber Eats, pizza delivery).
Same-Day Delivery

What’s new?

- Orders placed between 12pm and 2pm
- Orders placed between 2pm and 4pm
- Orders placed between 4pm and 6pm

Source: A. Erera
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.
Same-Day Delivery

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- Our Goal: Simple, “higher-level” model capturing typical system behavior.
  - What does the “average” SDD operating day look like?
Outline

Introduction

Tactical Model

Tactical Design Examples

Computational Validation

Ongoing Work and Conclusions
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.
Tactical Dispatching Model

Dispatch time

\[ n \quad f(n) \]

- 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

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- 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, Figliozi 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

\[ f(n) = \frac{5}{6} + \frac{1}{3n} + 3.3\sqrt{n} \times 6 \text{ minutes}. \]
Optimal Structure
Concavity abhors balance

Dispatches should be as unbalanced as possible:

- This looks nice,
Optimal Structure

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- This looks nice,

- but this is better,
Optimal Structure

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Dispatches should be as unbalanced as possible:

- This looks nice,

- 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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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:

\[
\begin{align*}
    t_1 + f(N) &= T, \\
    t_1 + f(t_1) + f(N - t_1) &= T, \\
    t_1 + f(t_1) + f(f(t_1)) + f(N - t_1 - f(t_1)) &= T, \ldots
\end{align*}
\]
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.
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![Diagram showing optimal utilization of vehicles with time intervals $t_1$, $t_2$, $t_3$, and $T$.]

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

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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 × 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

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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

  \[ \text{setup + service time + TSP = remaining time.} \]

• Repeat three times (update cutoff operationally).
Computational Validation

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

- 1,000 simulations
- 103.4 avg. orders served (predicted 105)
- 550 avg. minutes (predicted 554)
Ongoing Work: Choosing Service Region(s)

• For given $T$, choose both dispatch times and areas to maximize orders served.
  • Unit arrival rate per time, area unit.
  • Areas’ radii may change, but fixed geometry (e.g. circle).

• Dispatch time: $f(A, n) = c\sqrt{An}$
  • Serving orders in $A$ over $t$ takes $f(A, At) = cA\sqrt{t}$ time.
Ongoing Work: Choosing Service Region(s)

- One-vehicle, one-dispatch setting equivalent to

\[ \max_{0 \leq t_1 \leq T} (T - t_1)\sqrt{t_1}, \quad t_1^* = T/3. \]
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  \[ \max_{0 \leq t_1 \leq T} (T - t_1)\sqrt{t_1}, \quad t_1^* = T/3. \]

- For one vehicle, two dispatches,
  \[ t_1^* = T/9, \quad t_2^* = 5T/9 \quad A_1^* = 2A_2^*. \]
Ongoing Work: Choosing Service Region(s)

• One-vehicle, one-dispatch setting equivalent to

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\[ t_1^* = T / 9, \quad t_2^* = 5T / 9 \quad A_1^* = 2A_2^*. \]

Theorem

One-dispatch solution is 1/2-approximation of any solution with one vehicle, arbitrarily many dispatches.

• Empirically, two-dispatch solution is within about 1%. 
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%).
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• Future work:
  • Finite fleet of two or more.

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