Same-Day Delivery: Tactical Design

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Pre-COVID, e-commerce was already 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).

COVID has only accelerated these trends.
E-Commerce

Amazon Retail Ecommerce Sales
US, 2016-2019

Source: eMarketer, June 2018
Same-Day Delivery

- Intense competition, 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, 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.
Same-Day Delivery

What’s new?

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

• 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,20), 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

Tactical Model

Tactical Design Examples

Computational Validation

Conclusions and Ongoing Work
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

- A dispatch to serve $n$ orders takes $f(n)$ time, where

$$f(0) = 0, \quad f \text{ is increasing, concave, can “keep up”}.$$
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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, Figliozzi 07, van Heeswijk/Mes/Schutten 17).
For example, for

1. unit square service region, center depot,
2. Manhattan distances,
3. roughly 30 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

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

Concavity abhors balance

Dispatches should be as unbalanced as possible:

• This looks nice,
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• but this is better,
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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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$$t_1 + f(t_1) = T, \quad t_2 + f(t_2 - t_1) = T,$$
$$t_3 + f(N - t_2) = T,$$
$$\ldots$$
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:

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

- Optimality depends on parameters; no general structure.
- Hybrid heuristic: For $m$ vehicles,
  1. first $m - 1$ follow many-vehicle policy,
  2. last one serves remainder with one-vehicle policy.
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- Hybrid heuristic: For $m$ vehicles,
  1. first $m - 1$ follow many-vehicle policy,
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- For $f(n) = bn + c\sqrt{n}$, heuristic has approximation guarantee
  \[
  \frac{m - 1 + D_m\sqrt{D_m}}{m - 1 + D_m},
  \]
  $D_m$ is number of dispatches for $m$-th vehicle.
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.
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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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\[\text{Vehicle Utilization over Time: } t_1, t_2, t_3, T\]
Tactical Design
Choosing order cutoff $N$

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  - Assume fleet can be as large as necessary.
- 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

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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.
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3. Length of work day, size of service region, ...
Computational Validation
Case study in Northeastern Atlanta

- 22 census tracts, about 92,000 people.
  - Five addresses per tract, 110 total.
  - Depot in northeast border.
Computational Validation

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• 22 census tracts, about 92,000 people.
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• Service day: 9AM - 6PM.
  • Orders every six minutes.
  • Location chosen proportional to tract’s population times median income.
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- 22 census tracts, about 92,000 people.
  - Five addresses per tract, 110 total.
  - Depot in northeast border.
- Service day: 9AM - 6PM.
  - Orders every six minutes.
  - Location chosen proportional to tract’s population times median income.
- Driving times given by Google API.
  - Driving time calibrated to $24\sqrt{n}$ minutes.
  - 10-min setup per dispatch, 1.5-min service per order.
Computational Validation

Benchmarks

- Two-vehicle fleet:
  - Order cutoff at 3:40 ($N = 66.7$) for full utilization.
  - Model predicts 389 minutes of dispatch time.
Computational Validation

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- Operational benchmark:
  - Poisson arrivals (6-min. rate).
  - Compute TSP for all accumulated orders, dispatch when $\text{setup} + \text{service time} + \text{TSP} = \text{remaining time}$. 
Computational Validation

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

- Hindsight-optimal benchmark:
  - Dispatch with full knowledge of each order’s time and location.
  - Lower bound for any operational policy.
## Computational Validation

### Results

<table>
<thead>
<tr>
<th></th>
<th>Tactical</th>
<th>Operational</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dispatch 1</td>
<td>48.40 units</td>
<td>48.20 units</td>
</tr>
<tr>
<td></td>
<td>249.58 min.</td>
<td>249.69 min.</td>
</tr>
<tr>
<td>Dispatch 2</td>
<td>18.26 units</td>
<td>18.45 units</td>
</tr>
<tr>
<td></td>
<td>139.95 min.</td>
<td>139.16 min.</td>
</tr>
<tr>
<td>Total</td>
<td>66.66 units</td>
<td>66.65 units</td>
</tr>
<tr>
<td></td>
<td>389.53 min.</td>
<td>388.85 min.</td>
</tr>
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- Benchmark metrics computed over 300 simulations.
- Tactical predictions vs. operational observations within 1%.
- Similar results for one-vehicle case, different cutoff.
Computational Validation

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<tr>
<td>Dispatch 1</td>
<td>48.40 units</td>
<td>48.20 units</td>
<td>43.90 units</td>
</tr>
<tr>
<td></td>
<td>249.58 min.</td>
<td>249.69 min.</td>
<td>228.07 min.</td>
</tr>
<tr>
<td>Dispatch 2</td>
<td>18.26 units</td>
<td>18.45 units</td>
<td>22.75 units</td>
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<tr>
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<td>139.95 min.</td>
<td>139.16 min.</td>
<td>144.88 min.</td>
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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% or less).
Ongoing Work

- Choosing service region(s) and cutoff time(s).
  - Should we serve different customers differently?
  - In-town versus suburban, near versus far...
- Region partitioning and fleet sizing in tandem.
  - How many vehicles do we need assuming they serve different regions differently?

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