Same-Day Delivery: Tactical Design

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joint with Alex Stroh, Alan Erera

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E-Commerce

- 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
$149.79
$199.85
$258.22
$325.04
38.3%
44.1%
49.1%
53.7%
2016
2017
2018
2019
billions
% of total retail ecommerce sales
Source: eMarketer, June 2018
www.eMarketer.com

Same-Day Delivery

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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?

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Same-Day Delivery

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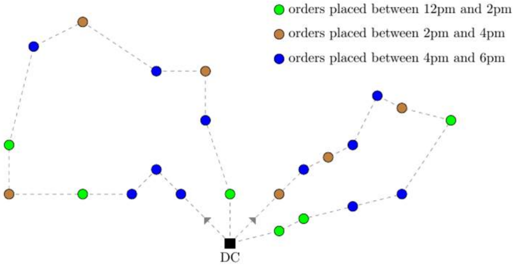
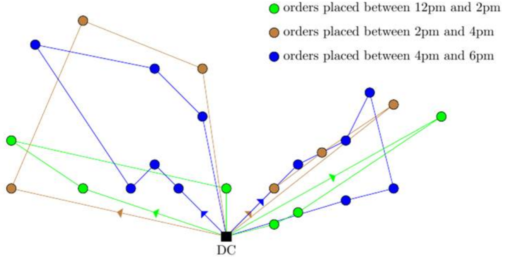
- Traditional delivery: order acceptance, picking and packing *before* last-mile distribution.
- Same-day delivery: *simultaneous* order acceptance, picking, packing and last-mile distribution.
  - This talk: Delivery by end of day/common order deadline.
  - Food/grocery delivery: order-specific delivery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

Same-Day Delivery

What's new?





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 (19), Voccia/Campbell/Thomas (17), ...
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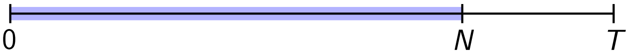
  - Can be used for tactical analysis, but complex and not transparent.
- Our Goal: Simple, “higher-level” model capturing typical system behavior.
  - What does the “average” SDD operating day look like?

Outline

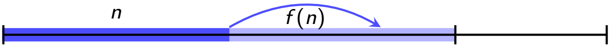
Tactical Dispatching Model



- 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

$$f(0) = 0, \quad f \text{ is increasing}, \quad \text{concave}, \quad \text{can ``keep up''}.$$

Tactical Dispatching Model

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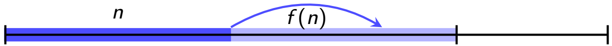

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- Motivation: $f(n) = a + bn + c\sqrt{n}$ for $n > 0$, where
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  - assuming order locations are randomly distributed.

Tactical Dispatching Model

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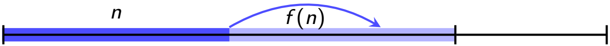

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  - $c\sqrt{n}$ is a BHH (59) routing time approximation,
  - assuming order locations are randomly distributed.

- *Continuous approximations* widely used in logistics (Franceschetti/Jabali/Laporte 17), including urban logistics (Carlsson/Song 18, Figliozzi 07, van Heeswijk/Mes/Schutten 17).

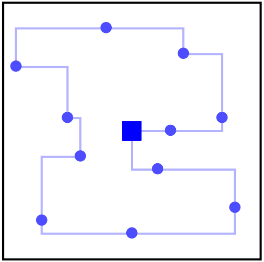
Tactical Dispatching Model

Dispatch time

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

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

$\mathbb{E}[\text{TSP}_n] \approx 1.04\sqrt{n}$



- Asymptotic constant in this case estimated at ≈ 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

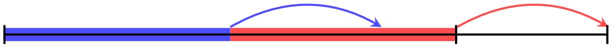
$$f(n) = 5/6 + 1/3n + 3.3\sqrt{n} \quad (\times\ 6 \text{ minutes}).$$

Optimal Structure

Concavity abhors balance

Dispatches should be as unbalanced as possible:

- This looks nice,



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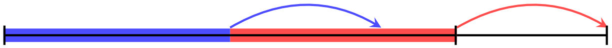

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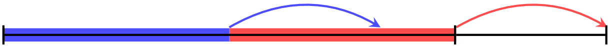
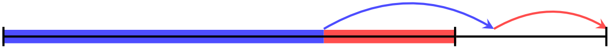


- but this is better,

- and so is this!



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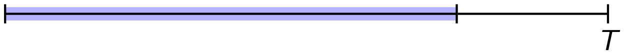
   - Matches empirical observations in operational models (KET 18a,b).
2. Dispatching (and each vehicle) start inactive, then become active and remain so for rest of day.
   - Useful for shift scheduling.
3. A dispatch takes all currently unserved orders.
   - Vehicles can be "pre-loaded".
   - Not necessarily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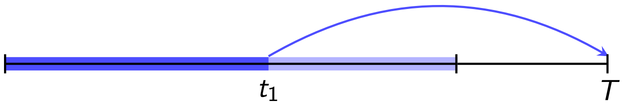

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$$t_1 + f(t_1) = T,$$

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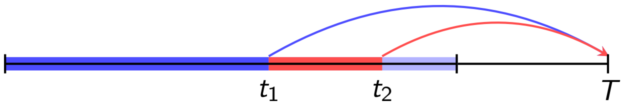

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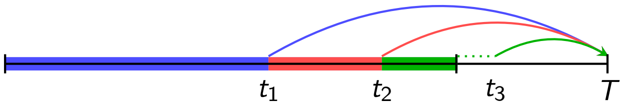

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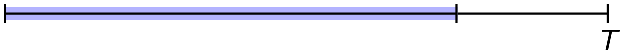
- Compute by solving equations of the form

$$t_1 + f(t_1) = T, \qquad t_2 + f(t_2 - t_1) = T,$$
$$t_3 + f(N - t_2) = T, \ldots$$

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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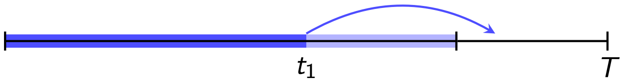

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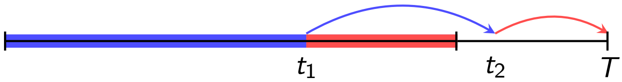

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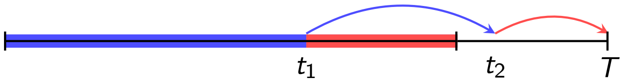

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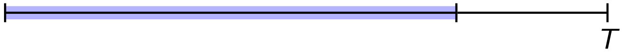
- Try solving progressively higher-order equations:

$$t_1 + f(N) = T, \qquad \text{(one dispatch)}$$
$$t_1 + f(t_1) + f(N - t_1) = T, \qquad \text{(two)}$$
$$t_1 + f(t_1) + f(f(t_1)) + f(N - t_1 - f(t_1)) = T, \ldots \qquad \text{(three)}$$

Finite Fleet



- Optimality depends on parameters; no general structure.
- Hybrid heuristic: For m vehicles,
    1. first $m-1$ follow many-vehicle policy,
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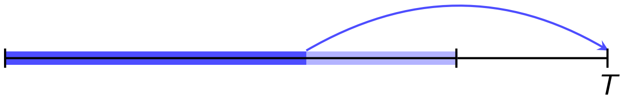

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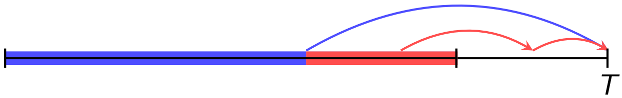

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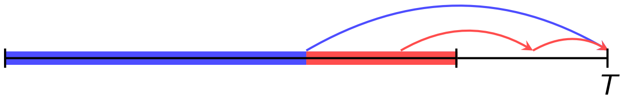

- Optimality depends on parameters; no general structure.
- Hybrid heuristic: For m vehicles,
  1. first $m-1$ follow many-vehicle policy,
  2. last one serves remainder with one-vehicle policy.
- For $f(n) = bn + c\sqrt{n}$, heuristic has approximation guarantee

$$\frac{m - 1 + D_m\sqrt{D_m}}{m - 1 + D_m},$$

D_m is number of dispatches for m-th vehicle.

Tactical Design

Fleet sizing

1. 8×8 mile region, uniformly random locations.
2. An order every 8 minutes for 10 hours, 12-hour day.
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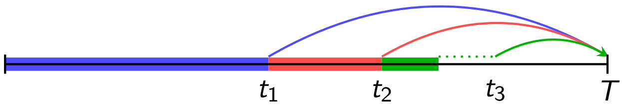
- Many Vehicles: Two dispatches, 64 and 11 orders.
- Single Vehicle: Two dispatches, 55 and 20 orders.
  - Dispatch time increase of only 4%!

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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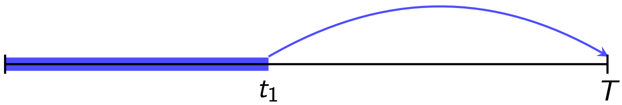

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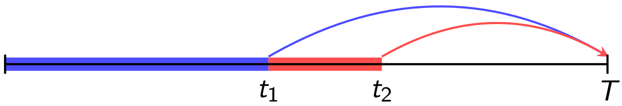

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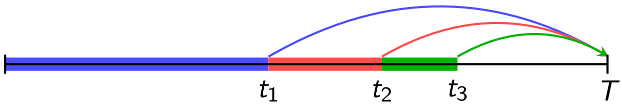

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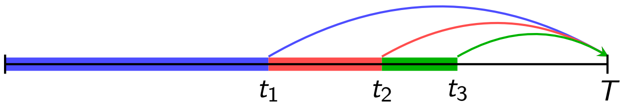

One vehicle: Can prove similar result for one, two dispatches.

Tactical Design

Other potential applications:

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

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Other potential applications:

1. Service region partitioning.
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2. Combining SDD and overnight deliveries.
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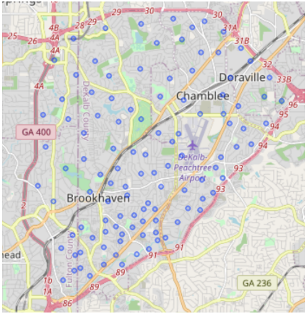
3. Length of work day, size of service region, ...

Computational Validation

Case study in Northeastern Atlanta

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



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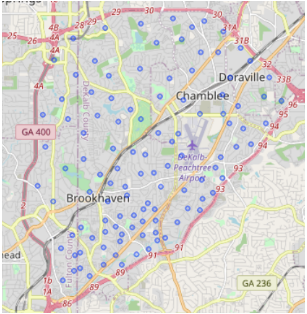

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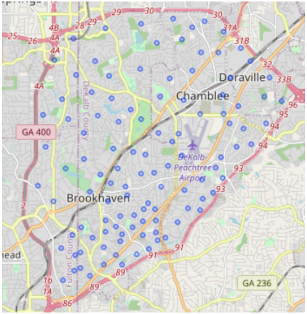
- Service day: 9AM - 6PM.
  - Orders every six minutes.
  - Location chosen proportional to tract's population times median income.
- Driving times given by Google API.
  - Driving time calibrated to $24\sqrt{n}$ minutes.
  - 10-min setup per dispatch, 1.5-min service per order.



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- Two-vehicle fleet:
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- Hindsight-optimal benchmark:
  - Dispatch with full knowledge of each order's time and location.
  - Lower bound for any operational policy.

Computational Validation

Results

	Tactical	Operational	
Dispatch 1	48.40 units	48.20 units	
	249.58 min.	249.69 min.	
Dispatch 2	18.26 units	18.45 units	
	139.95 min.	139.16 min.	
Total	66.66 units	66.65 units	
	389.53 min.	388.85 min.	

- Benchmark metrics computed over 300 simulations.
- Tactical predictions vs. operational observations within 1%.
- Similar results for one-vehicle case, different cutoff.

Computational Validation

Results

	Tactical	Operational	HSO
Dispatch 1	48.40 units	48.20 units	43.90 units
	249.58 min.	249.69 min.	228.07 min.
Dispatch 2	18.26 units	18.45 units	22.75 units
	139.95 min.	139.16 min.	144.88 min.
Total	66.66 units	66.65 units	66.65 units
	389.53 min.	388.85 min.	372.95 min.

- Benchmark metrics computed over 300 simulations.
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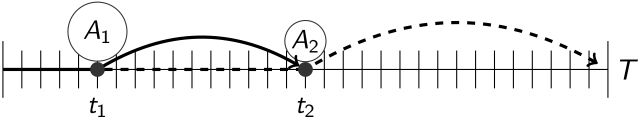
- Similar results for one-vehicle case, different cutoff.

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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http://www.isye.gatech.edu/~atoriello3/