Vergleichende Bewertung der Paketdistribution mit Drohnen und Lieferwagen

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82. Jahrestagung des VHB

Frankfurt, 19.03.2020

Outline

Motivation

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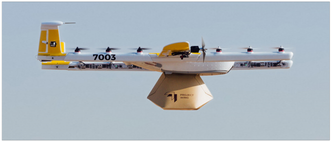

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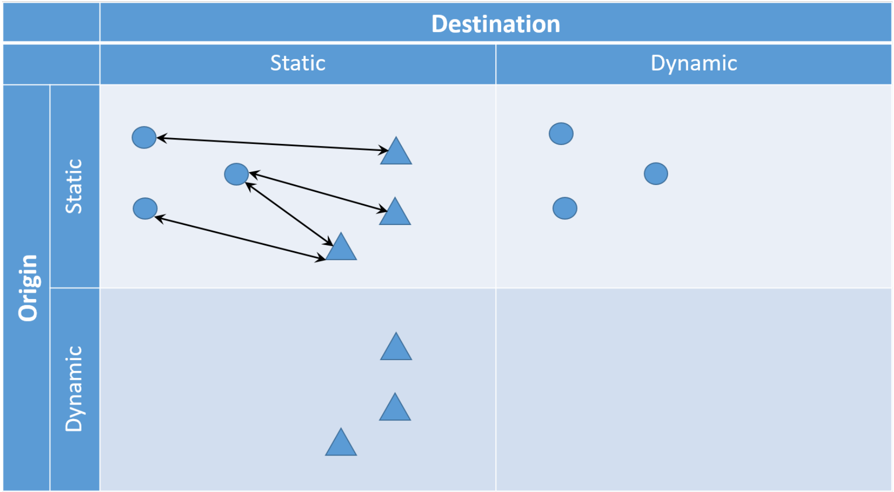
Perceived advantages:

- fast & flexible → same-day deliver within 30 minutes [Amazon, 2019]
- cost efficient → 1 $ per delivery [Wang, 2016], 1-5 ct per mile [Peers, 2018]
- green → no/less GHG emissions than trucks [Goodchild and Toy, 2018]
- save → less accidents, less congestion [Crowe, 2019]

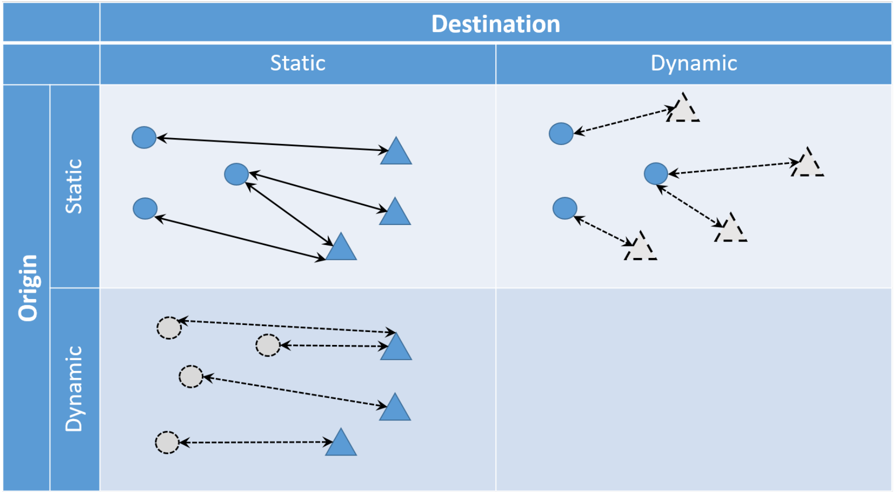
Current status:

- some pilot projects [e.g. blood samples, Scott et al., 2017]
- Alphabet Wing drones received regulatory permission in US and Australia [Lee, 2019]
- Amazon Prime Air expected to receive permission in 2019 [Lee, 2019]

Application scenarios



Application scenarios



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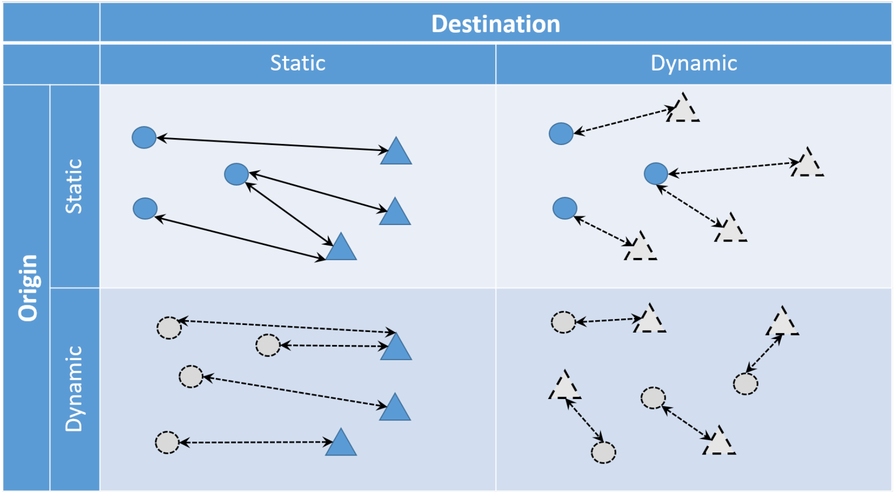
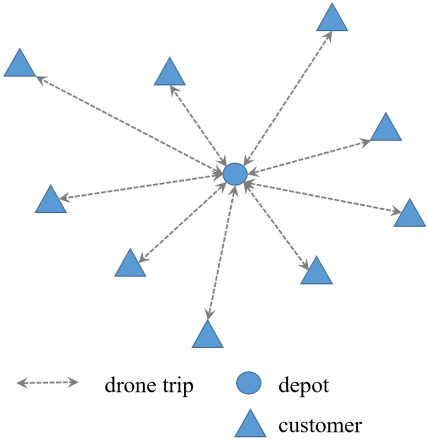


Application scenarios

		Destination	
		Static	Dynamic
Origin	Static		
	Dynamic		

Performance of stationary drone delivery systems



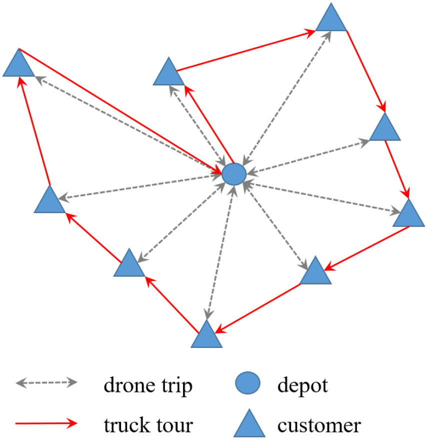
Assumptions:

- fixed depot & customer locations
- technological specifications
- drone capacity: 1 parcel

KPIs:

- service time
- investment cost
- operating cost
  - operator
  - wear-&-tear
  - energy
- emissions

Performance of stationary drone delivery systems



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- service time
- investment cost
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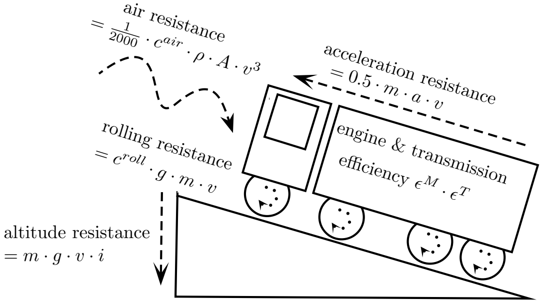
  - wear-&-tear
  - **energy**
- **emissions**

$\Longrightarrow$ comparison of energy demand and associated emissions between trucks and drones

Power demand & energy consumption

Demir et al. [2014], Kirschstein and Meisel [2015]



$$P^{EDV} = P^{roll} + P^{air} + P^{climb} + P^{acc} + P^{aux}$$

$$E^{DV} = \left(t \cdot \left(f^{idle} + \frac{f^{full} - f^{idle}}{\epsilon^T_{DV}(v) \cdot P} \cdot P^{EDV} \right) \cdot N_{Diesel} \right) \cdot \frac{1}{\epsilon^{wtt}_{Diesel}}$$

$$E^{EV} = t \cdot \frac{P^{EDV}}{\epsilon_{EV} \cdot \epsilon^{charg} \cdot \epsilon^{wtt}_{elec}}$$

Technical specifications of DV & EV

Saenz et al. [2016], Goeke and Schneider [2015], Murakami [2017]

DVs

©ramtrucks.com

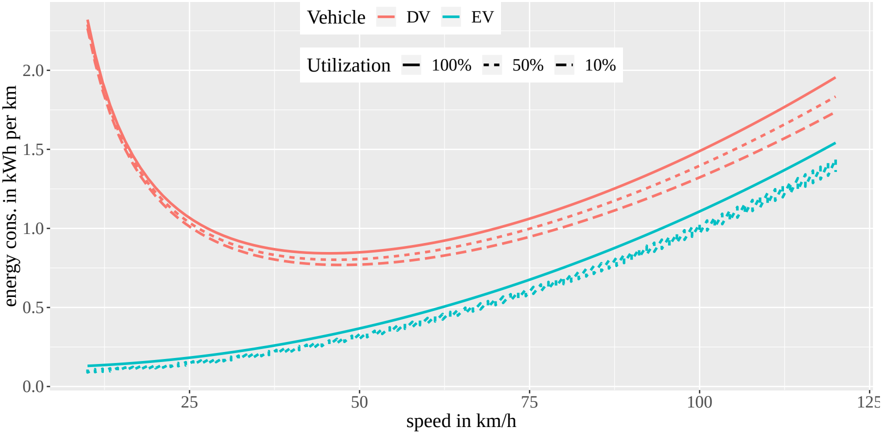
- engine power: 180 kW
- tare weight: 1.5 t
- max. payload: 0.8 t
- fuel cons.: 2-25 l/h

EVs

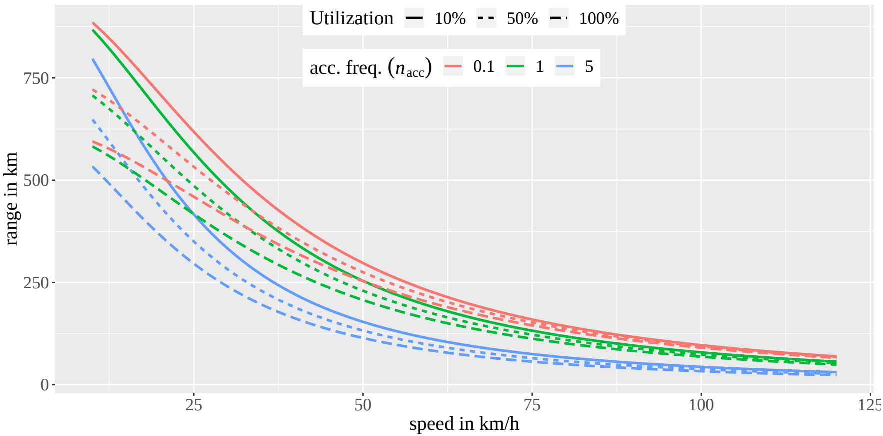
©ups.com

- engine power: 190 kW
- tare weight: 2.0 t
- max. payload: 0.75 t
- battery: 80 kWh

DV & EV energy consumption

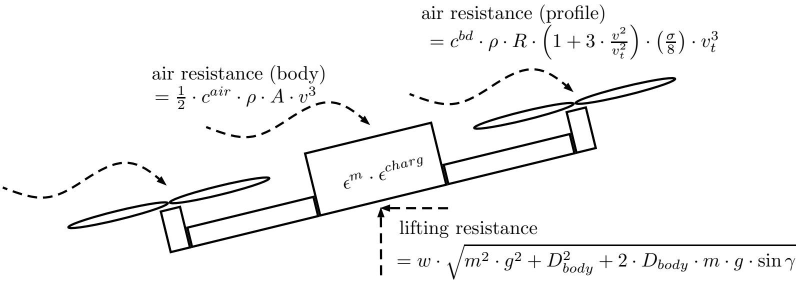


EV range


Utilization
10%
50%
100%
acc. freq. (n_{acc})
0.1
1
5
range in km
750
500
250
0
25
50
75
100
125
speed in km/h

Power demand UAVs

Langelaan et al. [2017], D'Andrea [2014], Figliozzi [2017]

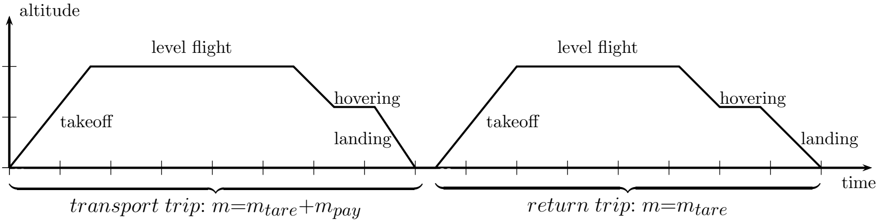


$$P^{UAV}(m, v, \gamma) = P^{air} + \kappa \cdot P^{lift} + P^{profile} + P^{climb} + P^{aux}$$

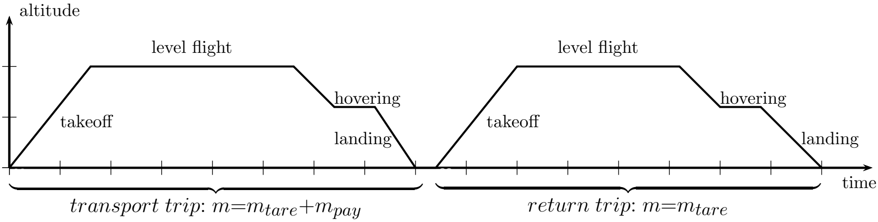
$$E^{UAV}(m, v, \gamma) = \frac{t}{\epsilon^{charg} \cdot \epsilon_{elec}^{wtt}} \cdot \left(\frac{P^{air} + \kappa \cdot P^{lift} + P^{profile} + P^{climb}}{\epsilon_{UAV}} + P^{aux} \right)$$

$\Longrightarrow$ time depends on speed v, distance d, and wind v_{head} $\rightarrow t = \frac{d}{v - v_{head}} = \frac{d}{v_{net}}$

UAV flight pattern & energy cosumption model



UAV flight pattern & energy cosumption model



$$E^{UAV} = \frac{1}{\epsilon_{UAV} \cdot \epsilon^{charg} \cdot \epsilon^{ttw}_{elec}} \cdot (\qquad \text{efficiency correction}$$

$$t_{tol} \cdot \left(P^{UAV}(m, \nu, 45^\circ) + P^{UAV}(m, \nu, -45^\circ)\right) + \qquad \text{take-off and landing}$$

$$t_{lf} \cdot P^{UAV}(m, \nu, 0^\circ) + \qquad \text{level flight}$$

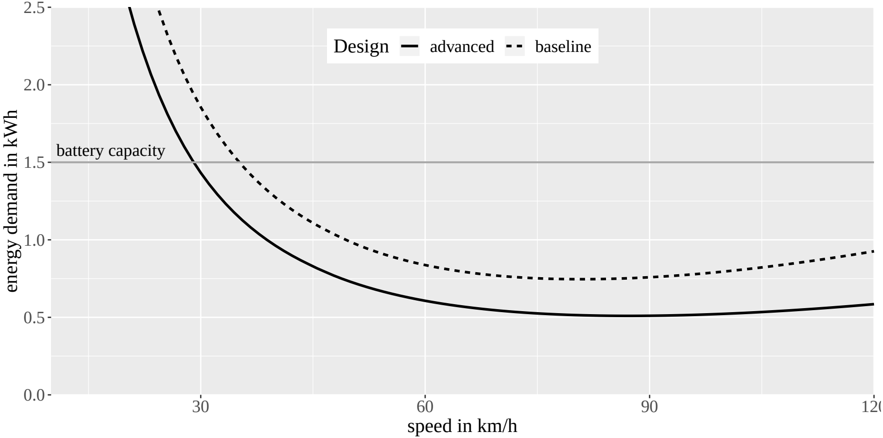
$$t_{hover} \cdot P^{UAV}(m, |\nu_{head}|, 0^\circ)) + \qquad \text{hovering}$$

$$t \cdot \frac{P^{aux}}{\epsilon^{charg}_{UAV}} \qquad \text{auxiliaries}$$

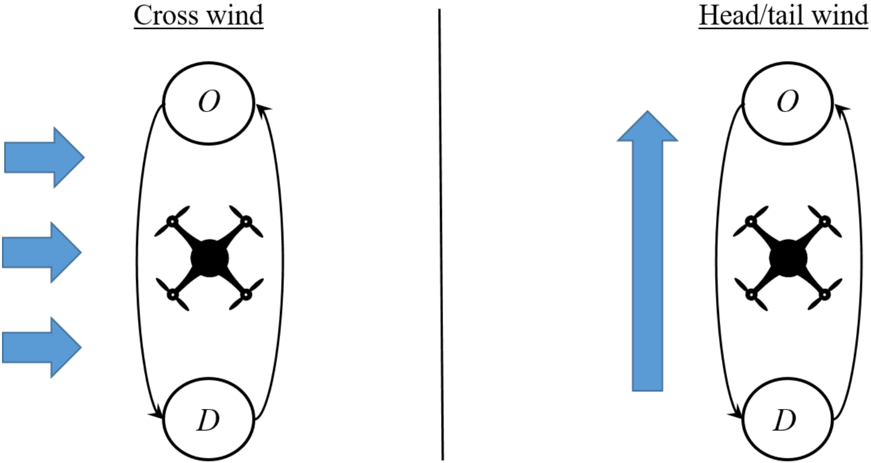
$\Longrightarrow t = t_{lf} + t_{hover} + 2 \cdot t_{tol}$ with $t_{lf} = \frac{d}{v_{net}} - 2 \cdot t_{tol}$ and $t_{tol} = \frac{a}{v_{net}}$

UAV energy consumption depending on speed

idealized trip with 16 km range

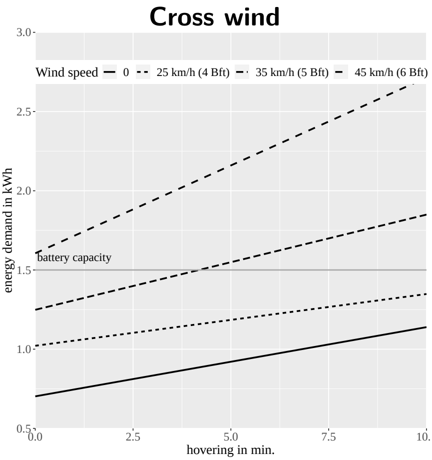


Wind effects



UAV energy consumption depending on wind & hovering

idealized trip with 16 km range



UAV energy consumption depending on wind & hovering

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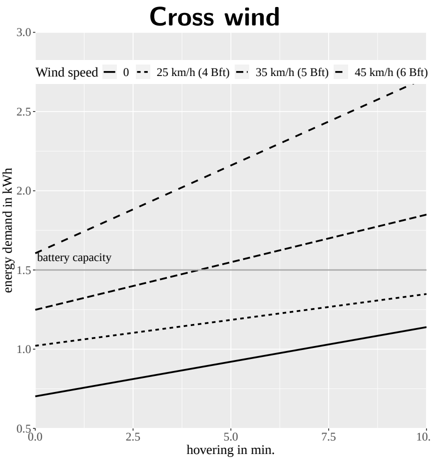
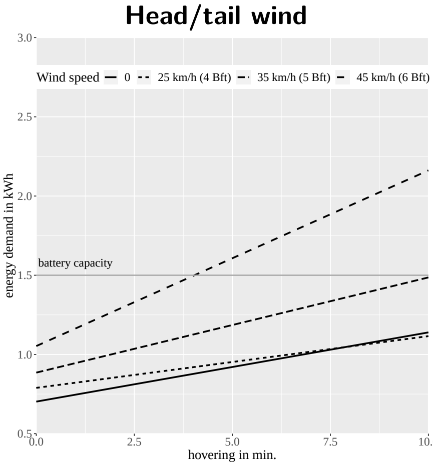
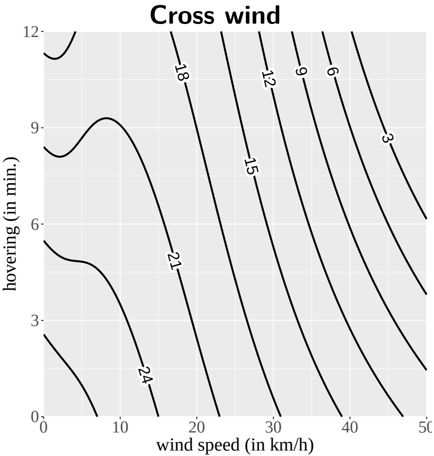
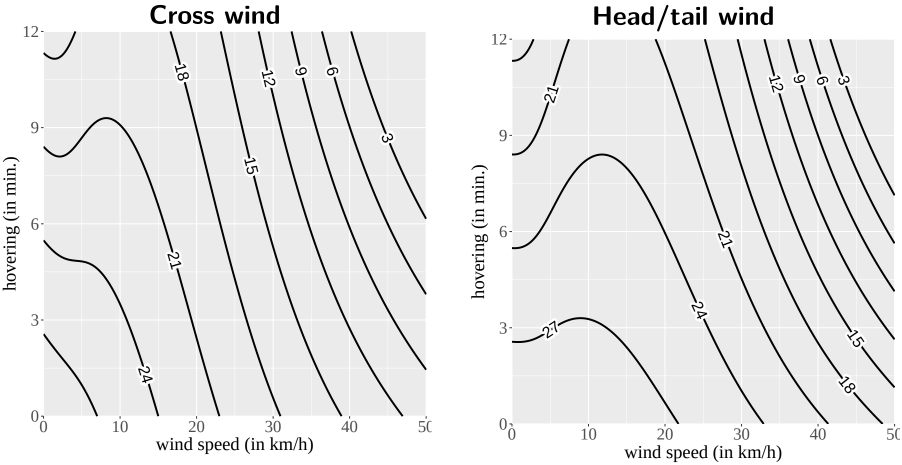




UAV range function (in km)

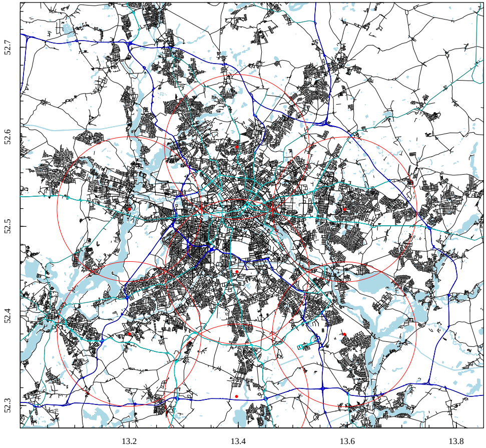


UAV range function (in km)



Simulation setting - general assumptions

Network data



- road network of city of Berlin; 3 road types (highways, primary, residential) differing w.r.t. speed and acceleration frequency
- each customer receives 1 parcel
- each parcel weighs 2.5 kg
- vehicles start from depot
- DVs and EVs use roads; UAVs fly directly
- UAVs hover for 5 minutes
- each UAV can carry 1 parcel
- delivery area with radius 9 km

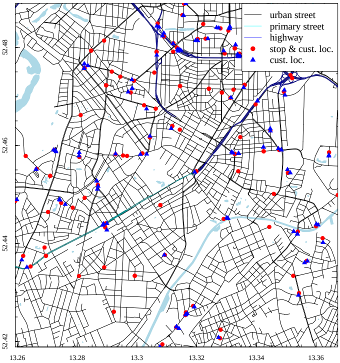
Simulation setting - experimental design

Customer data

- # customers/tour: $[110, 140, 170, 200]$
- # stops/tour: 100

$\rightarrow$ 1.1 - 2.0 cust./stop

- radius customer area: $[2, 4, 6, 8]$ km



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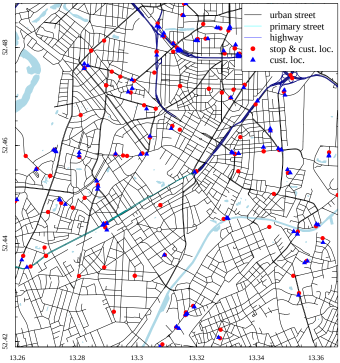

Traffic & wind conditions

level	traffic: mean speed $\bar{v}$	traffic: acc. freq. n_{acc}	wind: head wind v_{wind}
low	$1 \cdot \hat{v}$	$0.5 \cdot \hat{n}_{acc}$	$N(0, 5)$
medium	$0.95 \cdot \hat{v}$	$1 \cdot \hat{n}_{acc}$	$N(25, 5)$
high	$0.67 \cdot \hat{v}$	$2 \cdot \hat{n}_{acc}$	$N(45, 5)$

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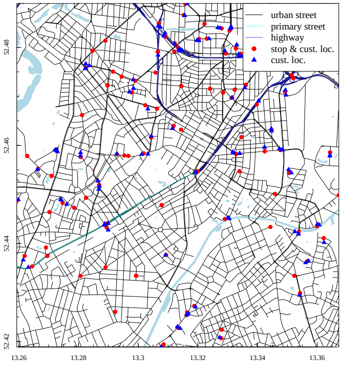

Traffic & wind conditions

	traffic		wind
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Design:

- full factorial design: 4 factors with 4 levels (cust. data) and 3 levels (env. cond.)

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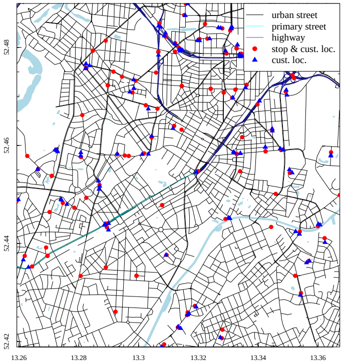

Traffic & wind conditions

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→ $4^2 \cdot 3^2 = 144$ settings

Simulation setting - experimental design

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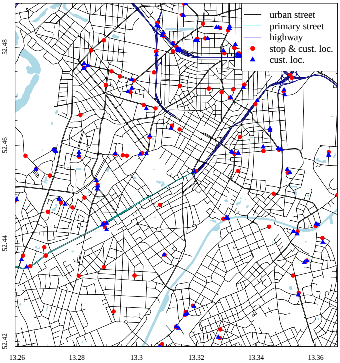

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- for each setting: 200 replications

Simulation setting - experimental design

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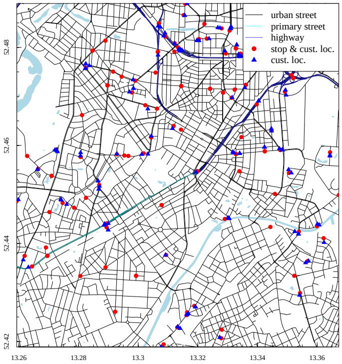

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Design:

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→ $4^2 \cdot 3^2 = 144$ settings

- for each setting: 200 replications

→ 28,800 instances

Simulation setting - experimental design

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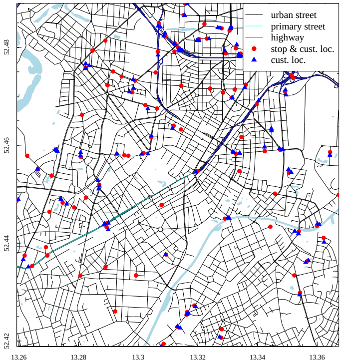

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→ $4^2 \cdot 3^2 = 144$ settings

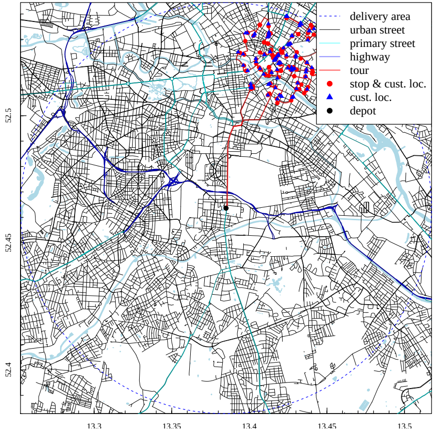
- for each setting: 200 replications

→ 28,800 instances

- per instance: solve TSP & calculate WTW energy demands

Delivery area & EV/DV tours (100 stops)

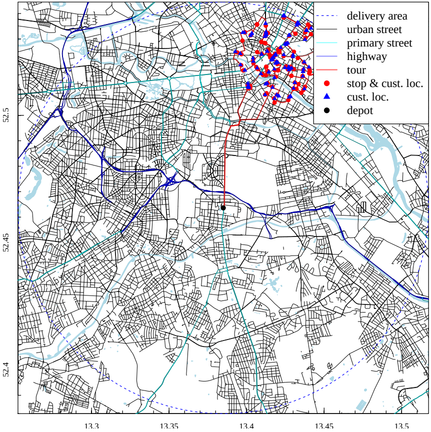
cust. radius: 2 km / # cust.: 200



average tour length: ≈ 45-55 km

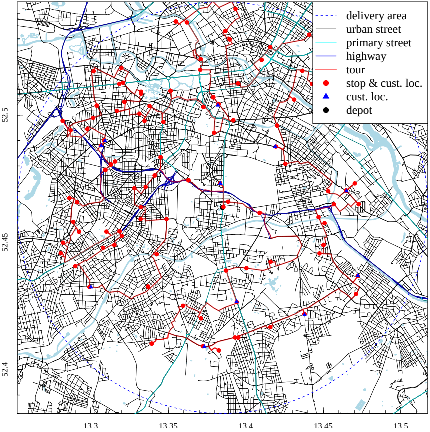
Delivery area & EV/DV tours (100 stops)

cust. radius: 2 km / # cust.: 200



average tour length: ≈ 45-55 km

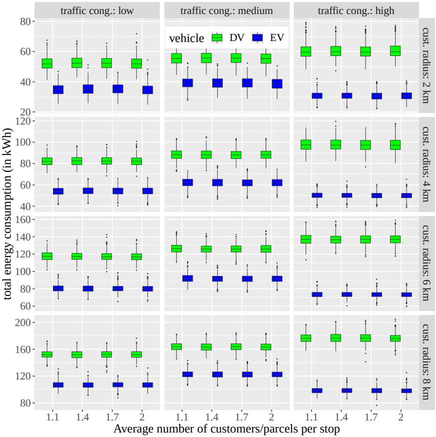
cust. radius: 8 km / # cust.: 110



average tour length: ≈ 145-155 km

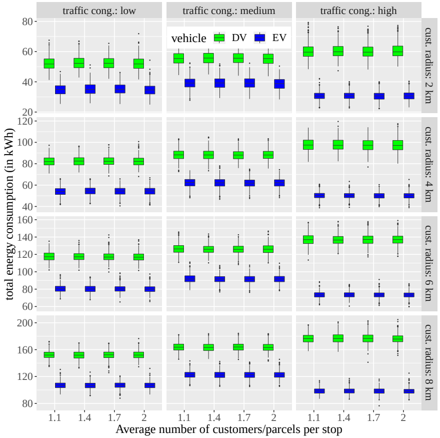
Total energy consumption

Ground-based vehicles only

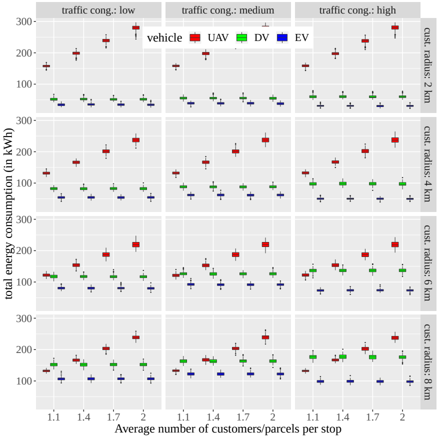


Total energy consumption (medium wind)

Ground-based vehicles only

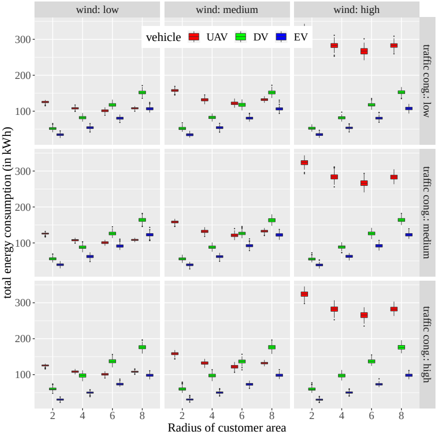


All vehicles



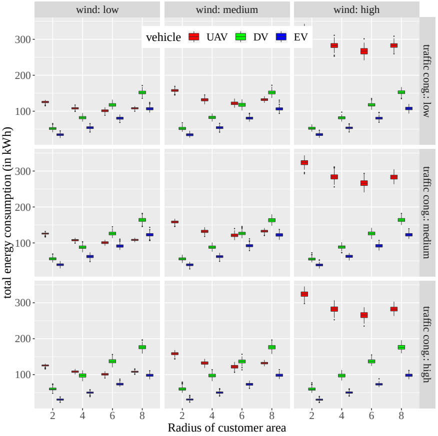
Total energy consumption

1.1 customers/stop

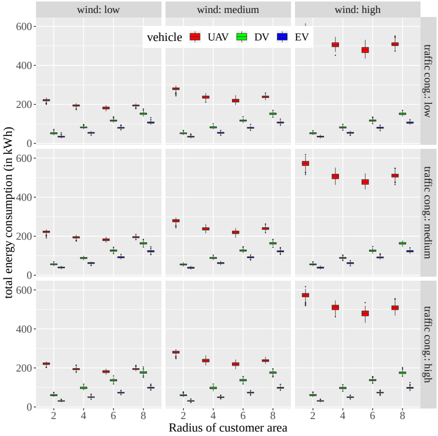


Total energy consumption

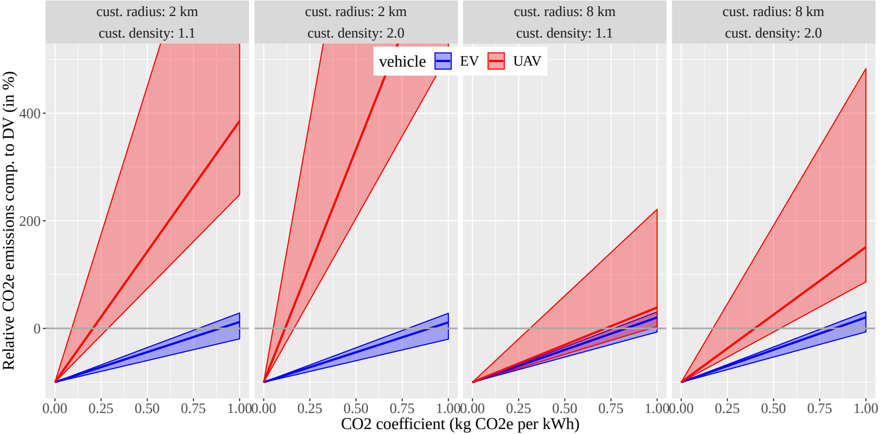
1.1 customers/stop



2.0 customers/stop



GHG reduction potential (compared to DVs)



Summary

- energy demand of drones heavily depends on environmental conditions
- hovering can be an important aspect for drone delivery systems
- delivery by drone typically requires more energy than EVs
- drones require less energy when parcel and customer density

→ most probably not useful in cities

→ but potentially useful in rural areas

  - less energy demand than trucks
  - less dense road infrastructure
  - more predictable weather conditions
  - potentially easier drop-down conditions
  - less regulatory concerns (e.g. due to accident risk etc.)

Finally...

Thanks for your attention.

Kirschstein, T. (2020): Comparison of energy demands of drone-based and ground-based parcel delivery services, *Transportation Research Part* D, 78.

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Simulation parameters

WTT energy efficiency:
Diesel: 90 % ; Electricity: 50 %

Technical vehicle parameters:

<table>
<tr><th rowspan="2">parameter</th><th rowspan="2">description</th><th rowspan="2">unit</th><th rowspan="2">DV</th><th rowspan="2">EV</th><th colspan="2">UAV</th></tr>
<tr><th>curr.</th><th>imp.</th></tr>
<tr><td>A</td><td>frontal surface area</td><td>m^2</td><td colspan="2">6</td><td>0.15</td><td>0.15</td></tr>
<tr><td>m_{tare}</td><td>tare weight</td><td>ton</td><td colspan="2">2.5</td><td>0.012</td><td>0.012</td></tr>
<tr><td>P</td><td>engine power</td><td>kW</td><td>150</td><td>190</td><td>—</td><td>—</td></tr>
<tr><td>P_{int}</td><td>power internal auxiliaries</td><td>kW</td><td>0.1</td><td>0.1</td><td>0.1</td><td>0.1</td></tr>
<tr><td>f_{idle}</td><td>fuel consumption (idle)</td><td>l/h</td><td>1</td><td>—</td><td>—</td><td>—</td></tr>
<tr><td>f_{full}</td><td>fuel consumption (full)</td><td>l/h</td><td>25</td><td>—</td><td>—</td><td>—</td></tr>
<tr><td>NHV_{diesel}</td><td>net heating value</td><td>kWh/l</td><td>10</td><td>—</td><td>—</td><td>—</td></tr>
<tr><td>cap_{batt}</td><td>battery capacity</td><td>kWh</td><td>—</td><td>80</td><td>1.5</td><td>1.5</td></tr>
<tr><td>z_{batt}</td><td>energy density</td><td>kg/kWh</td><td>—</td><td colspan="2">0.15</td><td>0.2</td></tr>
<tr><td>ϵ^{eng}</td><td>engine efficiency</td><td>—</td><td>—</td><td colspan="2">0.9</td><td>0.93</td></tr>
<tr><td>ϵ^{trans}</td><td>transmission efficiency</td><td>—</td><td>—</td><td colspan="2">0.9</td><td>0.93</td></tr>
<tr><td>ϵ^{char}</td><td>charging efficiency</td><td>—</td><td>—</td><td colspan="2">0.9</td><td>0.93</td></tr>
<tr><td>n_{rotor}</td><td>number rotors</td><td>—</td><td>—</td><td>—</td><td>8</td><td>8</td></tr>
<tr><td>n_{blades}</td><td>number blades</td><td>—</td><td>—</td><td>—</td><td>3</td><td>3</td></tr>
<tr><td>r</td><td>rotor radius</td><td>m</td><td>—</td><td>—</td><td>0.4</td><td>0.4</td></tr>
<tr><td>c_{air}</td><td>air drag</td><td>—</td><td colspan="2">0.65</td><td>0.5</td><td>0.3</td></tr>
<tr><td>c_{roll}</td><td>rolling resistence</td><td>—</td><td colspan="2">0.008</td><td>—</td><td>—</td></tr>
<tr><td>c_{bd}</td><td>blade drag</td><td>—</td><td>—</td><td>—</td><td>0.075</td><td>0.075</td></tr>
<tr><td>$\bar{c}$</td><td>rotor mean chord</td><td>—</td><td>—</td><td>—</td><td>0.1</td><td>0.1</td></tr>
<tr><td>$\bar{c}_l$</td><td>blade lift</td><td>—</td><td>—</td><td>—</td><td>0.4</td><td>0.4</td></tr>
<tr><td>κ</td><td>lifting power markup</td><td>—</td><td>—</td><td>—</td><td>1.15</td><td>1.15</td></tr>
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