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Realistic Models for Characterizing the Performance of Unmanned Aerial Vehicles

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National Science Foundation

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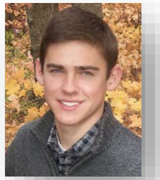

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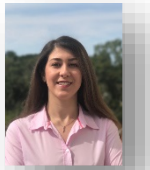

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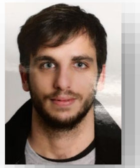

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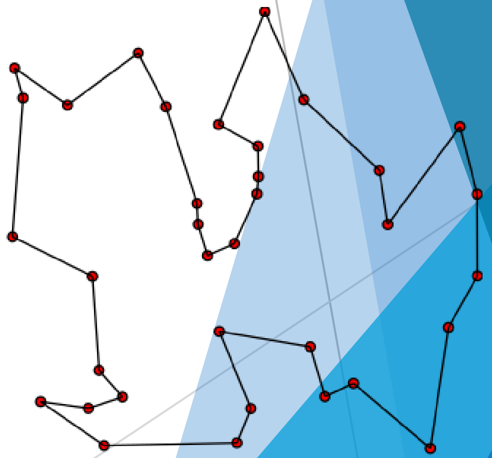
Let’s start from the Travel Salesman Problem

- Given a set of points to visit (e.g., to take a sensing measurement)
- Points i and j are at a distance $d_{i,j}$
- Find a flight path such that
  - The route traverses all points
  - The route begins at the initial UAV location
  - The route has minimum traversed distance
- This can be formulated as an ILP…



What are the expected performance?

- When you buy a drone usually you read:

Flight time: 25 minutes; 20 minutes with payload*

- How do they get this numbers? Hovering on the same spot for 25 minutes!!
- The little star (*) is there to say: "*Flight time varies with **payload, wind conditions, elevation, temperature, humidity, flying style and pilot skill**. Listed flight time applies to elevations less than 2,000 ft above sea level."
- How can I predict the performance of my drone?

https://3dr.com/blog/solo-specs-just-the-facts-14480cb55722/

Objective

- Define analytical models that given information such as:
  - UAV mass
  - Flight plan
- Predicts UAV performance:
  - Energy consumption
  - Flight time
  - Number of waypoints the UAV can traverse
- Benefits
  - Realistic simulations
  - Realistic optimizations
  - Accurate flight plans

Previous work

- Does not consider performance metrics other than flight time [1]
- Does not consider effects of the geometry of a flight path on power consumption [2]
- Provides a method to optimize a path for power consumption but not model the power consumption [3]
- Optimizes the control signals used to drive the motors, but not related to a whole flight path for a prolonged sensing mission [4]
- Does model power consumption, but only in a constant velocity setting, which does not generalize to arbitrary flights [5]

[1] P. Sujit and D. Ghose, "Search using multiple uavs with flight time constraints," IEEE Transactions on Aerospace and Electronic Systems, vol. 40, no. 2, pp. 491–509, 2004.
[2] B. Uragun, "Energy efficiency for unmanned aerial vehicles," in IEEE ICMLA, 2011.
[3] G. Nachmani, "Minimum-energy flight paths for uavs using mesoscale wind forecasts and approximate dynamic programming," DTIC Document, Tech. Rep., 2007.
[4] F. Morbidi, R. Cano, and D. Lara, "Minimum-energy path generation for a quadrotor uav," in IEEE ICRA, 2016.
[5] D.-K. Phung and P. Morin, "Modeling and energy evaluation of small convertible uavs," IFAC Proceedings Volumes, vol. 46, no. 30, pp. 212–219, 2013.

3dr Solo UAV

- ~25 minutes flight time fully autonomous
- On-board Linux computer interfaced with flight controller
- Communication options
  - Integrated wireless telemetry radio
  - Wi-Fi
- Open ports to interface a wide array of sensing hardware with on-board computer, flight controller, or both

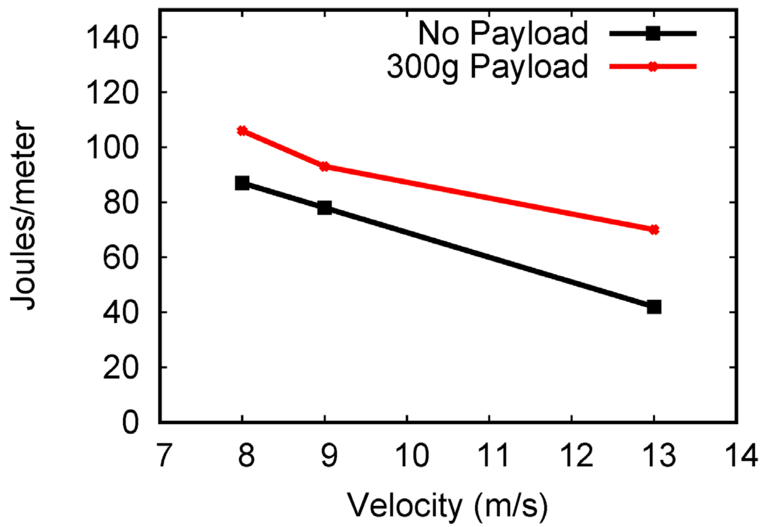
Basic Model (1)

Energy consumption of basic UAV operations

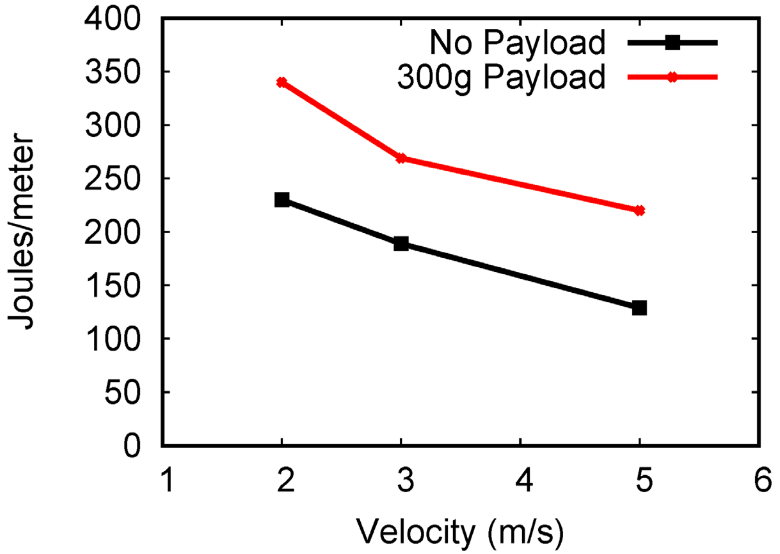
Operation	No Payload		300g Payload	
	Battery use	Joules	Battery use	Joules
Takeoff and Land	2.83%	7849 J	3.50%	9696 J
Hover	0.116 %/s	321 W	0.122 %/s	338 W
Vertical				
Slow (8 m/s)	0.083 %/m	230 J/m	0.123 %/m	340 J/m
Medium (9 m/s)	0.068 %/m	189 J/m	0.097 %/m	269 J/m
Fast (13 m/s)	0.047 %/m	129 J/m	0.079 %/m	220 J/m
Horizontal				
Slow (8 m/s)	0.031 %/m	86.58 J/m	0.038 %/m	106 J/m
Medium (9 m/s)	0.028 %/m	78 J/m	0.034 %/m	93 J/m
Fast (13 m/s)	0.015 %/m	43 J/m	0.025 %/m	70 J/m

Basic Model (2)

Basic Operations
Horizontal



Basic operations
Vertical

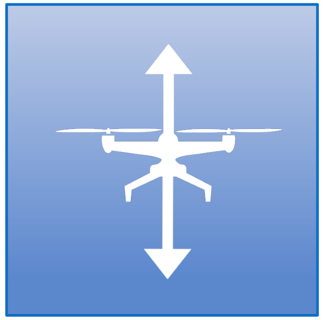


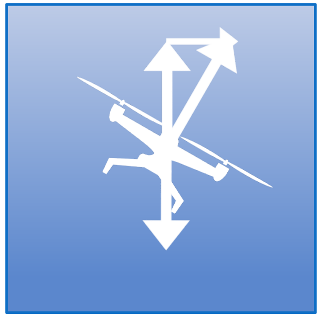
Basic Model Summary

- Good for gaining intuition concerning power cost differences in various configurations and movement combinations
- Overly simplistic – little to no consideration of acceleration
- No realistic or reliable way to compose these data for arbitrary flight path power modeling

Advanced Model

- Consider critical aspect concerning UAV Movement Physics
  - UAV thrust and gravity during vertical motion
  - UAV thrust components and gravity during lateral motion





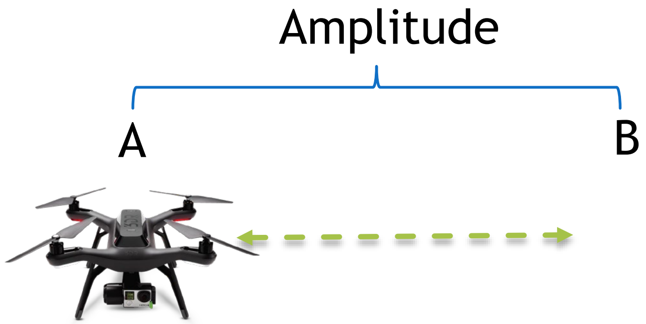
- Given a flight plan we want to be able to reliably predict:

  The UAV flight time

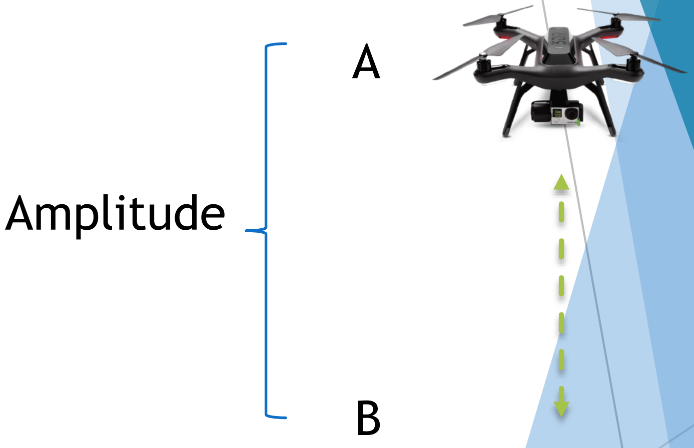
  The number of waypoints the UAV is able to traverse in a given flight path

Experimental setup and approach (1)

- We identify **three dimensions** that affect the performance
- Horizontal oscillations



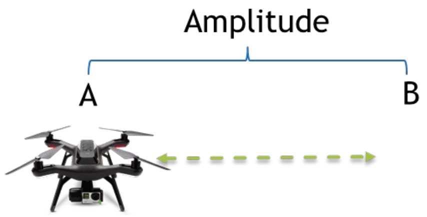
- Vertical oscillations



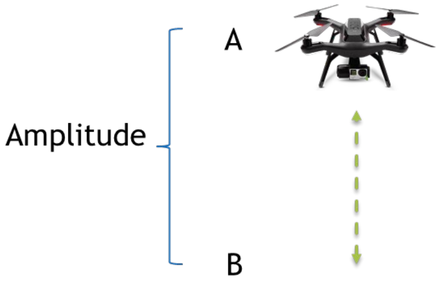
- UAV Mass

Experimental setup and approach (2)

- We focus on one dimension at a time (e.g. horizontal amplitude)
- We empirically measure the performance as a such dimension
- We find use regression to find a suitable function that fits the empirical data
- Constants depend on the specific UAV considered (3DR Solo)
  - Horizontal oscillations



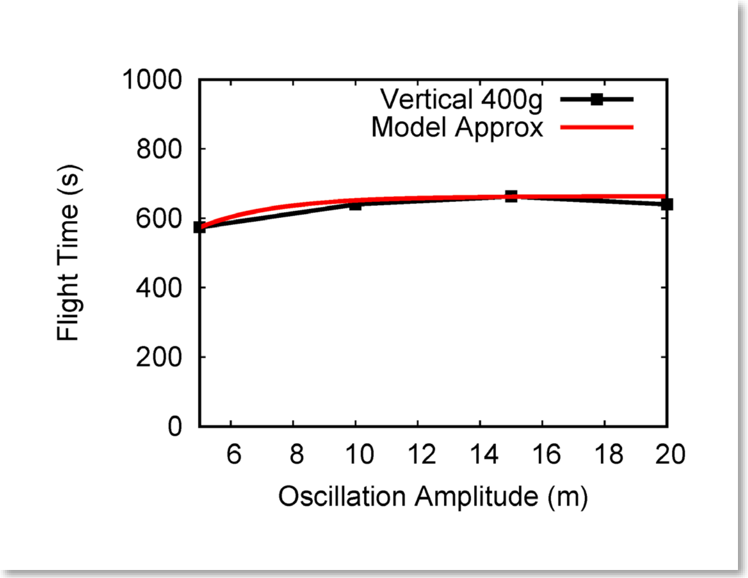
  - Vertical oscillations



  - UAV Mass

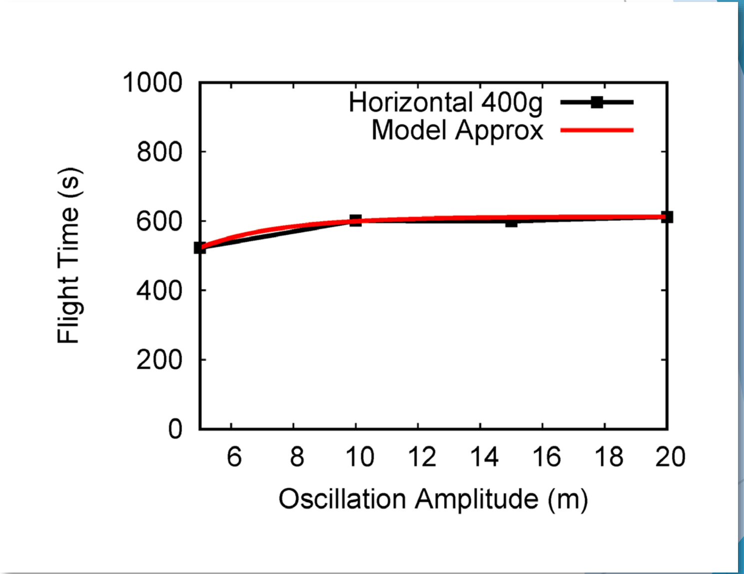
Model Validation

Vertical Flight Time vs Increasing Oscillation Amplitude



$$FT_V(A) = \alpha_{fva}(1 - e^{-A/\beta_{fva}})$$

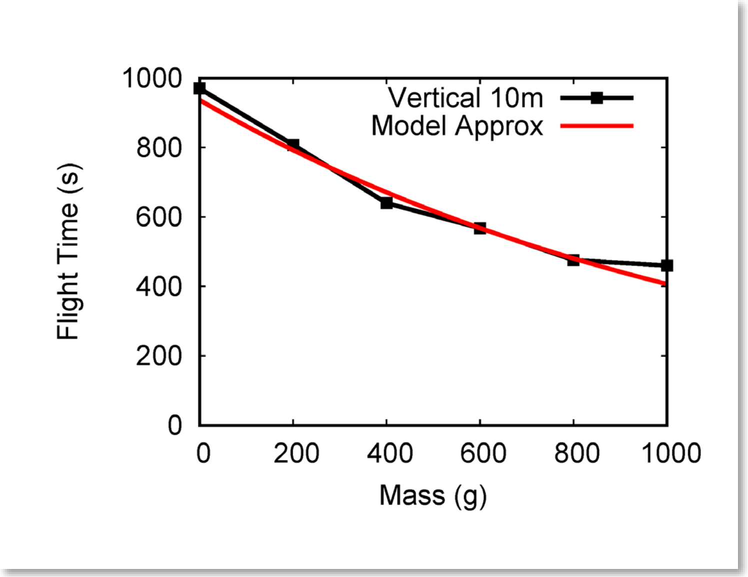
Horizontal Flight Time vs Increasing Oscillation Amplitude



$$FT_H(A) = \alpha_{fha}(1 - e^{-A/\beta_{fha}})$$

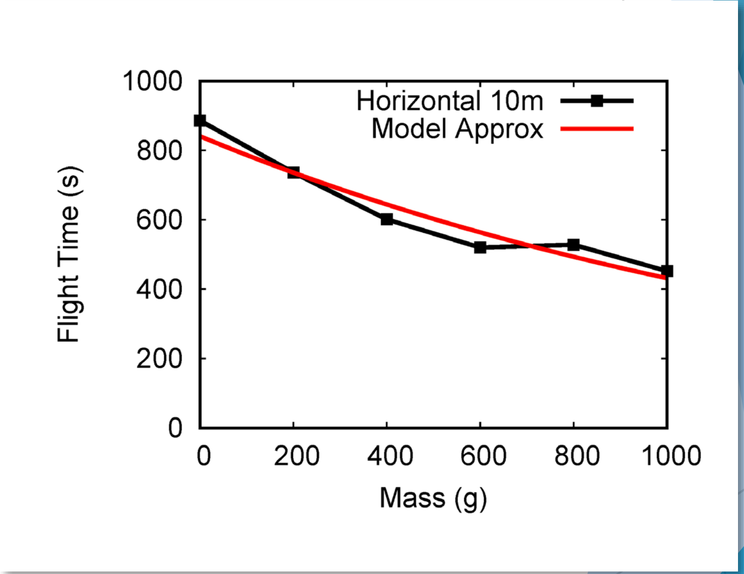
Model Validation

Vertical Flight Time vs Increasing Mass



$$FT_V(M) = \alpha_{fvm} e^{-M/\beta_{fvm}}$$

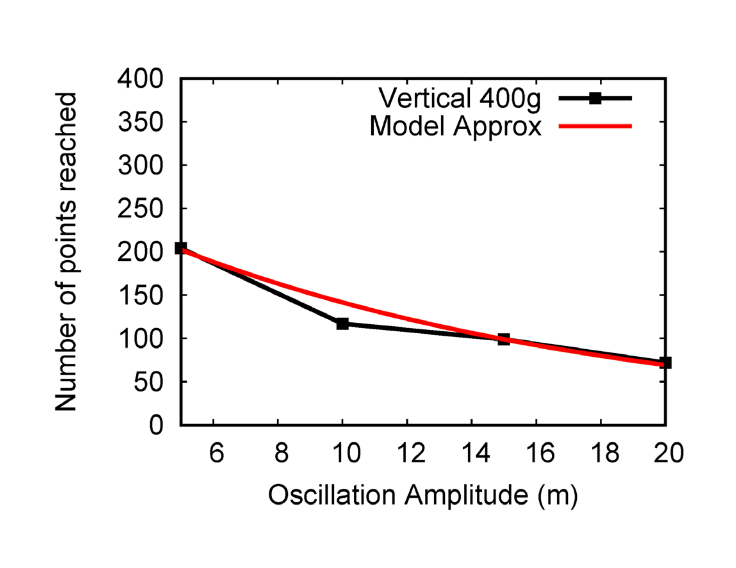
Horizontal Flight Time vs Increasing Mass



$$FT_H(M) = \alpha_{fhm} e^{-M/\beta_{fhm}}$$

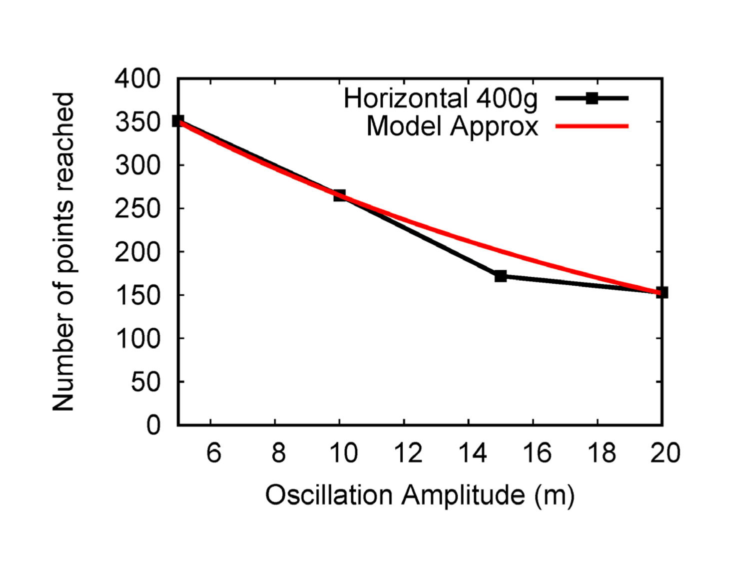
Model Validation

Vertical Point Completion vs Increasing Oscillation Amplitude



$$WP_V(A) = \alpha_{wva} e^{-A/\beta_{wva}}$$

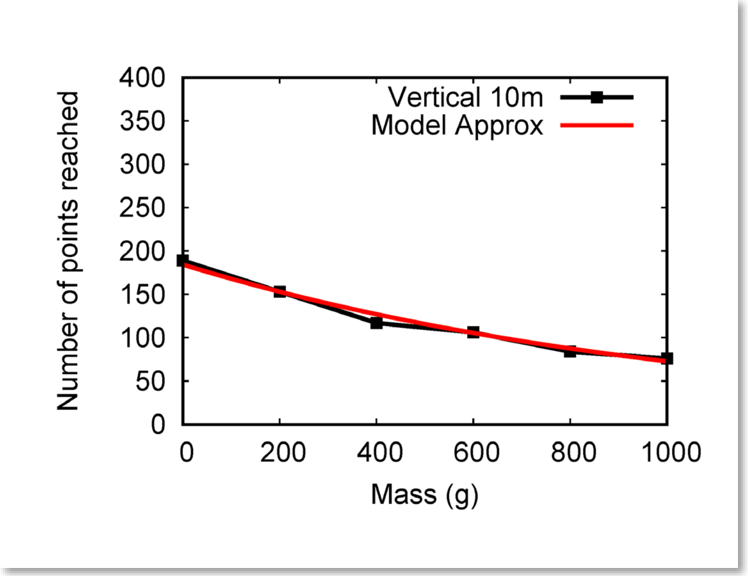
Horizontal Point Completion vs Increasing Oscillation Amplitude



$$WP_H(A) = \alpha_{wha} e^{-A/\beta_{wha}}$$

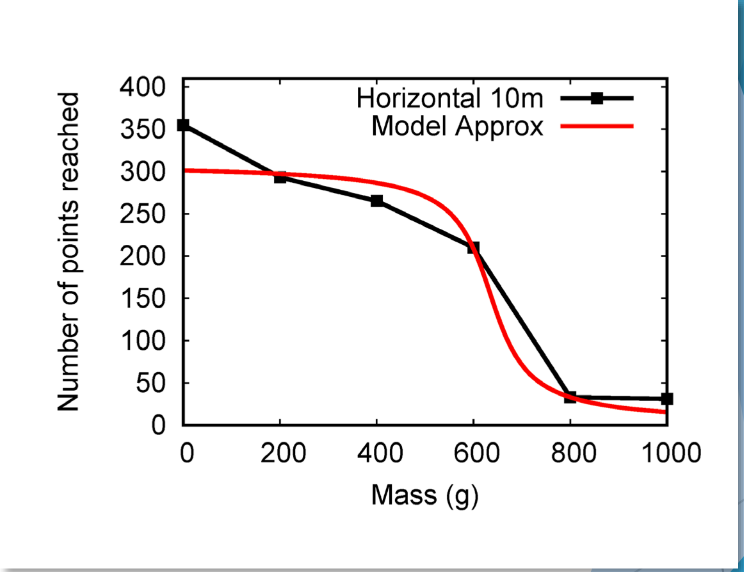
Model Validation

Vertical Point Completion vs Increasing Mass



$$WP_V(M) = \alpha_{wvm} e^{-M/\beta_{wvm}}$$

Horizontal Point Completion vs Increasing Mass



$$WP_H(M) = \frac{\alpha_{whm}}{\pi} arccot\left(\frac{M - \beta_{whm}}{\gamma_{whm}}\right)$$

Model Integration

- **Question: given a generic flight plan, how can we predict a lower bound on the UAV performance?**

- Each factor δ for the criteria of interest is aggregated (in this case flight time) to obtain a total Δ

$$\Delta_{FT} = 1 - \sum (1 - \delta)$$
$$\delta \in \{\delta_{FT_{DH}}, \delta_{FT_{DV}}, \delta_{FT_{MH}}, \delta_{FT_{MV}}\}$$

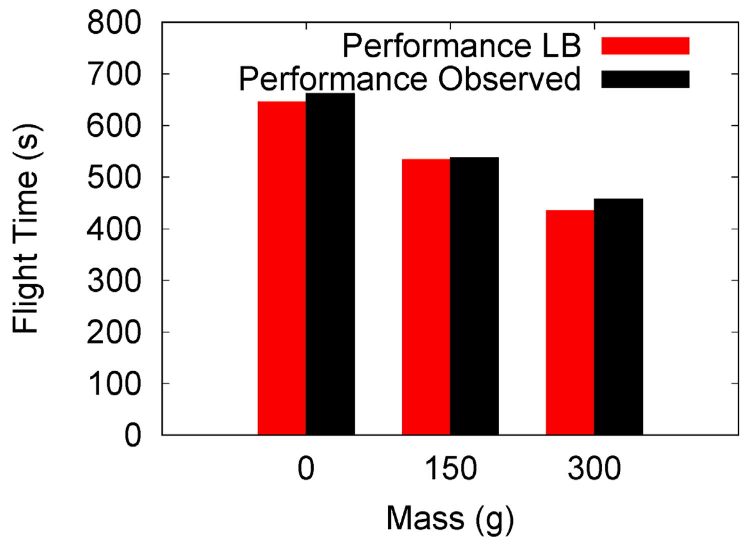
- and then this is multiplied by the minimum of the individual projected outcomes for the baseline to obtain the Lower Bound (LB) for performance

$$LB(FT) = \Delta_{FT} \cdot \min(\{FT_V(V_0), FT_H(V_0), FT_V(M_0), FT_H(M_0)\})$$

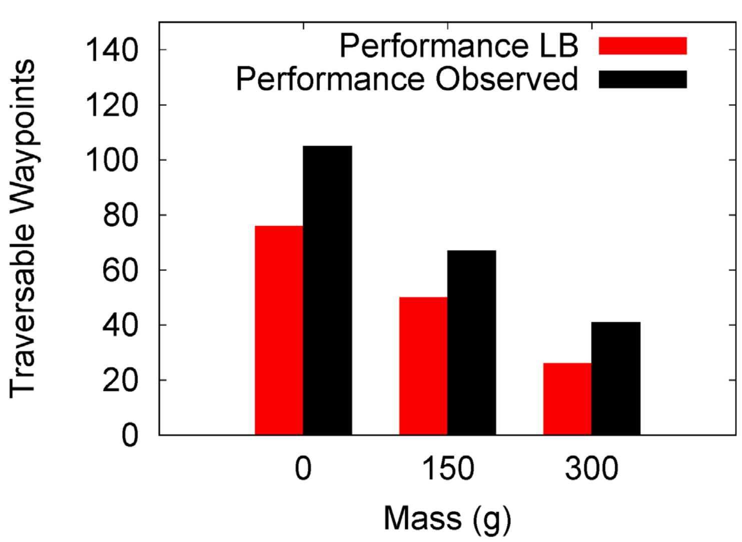
Validation for generic Flight Plans

- We generated a random flight plan, waypoints have random altitude and position

Flight time



Waypoint



Many open problems…

- Many other factors are relevant:
  - Altitude
  - Speed
  - Battery aging
  - Temperature
  - Non-random flight paths
  - Other ideas?

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Unmanned Aerial Vehicles to monitor the effects of climate change

Riccardo Musmeci, Ken Goss, **Simone Silvestri**

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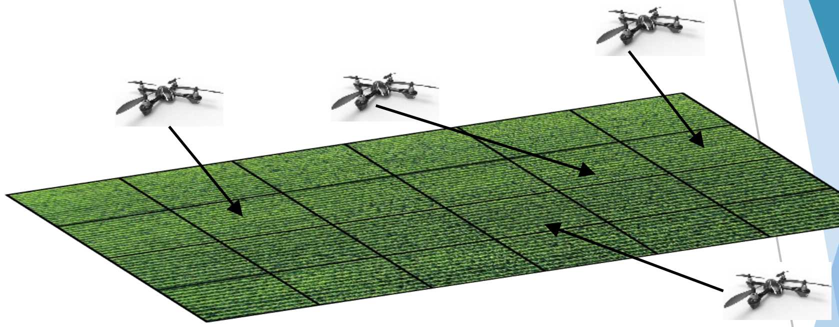
Unmanned Aerial Vehicles to monitor the effects of climate change

- Investigate the effects of **climate change** on **large scale crop fields**
- Enable the use of **autonomous monitoring networks**
- **Challenges**
  - Current UAV monitoring techniques use a single UAV with auto-pilot (typical image acquisition speed 5m/s, very limited scalability)
  - High network operational/deployment costs
- **Goals: reduce costs and improve scalability**
  - Statistical optimization
  - Design algorithms for the coordination of multiple UAVs
  - Enable remote monitoring (web application)

Unmanned Aerial Vehicles to monitor the effects of climate change

Statistical optimization

- **Objectives**: improve scalability, achieve high accuracy, reduce costs
- **Monitoring objectives:** plant growth, health, parasites, etc.
- **Sensing:** RGB, Thermal, Hyperspectral cameras
- **Idea**
  - Divide the field in sectors
  - Each sector produces a reading (e.g. crop health, size)
  - These readings are **correlated**
  - Exploit correlation to monitor only a subset of the sector and infer the others
- **Main problems to solve**
  - Infer readings of unobserved sectors minimizing the error
  - Select the best sectors
  - Detect changes in the distribution
  - Optimize UAV movements



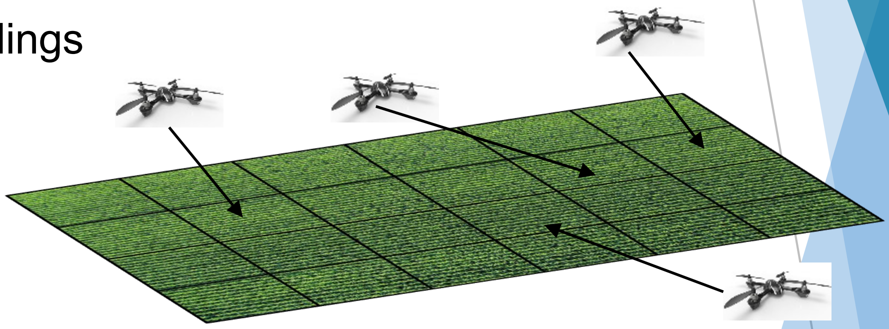
Unmanned Aerial Vehicles to monitor the effects of climate change

Technical approach

- Let X be the set of all sectors, Σ_X the covariance matrix
- Readings are modelled as jointly Gaussian random variables

$$f(X) \approx \frac{1}{\sqrt{2\pi\ det(\Sigma_X)}} \exp\left(-\frac{1}{2}(x-\bar{x})^T \Sigma^{-1}(x-\bar{x})\right)$$

- If we observe $S \subseteq X$, we have a closed form to infer the readings of the sectors in $Y = X \setminus S$ with minimum MSE



$$\mu_{Y|S} = \mu_Y + \Sigma_{YS}\Sigma_{SS}^{-1}(\mathbf{s} - \mu_S)$$

- The problem of selecting the best sectors is

$$S^* = arg \min_{S \subseteq X, |S| \leq M} \left(\frac{1}{T_{op}} \sum_{t=1}^{T_{op}} MSE(\hat{\mathbf{y}}_\mathbf{t}(\mathbf{s}^*_\mathbf{t}), \mathbf{y}_\mathbf{t})\right)$$

which is NP-Hard, but we have optimal solutions for special cases

Optimal single sector selection $$x_j^* = \arg\max_{x_l \in X} \left(\frac{\sum_{i=1}^N \sigma_{il}^2}{\sigma_{ll}}\right)$$

Technical approach

- We use the special cases as a building blocks for efficient heuristics

- We designed heuristics with different trade-off accuracy vs. complexity

- Top-W: pick top sectors ranked according to the weight $w_j = \frac{1}{c_j}\left(\frac{\sum_{i=1}^{N}\sigma_{ij}^2}{\sigma_{jj}}\right)$ $O(N^2)$

- Top-W-update: pick the top sectors but update the conditional covariance matrix $O(N^3)$

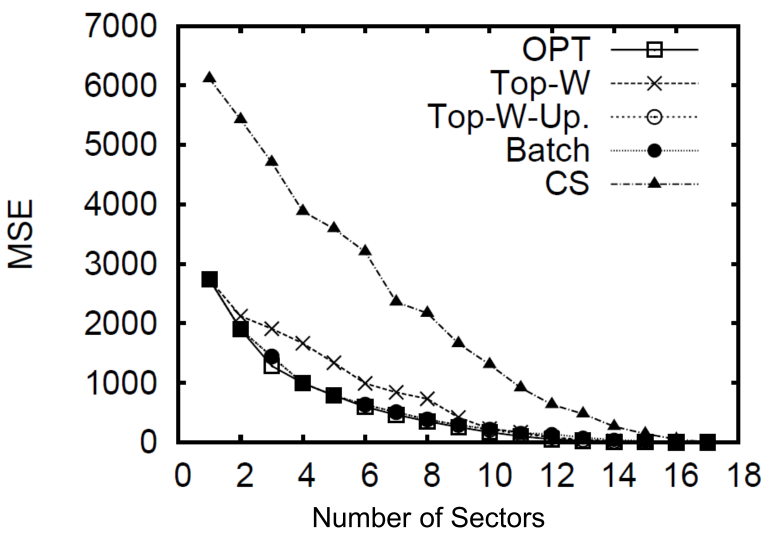
$$\Sigma_Y = \Sigma_{YY} - \Sigma_{Y x_i^*}\Sigma^{-1}_{x_i^* x_i^*}\Sigma_{x_i^* Y}$$

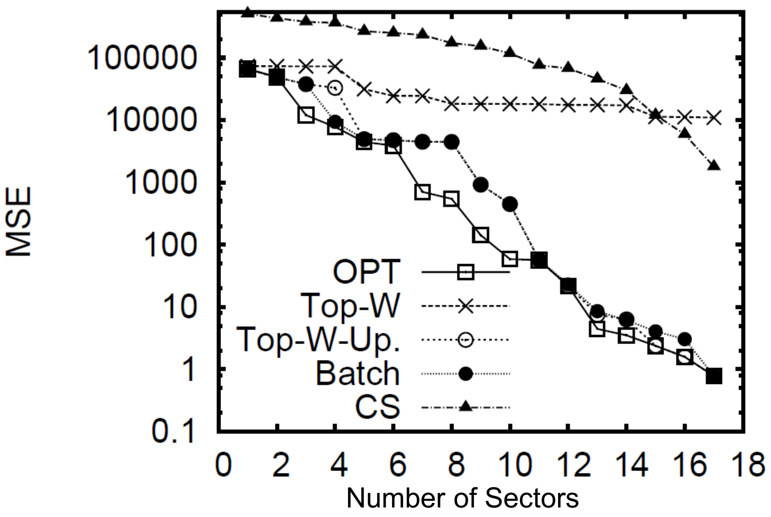
- Batch-selection: pick the variable that minimizes the MSE considering the already selected variables $O(N^5)$

$$x_i^* = \arg\min_{x_l \in Y} tr(\Sigma_{Y\setminus\{x_l\}|S\cup\{x_l\}})$$

Unmanned Aerial Vehicles to monitor the effects of climate change

- **Preliminary results**
  - Simulator based on synthetic and real traces
  - Comparison with Compressed Sensing (CS) approach





- **Papers:**
  - S. Silvestri, R. Urgaonkar, M. Zafer, B. Ko,*"An online method for minimizing network monitoring overhead"* in Proceedings of the IEEE International Conference on Distributed Computing Systems (ICDCS), 2015
  - S. Silvestri, R. Urgaonkar, M. Zafer, B. Ko, *"A Framework for the Inference of Sensing Measurements based on Correlation“,* in ACM Transactions on Sensor Networks (to appear).

A Web Application for the Remote Control of Multiple Unmanned Aerial Vehicles

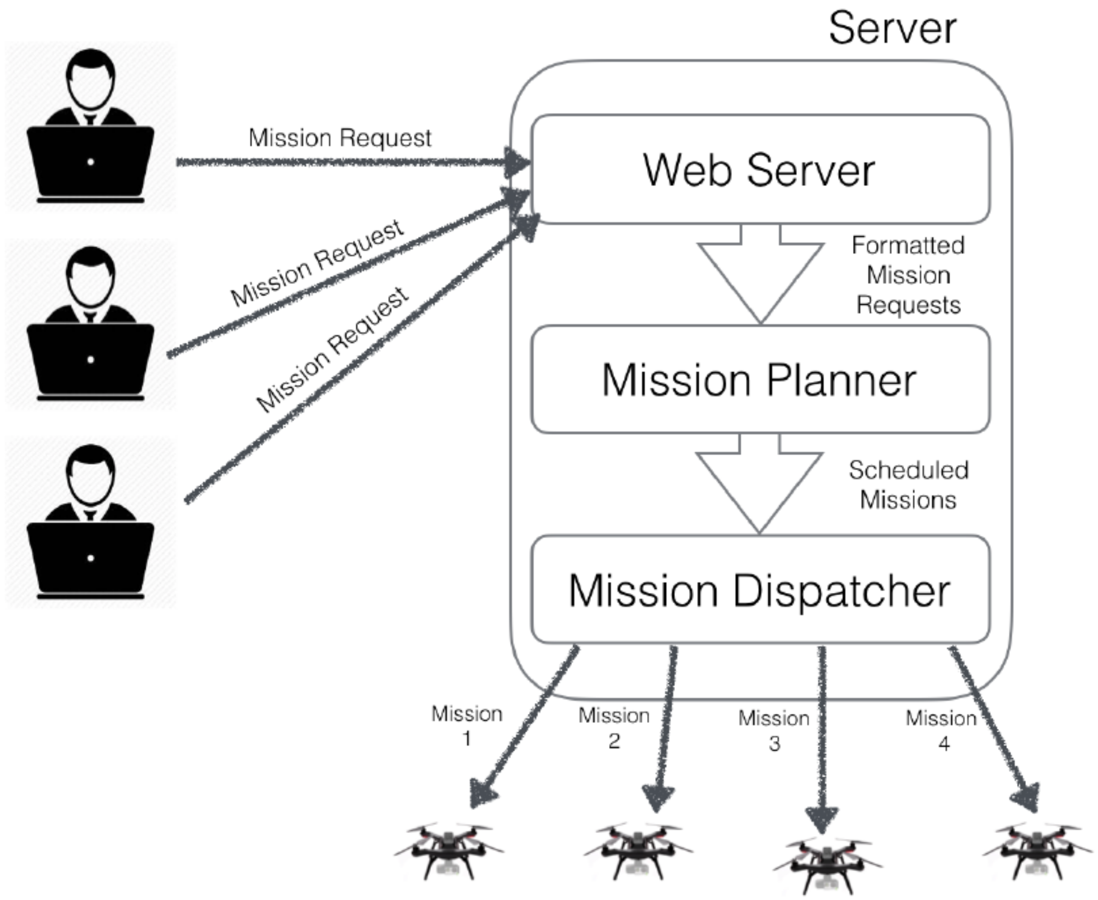
- In the context of our project multiple users (researchers) are interested in monitoring different sectors of a crop field

- We want to realize a web system thanks to which users can submit **monitoring missions**, composed by:
  - A set of sectors to be monitored
  - The sensing to be performed (RGB, hyperspectral, thermal, etc.)
  - A time range when the measurements should be collected

- The users should not be aware of the number, location, and flight operations of the UAVs

Structure of the Web application

- We realize a web application with the following structure



Web Client Interface

- It is used by the users to submit monitoring missions

UAV Info

UAV Id	UAV Status	UAV Battery	Sensing Type
Solo Gold	Connected	100	RGB
Solo Green	Connected	73	Thermal

Mission details

Drone	Marker	Latitude	Longitude	Altitude	Time Interval
Solo Gold	1	37.92472884	-91.77257647	5	[10.00am, 11.00am]
Solo Gold	2	37.92492772	-91.77286078	7	[10.00am. 11.00am]
Solo Green	3	37.92450668	-91.77207758	7	[09.00am, 09.45am]
Solo Gold	4	37.92483039	-91.77208563	6	[10.30am, 11.30am]
Solo	5	37.92446436	-91.77261670	9	[09.00am

Monitoring missions

Select type of monitoring missions:

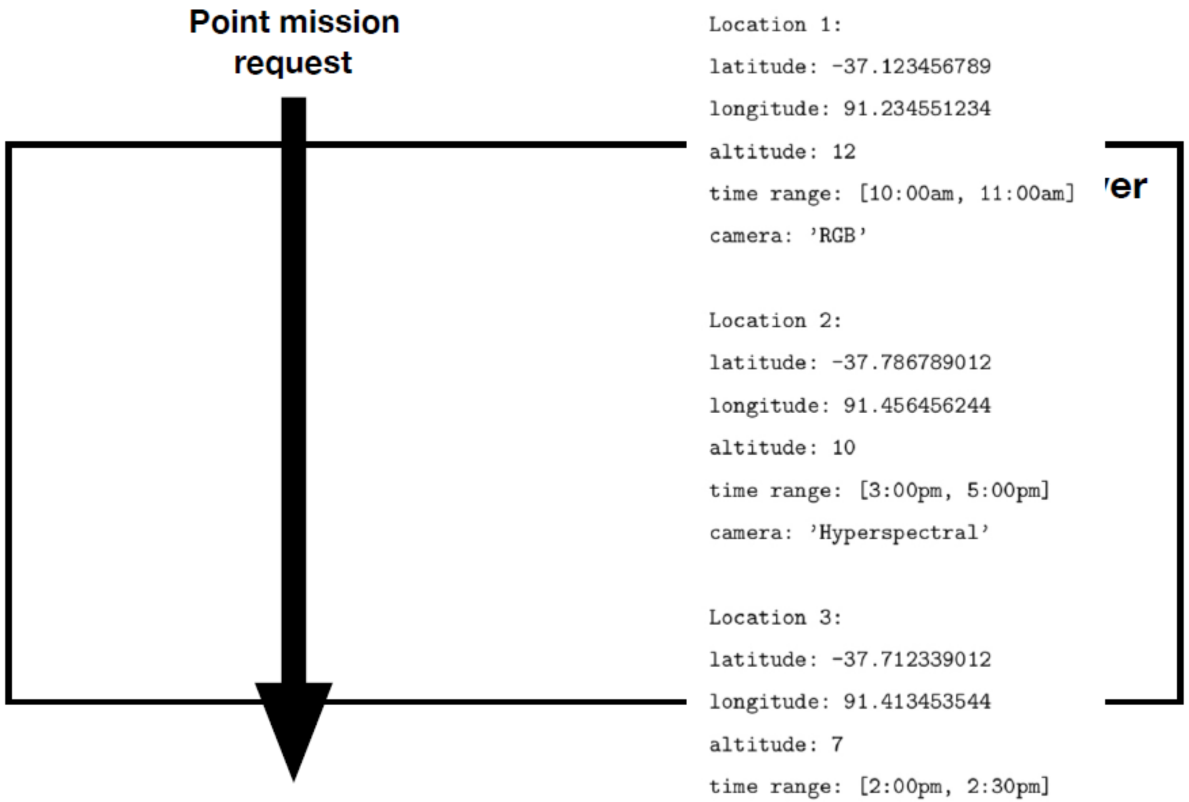
Point Mission

Live Flight Information

In this section will be displayed all the information sent by drones in flight

Web Server

- Receives monitoring missions and translates in a format for the mission planner




```
Location 1:
latitude: -37.123456789
longitude: 91.234551234
altitude: 12
time range: [10:00am, 11:00am]
camera: 'RGB'

Location 2:
latitude: -37.786789012
longitude: 91.456456244
altitude: 10
time range: [3:00pm, 5:00pm]
camera: 'Hyperspectral'

Location 3:
latitude: -37.712339012
longitude: 91.413453544
altitude: 7
time range: [2:00pm, 2:30pm]
camera: 'Thermal'
```

Mission Planner

- Solves a modified version of the Multi TSP

$$\text{maximize} \sum_{l=1}^{m} z_l + \alpha\Big(E_{max} - \sum_{r=1}^{L} E(P_r)\Big) \quad (1)$$

$$\text{subject to } z_l \leq \frac{1}{|P_l|} \sum_{r=1}^{L} \sum_{i=1}^{N} y_i^r q_{il} \ \forall l \quad (2)$$

$$\sum_{r=1}^{N} y_i^r \leq 1 \ \forall i \quad (3)$$

$$\sum_{i=1}^{N} x_{i,j}^r \leq 1 \ \forall j, r; \ \sum_{j=1}^{N} x_{i,j}^r \leq 1 \ \forall i, r \quad (4)$$

$$x_{i,j}^r \leq y_i^r \ \forall i, r; x_{i,j}^r \leq y_j^r \ \forall j, r \quad (5)$$

$$\sum_{i=1}^{N} x_{i,j}^r = \sum_{i=1}^{r} y_i^r \ \forall r \quad (6)$$

$$u_i^r - u_j^r + x_{i,j}^r N \leq N - 1 \ \forall r \quad (7)$$

$$u_i^r \leq y_i^r N \ \forall i, r \quad (8)$$

$$y_i^r t_i^{min} \leq t_i^r \leq t_i^{max} y_i^r \ \forall i, r \quad (9)$$

$$t_j^r - t_i^r + 2(1 - x_{ij}^r) T_{max} \geq \delta_{i,j} \quad (10)$$

$$\sum_{i=1}^{N} y_i^r \leq R(P_r) \ \forall r \quad (11)$$

Assignments constraints

TSP constraints

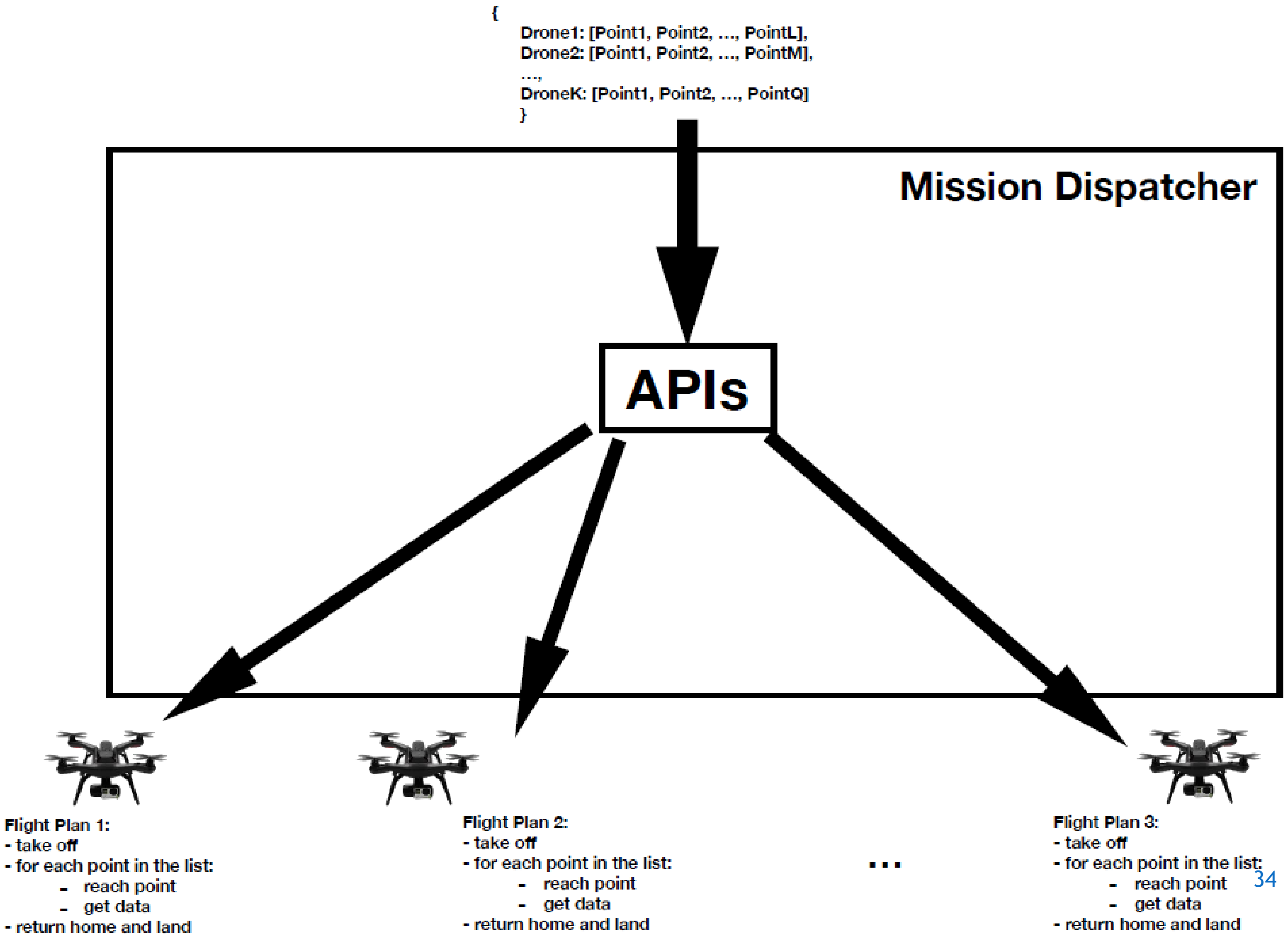
Time constraints

Drone can complete the path

- Optimize nr. of accomplished missions and energy consumption
- P_r is the path for drone r
- The function E(), R() come from the realistic models
- E(): Energy consumed
- R(): number of traversable points
- i,j are used to index sectors
r is used to index drones
l is used to index missions

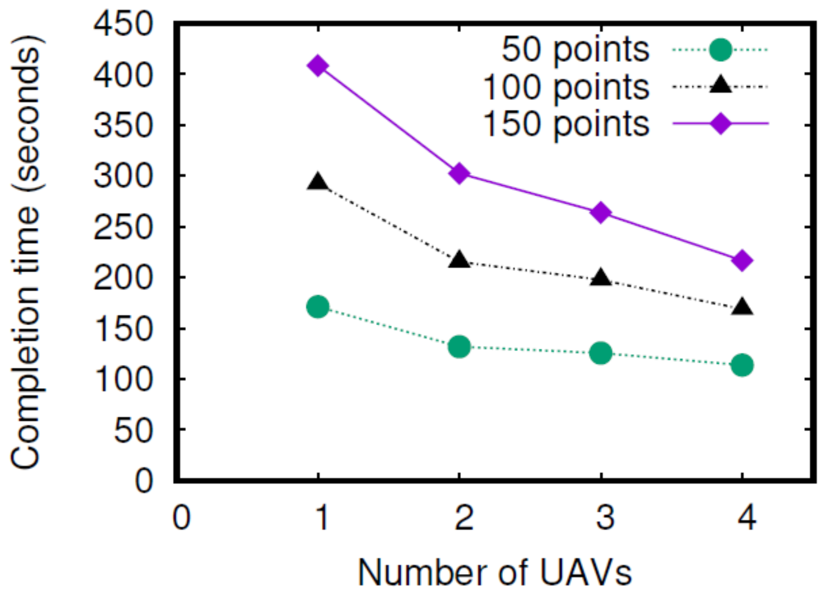
Mission dispatcher

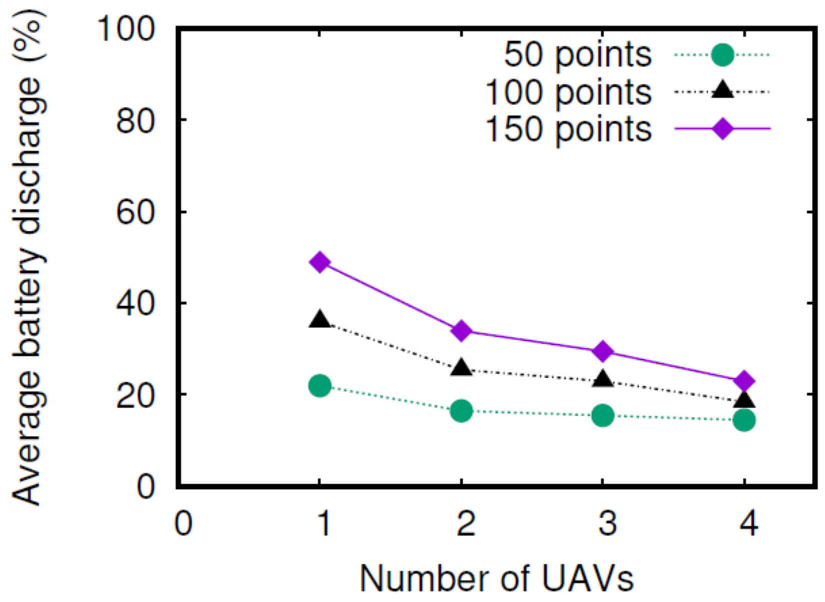
- Translates the output of the optimization problem into flight commands for the drones



Experimental results (1)

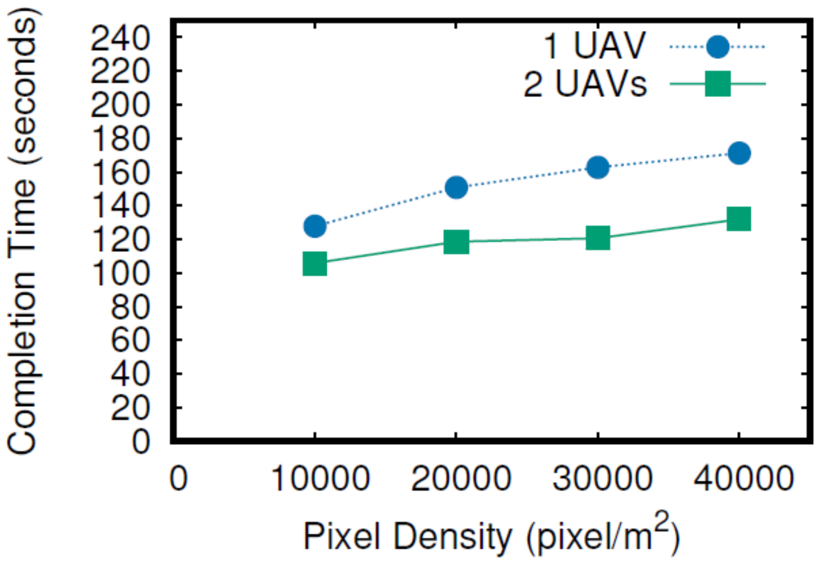
- The application improves the scalability, but 3DR Solo problems reduce the gains

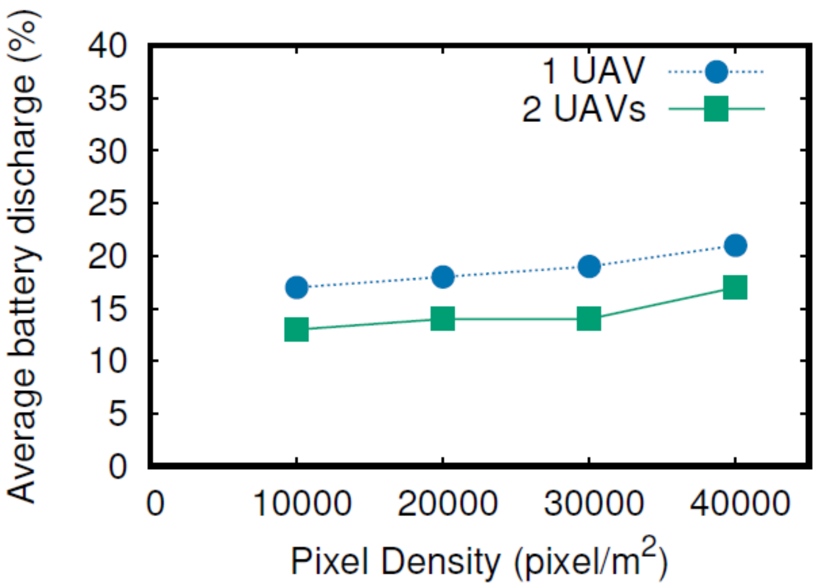




Experimental results (2)

- The application improves the scalability, but 3DR Solo problems reduce the gains





Experimental results (3)

- The application improves the scalability, but 3DR Solo problems reduce the gains