

MULTIROTOR DRONE SIZING & TRAJECTORY OPTIMIZATION WITHIN MODELON IMPACT

October 26th, 2022



Modelon

AGENDA

- Case study
 - Use case
 - Drone architecture
- Drone model
 - Model choices
 - Propeller model (as an example)
 - Sizing scenarios
- Optimization
 - Problem statement
 - Solving
 - Implementation and results
- Conclusions and Perspectives



The background image is a composite of two scenes. On the left, a person is seen from the side, focused on a laptop screen. Their hands are on the keyboard, and they appear to be in a professional or technical setting. On the right, a large, detailed jet engine turbine is shown, highlighting the complex, multi-bladed structure of the compressor section. The entire image is rendered in a dark, monochromatic blue-grey tone, with the text 'CASE STUDY' overlaid in a bright orange color.

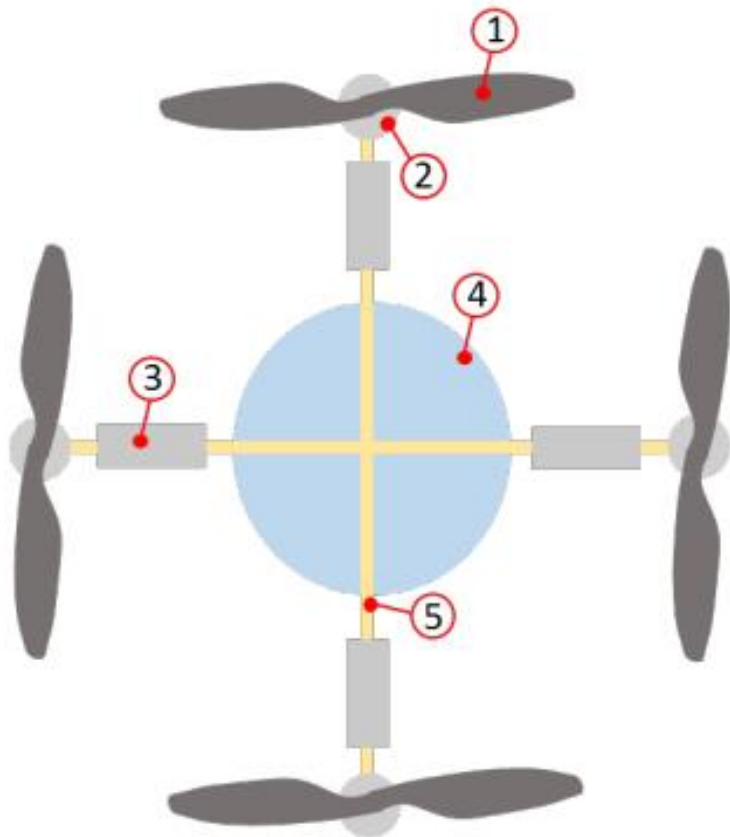
CASE STUDY

CASE STUDY PAYLOAD LIFTING

- Use case - lifting small payloads on top of buildings
 - Maximum 25 kg
 - 150 climbs of 10m height with 5secs hovering
- What we want to solve, for a fixed drone architecture – simultaneously:
 - Optimize the drone trajectory to minimize energy consumption
 - Size the drone main parts



DRONE ARCHITECTURE SELECTED



1. Four fixed pitch propellers
2. Four out-runner brushless motors
3. Four electronic speed controllers (ESC) mainly made from MOSFET inverters
4. One battery based on Li-Ion cells
5. One mechanical structure (frame) consisting of four arms and one central body

The background image is a composite of two scenes. On the left, a person is seen from the side, focused on a laptop screen. On the right, a large, detailed jet engine turbine is shown, representing a complex engineering model. The text 'DRONE MODEL' is centered over the image in a bright orange color.

DRONE MODEL

DRONE MODEL CHOICES

- Model purpose
 - 1-D trajectory optimization
 - Component sizing



All equations are, at least, C2-continuous (optimization algorithm based on gradients)

Design variables have max, min, nominal attributes for bounds and scaling

Initial (not optimized) trajectory provided



A-causality: use of Modelica language

- Sizing requires inverse simulation
- Performance flight simulation requires direct simulation

Scaling laws and meta models for sizing

Efficiency-based modeling (low fidelity)



DRONE PROPELLER MODEL

- Model purpose
 - Physics (performance)
 - Scaling laws (sizing)



$$\begin{aligned} \text{Thrust} &= C_T \rho_{air} n^2 D^4 \\ \text{Power} &= C_P \rho_{air} n^3 D^5 \end{aligned}$$

Buckingham
 π theorem

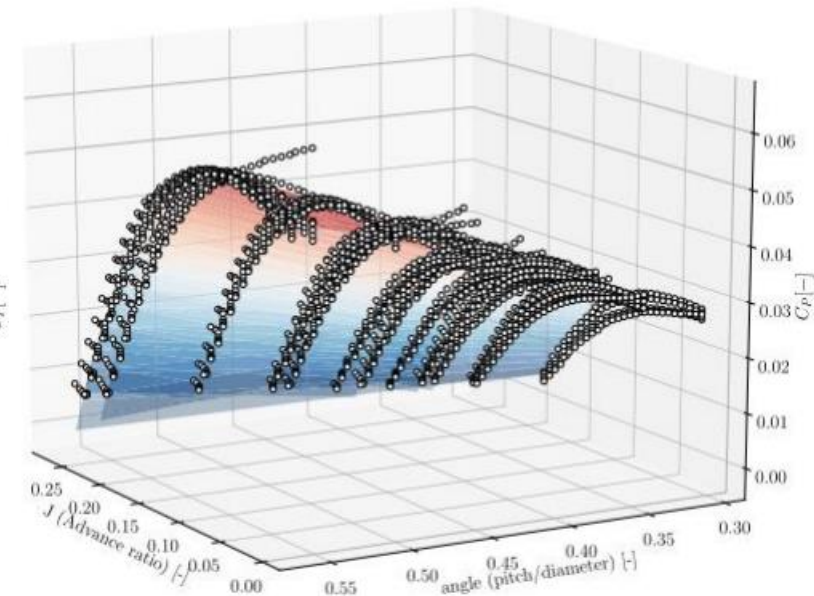
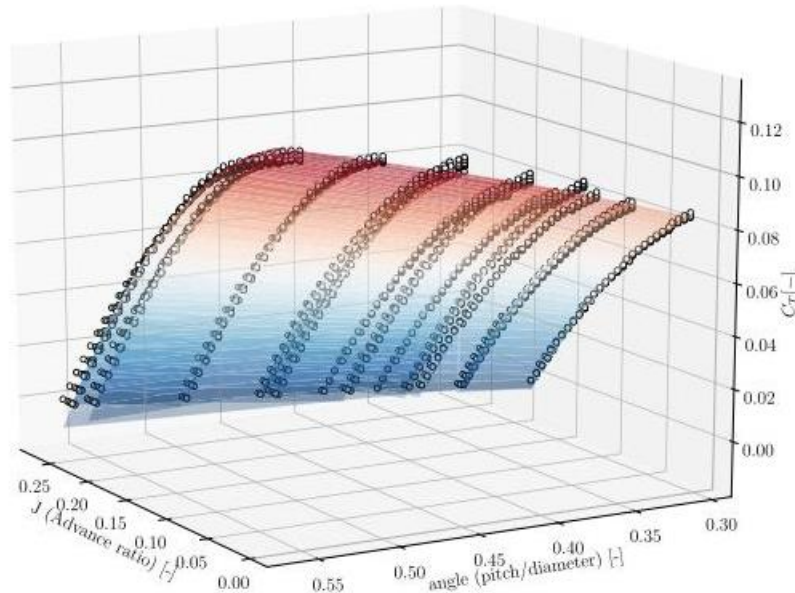
$$\left\{ \begin{aligned} C_T &= f(\beta, J, B) \\ C_p &= f(\beta, J, B) \\ \beta &= \text{pitch}/D \\ J &= V/(nD) \\ B &= K/(\rho n^2 D^2) \end{aligned} \right.$$



$$\begin{aligned} M_{prop} &= M_{ref} (D_{prop}/D_{ref})^2 \\ I_{prop} &= M_{prop} (D_{prop}/2)^3 / 3 \end{aligned}$$

Polynomial fitting on maps

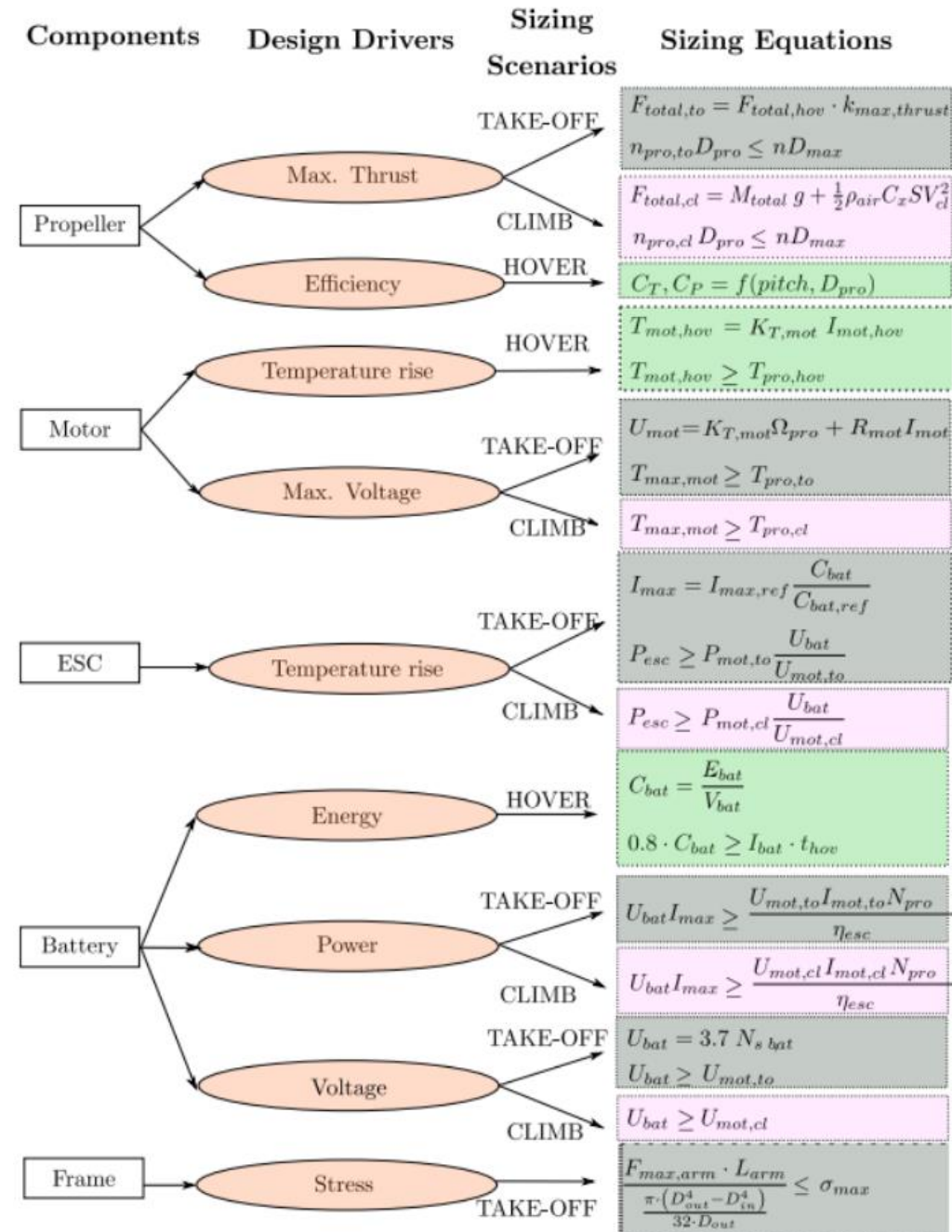
$\left\{ \begin{aligned} \beta &= \text{pitch}/D && \text{pitch to diameter ratio} \\ J &= V/(nD) && \text{advance ratio} \\ B &= K/(\rho n^2 D^2) && \text{air compressibility indicator} \end{aligned} \right.$



DRONE SIZING MODEL

- Sizing scenarios
 - Hover – $J=0$ (as $V=0$)
 - Takeoff – maximum power, increasing J
 - Climb – constant J

$$\left\{ \begin{array}{l} \beta = \text{pitch}/D \quad \text{pitch to diameter ratio} \\ J = V/(nD) \quad \text{advance ratio} \\ B = K/(\rho n^2 D^2) \quad \text{air compressibility indicator} \end{array} \right.$$

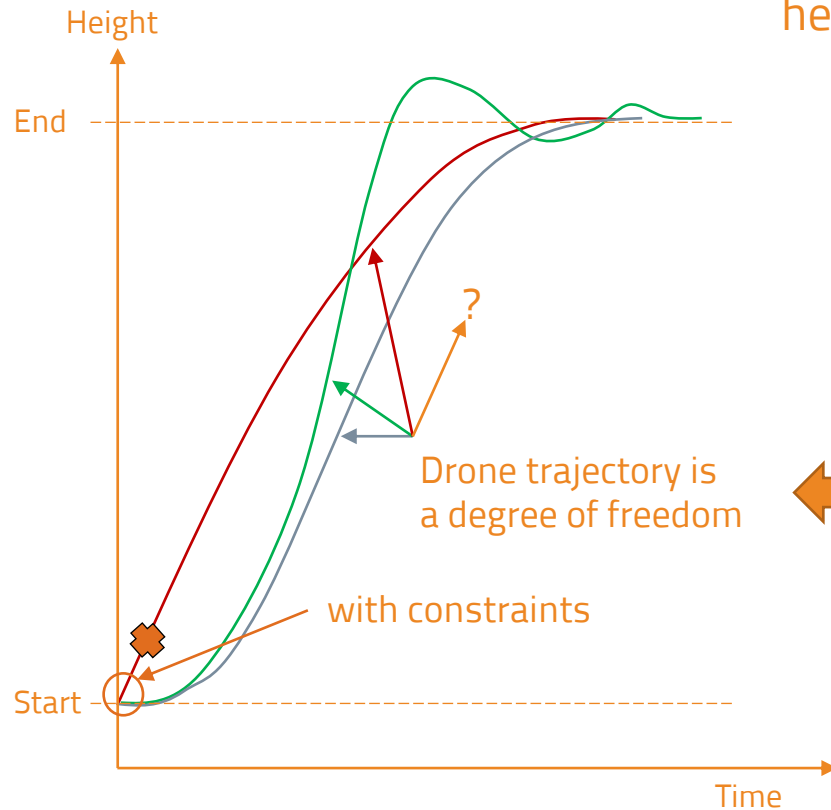


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OPTIMIZATION

OPTIMIZATION PROBLEM STATEMENT

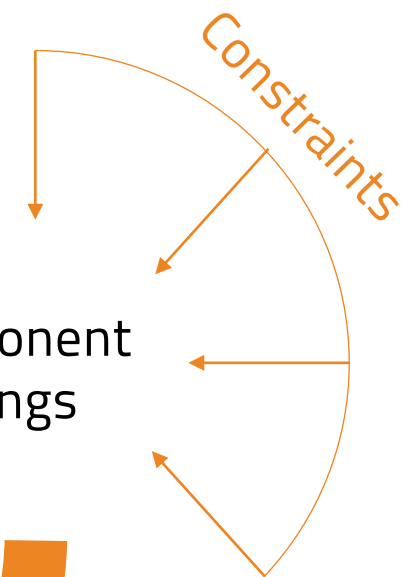
We want to maximize the number of flights;
hence our objective is to minimize the energy consumption per flight.



Power requirements

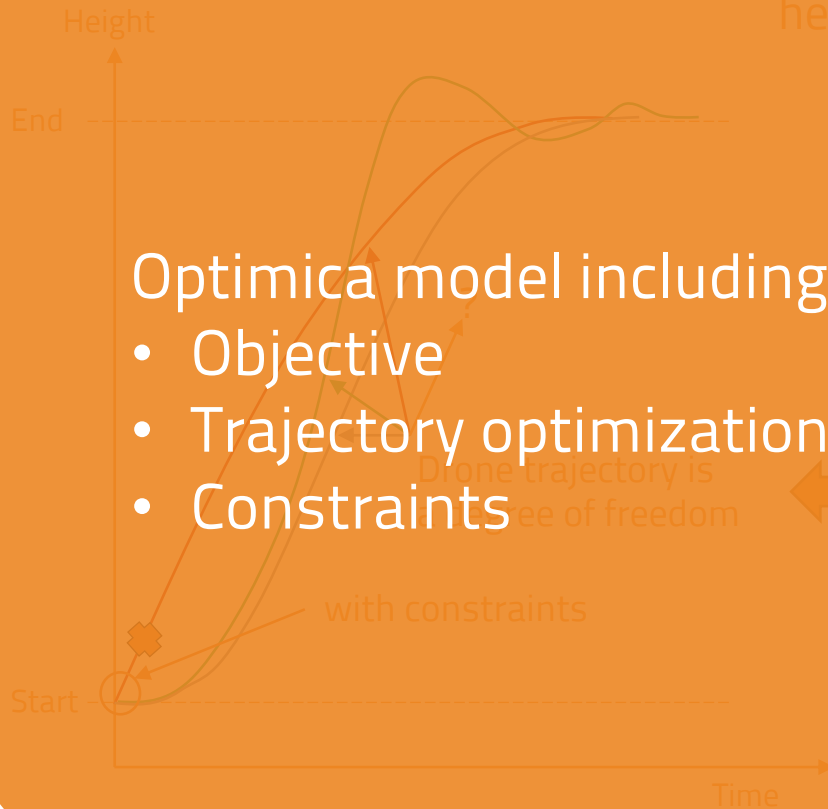
Component sizings

Total mass



OPTIMIZATION PROBLEM SOLVING

We want to maximize the number of flights;
hence our objective is to minimize the energy consumption per flight.



Modelica Drone model with

- Pre-sizing
- Mass estimation
- Behavior

OPTIMIZATION OPTIMICA IMPLEMENTATION

```
optimization SizingAndTrajectoryOptim (  
  objective=M_total(startTime), ← objective  
  finalTime(free=true, min=1, max=10, start=5)  
  // Minimize the total drone mass and relax the final simulation time within bounds.
```

```
import Modelica.Units.SI.DimensionlessRatio;
```

```
extends Drone(  
  x(start = 0, fixed=true),  
  xp(start = 0, fixed=true),  
  a(start = 0, fixed=true),  
  beta(free=true, min=0.3, max=0.6, start=0.4),  
  D(free=true, min=0, max=1),  
  T_nom_mot(free=true, min=0),  
  K_mot(free=true, min=0),  
  M_bat(free=true, min=0, max=100),  
  P_esc(free=true, min=0),  
  k_D(free=true, min=0.01, max=1, start=0.05),  
  D_out_arm(free=true, min=0.001, max=1));
```

Modelica Drone model with

- Pre-sizing
- Mass estimation
- Behavior

```
// Inherit the Modelica drone model, fix initial conditions and relax design parameters within bounds.
```

```
Modelica.Blocks.Interfaces.RealInput Traj_in;
```

```
// Add input to the trajectory to optimize
```

```
...
```

trajectory

Optimization attribute

```
DimensionlessRatio n_norm(start=1, fixed=true)=n/n_hover;  
DimensionlessRatio N_norm(min=-1, max=1, nominal=0.8)=ND/ND_max;  
DimensionlessRatio T_hov_norm(min=0, max=1, nominal=0.6) = T_hover/T_nom_mot;  
DimensionlessRatio T_norm(min=-1, max=1, nominal=0.95) = T/T_max_mot;  
DimensionlessRatio U_norm(min=0, max=1, nominal=0.5) = U_mot/V_bat;  
DimensionlessRatio P_norm(min=0, max=1, nominal=0.5) = P_mot/P_esc;  
DimensionlessRatio E_norm(min=0, max=1, nominal=0.25) = E_drone/E_bat;  
DimensionlessRatio sigma_norm(min=-1, max=1, nominal=0.15) = sigma/sigma_max;  
// Create additional normalized variables with bounds as inequality constraints
```

```
equation
```

```
T=Traj_in; // Bind drone trajectory with optimization input
```

```
constraint
```

```
x(finalTime) = 10;
```

```
xp(finalTime) = 0;
```

```
a(finalTime) = 0;
```

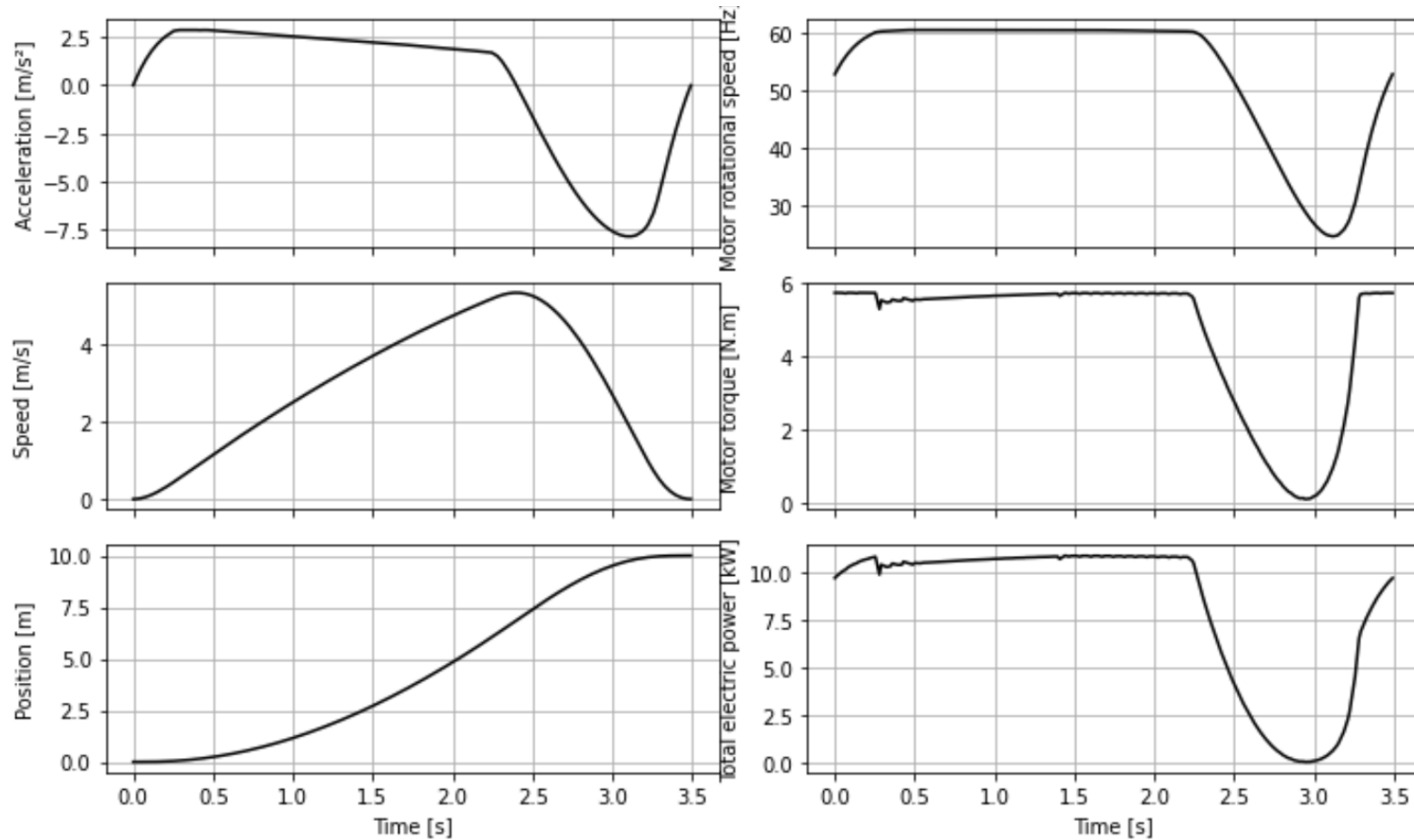
```
// Define end time constraints.
```

```
end SizingAndTrajectoryOptim;
```

constraints

Optimica

OPTIMIZATION RESULTS



Drone ~45kg
Incl. ~27kg battery
+ 25kg payload

The background image is a dark, semi-transparent composite. On the left, a person is seen from the side, focused on a laptop. On the right, a large, detailed jet engine turbine is visible, showing its complex internal structure. The overall tone is professional and technical.

CONCLUSIONS & PERSPECTIVES

MODELON IMPACT BENEFITS

In comparison with a FAST-OAD optimization, relying on a drone FMU

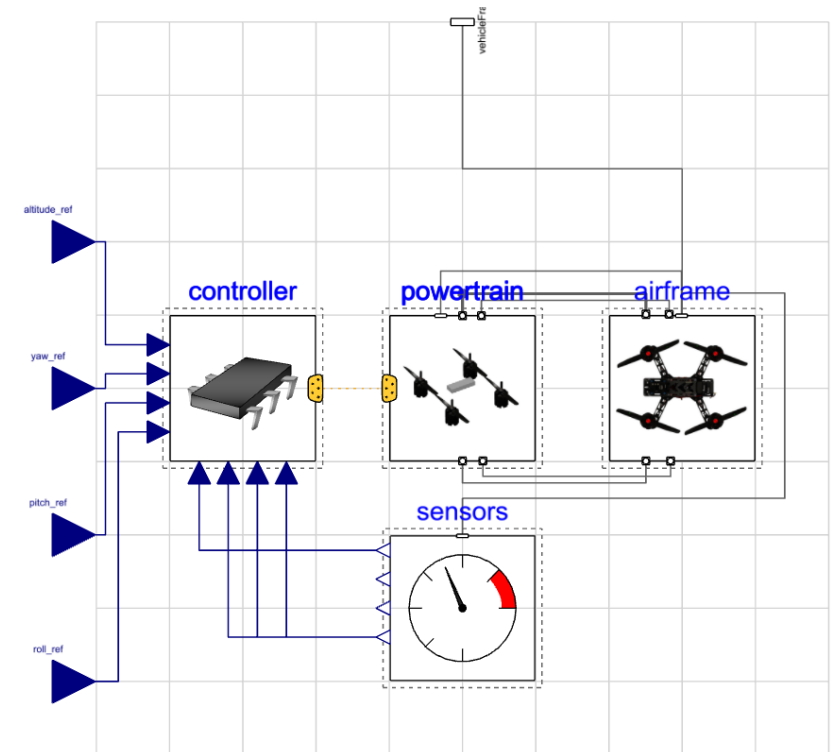
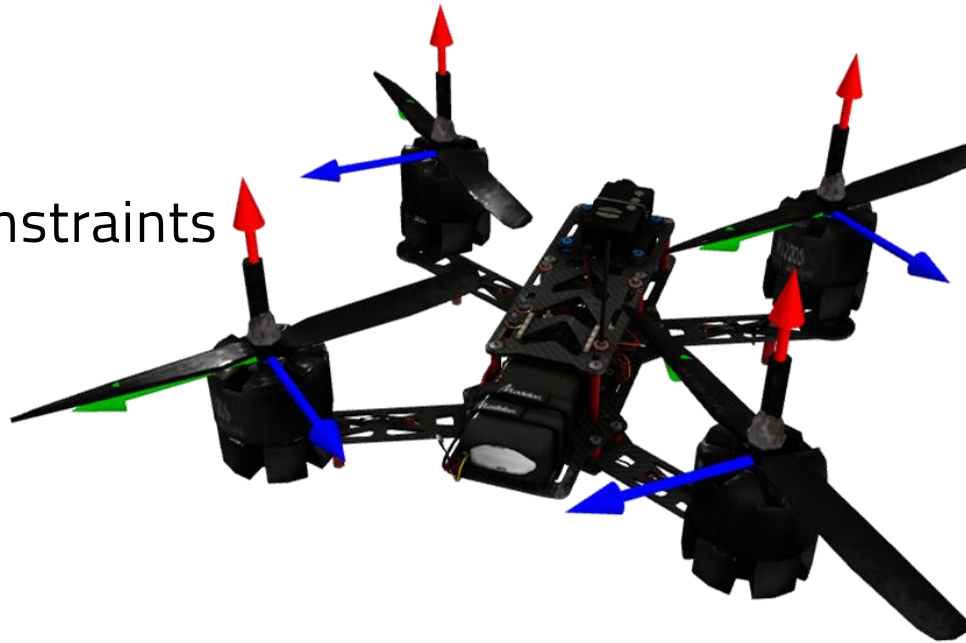
- Solving initialization problem
 - No need to adapt the code for solving an IVP
- A-causality
 - Torque trajectory optimization fed with an initial Position-controlled trajectory, simulated from the same model
- Normalization for convergence, based on nominal attributes and bounds
- Derivatives at hand of the optimizer
- “Simple, fast and robust”
 - Optimica language is similar to Modelica language (as it is an extension from it)
 - 30sec optim vs 2min for the FAST-OAD solution
- Everything is never all black or white: FAST-OAD allows integration of models from different fidelities (e.g. CFD) and well suited for large scale optimizations



CONCLUSION & PERSPECTIVES

- Simultaneous drone 1-D trajectory optimization and sizing, in Modelon Impact
- Scaling-law based sizing and efficiency-based performance models
- Results obtained with FAST-OAD and Modelon Impact were similar – though the Optimica implementation was of low threshold for a Modelica engineer (the model requires preparation)

- 6-DOF
- Regulatory constraints



THANK YOU

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