

# Launch Vehicle Trajectory Module For Multidisciplinary Design Analysis and Optimization

Jorge L. Valderrama <sup>1</sup>

Dr. Annafederica Urbano <sup>2</sup> Dr. Mathieu Balesdent <sup>3</sup> Dr. Loïc Brevault <sup>3</sup>

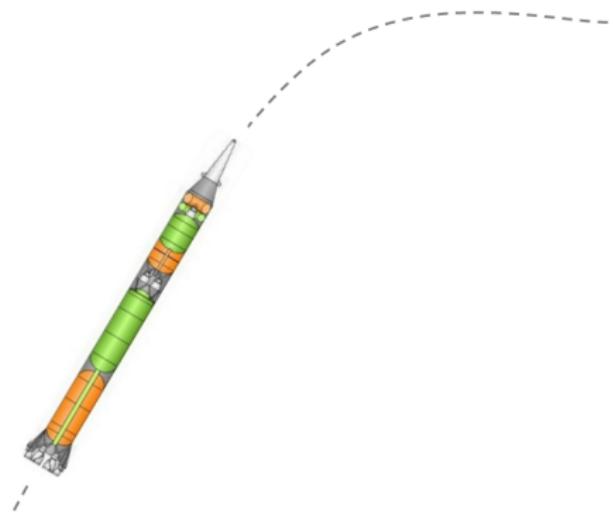
<sup>1</sup>ISAE-SUPAERO, MSc. Student

<sup>2</sup>ISAE-SUPAERO, DCAS      <sup>3</sup>ONERA, DTIS

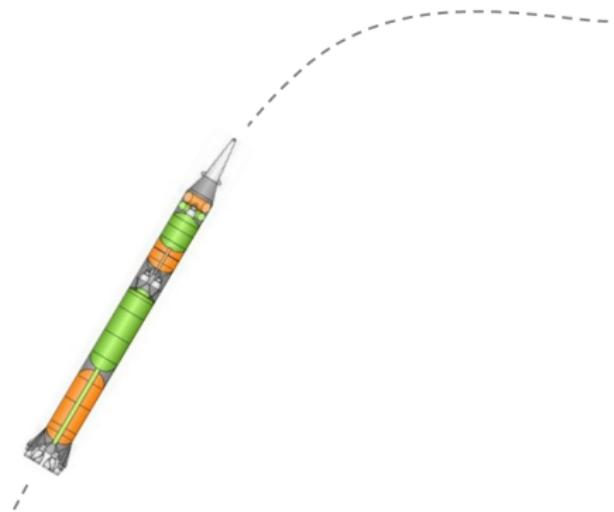


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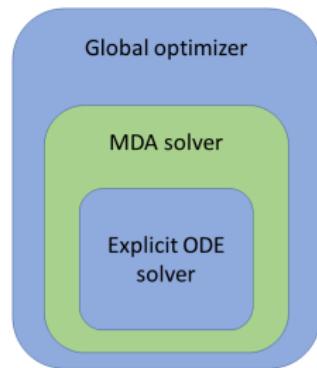
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Non-linear  
Programming (NLP)  
Solver

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- Using Multidisciplinary Design, Analysis and Optimization (MDAO)
- The most common methods involve 3 solvers. Costly Multidisciplinary Analysis (MDA)
- We propose an approach with 1 solver
- Two-stage-to-orbit (TSTO)

Non-linear  
Programming (NLP)  
Solver

- 1 Objectives
- 2 MDAO
- 3 Description of disciplines
- 4 Description of Benchmark method
- 5 Proposed optimization method
- 6 Results and comparison
- 7 Conclusions

- To integrate a trajectory optimization module using a pseudospectral method into the MDAO of a launch vehicle

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- To integrate a trajectory optimization module using a pseudospectral method into the MDAO of a launch vehicle
- To develop the trajectory module using gradient-based optimization with analytic derivatives
- To evaluate the performance of the optimization process and compare it against an existing method

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Multiple disciplines coupled with complex interactions. For example:

- Trajectory
- Propulsion
- Sizing

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<sup>1</sup>Balesdent et al. 2012.

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Single-level architectures of our interest:

- Multi-Discipline Feasible (MDF):
  - Coupled approach. Requires MDA
  - The most used in launch vehicle design<sup>1</sup>
- All-At-Once (AAO)
  - Decoupled approach. No MDA

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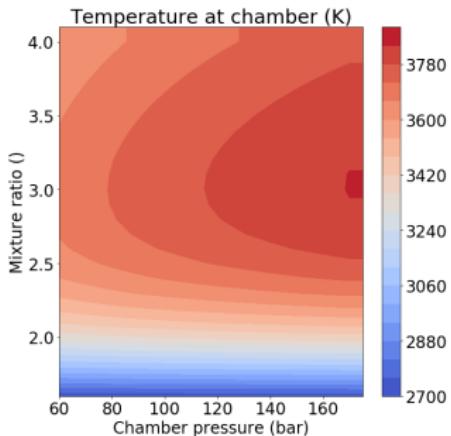
# Description of disciplines

## Propulsion

Design variables:

- Pressure at combustion chamber ( $P_c$ )
- Pressure at nozzle exit ( $P_e$ )
- Mixture ratio ( $O/F$ )
- Thrust at vacuum ( $T_{vac}$ )

$$\mathbf{z}_p = \begin{bmatrix} P_{c_1} \\ P_{c_2} \\ P_{e_1} \\ P_{e_2} \\ O/F_1 \\ O/F_2 \\ T_{vac_1} \\ T_{vac_2} \end{bmatrix}$$



Methods:

Rocket CEA<sup>2</sup> with bivariate interpolation

<sup>2</sup>Sanford and McBride 1994.

# Description of disciplines

## Mass - Sizing

Design variables:

- Mass of propellants ( $m_p$ )
- Stage diameter ( $D$ )
- Mixture ratio ( $O/F$ )
- Thrust at vacuum ( $T_{vac}$ )

$$\mathbf{z}_m = \begin{bmatrix} m_{p_1} \\ m_{p_2} \\ D \end{bmatrix}$$

$$\mathbf{y}_{fb} = \begin{bmatrix} n_{max} \\ q_{max} \end{bmatrix}$$

Feedback couplings:

- Max. load factor ( $n_{max}$ )
- Max. dynamic pressure ( $q_{max}$ )

Methods:

Regressions on existing launchers<sup>3</sup>

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<sup>3</sup>Castellini 2012.

# Description of disciplines

Trajectory

Methods:

- 2D polar coordinates

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# Description of disciplines

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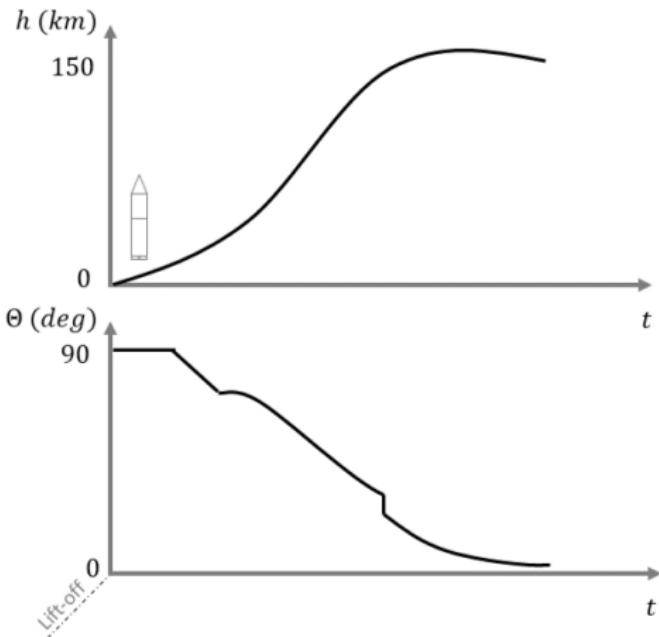
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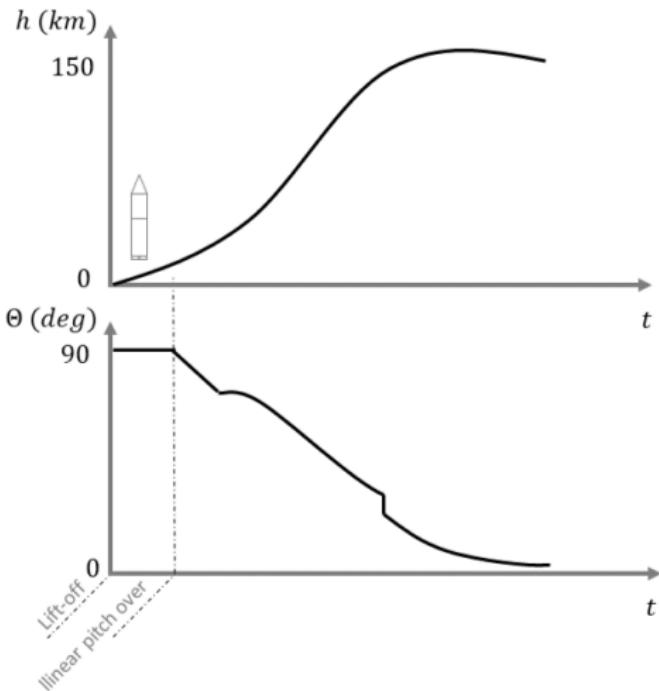


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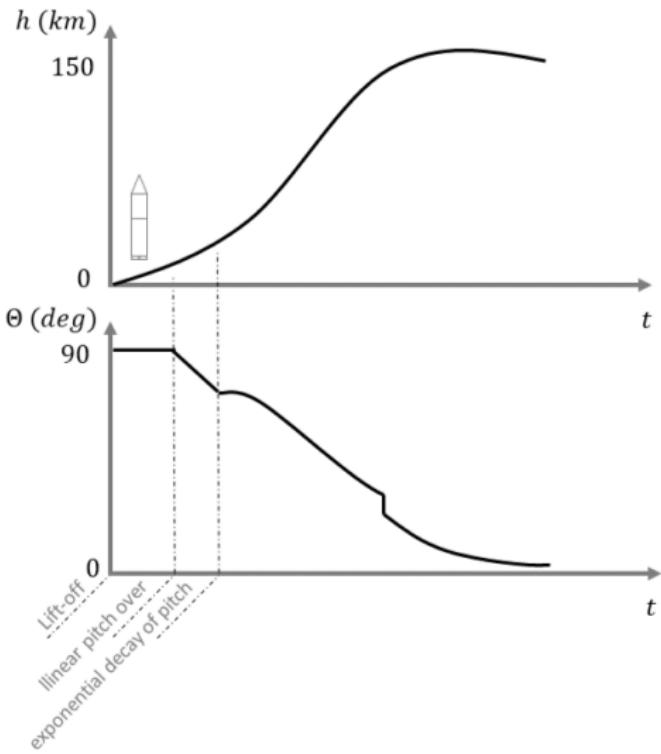


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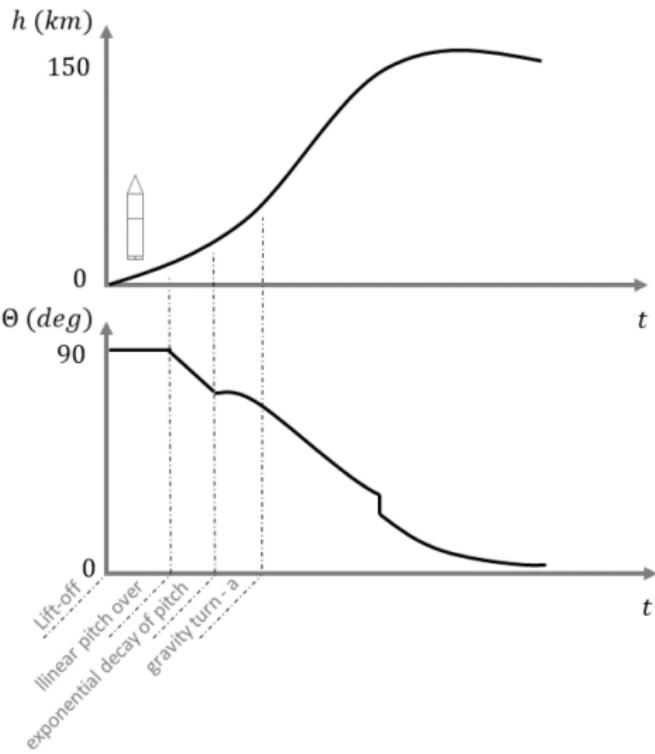


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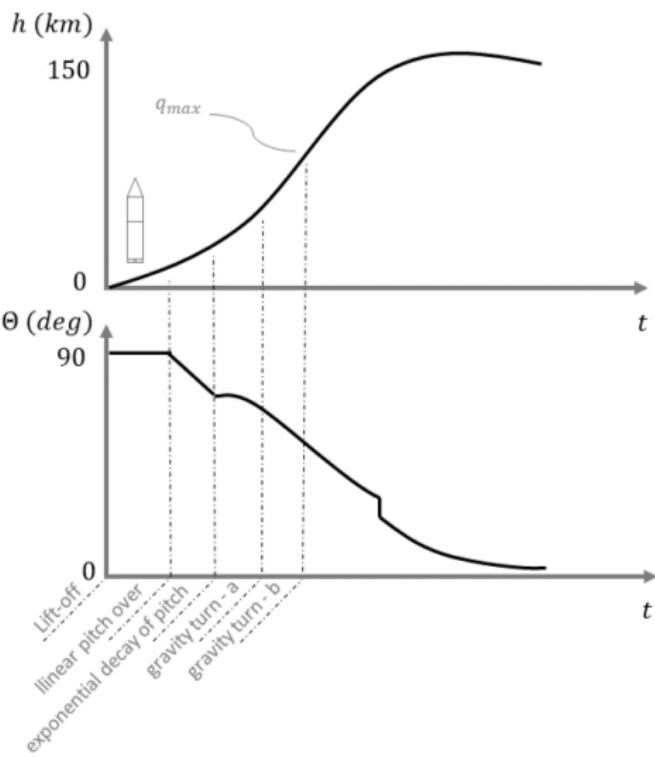


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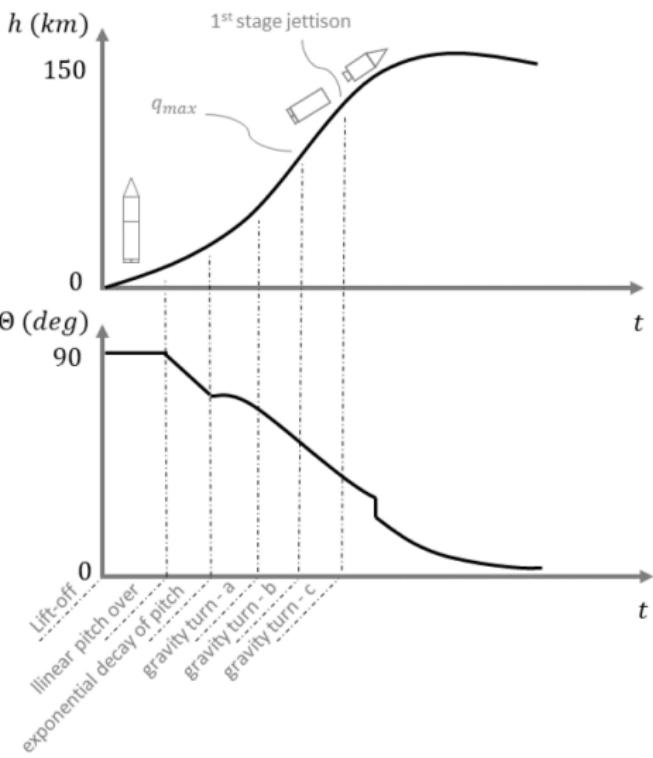


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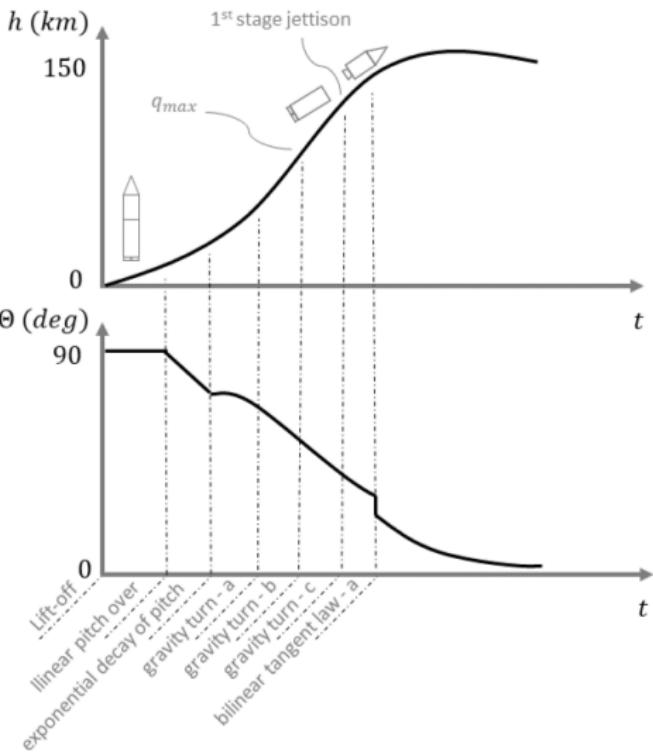


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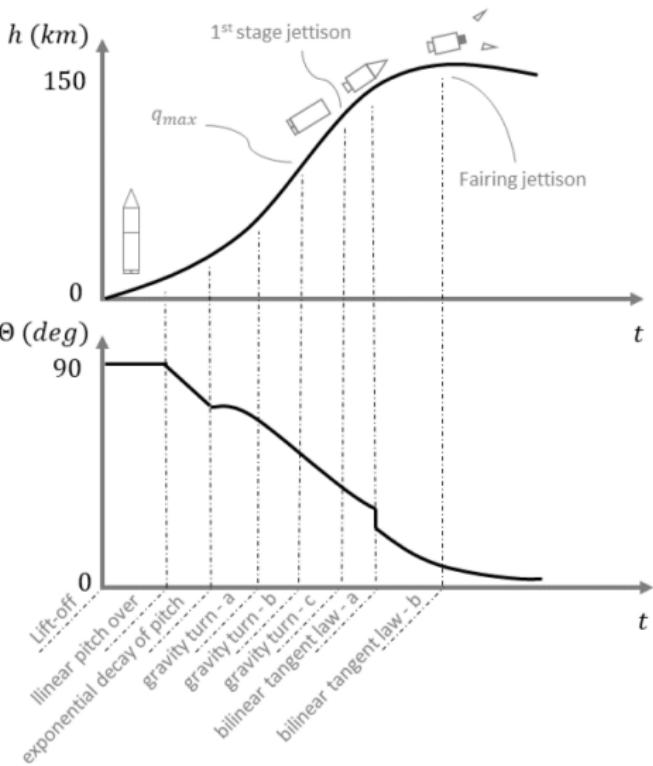


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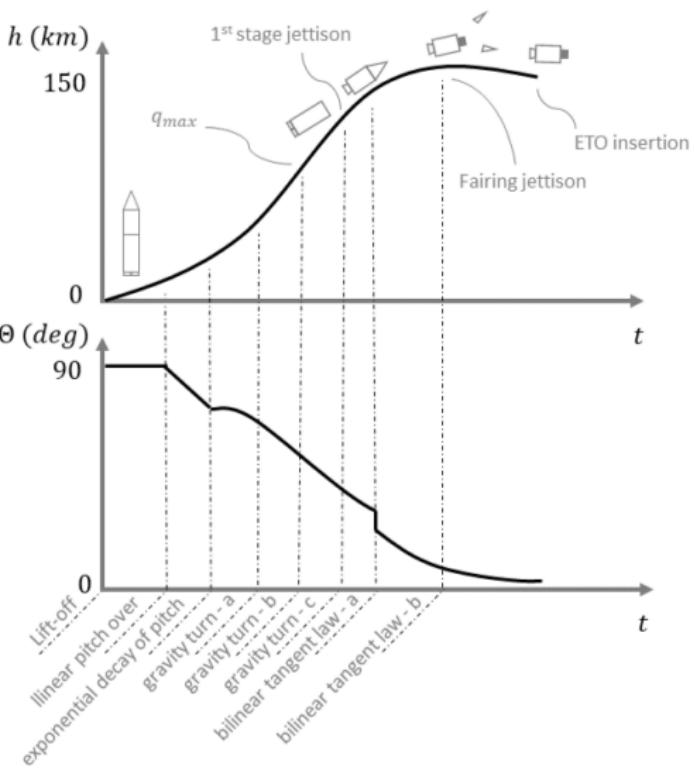


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# Description of disciplines

## Trajectory

Design variables:

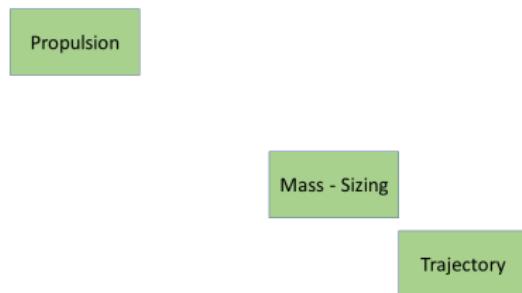
- Pitch angle guidance variables
  - Change in pitch angle during pitch over ( $\Delta\theta_{lpo}$ )
  - Change in pitch angle during bilinear tangent law ( $\Delta\theta_{btl}$ )
  - Final pitch angle ( $\theta_{btl_f}$ )
  - Shape parameter bilinear tangent law ( $\xi$ )
- Time variables ( $t$ )

$$\mathbf{z}_t = \begin{bmatrix} \Delta\theta_{lpo} \\ \Delta\theta_{btl} \\ \theta_{btl_f} \\ \xi \end{bmatrix}$$

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# Description of Benchmark method

Onera's FELIN<sup>4</sup> - "MDF-like" formulation

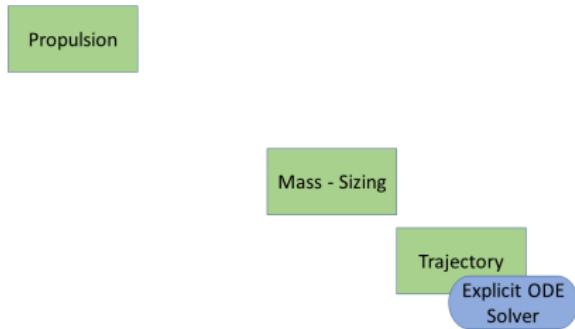


<sup>4</sup>Framework for Evolutive Launcher optimization.

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- Explicit ODE Solver.  
Runge-Kutta.

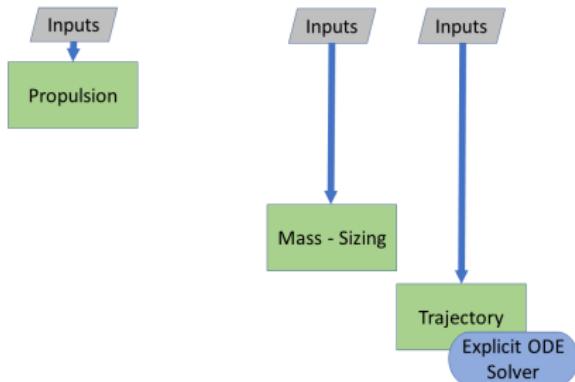


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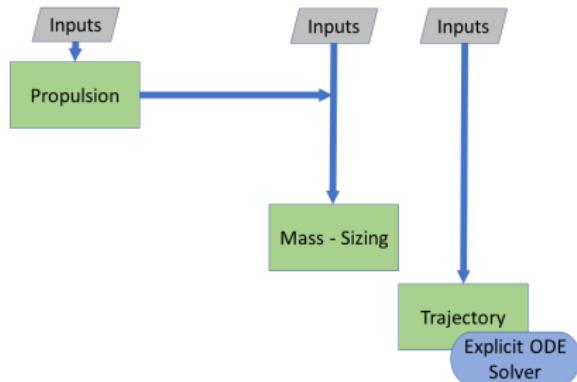


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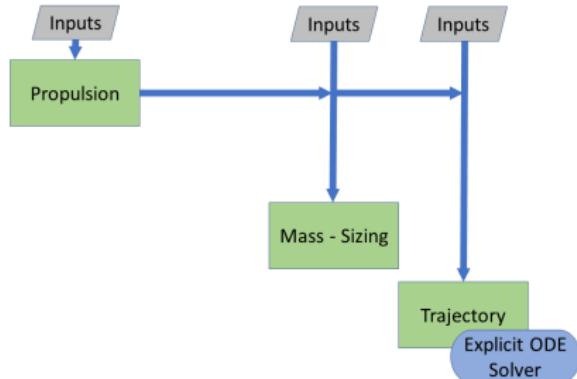


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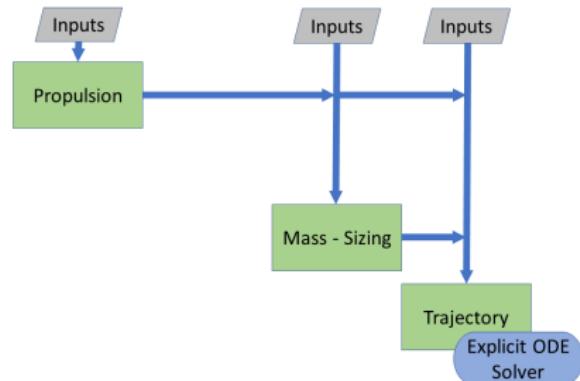


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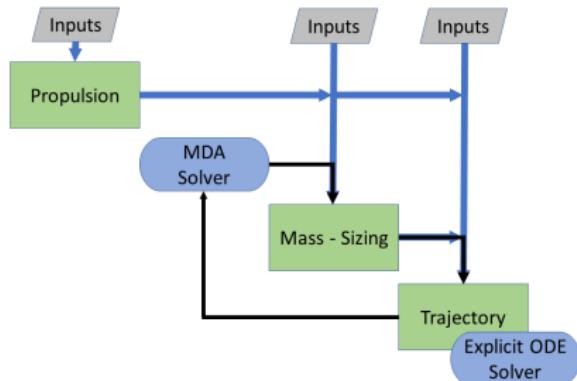


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Fixed point iteration.

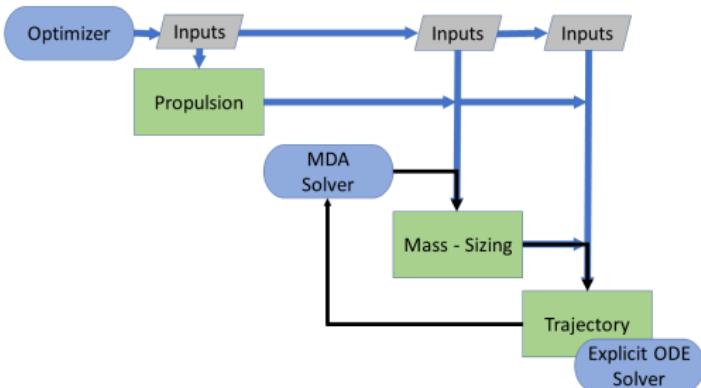


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Fixed point iteration.
- Optimizer: Covariance matrix adaptation evolution strategy  
(CMA-ES)

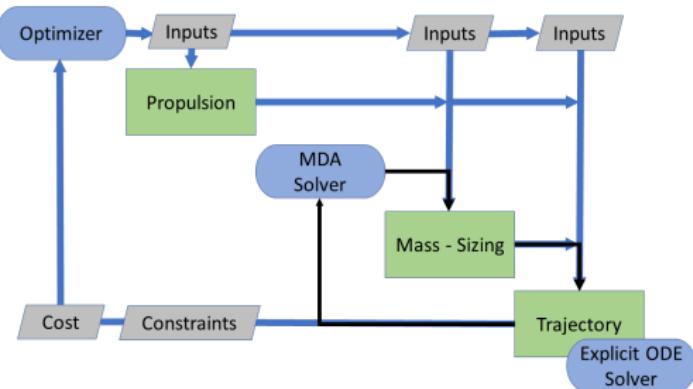


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## Main features

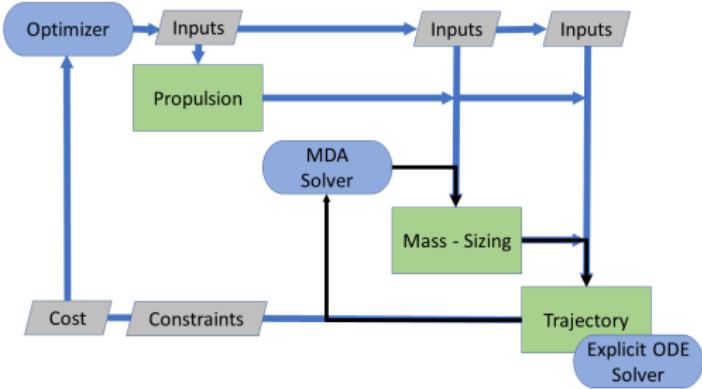
- Pseudospectral transcription for the optimal control problem using Dymos<sup>5</sup>
- Replacement of feedback couplings in an "AAO-like" fashion
- Analytic gradient calculation for all disciplines
- Chain rule with OpenMDAO<sup>6</sup>

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<sup>5</sup>Falck and Gray 2019.

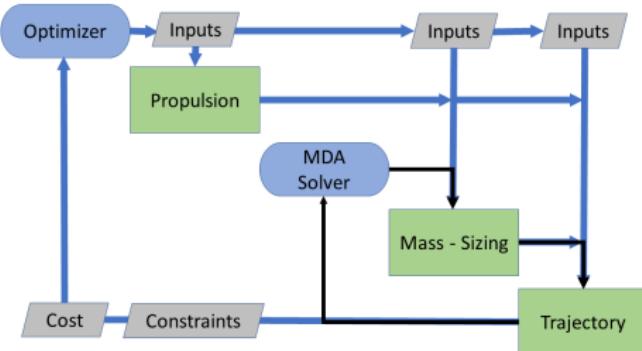
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# Proposed optimization method



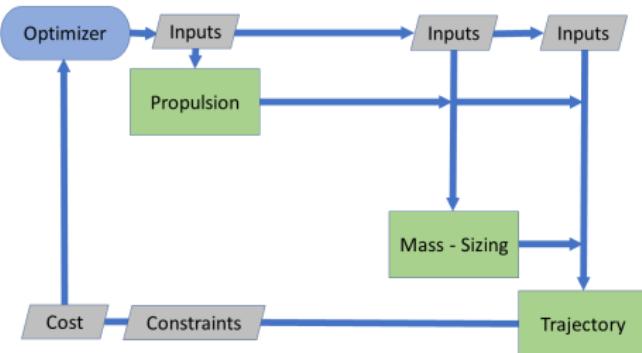
# Proposed optimization method

- Remove explicit ODE solver



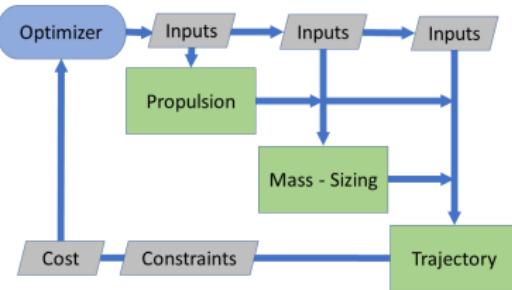
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- Remove explicit ODE solver
- Remove MDA solver



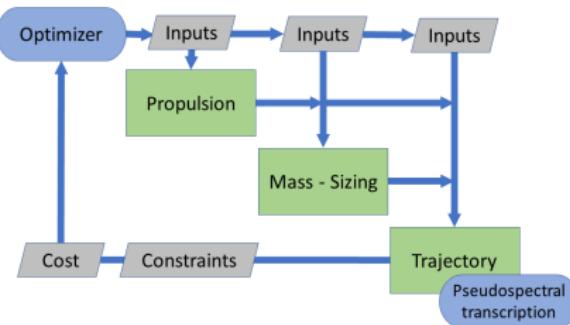
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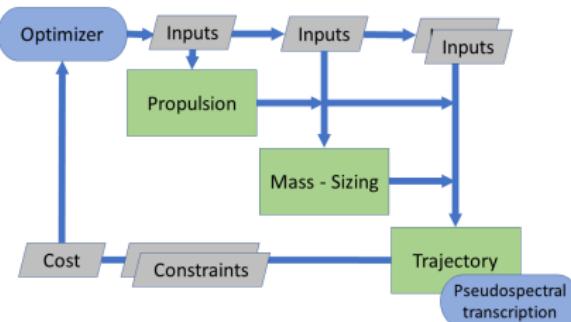
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- Remove explicit ODE solver
- Remove MDA solver
- Use of pseudospectral transcription



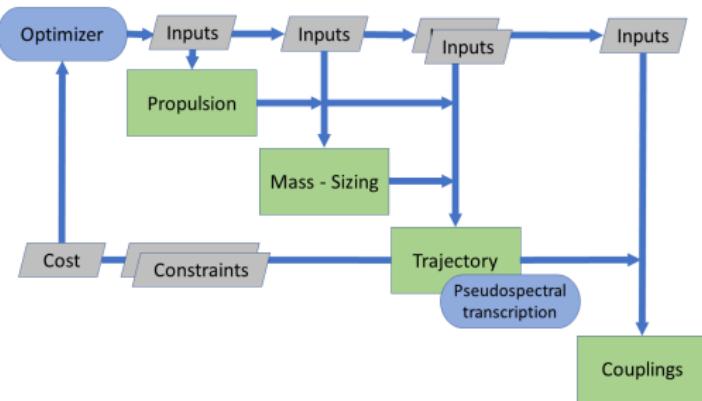
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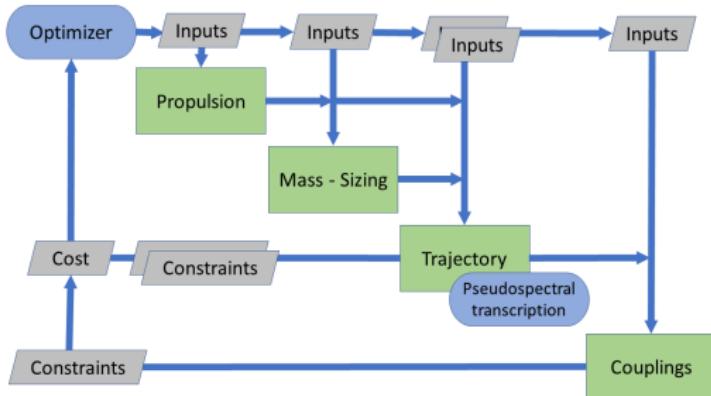
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- Remove explicit ODE solver
- Remove MDA solver
- Use of pseudospectral transcription
- Duplicated variables for feedback couplings



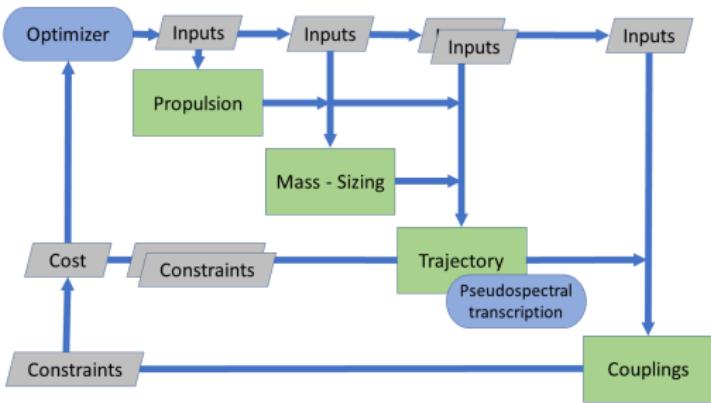
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# Proposed optimization method

- Remove explicit ODE solver
- Remove MDA solver
- Use of pseudospectral transcription
- Duplicated variables for feedback couplings
- Optimizer: Sequential Least Squares Programming (SLSQP)

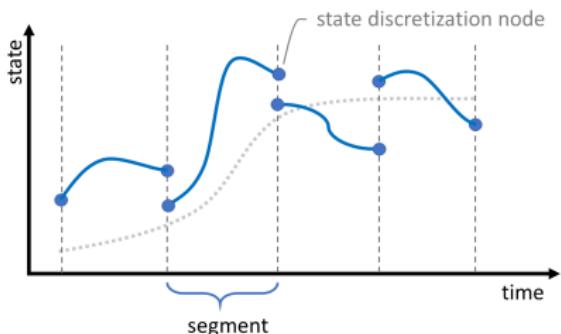


# Proposed optimization method

## Pseudospectral transcription

### Legendre-Gauss-Lobatto - Order 3

- 5 states
- 56 segments
- 560 state discretization nodes ( $x_t$ )
- 15 time variables ( $t$ )
- 566 equality constraints

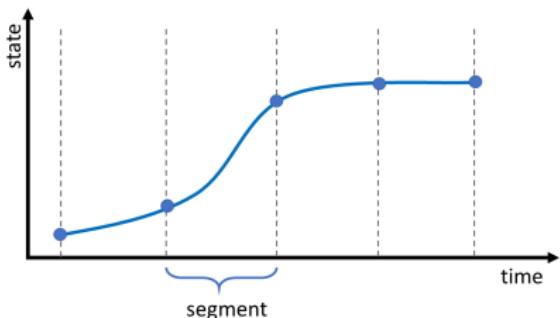


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# Proposed optimization method

Definition and size of MDAO problem

minimize : Gross lift-off weight (GLOW)

with respect to :  $[\mathbf{x}_t, \mathbf{t}, \mathbf{y}_{fb}, \mathbf{z}_p, \mathbf{z}_m, \mathbf{z}_t] \in \mathbb{R}^{592}$

subject to

equality constraints :  $\mathbf{h}(\mathbf{x}_t, \mathbf{t}, \mathbf{y}_{fb}, \mathbf{z}_p, \mathbf{z}_m, \mathbf{z}_t) = \mathbf{0}$  ,  $\mathbf{h} \in \mathbb{R}^{567}$

inequality constraints :  $\mathbf{g}(\mathbf{x}_t, \mathbf{t}, \mathbf{y}_{fb}, \mathbf{z}_p, \mathbf{z}_m, \mathbf{z}_t) \leq \mathbf{0}$  ,  $\mathbf{g} \in \mathbb{R}^{13}$

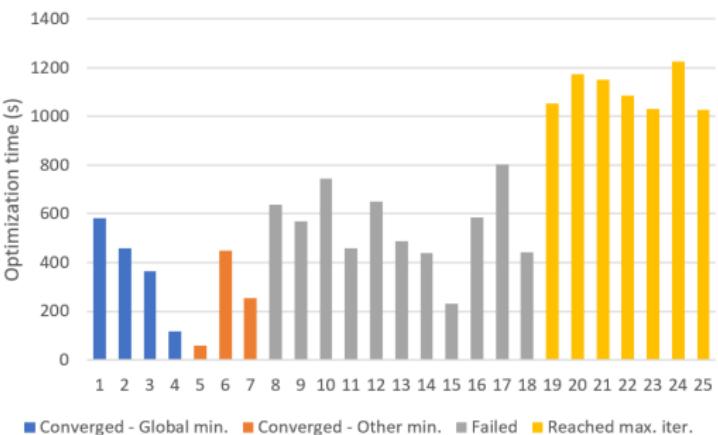
The NLP solver SLSQP drives the whole problem

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# Results and comparison

Case study of TSTO with 11ton payload to 400 km orbit

- SLSQP is a local optimizer
- 25 runs with partially random initialization
- 4 runs converged to the global minimum



# Results and comparison

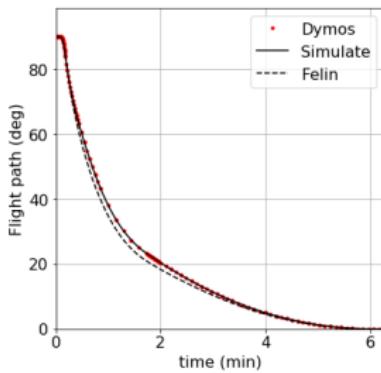
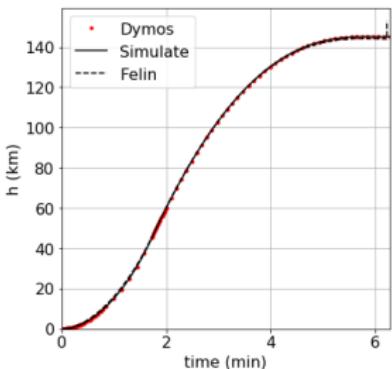
Global optimum

Dymos:  
Proposed method

Felin:  
Benchmark method

Simulate:  
Test for discretization

Coast test:  
Orbit verification



# Results and comparison

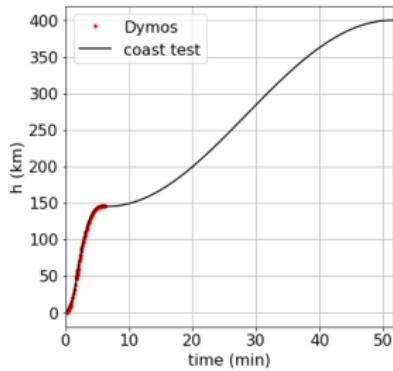
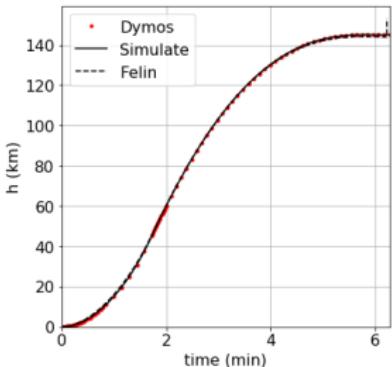
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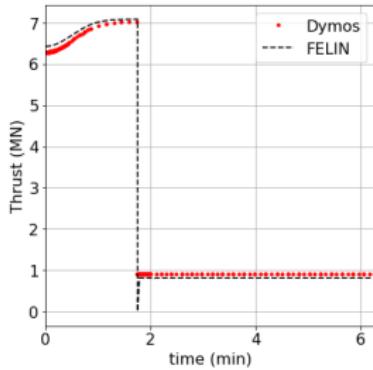
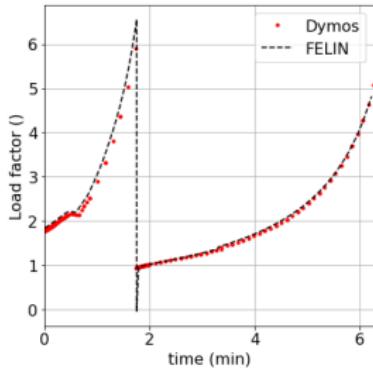
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# Results and comparison

## Performance

	Dymos Global optimum Best run	Dymos 25 runs	Felin Unique run
GLOW (tons)	359.08	359.08	355.6
Function evaluations	169	31 035	51 019
Optimization time (h)	0.03	4.4	1.88

# Results and comparison

## Performance

Design Variables				
Discipline	Variable	Dymos	Felin	Error
Propulsion	$T_{vac_1}$	7 026 653.2	7 084 316.2	$8.14 \times 10^{-3}$
	$T_{vac_2}$	911 354.5	804 667.2	$1.33 \times 10^{-1}$
	$O/F_1$	2.3026	2.3298	$1.17 \times 10^{-2}$
	$O/F_2$	2.3445	2.3556	$4.71 \times 10^{-3}$
	$P_{c_1}$	10 000 000.0	9 953 515.2	$4.67 \times 10^{-3}$
	$P_{c_2}$	10 000 000.0	9 999 345.6	$6.54 \times 10^{-5}$
	$P_{e_1}$	53 760.9	62 725.4	$1.43 \times 10^{-1}$
	$P_{e_2}$	3 540.8	3 439.2	$2.95 \times 10^{-2}$
Mass/Sizing	$m_{p_1}$	238 461.2	244 349.4	$2.41 \times 10^{-2}$
	$m_{p_2}$	74 853.7	65 174.2	$1.49 \times 10^{-1}$
	$D$	3.8066	3.6189	$5.19 \times 10^{-2}$
Trajectory	$\Delta\theta_{lpo}$	7.9985	9.2866	$1.39 \times 10^{-1}$
	$\Delta\theta_{btl}$	2.1142	-	-
	$\theta_{btlf}$	0.8422	0.77	$9.38 \times 10^{-2}$
	$\xi$	-0.152	-0.286	$4.69 \times 10^{-1}$

Average error in design variables between global optimum in Dymos and Felin : 4%

# Results and comparison

Use of existing solution as initial guess

Optimization time: 222 s

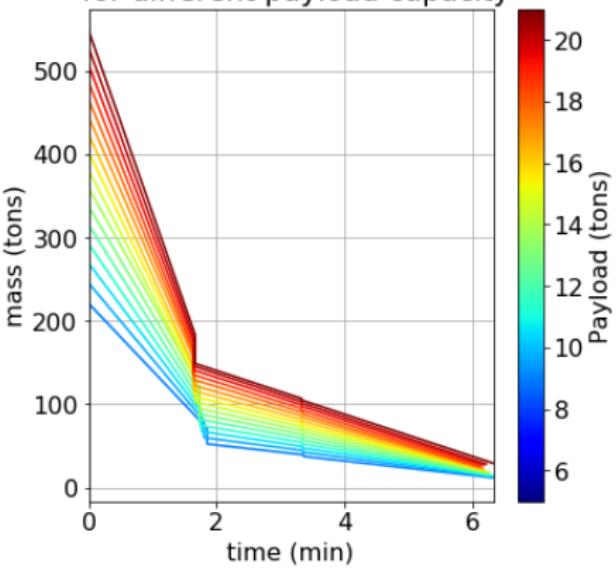
# Results and comparison

Use of existing solution as initial guess

Use of obtained results as initial guess to optimize vehicles with different payloads.

- 93% convergence rate
- Total optimization time 0.8 h.

Optimization of 16 different vehicles for different payload capacity



- 1 Objectives
- 2 MDAO
- 3 Description of disciplines
- 4 Description of Benchmark method
- 5 Proposed optimization method
- 6 Results and comparison
- 7 Conclusions

- A new methodology for the MDAO of launch vehicles was proposed using a pseudospectral method for optimal control.
- The current model is sensitive to random initialization.
- A comparison with a existing methodology was done to verify the accuracy of the new methodology.

# Conclusions

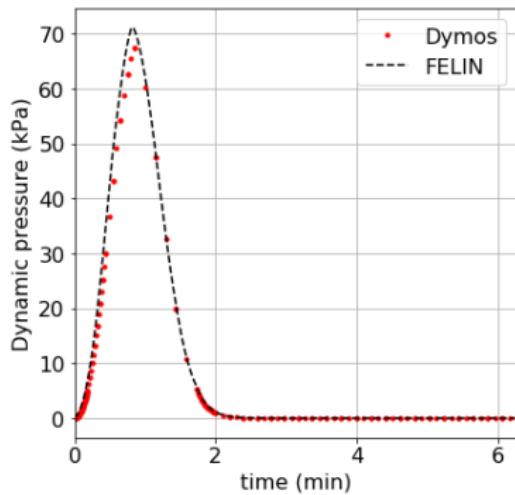
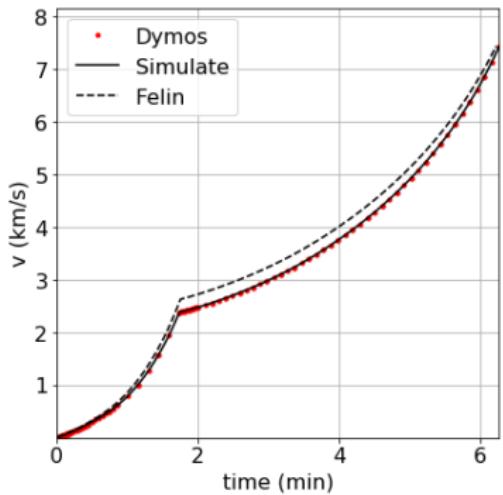
## Future work

- Improve the models to reduce the sensitivity to random initialization
- Use more performant optimizers like SNOPT with bounds on state discretization nodes
- This work will be presented in the 14th World Congress on Structural and Multidisciplinary Optimization in June 2021

- Balesdent, Mathieu et al. (May 2012). "A Survey of Multidisciplinary Design Optimization Methods in Launch Vehicle Design". en. In: *Struct Multidisc Optim* 45.5, pp. 619–642. ISSN: 1615-1488. DOI: 10.1007/s00158-011-0701-4.
- Brevault, Loic and Mathieu Balesdent. *Framework for Evolutive Launcher optimization*. <https://github.com/l-brevault/FELIN>.
- Castellini, Francesco (2012). "MULTIDISCIPLINARY DESIGN OPTIMIZATION FOR EXPENDABLE LAUNCH VEHICLES". en. In:
- Falck, Robert D. and Justin S. Gray (2019). "Optimal Control within the Context of Multidisciplinary Design, Analysis, and Optimization". In: *AIAA Scitech 2019 Forum*. American Institute of Aeronautics and Astronautics.
- Gray, Justin S. et al. (Apr. 2019). "OpenMDAO: An Open-Source Framework for Multidisciplinary Design, Analysis, and Optimization". en. In: *Struct Multidisc Optim*. ISSN: 1615-1488. DOI: 10.1007/s00158-019-02211-z.

Sanford, Gordon and Bonnie J. McBride (Oct. 1994). *Computer Program for Calculation of Complex Chemical Equilibrium Compositions and Applications. Part 1: Analysis.*

# more results I



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===== Optimization Report =====
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Design parameters: All values in standard SI units. Angles in radians.  
 Design parameters marked with (\*\*\*) are close to their bounds or violate them

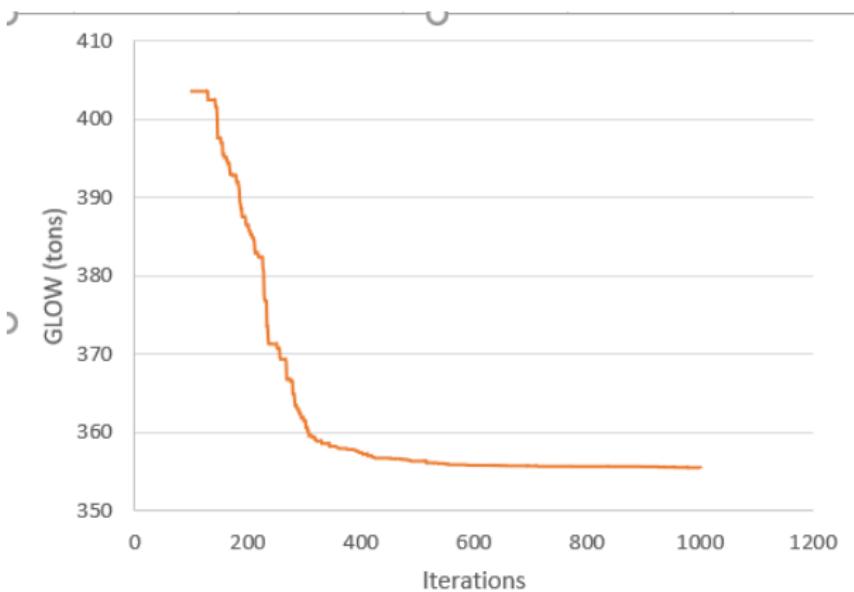
Name	lower	value	upper
lift_off_t_duration	1.0	5.912	100.0
pitch_over_linear_t_duration (***)	5.0	5.0	10.0
pitch_over_exponential_t_duration	1.0	11.2118	100.0
gravity_turn_t_duration	1.0	27.6856	150.0
gravity_turn_b_t_duration	1.0	50.7093	150.0
gravity_turn_c_t_duration	1.0	58.1435	150.0
exoatmos_a_t_duration	1.0	39.6573	250.0
exoatmos_b_t_duration	1.0	174.6421	250.0
delta_theta_pitch_over	0.0175	0.1735	0.1745
xi	-1.0	-0.1038	1.0
delta_theta_exoatmos	-1.0472	0.0439	1.0472
theta_f	-0.3491	0.0141	0.3491
P_c_stage_2 (***)	6000000.0	10000000.0	10000000.0
P_e_stage_2	1.0	3572.0683	10000.0
o_f_stage_2	2.0	2.3442	4.0
thrust_vac_stage_2	100000.0	911856.4145	1400000.0
mp_2 (***)	50000.0	75000.0	75000.0
P_c_stage_1 (***)	6000000.0	10000000.0	10000000.0
P_e_stage_1	40530.0	56464.0449	200000.0
o_f_stage_1	2.0	2.3016	4.0
thrust_vac_stage_1	5000000.0	7234644.1341	15000000.0
mp_1	230000.0	237753.0767	280000.0
max_n_f_1	1.0	6.0468	10.0
max_q_dyn_1	10.0	71880.9436	100000.0
D_stage_1	1.0	3.7947	5.0

Constraints: All values in standard SI units. Angles in radians.			
Name	lower	value	upper
Jettison.residual_ms_1	0.0	-0.0	1e+30
Jettison.residual_mp1f	0.0	-0.0	1e+30
Jettison.residual_m_final	0.0	-0.0	1e+30
ExitArea.residual_area_1	0.0	-0.0	1e+30
ExitArea.residual_area_2	0.0	-0.0	1e+30
DynamicPressure.residual_max_q_dyn	0.0	-0.0	1e+30
Propellants.residual_mp_1	0.0	-0.0	1e+30
Propellants.residual_mp_2	0.0	-0.0	1e+30
LoadFactor.residual_max_n_f_1	0.0	0.0	1e+30
lift_off_final_value:r	6378285.0	6378285.0	6380135.0
gravity_turn_final_value:qdot	-1e+30	-0.0	1e+30
gravity_turn_c_final_value:qdyn	-1e+21	10.5702	1000.0
exoatmos_a_final_value:q_heat	-1e+21	1135.0	1135.0
exoatmos_b_final_value:ra	6778135.0	6778135.0004	6798135.0
exoatmos_b_final_value:rp	6523135.0	6523134.9996	1e+21

Vehicle parameters

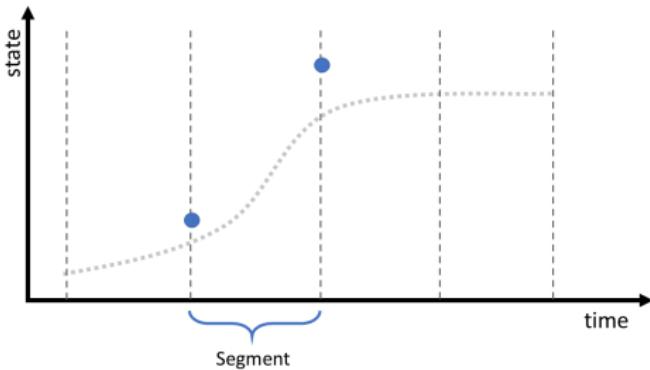
Payload mass (kg):	11000.0
Fairing mass (kg):	1900.0
Aux mass first stage (kg):	3000.0
Propulsion type ():	LOX + RP_1
First stage:	
Structural mass (kg):	26499.14
Propellants mass (kg):	237753.08
Structural coef ():	0.1
Thrust (N):	7234644.13
Isp (vac) (s):	311.9
number of engines ():	9
Ae_t (m^2):	7.24
Second stage:	
Structural mass (kg):	6928.2
Propellants mass (kg):	75000.0
Structural coef ():	0.08
Thrust (N):	911856.41
Isp (vac) (s):	339.59
number of engines ():	1
Ae_t (m^2):	7.24
First stage flight with fairing:	
Tw_ratio ():	2.05
Second stage flight with fairing:	
Tw_ratio ():	0.98

# Convergence FELIN I



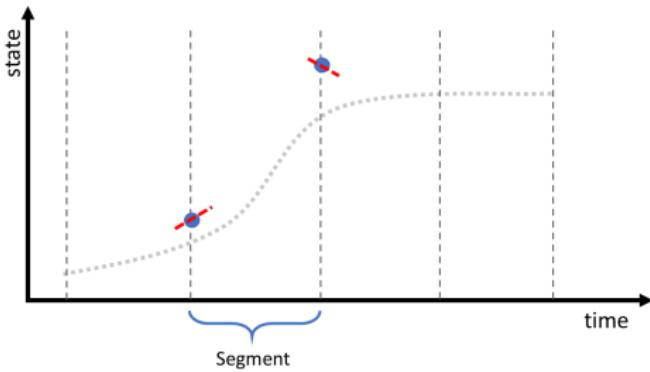
## Legendre-Gauss-Lobatto - Order 3

- Time discretization



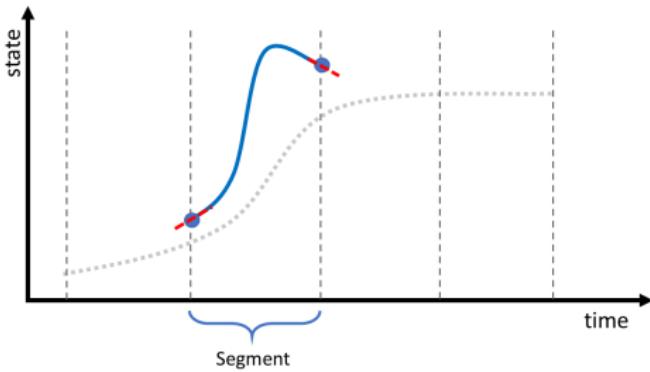
## Legendre-Gauss-Lobatto - Order 3

- Time discretization
- ODE evaluation



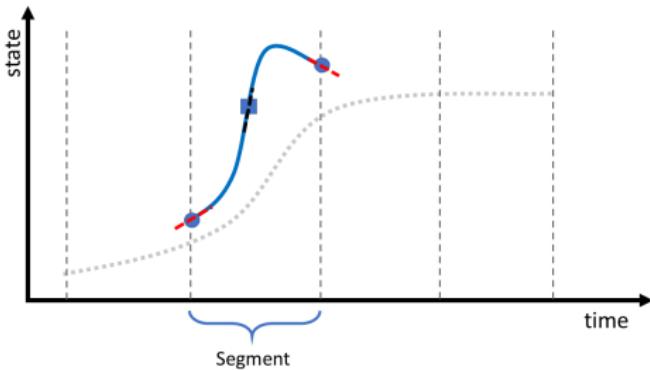
## Legendre-Gauss-Lobatto - Order 3

- Time discretization
- ODE evaluation
- Interpolation



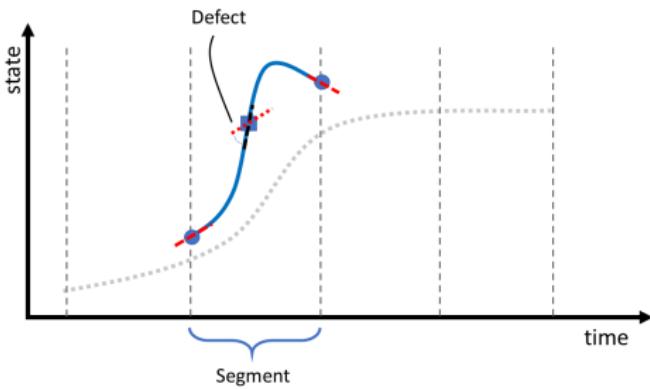
## Legendre-Gauss-Lobatto - Order 3

- Time discretization
- ODE evaluation
- Interpolation
- Polynomial derivative



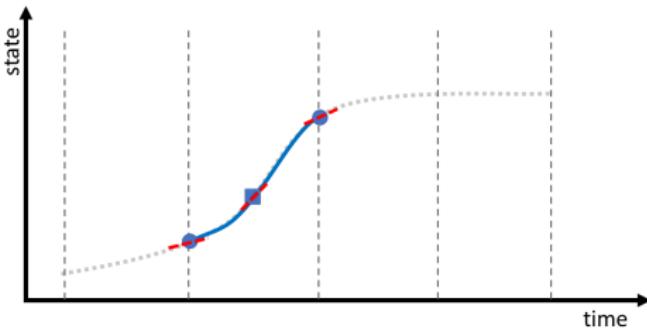
## Legendre-Gauss-Lobatto - Order 3

- Time discretization
- ODE evaluation
- Interpolation
- Polynomial derivative
- ODE evaluation



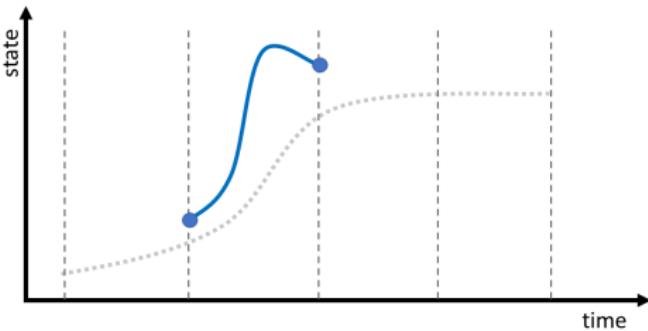
## Legendre-Gauss-Lobatto - Order 3

- Time discretization
- ODE evaluation
- Interpolation
- Polynomial derivative
- ODE evaluation
- NLP optimizer



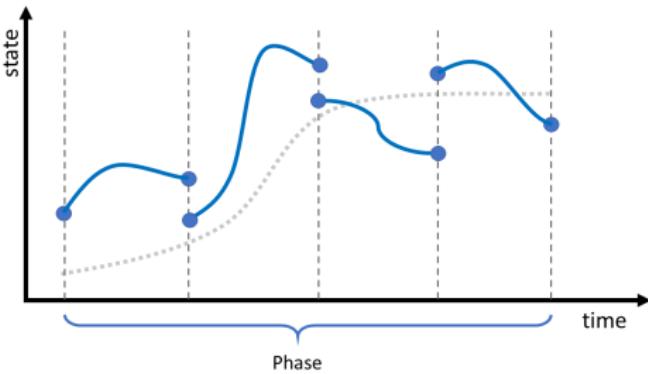
## Legendre-Gauss-Lobatto - Order 3

- Time discretization
- ODE evaluation
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## Legendre-Gauss-Lobatto - Order 3

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## Legendre-Gauss-Lobatto - Order 3

- Time discretization
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