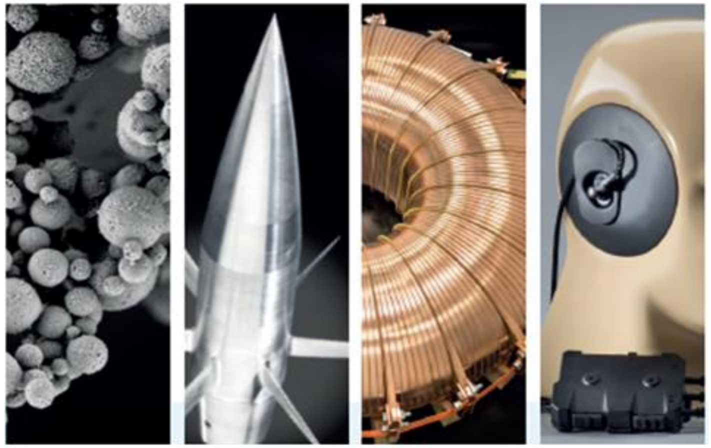

Artificial Intelligence Techniques applied to Aerodynamics and Ballistics

12/05/2022

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Marion GILSON (CRAN), Xavier BOMBOIS (CNRS)

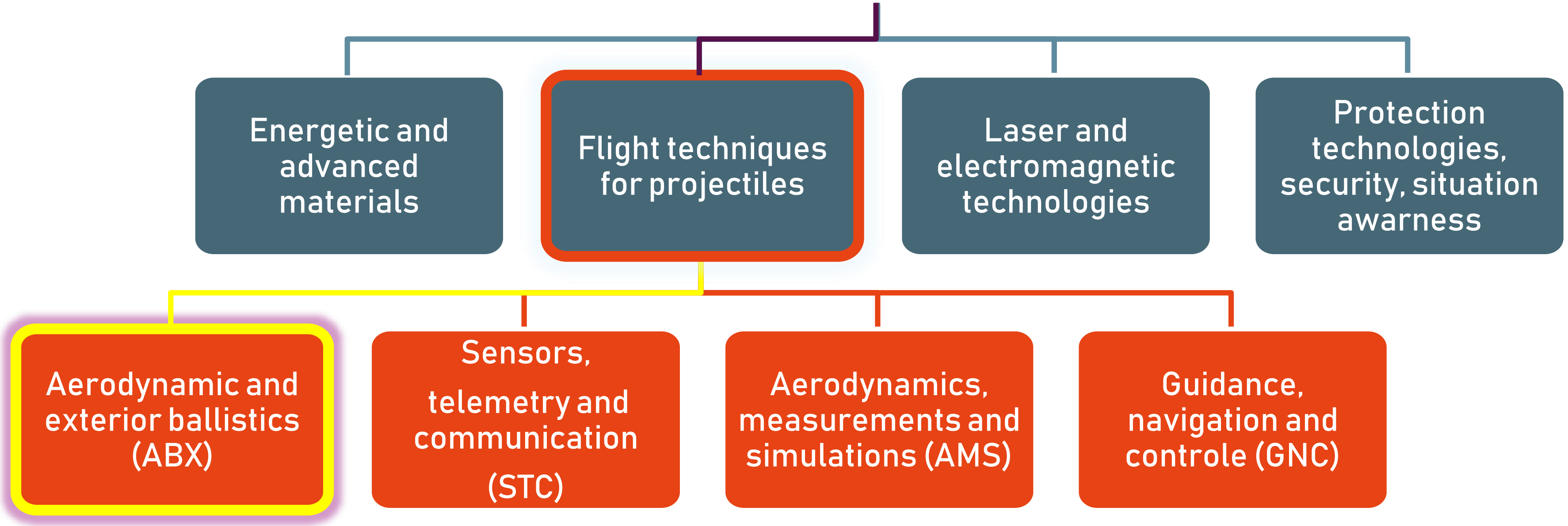
Summary

- **Prediction of experimental conditions using machine learning**
  - Context
  - Data processing
  - Machine learning
  - Results

- **Artificial Intelligence applied to aerodynamics**
  - Thesis subject
  - Aerodynamic database
  - Aerodynamic predictions
  - Geometry design

French-German Research Institute of Saint-Louis

- 200 Scientists
- Defense and security

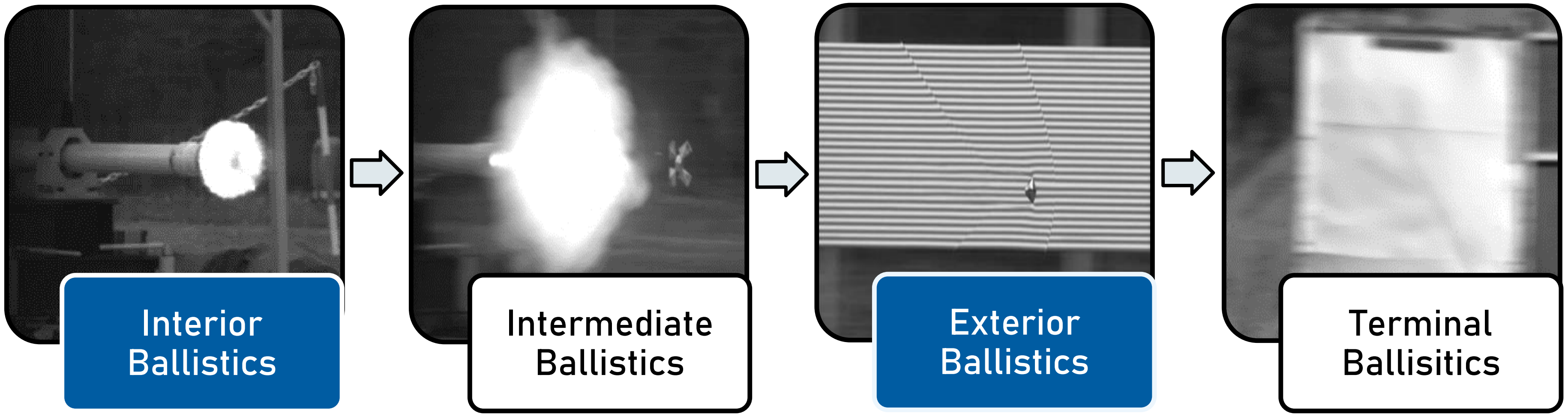


Prediction of experimental conditions using Machine Learning

Context

User requirements, objectives and experimental framework

Aerodynamic testing



Carrying out Experimental Campaigns → Aerodynamic characterizations from free flight data

- **Measurements of Velocities, Accelerations, Pressures… ➔ Over 2100 samples**

Study on launchers 91L100 and 105L33

- **Predict experimental values (Initial velocity, Pressure, Mass of powder) ➔ smooth running of experiments**
  - ➢ **Functions that will give the experimental values**

Initial Velocity V_0 (m/s)

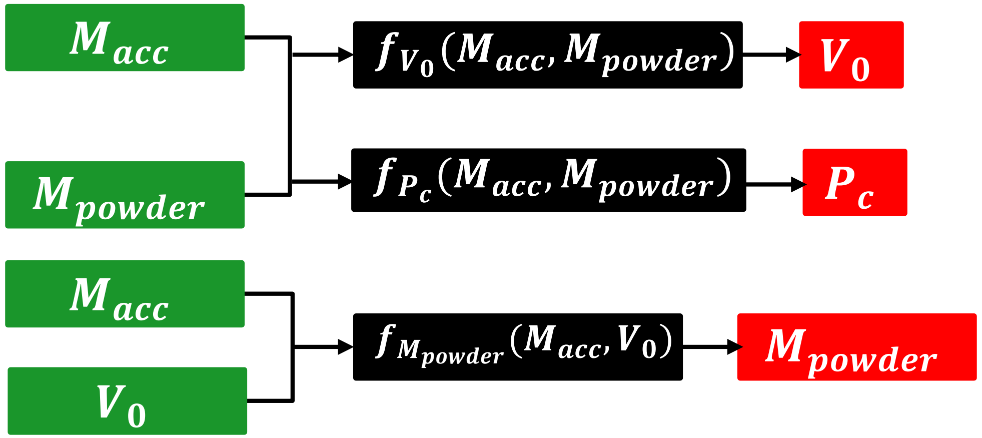
- SITT (Trajectory tracker)
  - ➢ $V_0 = f(M_{acc}, M_{powder})$

Chamber Pressure P_c (bar)

- Maximum Pc per launcher
- Acceleration
  - ➢ $P_c = f(M_{acc}, M_{powder})$

Mass of powder M_{powder} (g)

- Quantity of powder needed to reach V_0
  - ➢ $M_{powder} = f(M_{acc}, V_0)$



- **Other tools to determine these experimental parameters : IntBal Predictions and Ami Simulations**

V_0 : Initial Velocity, M_{acc}: Accelerated mass, M_{powder}: Powder mass

Data processing

Data processing and analyze

Data processing

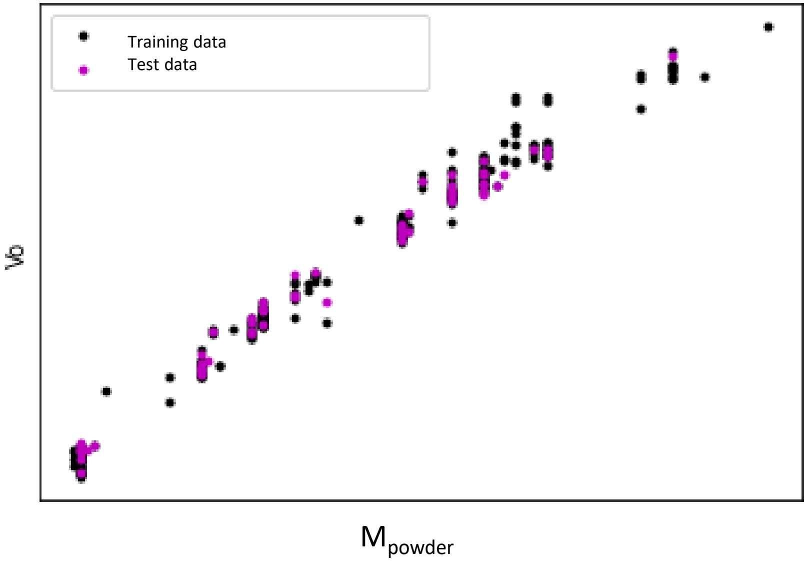
Removal of observations with missing values → Add of virtual data related to prior-knowledge → Data standardization → Mixing and splitting data

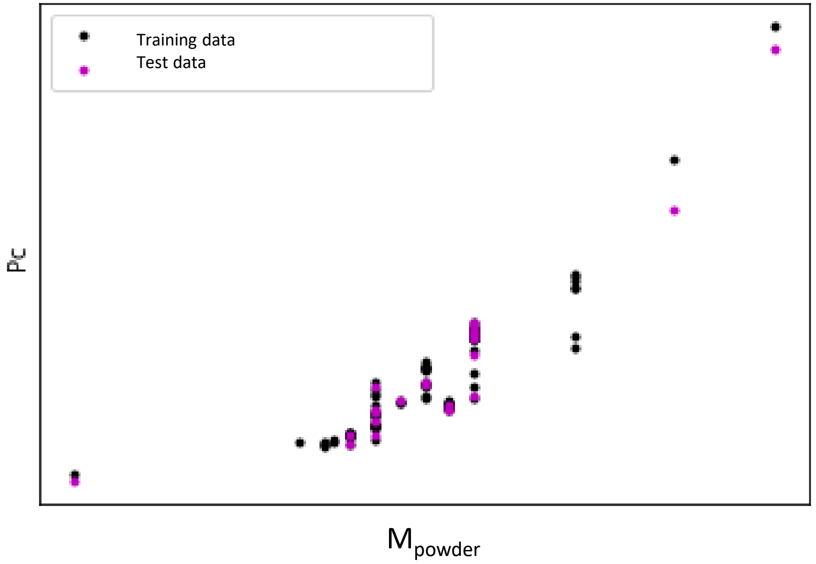
- Sensors faults…

- Zero mass powder ➔ Zero Velocity, pressure and acceleration

- Mean= 0 and Standard deviation = 1

- Training, validation and test base

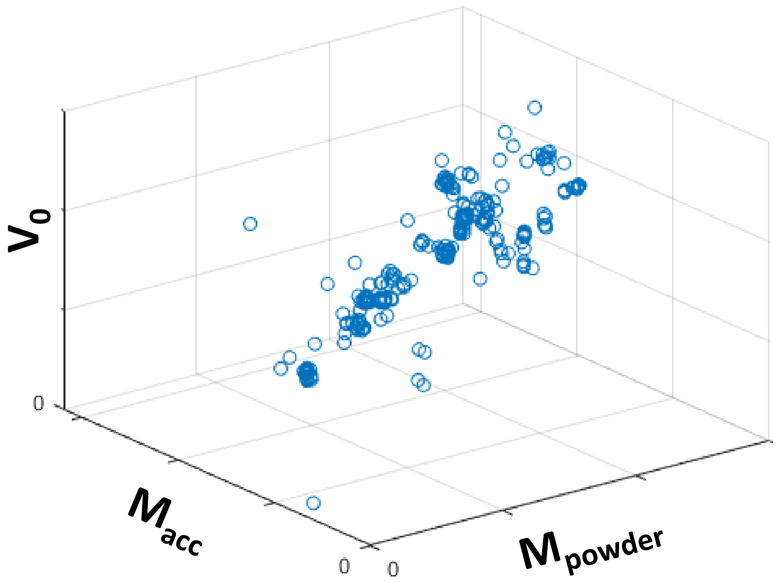


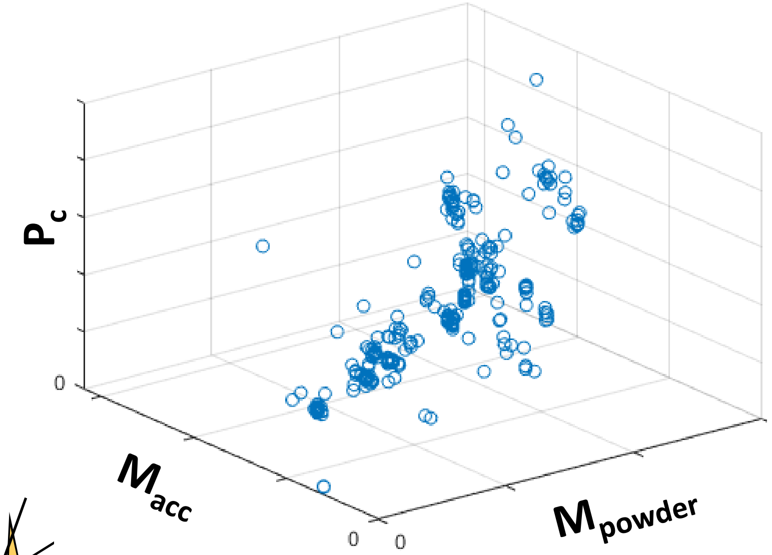


Model Identification

Algorithms, evaluation factors and validation method

Algorithm choice





Criteria

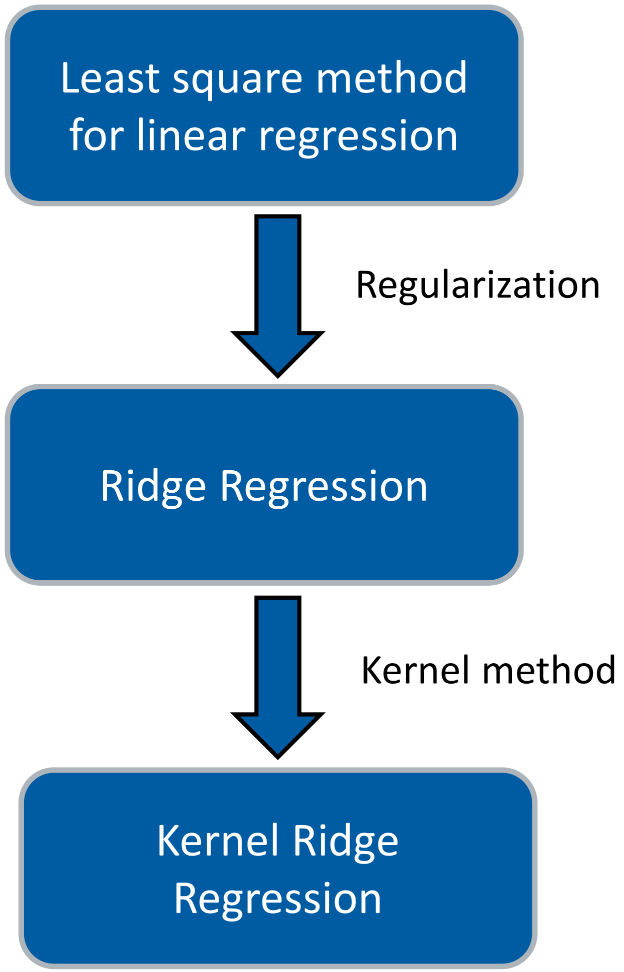
- Capable of dealing with non linear function
- Efficient to process few data

Possibilities

- Support Vector Regression
- Kernel Ridge Regression
- Gaussian Process Regression
- Multi Layer Perceptron
- Polynomial Regression

Used tools : Python
+ Scikit-Learn Library

Kernel Ridge Regression (KRR) algorithm



$$\hat{f} = \arg min_{f \in H} \sum_{i=1}^{n} \left(y_i - f(x_i)\right)^2 + \lambda \, \|f\|_H^2$$

If H is a **RKHS** then according to the **Representer Theorem** the form of the solution is :

$$f(x) = \sum_{i=1}^{n} \alpha_i K(x_i, x)$$ with α a parameter vector $\alpha = [\alpha_1, \ldots, \alpha_n]$

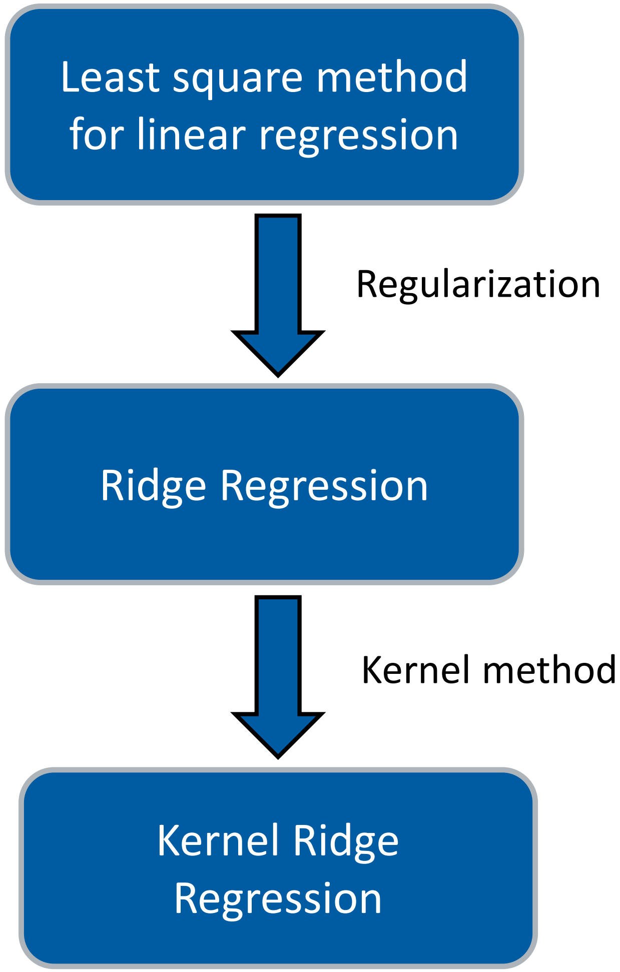
$$\hat{\alpha} = \arg min_{\alpha \in R} \sum_{i=1}^{n} \left(y_i - \sum_{j=1}^{n} \alpha_j K(x_j, x_i)\right)^2 + \lambda \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j K(x_j, x_i)$$

$$\hat{\alpha} = (\boldsymbol{K} + \boldsymbol{\lambda I})^{-1} \boldsymbol{y}$$

RKHS : Reproducing Kernel Hilbert Space

https://mlweb.loria.fr/book/en/kernelridgeregression.html

Kernel Ridge Regression (KRR) algorithm



KRR with Polynomial kernel of order γ

$$f(x) = \sum_{i=1}^{n} \alpha_i (x_i x + 1)^{\gamma}$$

KRR with Gaussian kernel

$$f(x) = \sum_{i=1}^{n} \alpha_i e^{\left(\frac{-(x-x_i)^2}{2\sigma^2}\right)}$$

https://mlweb.loria.fr/book/en/kernelridgeregression.html

Evaluation factors

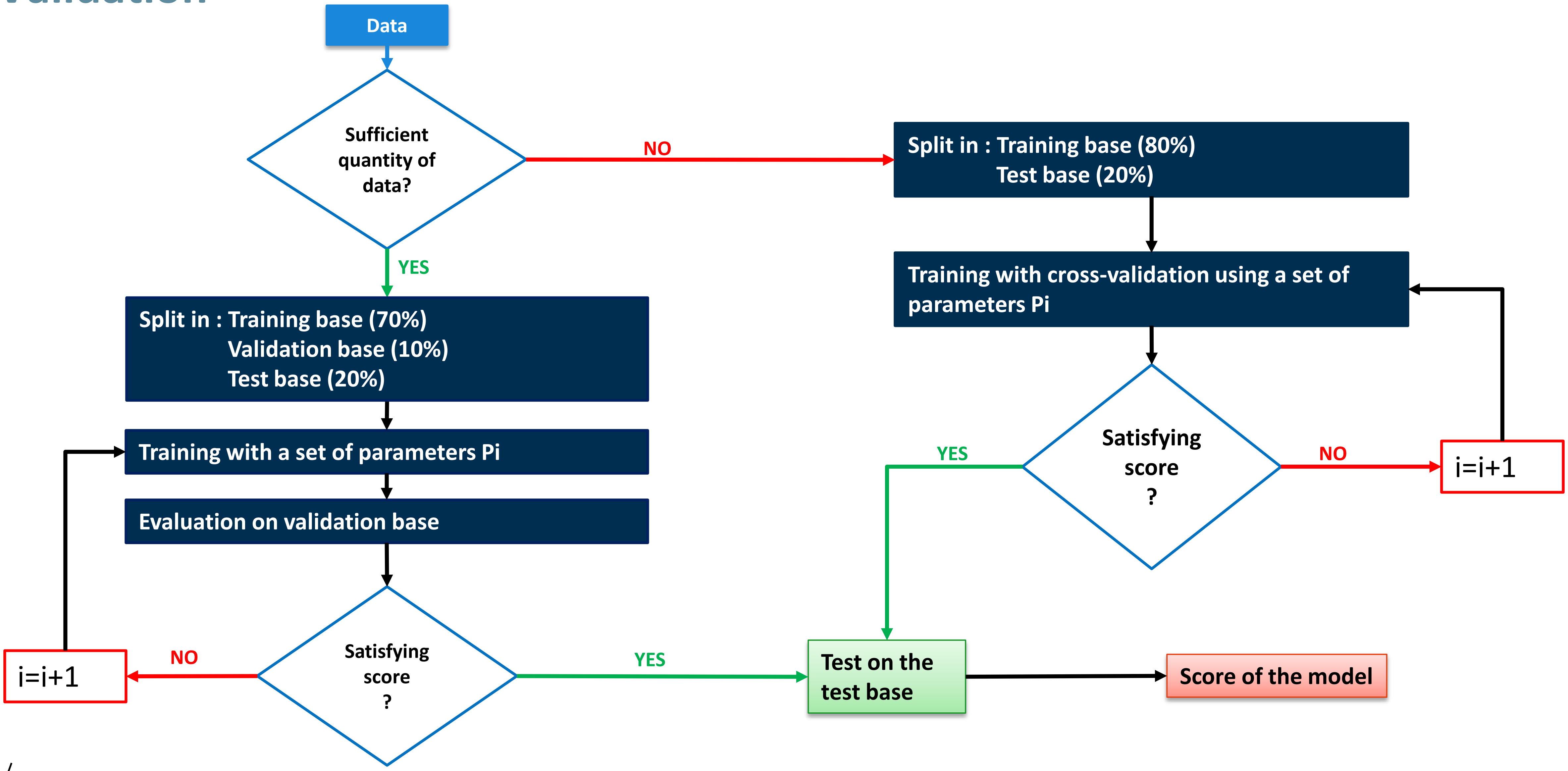
1. RMSE (Root Mean Squared Error)

- $\sqrt{\frac{\sum_{i=1}^{n}(Ymeas_i - Ypred_i)^2}{n}}$

2. MAE (Mean Absolute Error)

- $\frac{\sum_{i=1}^{n}|Ymeas_i - Ypred_i|}{n}$

Validation



Parameters Pi : λ, Kernel, Degree of Kernel…

Results

Predictions of initial velocity, chamber pressure, mass of powder and application

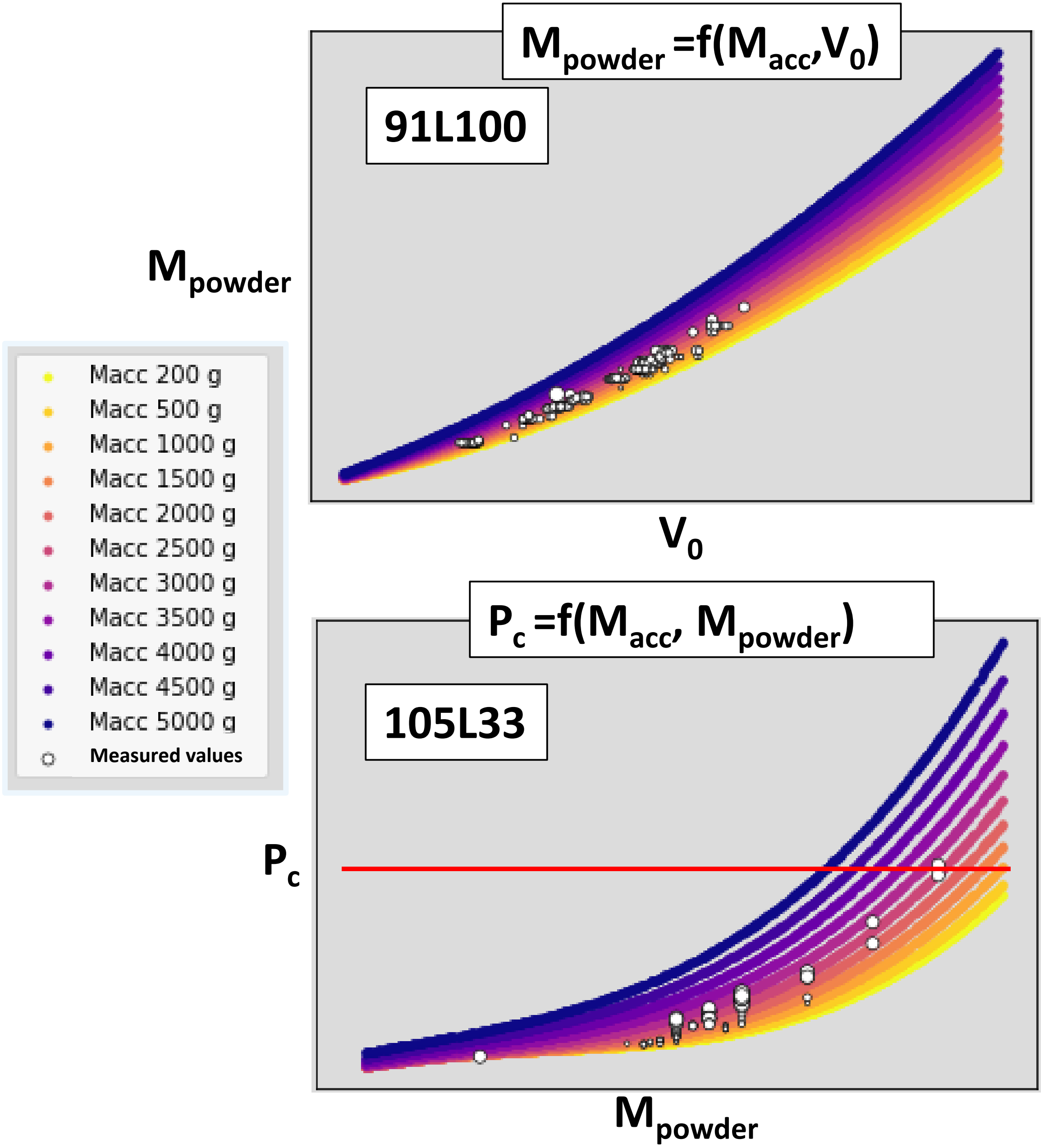
91L100 and 105L33 Launchers

Initial Velocity V_0 , Pc and Mpowder

$V_0 = f(M_{acc}, M_{powder})$				
Evaluation factor	91L100		105L33	
Errors	metric (m/s)	% w.r.t. mean	metric (m/s)	% w.r.t. mean
RMSE	16	2%	28	2.7%
MAE	13	1.6%	22	2.1%

$P_c = f(M_{acc}, M_{powder})$				
Evaluation factor	91L100		105L33	
Errors	metric (bar)	% w.r.t. mean	metric (bar)	% w.r.t. mean
RMSE	21	7%	76	9.5%
MAE	15	5.2%	52	6.5%

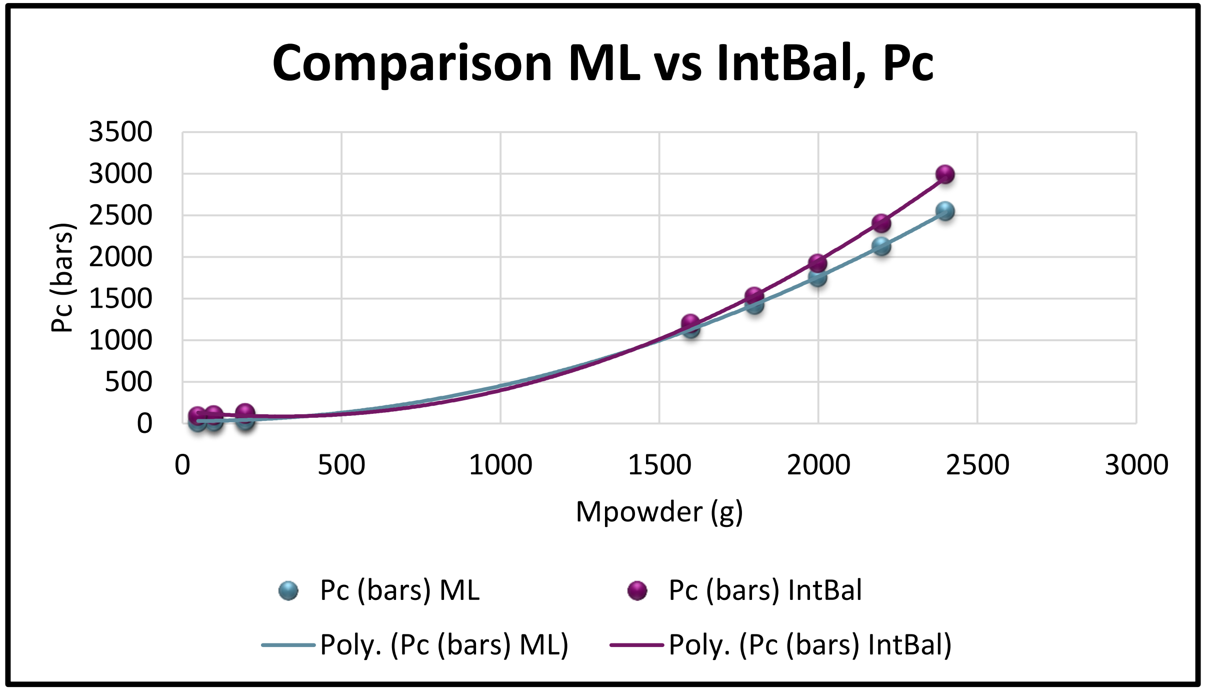
$M_{powder} = f(M_{acc}, V_0)$				
Evaluation factor	91L100		105L33	
Errors	metric (g)	% w.r.t. mean	metric (g)	% w.r.t. mean
RMSE	20	2.7%	36	3.2%
MAE	16	2.2%	29	2.6%

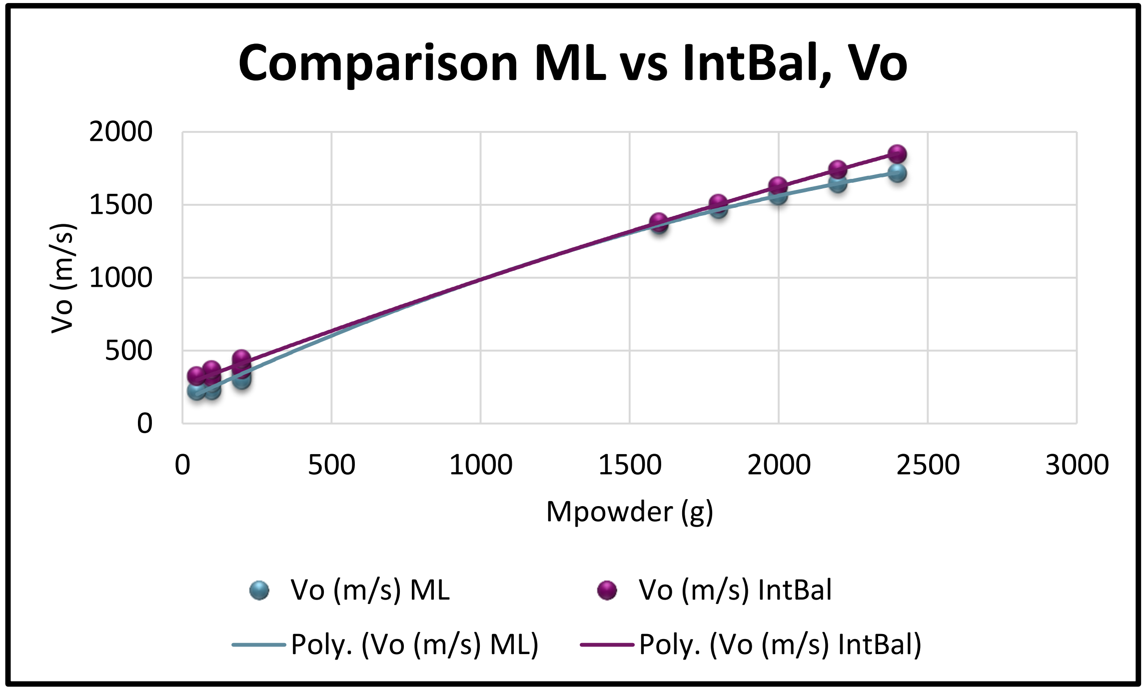


Comparison with IntBal

Parameters		Proximity to real values			
		ML Prediction		IntBal Predictions	
Macc (g)	Mpowder (g)	Pc	Vo	Pc	Vo
1519	310	88%	95%	50%	93%
1613	580	97%	99%	80%	99%
1552	1000	97%	99%	86%	98%
2167	1400	97%	99%	93%	99%

Comparison with IntBal





Conclusions on experimental conditions predictions

Advantages and limitations of Machine learning

Conclusions

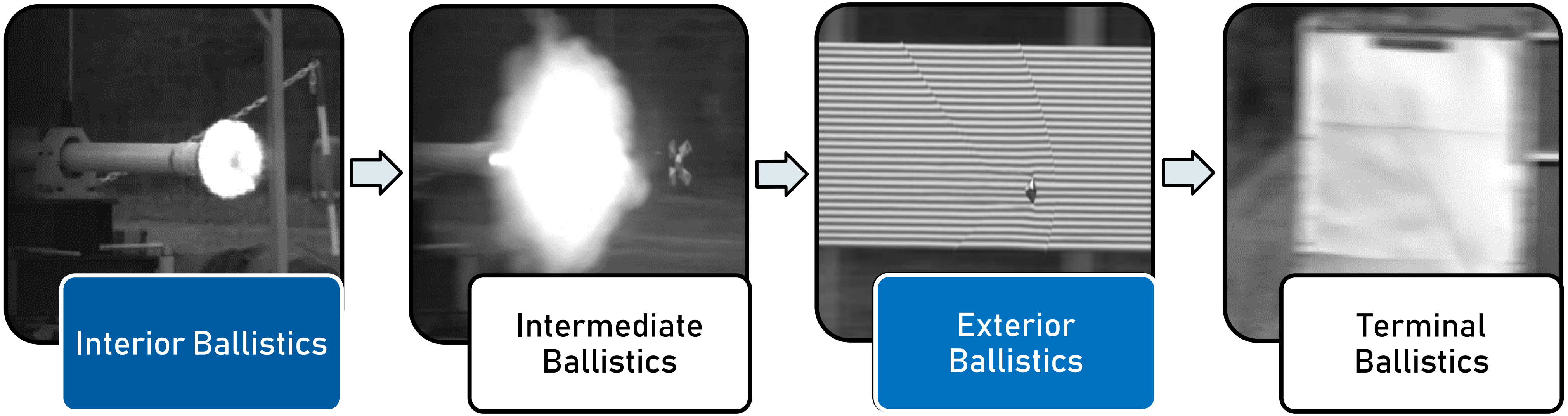
Advantages

- Physical knowledge coherency
- Knowledge on launchers limits
- As precise as Interior ballistics softwares
  - Needs less knowledge

Limitations

- Poor precision for cases with few data
- Risk of incoherence

Overview



- ML works for experimental conditions
  - ➢ Directly interpretable results

Apply AI/ML for more advanced problems

- AI applied to aerodynamics
  - ➢ Projectile design
  - ➢ Aerodynamic characterization
  - ➢ Trajectory shaping

Artificial Intelligence applied to aerodynamics

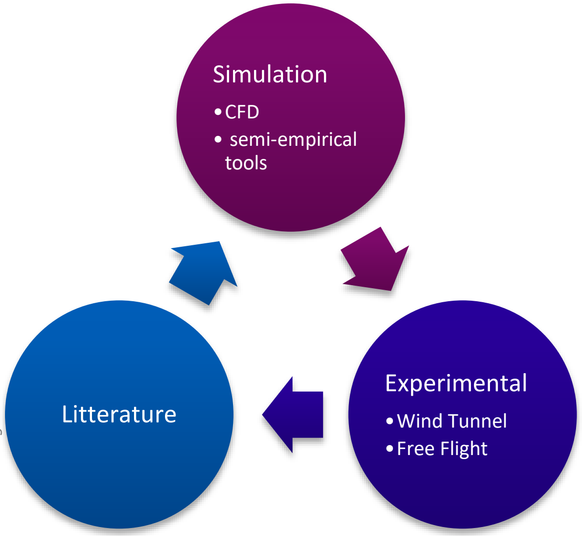
Database creation and Aerodynamic predictions

Thesis

PhD Topics

Data gathering and generation from different sources

Aerodynamic database creation *(fin, spin and drag stabilized)*



Data type and tools

Contents

- Projectile geometries
- Aerodynamic characteristics

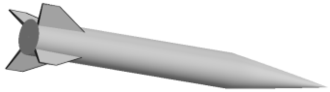
Data type

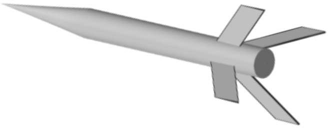
- Numerical
- Images, STL files, CAD …

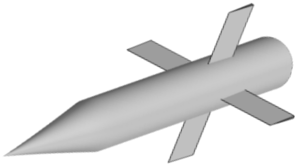
Tools

- SQlite3
- DB Explorer for SQLite
- Python

CX0	CX2	CNa	Cma	Cmq
0.304295	3.20889	6.31632	-6.7449	-172.144
0.305534	3.20889	6.51464	-7.27177	-174.923
0.30617	3.20889	6.61634	-7.53709	-176.348
0.318307	3.44889	6.76396	-7.86649	-178.324
0.324376	3.56889	6.83776	-8.02921	-179.312
0.330445	3.68889	6.91157	-8.1906	-180.3





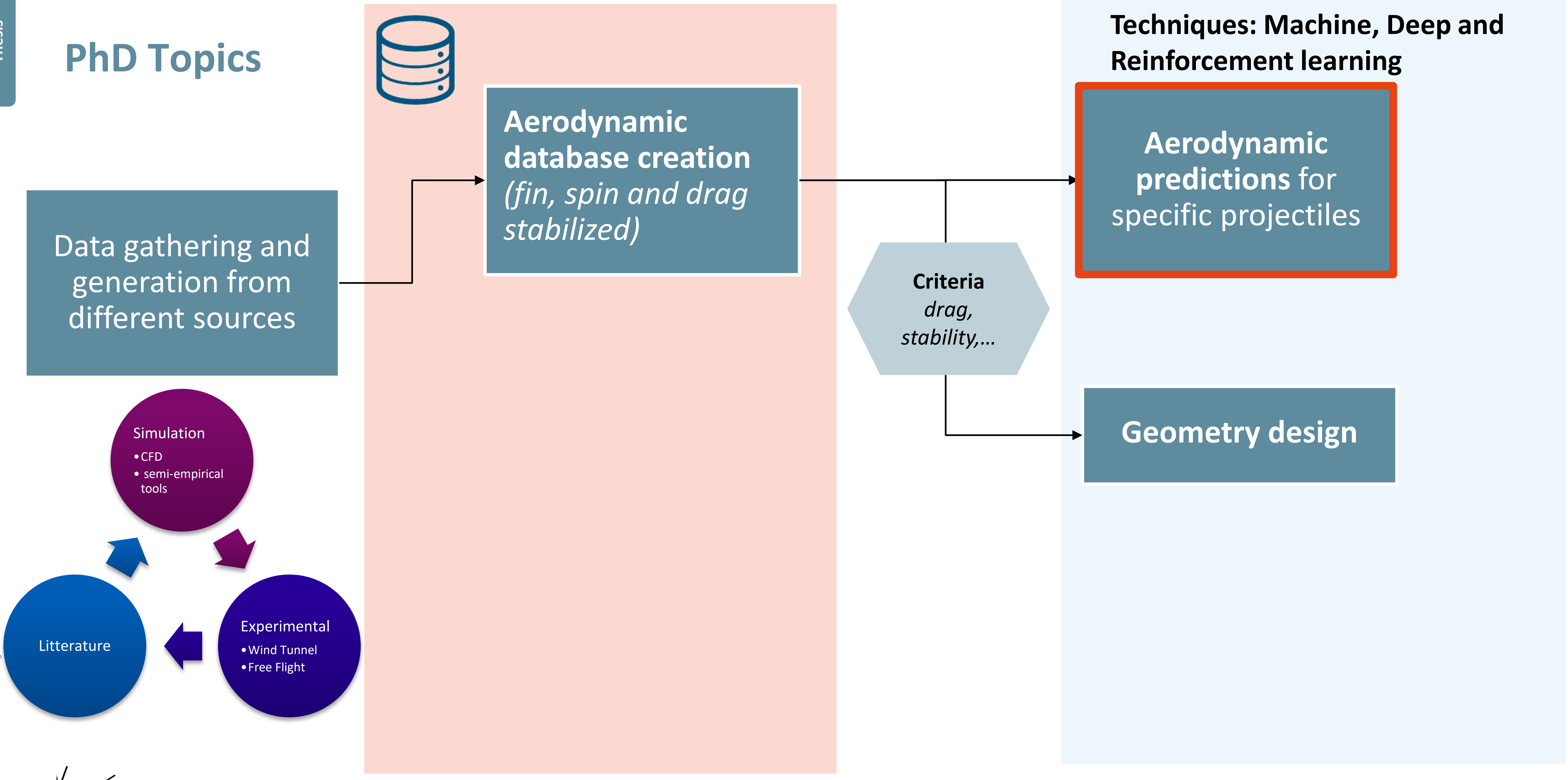


```
Prodas Macro Output
Generated on 11/03/2022 11:06:07

TESTING SCRIPT INTERFACE

PROJ CALIBER (MM) = 28
ISL FINNER 4 RECTANGULAR 28_10_15_5.82_1_1_0_0.5_0
NOSE-BODY-TOTAL LENGTH(CAL)  = 3.80 5.20 10.00
MASS    IX       IY
0.318474       3.0883E-05      1.06834E-03
Data Table AERODYNAMICS BASICAEROS
Mach           CX0            CX2            CX4
   .1000000E-01   .3042950E+00   .3208890E+01   .0000000E+00
   .4000000E+00   .3055340E+00   .3208890E+01   .0000000E+00
   .6000000E+00   .3061700E+00   .3208890E+01   .0000000E+00
   .7000000E+00   .3183070E+00   .3448890E+01   .0000000E+00
   .7500000E+00   .3243760E+00   .3568890E+01   .0000000E+00
   .8000000E+00   .3304450E+00   .3688890E+01   .0000000E+00
   .8500000E+00   .3623990E+00   .3927410E+01   .0000000E+00
   .8750000E+00   .3783760E+00   .4046680E+01   .0000000E+00
   .9000000E+00   .3943530E+00   .4165940E+01   .0000000E+00
   .9250000E+00   .4173050E+00   .4407630E+01   .0000000E+00
   .9500000E+00   .4402570E+00   .4649330E+01   .0000000E+00
   .9750000E+00   .4849520E+00   .5006240E+01   .0000000E+00
   .1000000E+01   .5296470E+00   .5363150E+01   .0000000E+00
   .1025000E+01   .5436460E+00   .5722730E+01   .0000000E+00
   .1050000E+01   .5576460E+00   .6082310E+01   .0000000E+00
   .1100000E+01   .5407730E+00   .6803380E+01   .0000000E+00
   .1200000E+01   .5026490E+00   .7725380E+01   .0000000E+00
   .1350000E+01   .4790190E+00   .7153080E+01   .0000000E+00
   .1500000E+01   .4538690E+00   .6560800E+01   .0000000E+00
   .1750000E+01   .4115070E+00   .5946910E+01   .0000000E+00
```

PhD Topics


Techniques: Machine, Deep and Reinforcement learning
Data gathering and generation from different sources
Aerodynamic database creation (fin, spin and drag stabilized)
Criteria drag, stability,…
Aerodynamic predictions for specific projectiles
Geometry design
Simulation
• CFD
• semi-empirical tools
Experimental
• Wind Tunnel
• Free Flight
Litterature

Prediction of aerodynamic coefficients for a finner projectile

$$Coefficients = f(Geometry, Mach)$$

Inputs		Outputs	
X	Geometry + Mach	Y	Coefficients
X_0	Fins configuration	**Y_0**	**CX_0**
X_1		Y_1	CX_2
X_2		Y_2	CN_α
X_3		**Y_3**	**Cm_α**
X_4	Body Configuration	**Y_4**	**Cm_q**
X_5		Y_5	Cl_p
X_6	Mach number	Y_6	Cl_δ

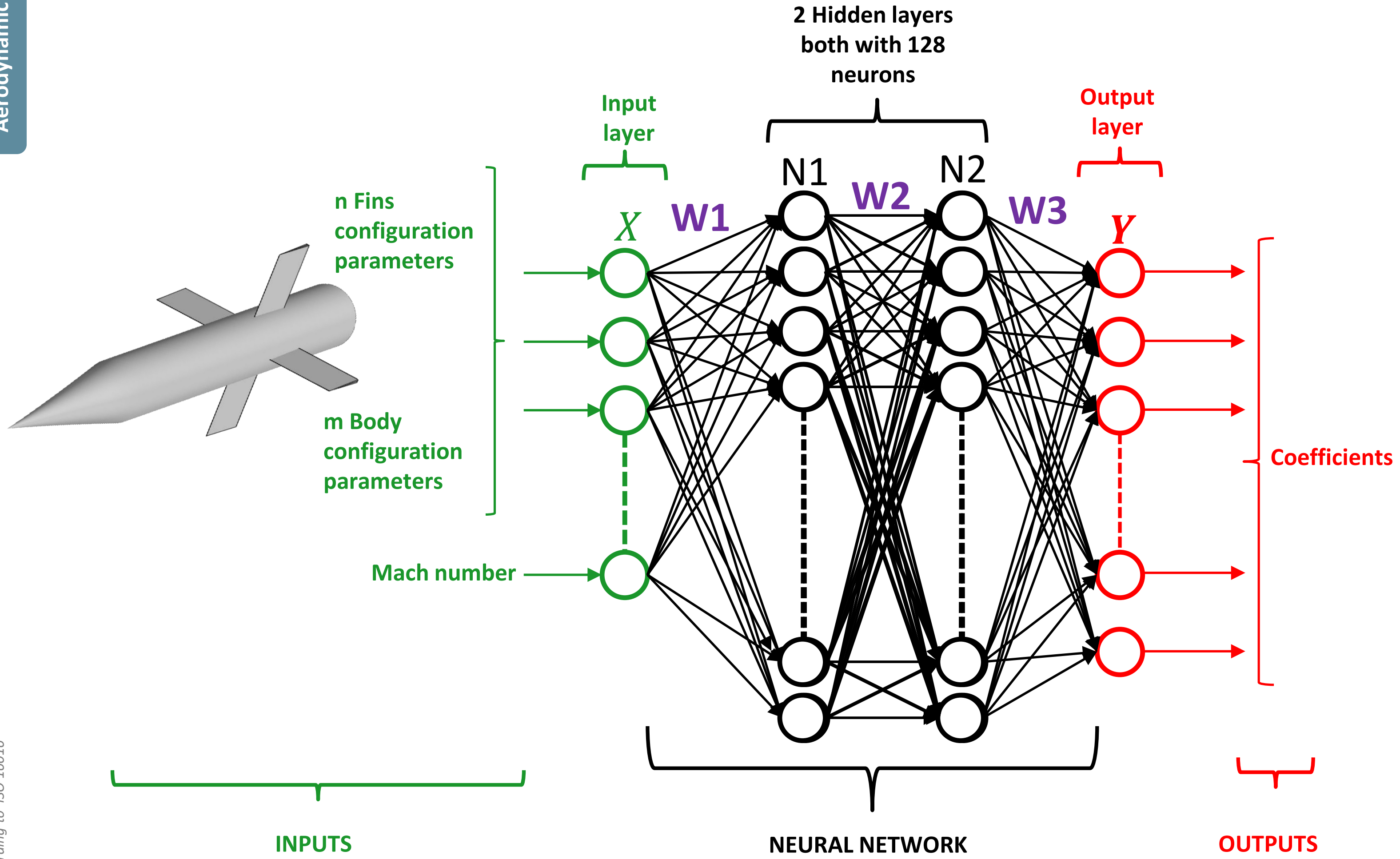
$$N1_j = \max(0, \sum_{i=0}^{6} (W1_{ij} X_i + b1_j))$$

$$N2_k = \max(0, \sum_{j=0}^{127} (W2_{jk} N_j + b2_k))$$

$$Y_l = (\sum_{k=0}^{127} N2_k * W3_{kl}) + b3_l$$

R^2 : Coefficient of determination

Prediction of aerodynamic coefficients for a finner projectile



Model Global R²
0.97

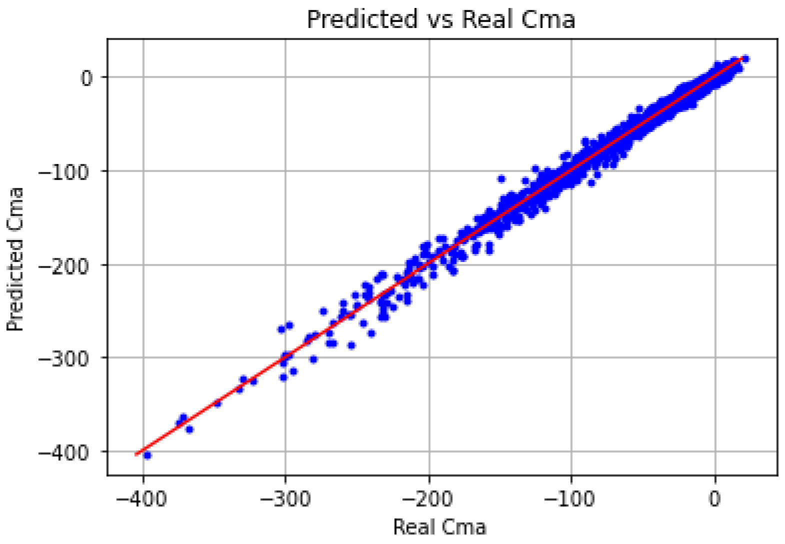
$$N1_j = \max(0, \sum_{i=0}^{6} (W1_{ij} X_i + b1_j))$$

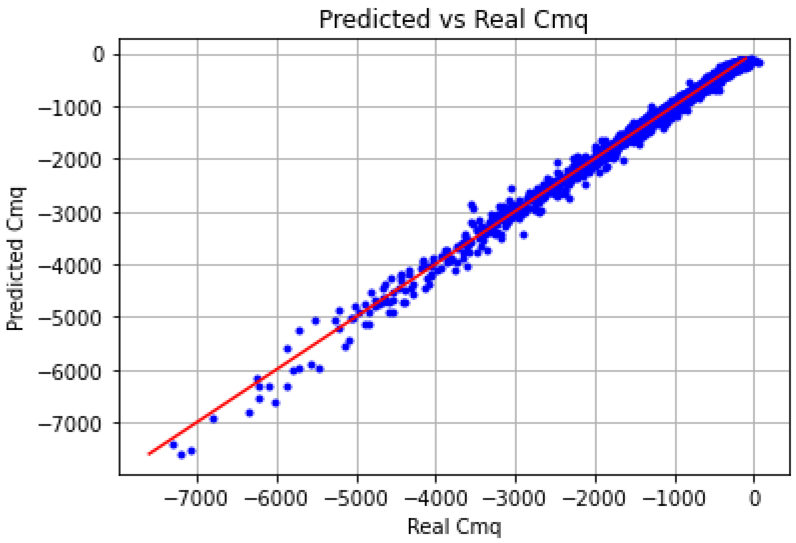
$$N2_k = \max(0, \sum_{j=0}^{127} (W2_{jk} N_j + b2_k))$$

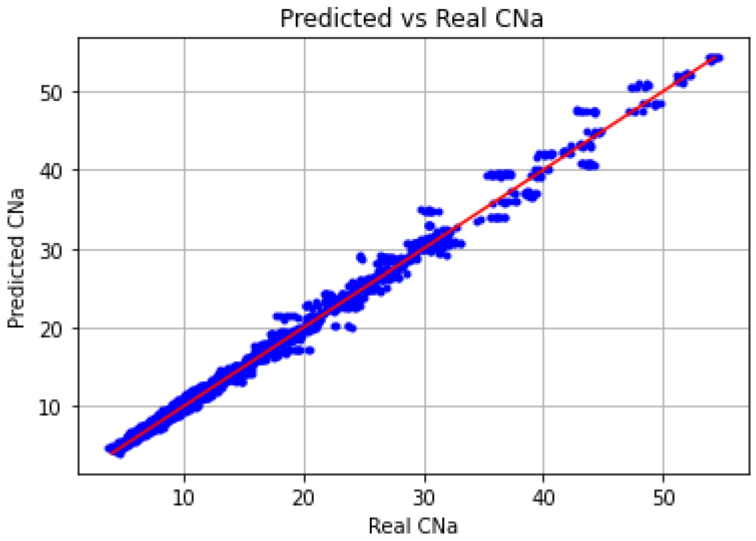
$$Y_l = (\sum_{k=0}^{127} N2_k * W3_{kl}) + b3_l$$

R^2 : Coefficient of determination

Prediction of aerodynamic coefficients for a finner projectile



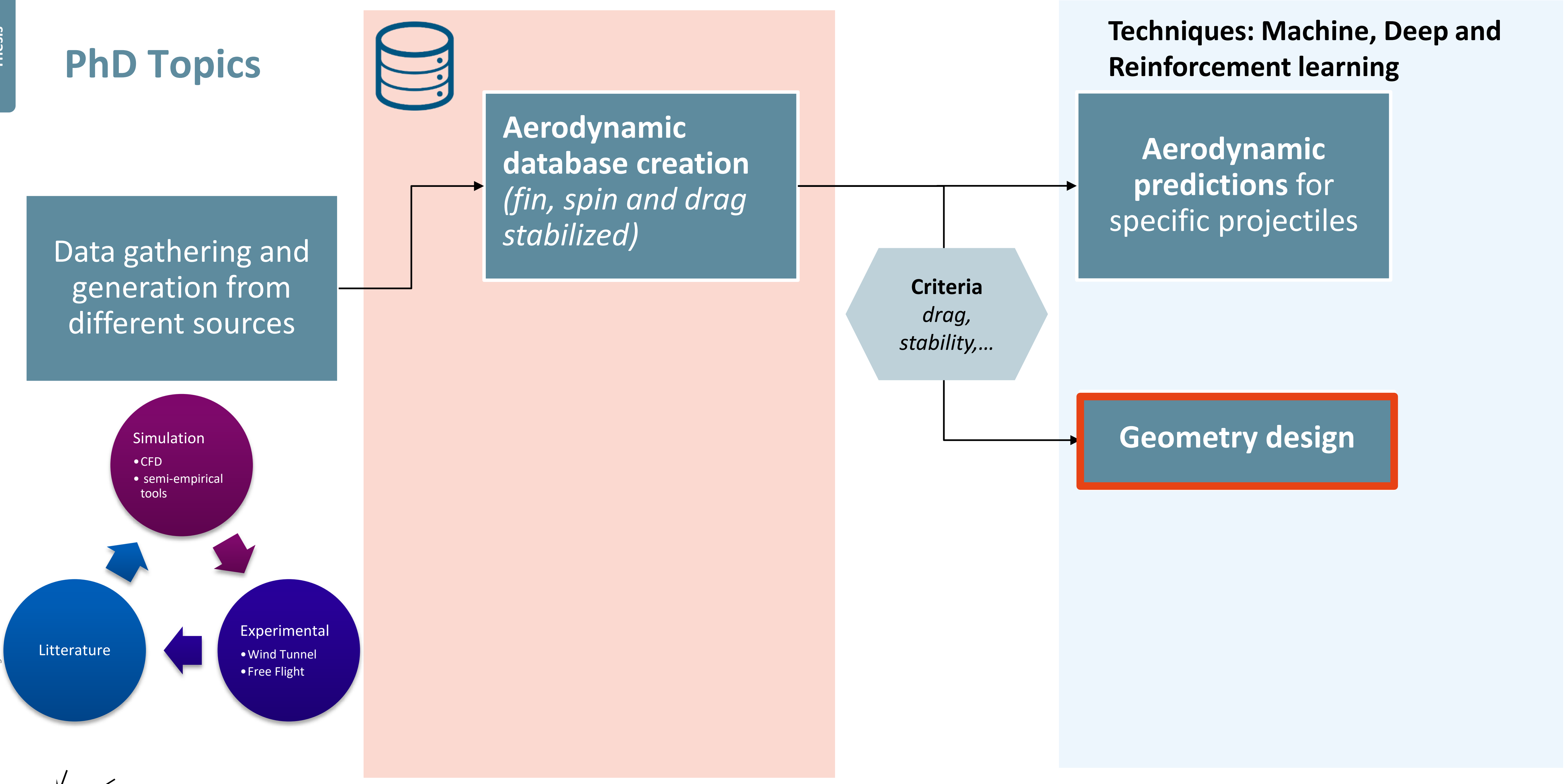




Model Global R^2
0,97

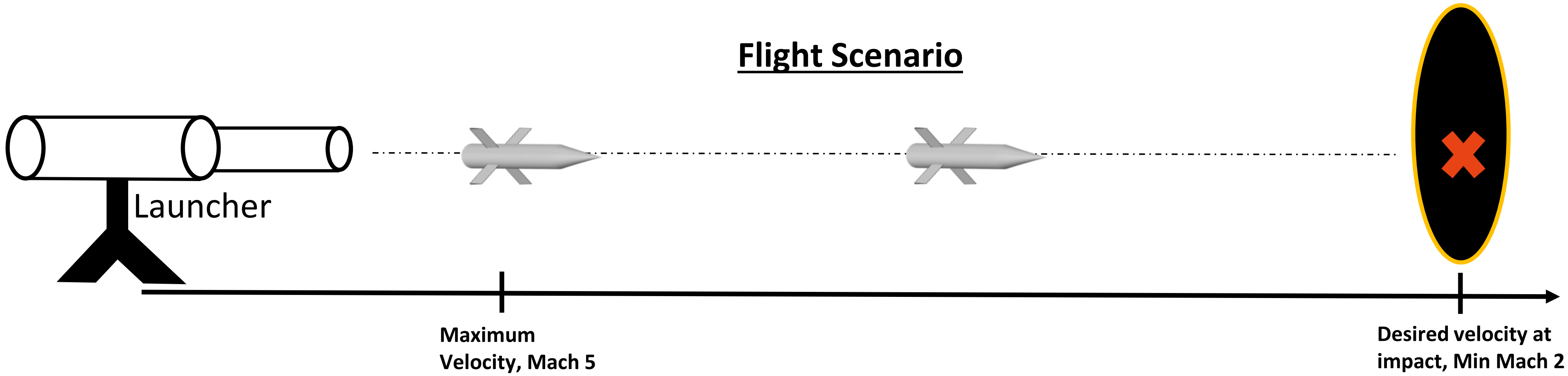
Thesis

PhD Topics



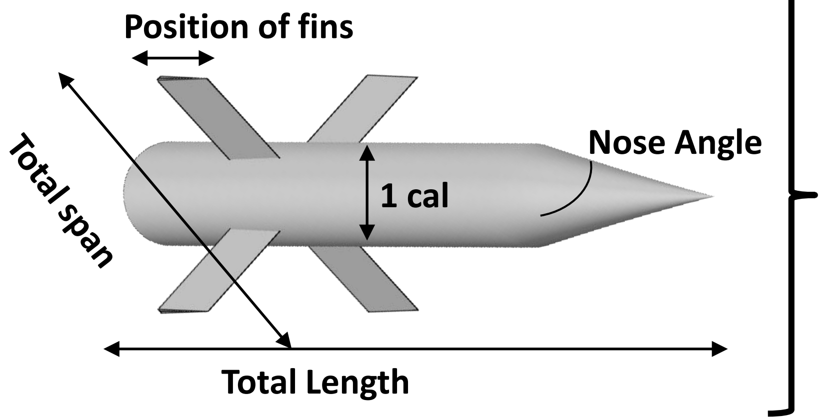
Geometry optimization : Flight Scenario

Flight Scenario



Design objective : Stable geometry with the minimum drag along the trajectory (Mach 5 to Mach 2) with the following geometry constraints

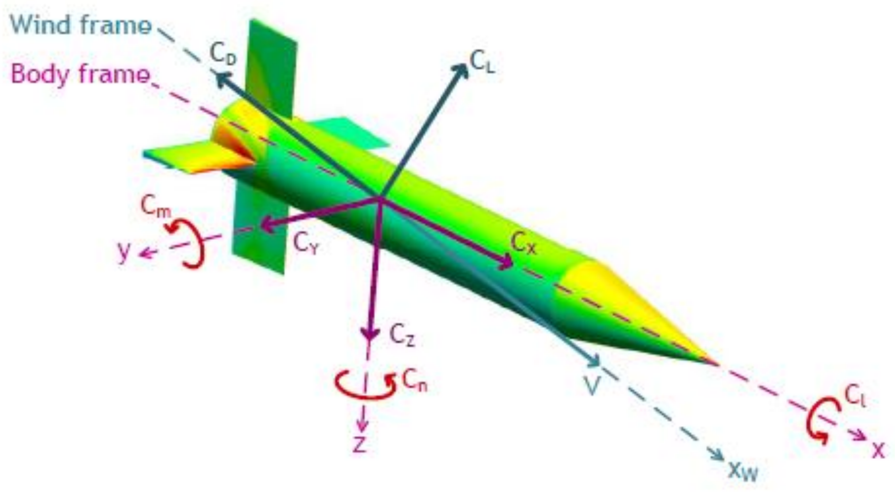
Geometry constraints



Parameter	Boundaries	
	Min	Max
X_0 Total Length () (cal)	5	20
X_1 Nose Angle () (°)	5	50
X_2 Fins height (cal)	2	3
X_3 Fins width (cal)	1	5
X_4 Number of fins	2	6
X_5 Position of fins (cal)	0	3

Geometry optimization : Aerodynamic Coefficients

Coefficient	Description
$C_{X0,x2...}$	**Axial force coefficients**
$C_{N\alpha}$	Normal force coefficient slope
C_{mq}	**Pitch damping coefficient**
$C_{m\alpha}$	**Pitch moment coefficient**
C_{lp}	Roll damping coefficient
$C_{l\delta}$	Roll moment coefficient due to fin cants



- **Drag**
  - Minimum C_{x0} ➔ Lowest drag (for zero angle of attack)
- **Stability**
  - $C_{m\alpha} < 0$ ➔ Static stability
  - $C_{mq} < 0$ ➔ Dynamic stability

- **Knowledge on Coeffs**
  - Maximum C_{X0} is at lowest Mach number
  - Highest $C_{m\alpha}$ **and** C_{mq} are at highest Mach number

Geometry optimization : optimization problem

$$N1_j = \max(0, \sum_{i=0}^{6}(W1_{ij}X_i + b1_j))$$

$$N2_k = \max(0, \sum_{j=0}^{128}(W2_{jk}N1_j + b2_k))$$

$$Y_l = (\sum_{k=0}^{128} N2_k * W3_{kl}) + b3_l$$

Inputs		Outputs	
X	Geometry + Mach	Y	Coefficients
X_0	Fins configuration	**Y_0**	**CX_0**
X_1		Y_1	CX_2
X_2		Y_2	CN_α
X_3		**Y_3**	**Cm_α**
X_4	Body Configuration	**Y_4**	**Cm_q**
X_5		Y_5	Cl_p
X_6	Mach number	Y_6	Cl_δ

Optimization problem :

$$\hat{X}_{0\to5} = Arg\ Min_{X_{0\to5}}\left(\frac{1}{4}\sum_{M=2}^{5} Y_0(X_6 = M)\right)$$

→ **Other possible approaches for the function to minimize**

→ **Lowest drag → Lowest mean CX_0 from Mach 2 to Mach 5**

Subject to :

$Y_3(X_6 = 5) \leq -10$ → **Static stability, Cm_α < -10 at highest Mach number**

$Y_4(X_6 = 5) \leq -100$ → **Dynamic stability, Cm_q < -100 at highest Mach number**

$Y_0(X_6 = 5) > 0$ → **CX_0 is a positive value**

Bounds on $X_{0\to5}$: $X_0, X_1, X_2, \ldots X_5$

- $X_{0\to5}$: $X_0, X_1, X_2, \ldots X_5$
- $Y_0(X_6 = M), Y_0$ for $X_6 = M$

Geometry optimization : Solution

Optimization problem :

SciPy

$$\hat{X}_{0\to5} = Arg\ Min_{X_{0\to5}}\left(\frac{1}{4}\sum_{M=2}^{5} Y_0(X_6 = M)\right)$$

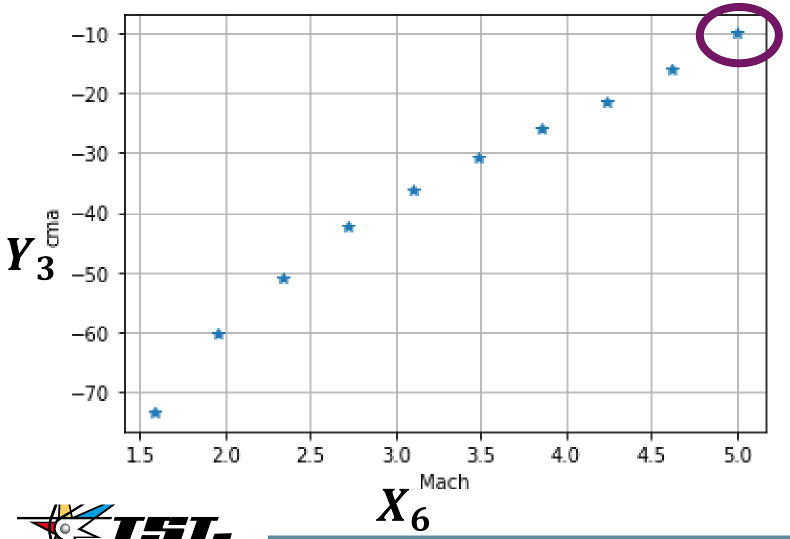
Subject to :

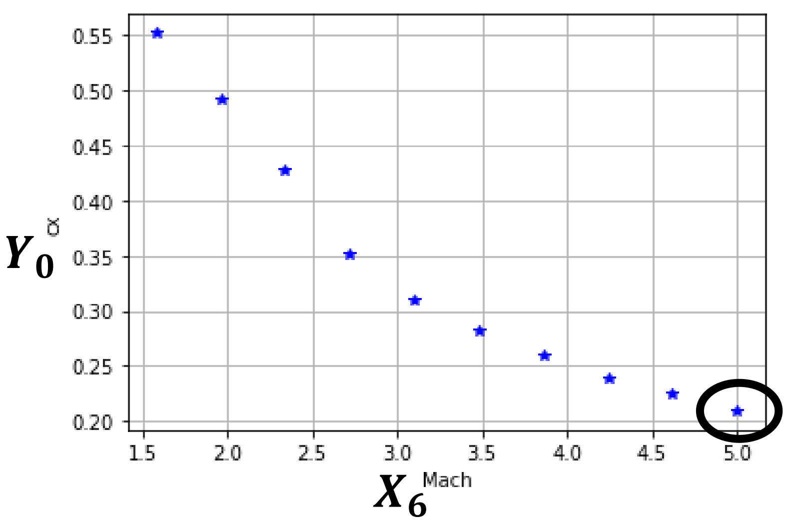
$$Y_3(X_6 = 5) \leq -10$$
$$Y_4(X_6 = 5) \leq -100$$
$$Y_0(X_6 = 5) > 0$$

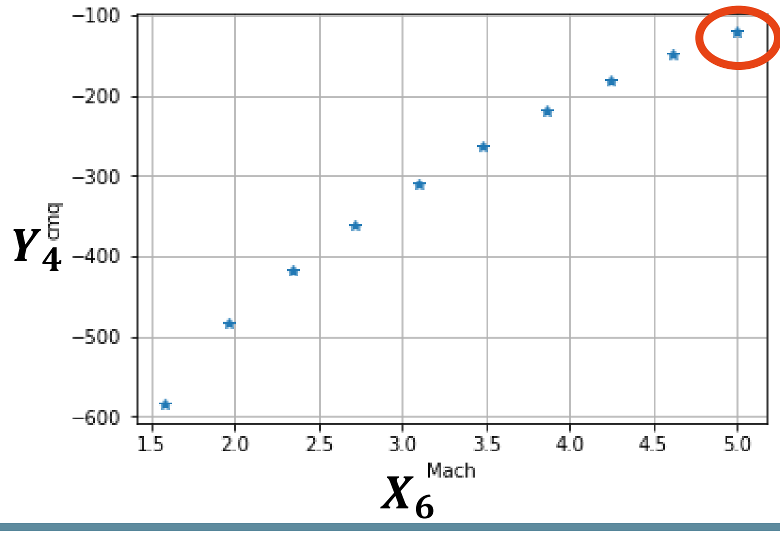
Python library Scipy optimization tools

- Method : Sequential Least Squares Programming
  - Minimize a function subject to constraints

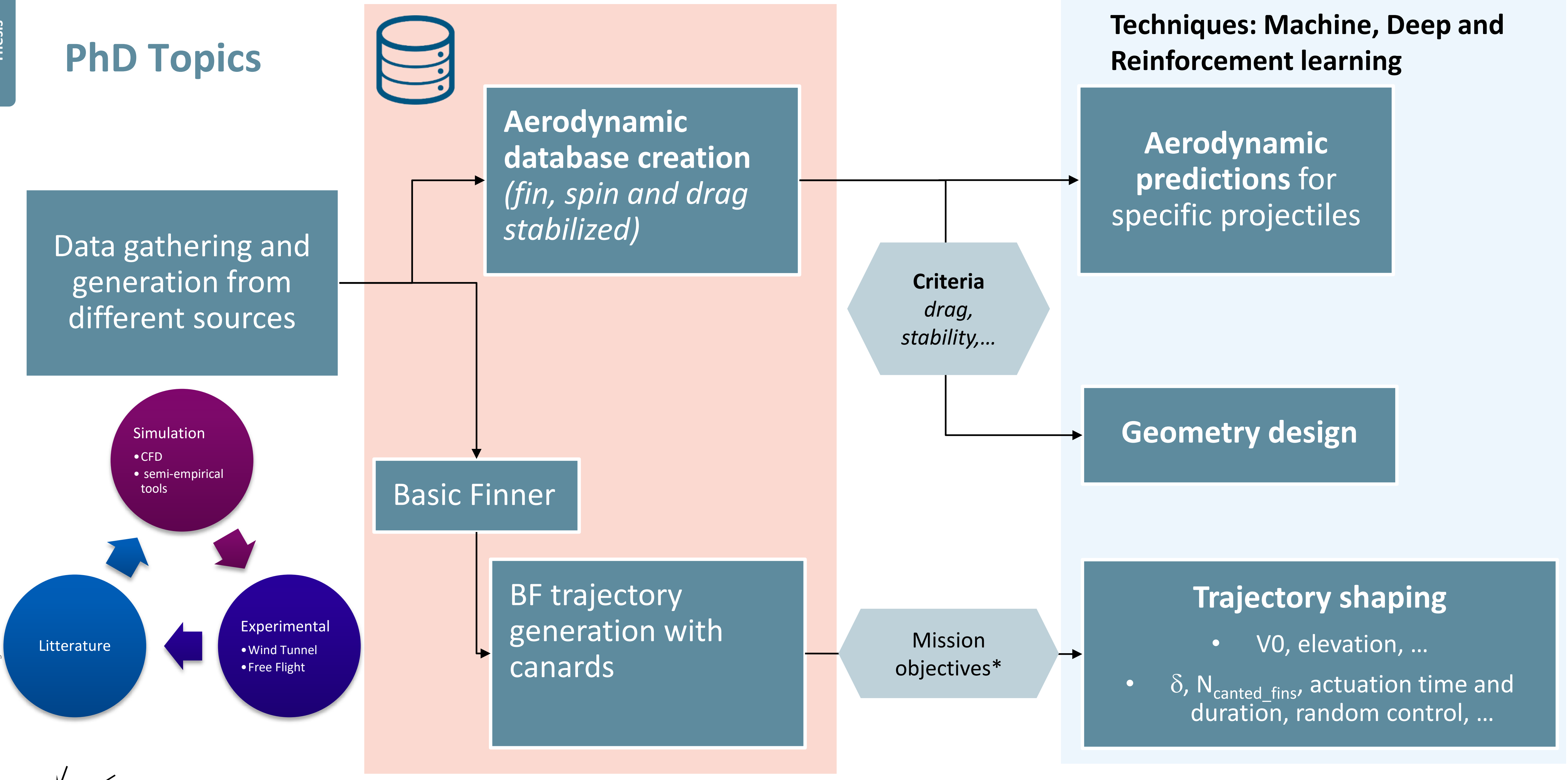
Parameter	Boundaries		Optimal Solution
	Min	Max	
X_0 Total Length (cal)	5	20	9
X_1 Nose Angle (°)	5	50	10
X_2 Fins height (cal)	2	3	2
X_3 Fins width (cal)	1	5	2
X_4 Number of fins	2	6	2
X_5 Position of fins (cal)	0	3	0



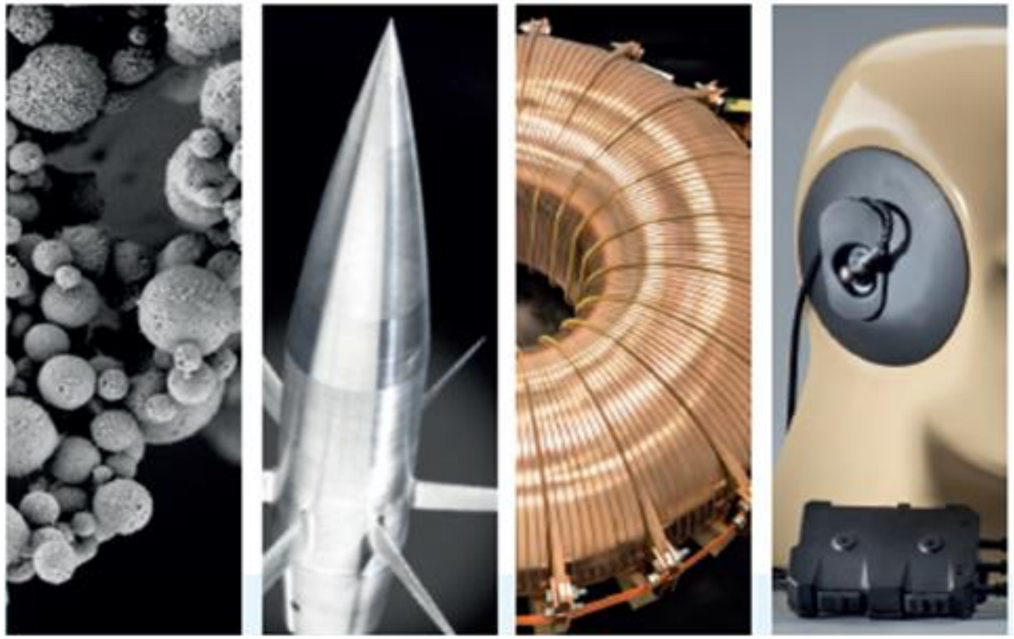




PhD Topics



* reach an impact point in the shortest possible time, decrease drag effect, increase hit velocity or the range, counter-measures, …



Forschung für den Einsatz
L’innovation au contact
Frontline research

Thank you for attention!
Any questions ?

Contact:
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