Avoid aeroelasticity instabilities with a morphing airfoil using neural networks

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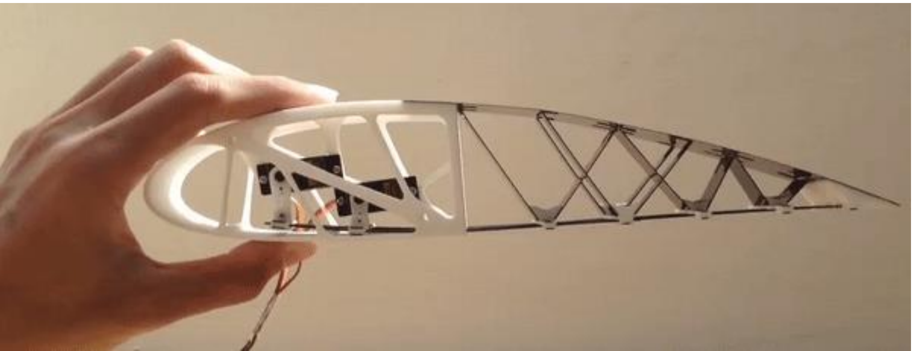

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Overview

- Context
- State of art
- Methodology
  - Database construction
  - Neural Network Training
  - Aeroelasticity
- Results
- Final discussions and future work

Context

- Importance of studying the airfoil;
- Morphing airfoils;
- Situations that can cause variation in the CG: jettisoning and fuel consumption;
- Aeroelastic instabilities;
- Neural networks.

GOAL: Try to avoid 2D aeroelastic instability, generated by an instantaneous change in the CG position, using a morphing airfoil selected by a neural network.

Aeroelastic instabilities

State of art

- Airfoil parametrization was performed using Bezier-Parsec 3434 curves and parameters;
- Optimization using differential evolution;
- Neural network modelling;
- Aeroelastic system;
- **Final coupling: Aeroelastic airfoil modelling and with neural network;**

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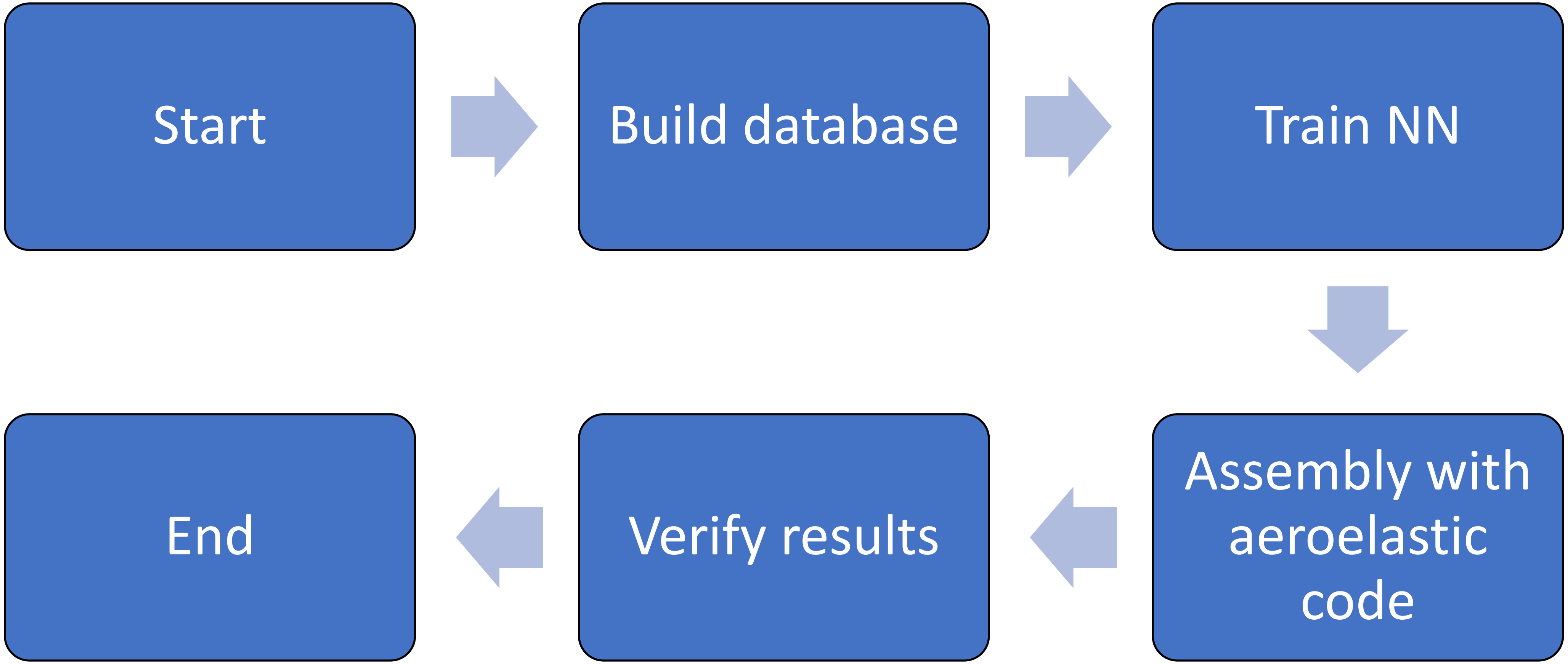
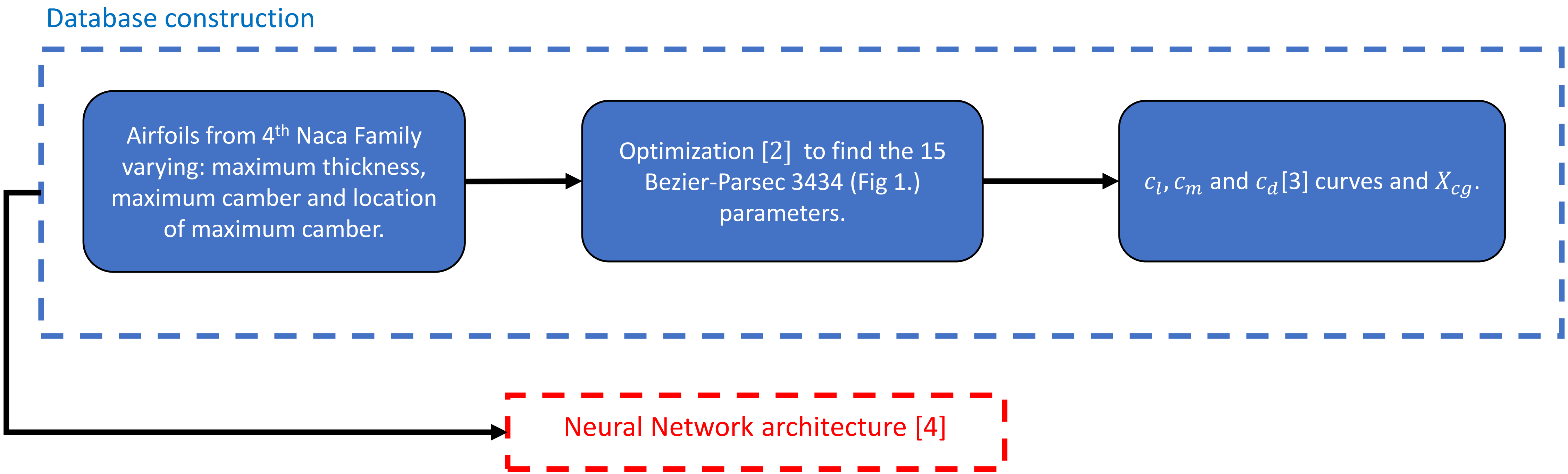
[1] Athar Kharal and Ayman Saleem. **Neural networks based airfoil generation for a given cp using Bezier–Parsec parameterization**. Aerospace Science and Technology, 23:330–344, 2012

Methodology



Inspired from : *Neural networks based airfoil generation for a given Cp using Bezier–PARSEC parameterization [1]*



[1] Athar Kharal and Ayman Saleem. **Neural networks based airfoil generation for a given cp using Bezier–Parsec parameterization**. Aerospace Science and Technology, 23:330–344, 2012.
[2] R. Storn. **http://www.icsi.berkeley.edu/~storn/code.html.**
[3] Mark Drela. **https://web.mit.edu/drela/Public/web/xfoil/.**
[4] François Chollet et al. **Keras**. https://github.com/fchollet/keras, 2015.

Database construction

Inspired from : *Neural networks based airfoil generation for a given Cp using Bezier–PARSEC parameterization [1]*

Problem: Given the airfoil's coordinates, find the 15 Bezier-Parsec parameters that parameterize the airfoil with 4 curves: 2 to describe the thickness curve and 2 to describe the camber line.

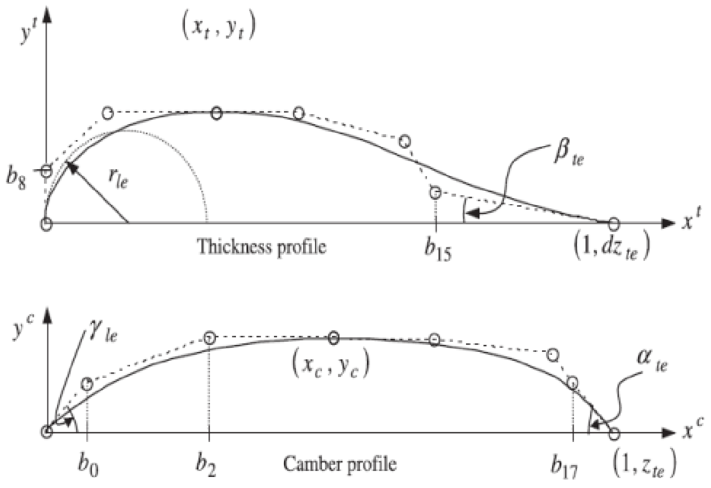


Figure 1. BP 3434 airfoil geometry and Bezier control points defined by ten aerodynamic and five Bezier parameters

Parametrically a third degree Bezier curve is given by

$$x(u) = x_0(1-u)^3 + 3x_1u(1-u)^2 + 3x_2u^2(1-u) + x_3u^3$$

and

$$y(u) = y_0(1-u)^3 + 3y_1u(1-u)^2 + 3y_2u^2(1-u) + y_3u^3$$

Leading edge thickness curve

The control points are given by

$x_0=0$	$y_0=0$
$x_1=0$	$y_1=b_8$
$x_2= -3b_8^2/2r_{le}$	$y_2=y_t$
$x_3=x_t$	$y_3=y_t$

Trailing edge thickness curve

The control points are given by

$x_0=x_t$	$y_0=y_t$
$x_1=(7x_t+9b_8^2/2r_{le})/4$	$y_1=y_t$
$x_2= 3x_t+15b_8^2/4r_{le}$	$y_2=(y_t+b_8)/2$
$x_3=b_{15}$	$y_3=dZ_{te}+(1-b_{15})\tan(\beta_{te})$
$x_4=1$	$y_4=dZ_{te}$

Parametrically a fourth degree Bezier curve is given by

$$x(u) = x_0(1-u)^4 + 4x_1u(1-u)^3 + 6x_2u^2(1-u)^2 + 4x_3u^3(1-u) + x_4u^4$$

and

$$y(u) = y_0(1-u)^4 + 4y_1u(1-u)^3 + 6y_2u^2(1-u)^2 + 4y_3u^3(1-u) + y_4u^4$$

Leading edge camber curve

The control points are given by

$x_0=0$	$y_0=0$
$x_1=b_0$	$y_1=b_0\tan(\gamma_{le})$
$x_2= b_2$	$y_2=y_c$
$x_3=x_c$	$y_3=y_c$

Trailing edge camber curve

The control points are given by

$x_0=x_c$	$y_0=y_c$
$x_1=(3x_c-y_c\cot(\gamma_{le}))/2$	$y_1=y_c$
$x_2= (-8y_c\cot(\gamma_{le})+13x_c)/6$	$y_2=5y_c/6$
$x_3=b_{17}$	$y_3=Z_{te}-(1-b_{17})\tan(\alpha_{te})$
$x_4=1$	$y_4=Z_{te}$

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[1] Athar Kharal and Ayman Saleem. **Neural networks based airfoil generation for a given cp using Bezier–Parsec parameterization**. Aerospace Science and Technology, 23:330–344, 2012.

Inspired from : *Neural networks based airfoil generation for a given Cp using Bezier–PARSEC parameterization [1]*

Problem: Given the airfoil's coordinates, find the 15 Bezier-Parsec parameters that parameterize the airfoil with 4 curves: 2 to describe the thickness curve and 2 to describe the camber line.

Reducing the number of inputs: Some BP3434 parameters are easy to determine: dzte, zte, rle, xc, yc, xt, yt.

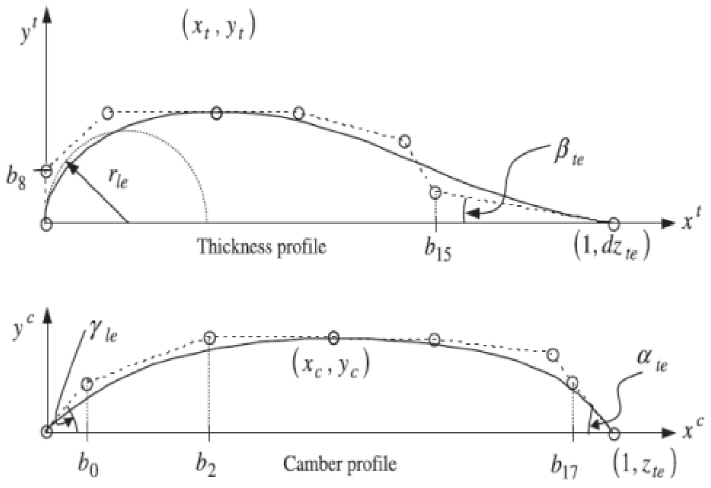

Figure 1. BP 3434 airfoil geometry and Bezier control points defined by ten aerodynamic and five Bezier parameters

Input

- 4th familly Naca Airfoils coordinates
- Built with 60 points
- Try to optimize just 8 parameters.

Differential Evolution

- **Objective Function:** Mean square error between real curve and fitted curve
- Constrained
- Without derivate
- Number of members of the population: 120
- Desirable value for objective function: 1e-6

Output

- 8 parameters opimized + 7 parameters pre determined.
- Find BP3434 control points
- Build airfoils curve.

Finally: cl, cm and cd curves (for α from 1° to 11°) using Xfoil [2] and also X_{cg} for each airfoil.

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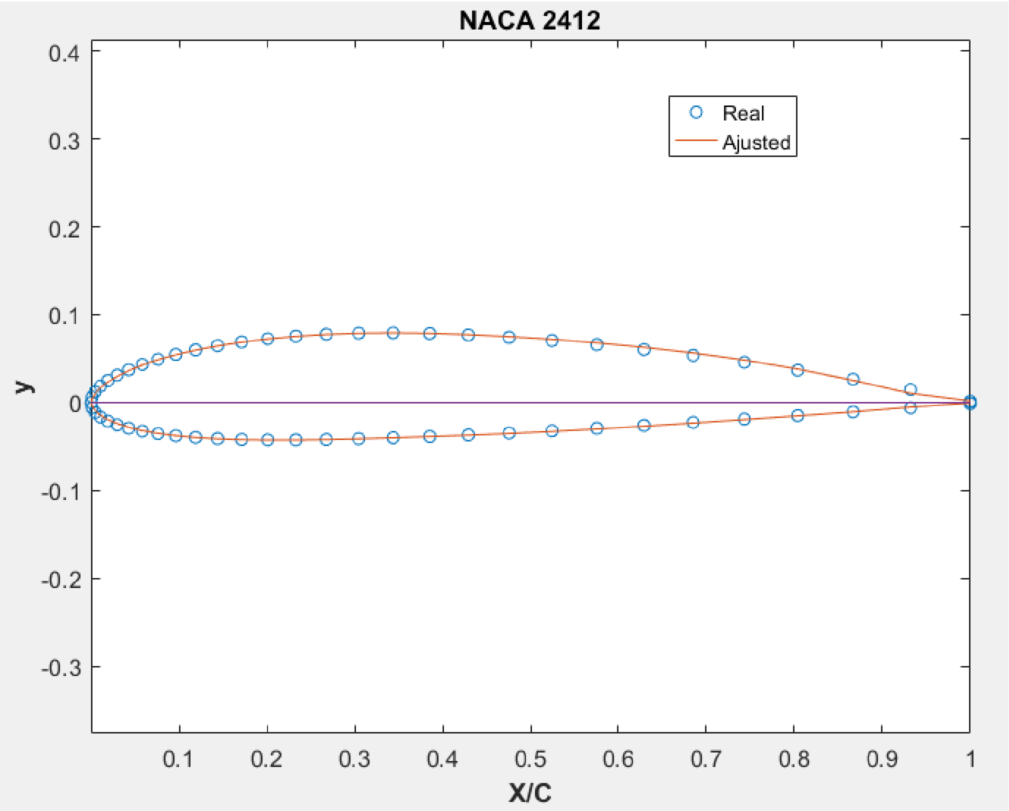
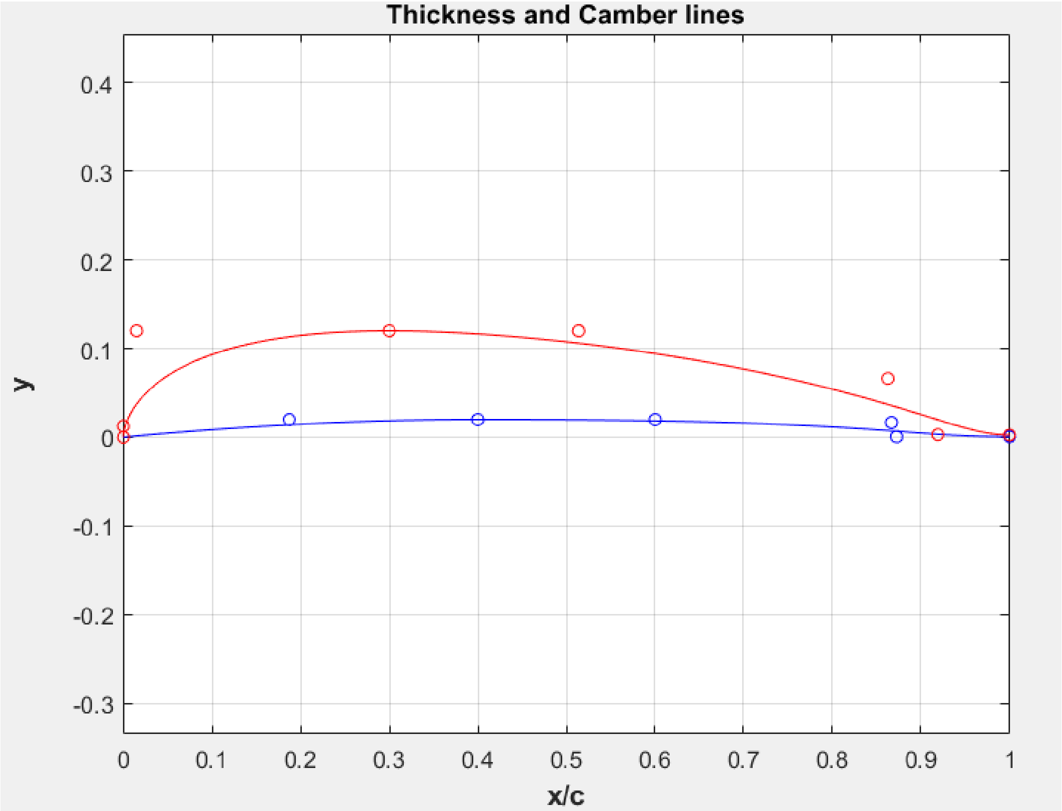
Results and validation: BP3434 Parametrization





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Inspired from : *Neural networks based airfoil generation for a given Cp using Bezier–PARSEC parameterization*

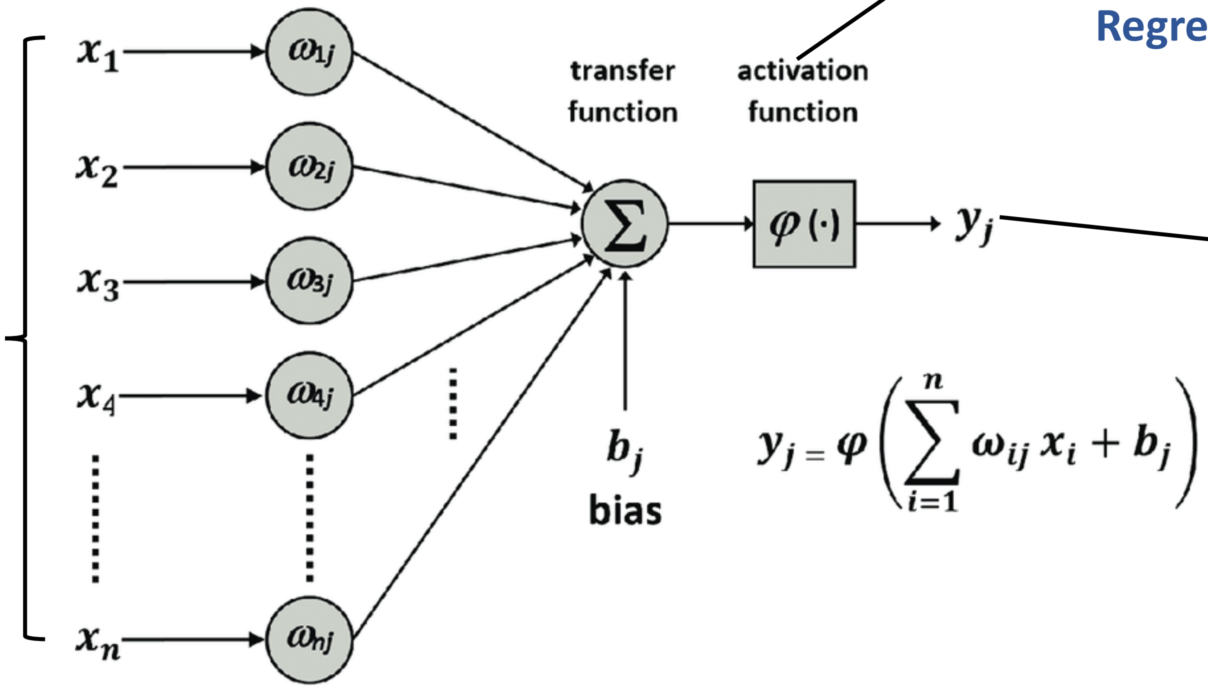
Problem: Given cl, cd and cm curves and the X_{cg} of an unknow airfoil, predict the 15 parameters for a Bezier-Parsec 3434 curve.

- Activation function **LeakyReLu** for hidden layers.
- **No activation function in the last layer: Regression task.**

Inputs:

- cm, cd, cl curves and X_{cg}
- ~~Normalized to **0 mean and 1 standard deviation.**~~

Mean was close to 0 and with a small standard deviation.

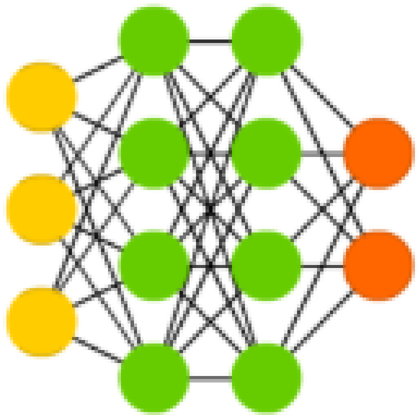


Outputs:

- **15**: BP3434 parameters that describes the airfoil

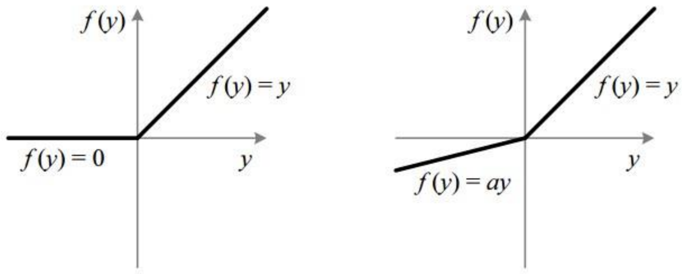
Problem: Given cl, cd and cm curves and the X_{cg} of an unknow airfoil, predict the 15 parameters for a Bezier-Parsec 3434 curve.

Deep Feed Forward (DFF)



DFF	
Layers	3
Hidden layers	LeakyReLU
Architecture	500-100-50
Output layer	-
Optimizer	Adam(learning rate=0.001) [5]
Loss	MSE
Data division	Training 80% Test 20%

$$f(x) = ax, x < 0$$
$$f(x) = x, x \geq 0$$

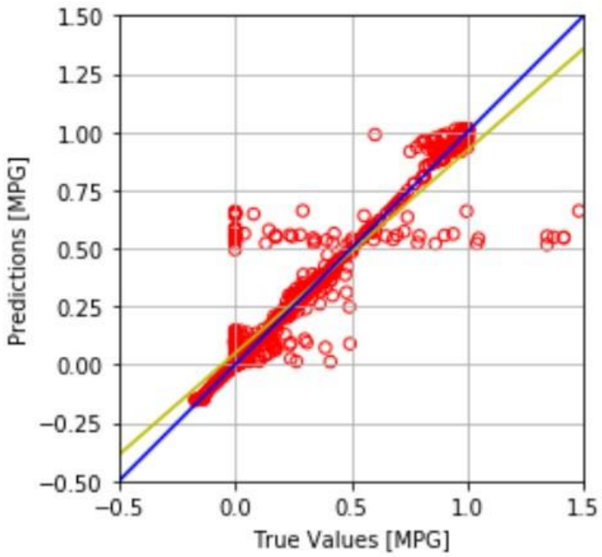


The main advantage of using the ReLU : it does not activate all neurons at the same time. However, in the ReLU function, the gradient is 0 to x < 0, which causes neurons to ”die” from activations in that region. Hence the use of Leaky ReLU, which helps to solve this problem.

[5] Jimmy Ba Diederik P. Kingma. **Adam: A method for stochastic optimization**. 3rd International Conference for Learning Representations, 2015.

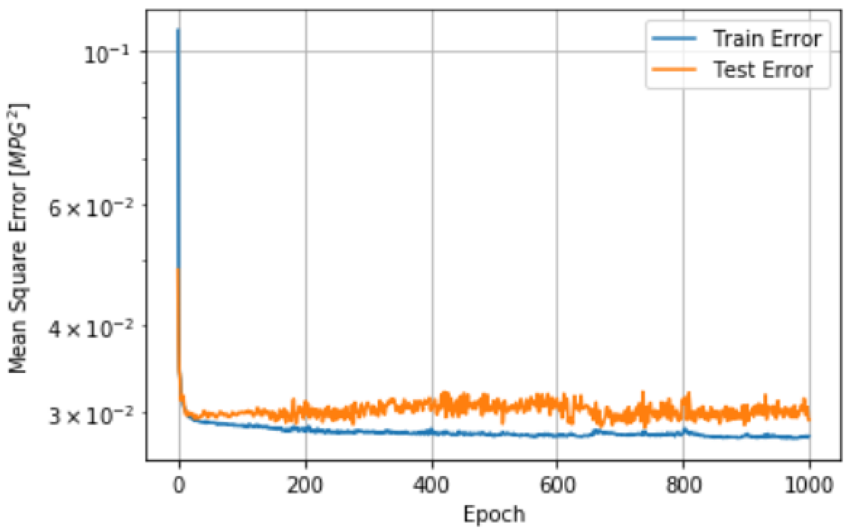
Results and validation: Neural network over 1000 airfoils from 4th Naca Family.

Test predictions

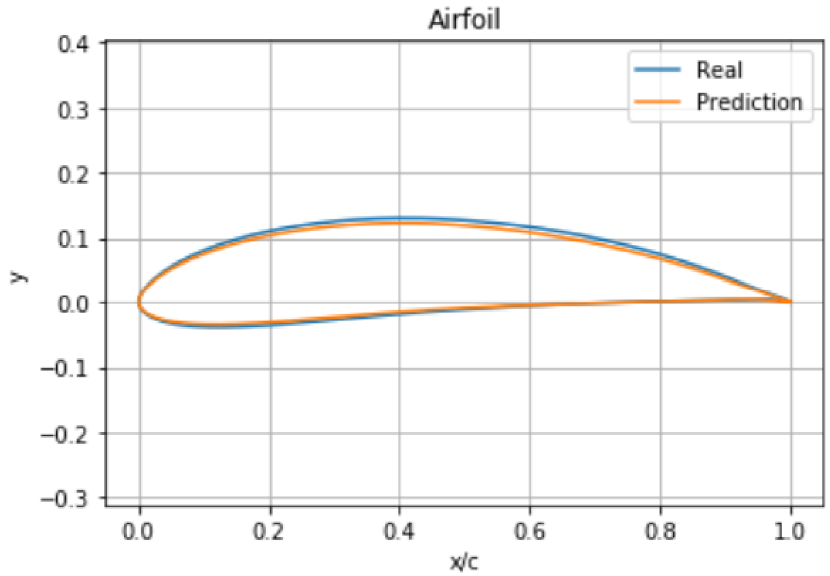


- y = 1.0x + 0.0
- y = 0.88x+0.04

MSE



Example



- **K-fold cross-validation**: k = 10 number of splits in the dataset, $\mu = -0.024$ and $\sigma = 0.00412$ [6]
- **Pearson's coefficient:** 0.919

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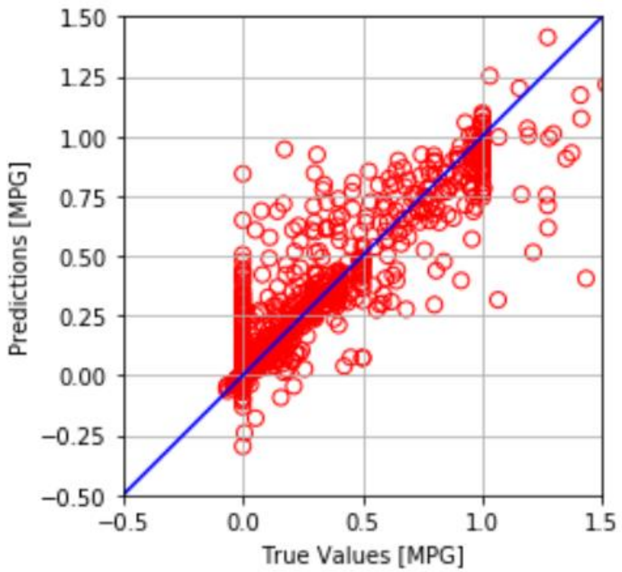
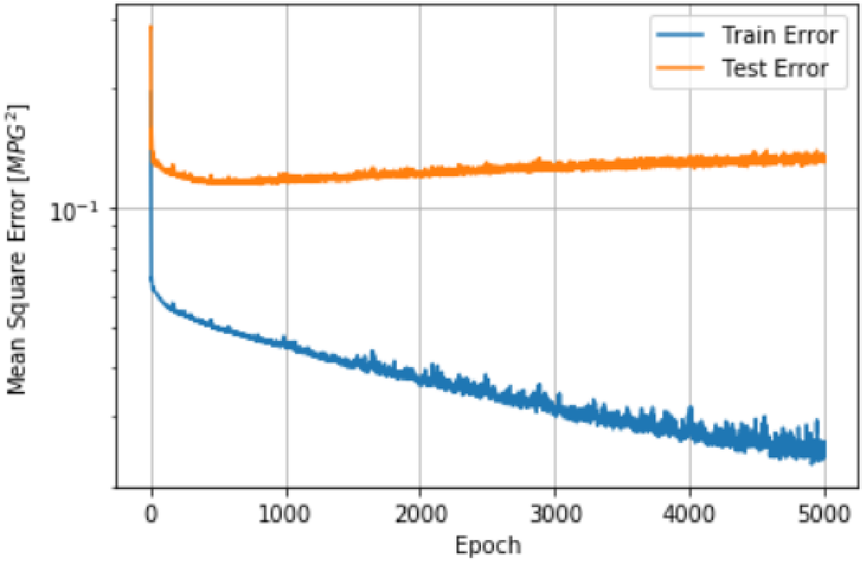
[6] Jason Brownlee. https://machinelearningmastery.com/ k-fold-cross-validation/

Results and validation: Neural network over 995 mixed airfoils types (same architecture).

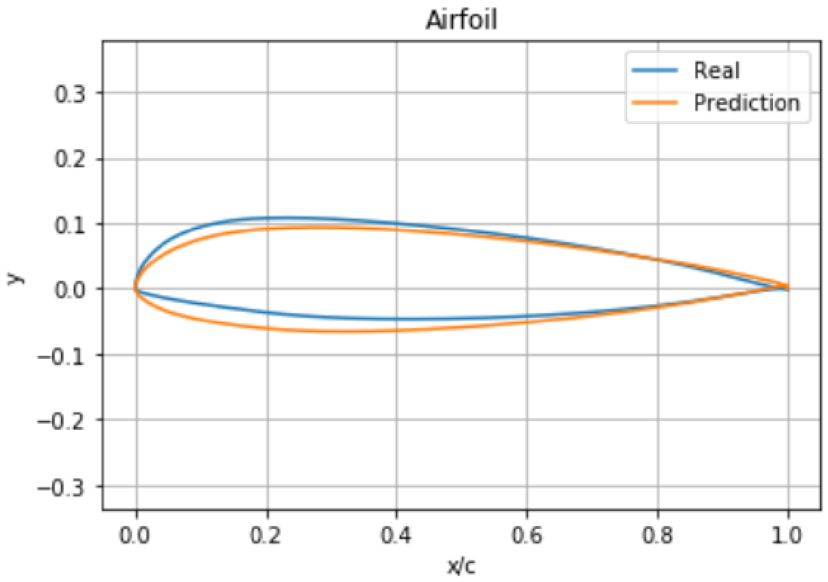
Test predictions



MSE

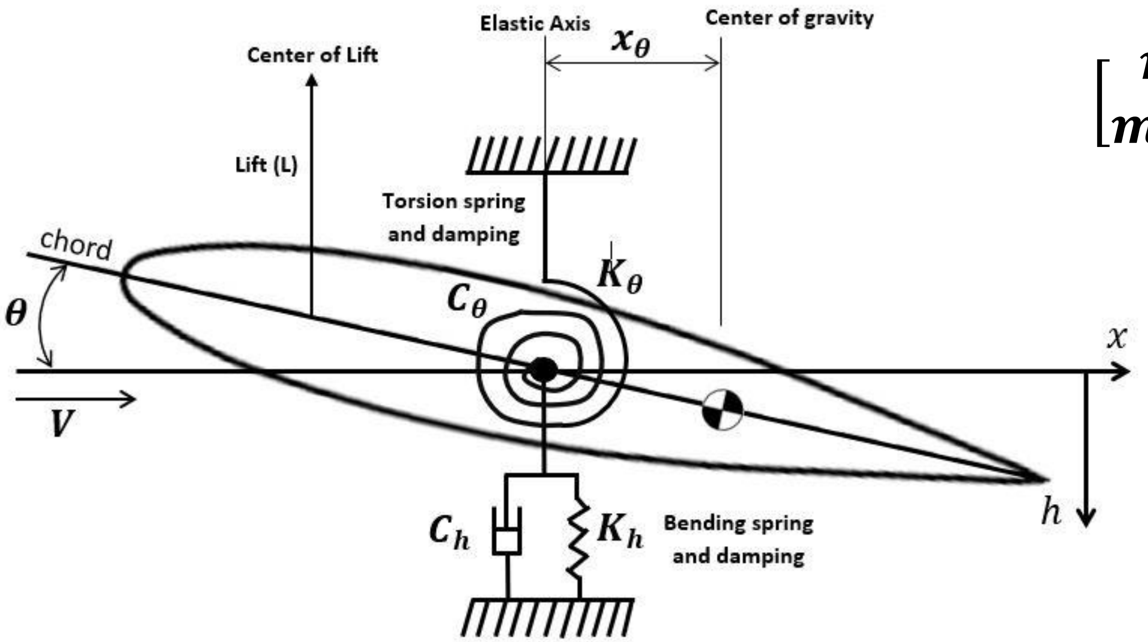


Example



Possible cause: overfitting

Solutions: Dropout/ Early Stopping



$$\begin{bmatrix} m & mx_\theta \\ mx_\theta & I_\theta \end{bmatrix} . \begin{bmatrix} \ddot{h} \\ \ddot{\theta} \end{bmatrix} + \begin{bmatrix} C_h & 0 \\ 0 & C_\theta \end{bmatrix} . \begin{bmatrix} \dot{h} \\ \dot{\theta} \end{bmatrix} + \begin{bmatrix} K_h & 0 \\ 0 & K_\theta \end{bmatrix} . \begin{bmatrix} h \\ \theta \end{bmatrix} = \begin{bmatrix} F \\ M \end{bmatrix}$$

$$\begin{cases} \ddot{h}_t = \dfrac{I_\theta\left(F - C_h \dot{h}_t - K_h h_t\right) - mx_\theta\left(M - C_\theta \dot{\theta}_t - K_\theta \theta_t\right)}{mI_\theta - m^2 {x_\theta}^2} \\ \ddot{\theta}_t = \dfrac{-mx_\theta\left(F - C_h \dot{h}_t - K_h h_t\right) + m\left(M - C_\theta \dot{\theta}_t - K_\theta \theta_t\right)}{mI_\theta - m^2 {x_\theta}^2} \end{cases}$$

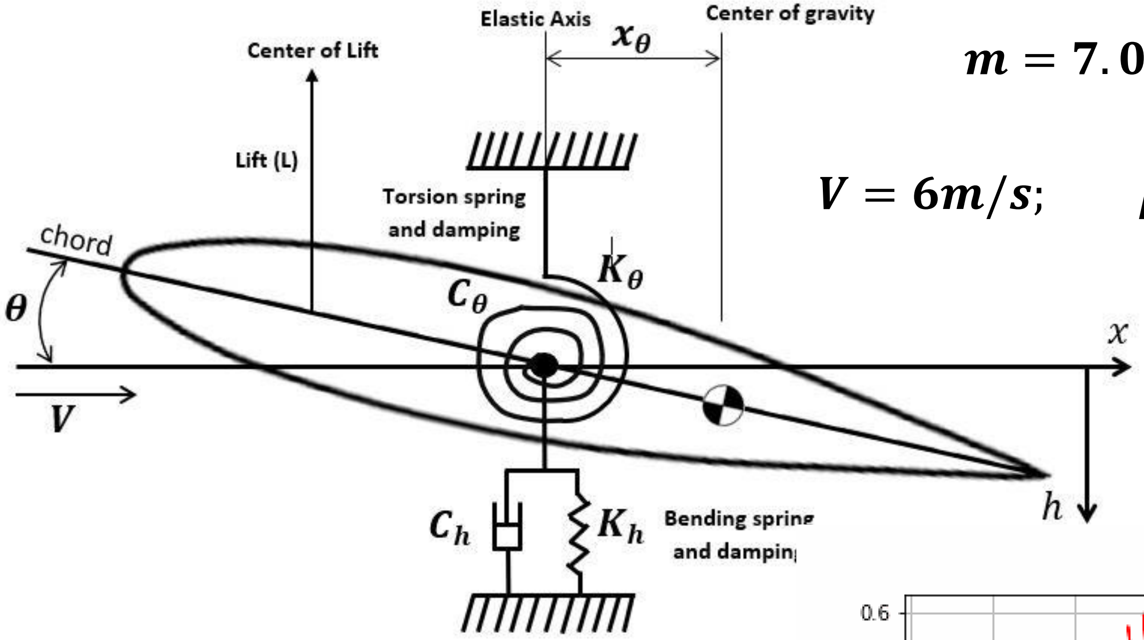
$$I_\theta = I_0 + m{x_\theta}^2$$

Doing $u = \begin{bmatrix} h \\ \theta \end{bmatrix}$ and using Taylor series (Euler explicit method):

$$\dot{u}_{t+\Delta t} = \dot{u}_t + \Delta t . \ddot{u}_t$$

$$u_{t+\Delta t} = u_t + \Delta t . \dot{u}_t$$

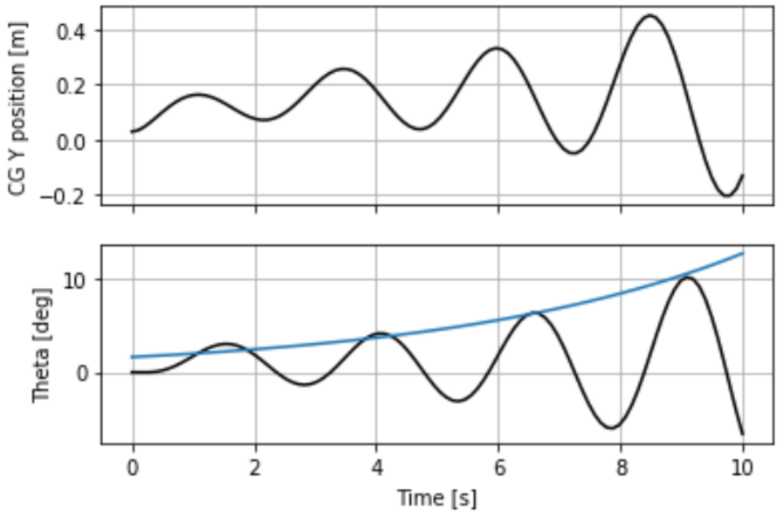
[7] Earl H. Dowell. **A Modern Course in Aeroelasticity**. Springer, fifth revised and enlarged edition edition, 1999.

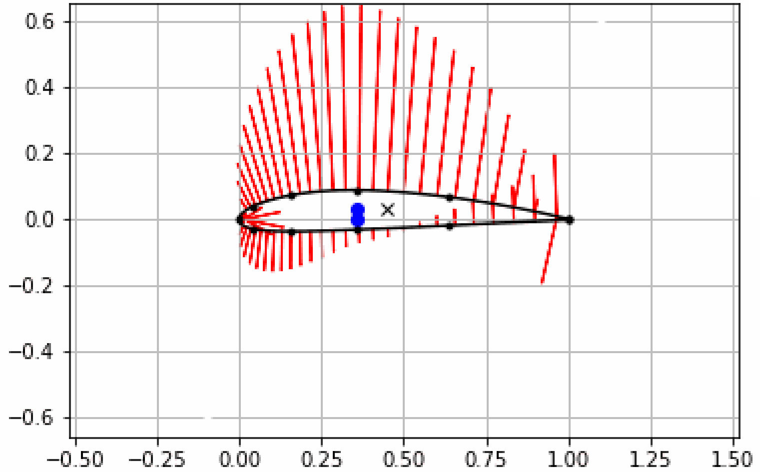


$$m = 7.0\ kg; \quad I_0 = 7.0\ kg.m^2; \quad X_{cg} = 0.4; \quad X_{EA} = 0.35;$$

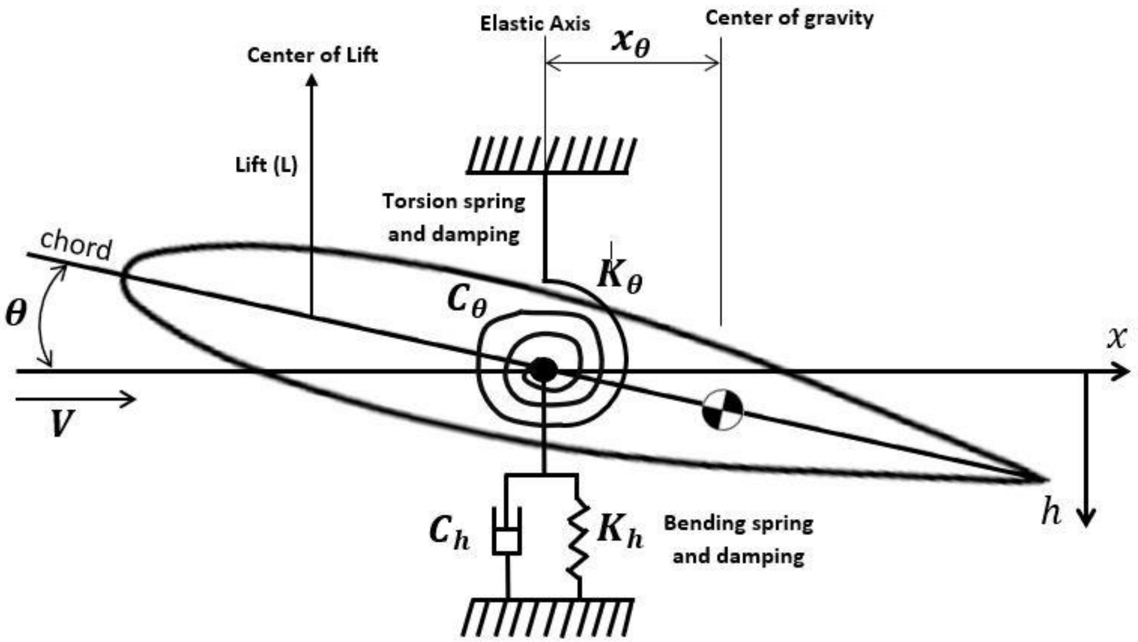
$$V = 6m/s; \quad \rho = 1.225\frac{kg}{m^3}; \quad K_h = 30\ N/m; \quad K_\theta = 50\ N/rad;$$

$$C_h = 2.0\frac{N}{m/s^2}; \quad C_\theta = 6.0\frac{N}{m/s^2}$$

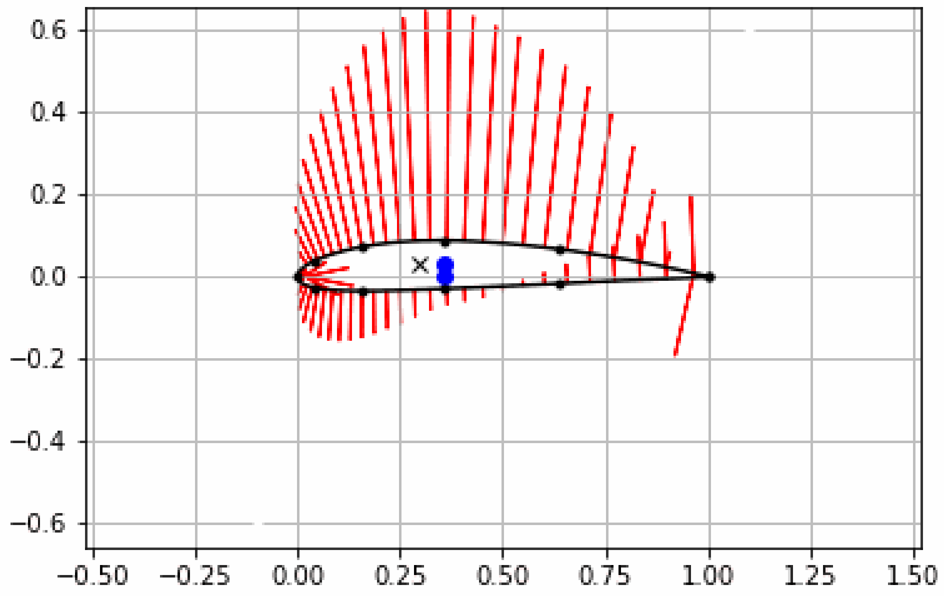




Methodology



- Changing Cg position instantaneously from 0.3 to 0.5 (an unstable position)



- **Flutter situation:** The shift in the CG causes an alteration in the phase relation between the two modes of the system, producing a change in the aerodynamic damping, increasing the energy of the system. Usually occurs before divergence.

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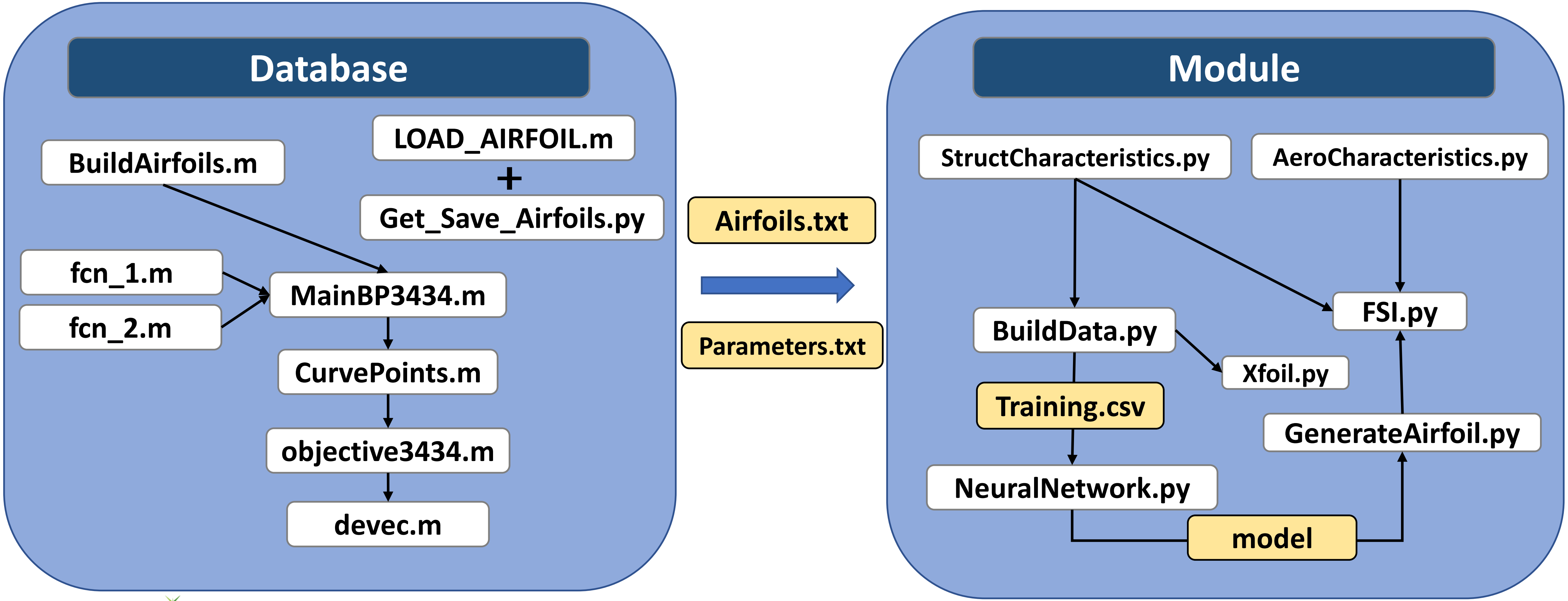
Codes and dependencies



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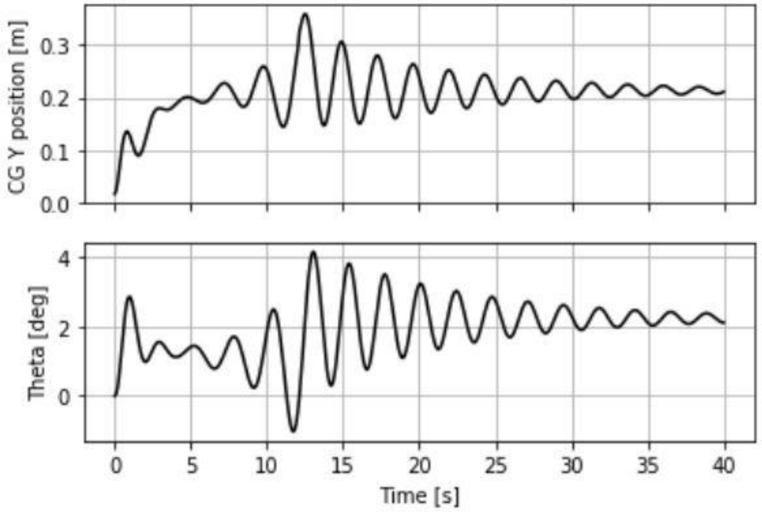
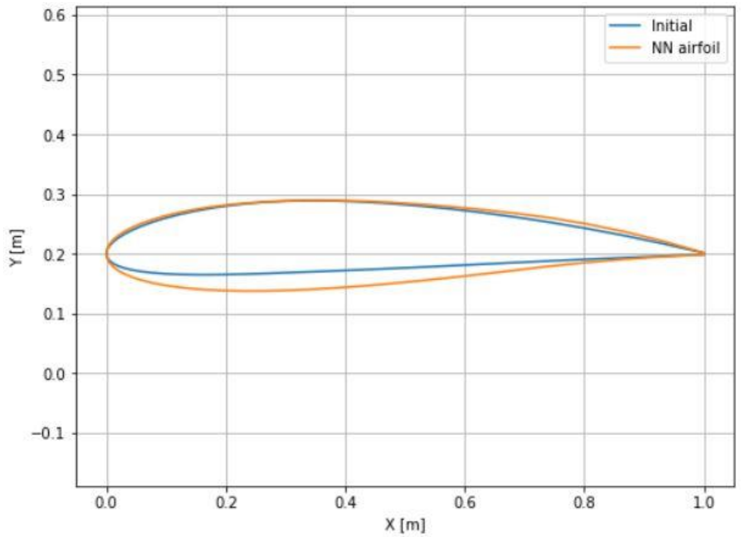
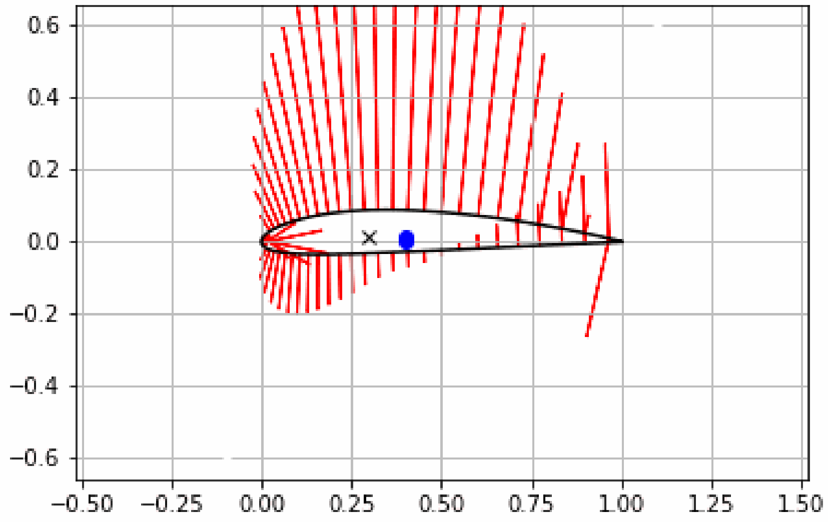
Results

- Start: $X_{cg} = 0.3;\ X_{EA} = 0.4$ (stable system, as the center of gravity would be in front of the elastic axis);
- $8s$ of real time, the value of was abruptly changed to $X_{cg} = 0.5$, bringing the system to a region of instability
- The code changed the airfoil, bringing the Cg to an stable position.







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Final discussions and future work

- **All process worked well and final coupling was performed**
- Simplicity of the aeroelastic model;
- Inability of the neural network to predict different families of airfoils;
- Sudden change in profile geometry;
- Delay in building the database necessary for the training;
- **Instability of the neural network's code and because it can generate different results depending on the database used for training.**

Future work

- Make NN more generic;
- Change NN architecture;
- Reduce overfitting;
- Improve aeroelastic model;
- Add new capabilities in the airfoil;
- 3D approach;
- Add airfoil's transient modification;

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Thank you for your attention!

Questions?

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