ADAGOS

NeurEco

Parsimonious Neural Networks

May 2021

Outline

- **ADAGOS Technology**
  - About ADAGOS
  - Parsimony
  - NeurEco
- **Main applications**
  - Embedded applications
  - Energy
  - Space applications

NEURECO

About ADAGOS

ADAGOS is a **spinoff** of the **IMT** (Institute of Mathematics of Toulouse, France), founded in 2011

ADAGOS is developing **NeurEco** a **parsimonious deep learning technology**, based on the topological gradient approach

The company has **12 employees including seven PhDs in applied mathematics and two PhD students**

ADAGOS is the winner of the GRAND PRIX of the Continental Start-up Challenge 2019

ADAGOS is laureate of the I-NOV 2019 competition

i-Nov concours d'innovation

GreenTech Innovation label from the French Ministry of Ecology

Soutenu par

MINISTÈRE DE LA TRANSITION ÉCOLOGIQUE

Liberté Égalité Fraternité

GREENTECH INNOVATION

Business model

- **AI Software edition:** ADAGOS markets 4 main products:
  - **NeurEco:** Parsimonious ANN factory
  - **xROM:** Parsimonious RNN factory (time series)
  - **coROM:** Parsimonious CNN factory (images, grids input)
  - **AWB:** Adagos Workbench (coupling models, system simulation)

- **Creation of sector-specific products with leading partners in this business:**
  - **ANSYS:** Discussion to include NeurEco in their *twin builder* platform
  - **STM:** Discussion to distribute our tools via their *Cube.ai* platform
  - **FRAMATOME:** Exclusive partnership to bring artificial intelligence to the nuclear energy industry
  - **THALES:** Parsimonious control of active antennas

Main industrial references

- **ANSYS:** Digital twin building
- **FRAMATOME:** *Reliability models*
- **CONTINENTAL:** Embed AI for autonomous driving. Real-time combustion control model
- **Renault Sport Racing:** *Embed AI for real-time control of engine components*
- **MBDA:** Reduced order models for thermal engineering. Satellite image classification
- **MICHELIN:** Supply chain modeling. Aircraft tire wear prediction model
- **STMicroelectronics:** *Embedded AI on small microcontrollers*
- **TEREGA:** Gas consumption forecast model. *Digital twin of a gas network*
- **THALES (TDMS, TAS, TLAS):** *Digital twin of antennas*
- **CNES:** Satellite image segmentation

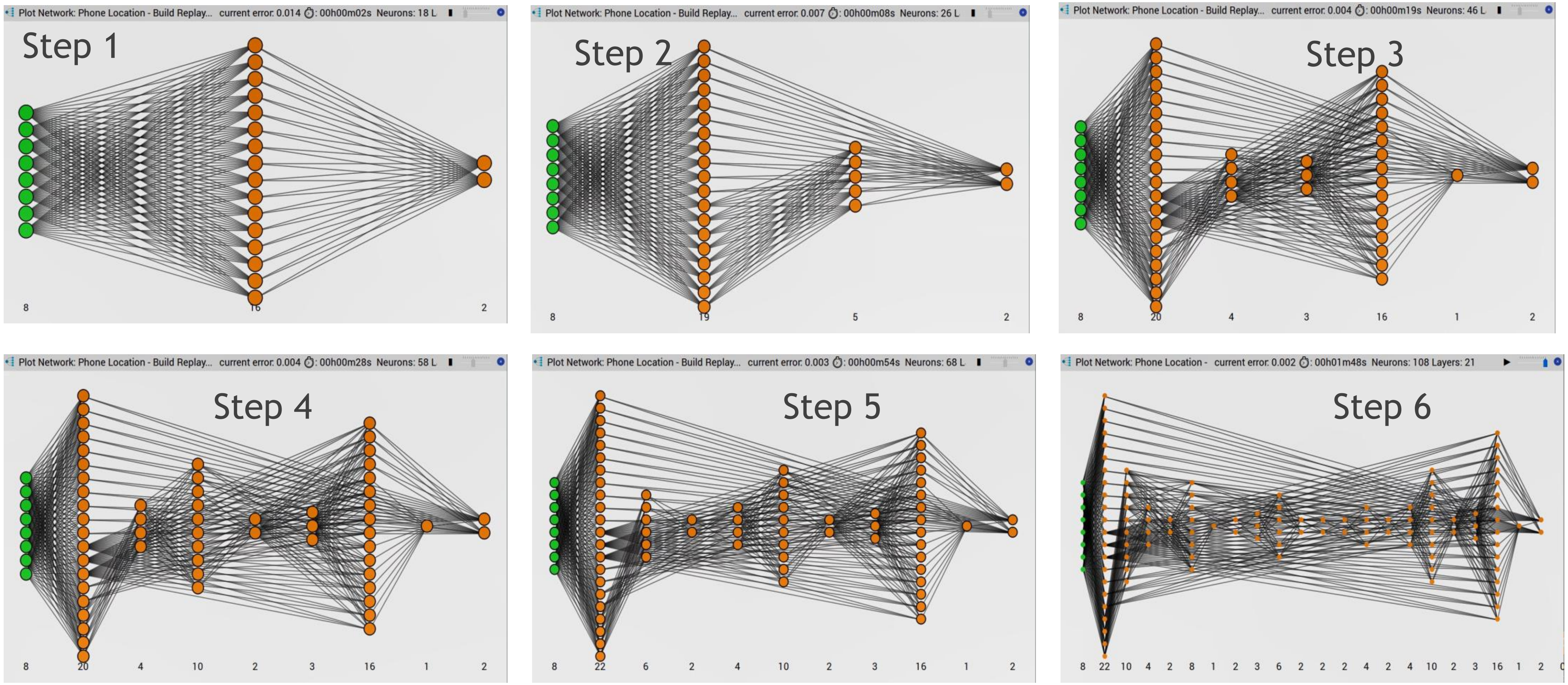
Parsimonious NN

- **Classical AI goes hand in hand with big data**
  - It works by analogy
  - The prediction for a given pattern is based on its similarity to some samples of the learned **big data**set
- **We are following a "small data" paradigm**
  - Our approach is based on parsimony, frugality, reduction of neural network connections…
  - Less neural connections => **less learning data** and **less computing resources**
  - Less neural connections => the learning process is obliged to extract hidden structures in the data => **more intelligent learning and a better prediction**

Topological Optimization

***Parsimony** goes hand in hand with **automatic** creation of neural networks*

View online video

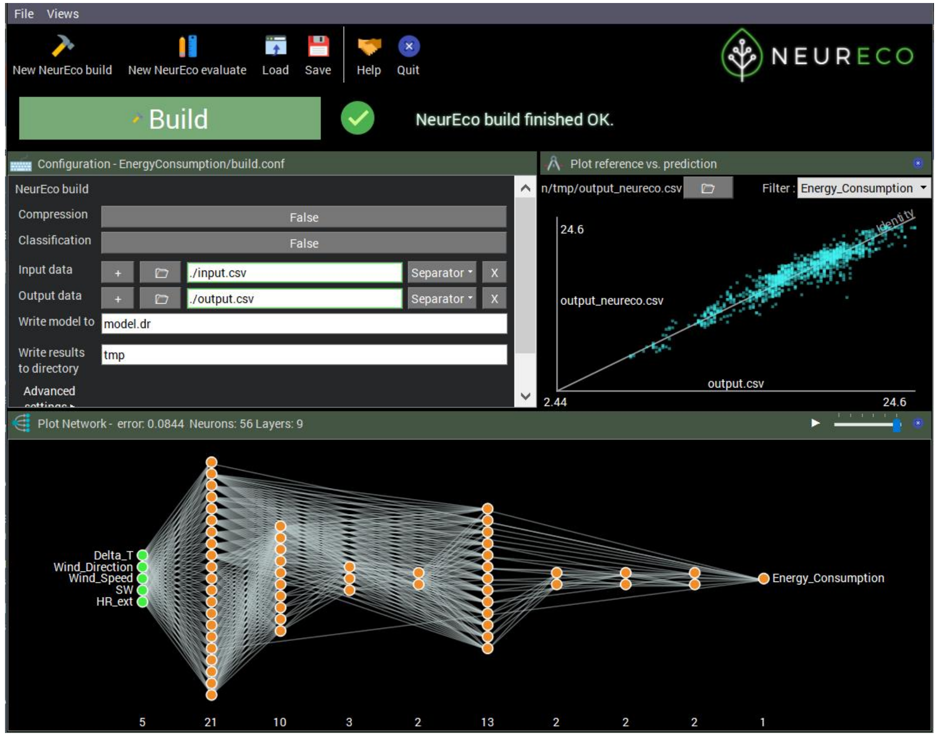


Comparison with classical AI

- **Leading players aren't interested in parsimony**
  - It is not compatible with their business model
  - They provide the tools for free and you pay later
    - Cloud computing due to the immensity of classical neural networks
- **In our case, there is no hidden costs**
- **Our solution has nothing to do with NN simplification and TinyML**
  - **Before simplifying a huge neural network, you need to build it**
    - **You need a large amount of learning data**
- **Our solution has nothing to do with AutoML (Automatic Machine Learning)**
  - **AutoML is based on huge NN and big data**

NeurEco non convolutional neural networks

- **Can be used for different kind of problems**
  - Compression
  - Regression
  - Classification



- **Makes AI accessible for the non specialists**
  - Just provide the data
  - And press the build button

- **And if you are familiar with AI**
  - NeurEco is interfaced with standard AI environments (wrapper Python)
  - Compatible with Google, Azure, AWS

NeurEco models are much smaller and more accurate

Comparison on 100 test cases:

⇨ **The error is reduced by 7% (17% on regression test cases)**

⇨ **The network size is reduced by a 3 000 factor**

Full results are available at https://www.adagos.com/adagos-versus-state-of-the-art/

Test Case	Task	Number of inputs	Number of outputs	TF Test Error *	NeurEco Test Error **	Error NeurEco / Error TF	TF Total Parameters	NeurEco Total Parameters	Size TF / Size NeurEco
Mean						**0,93**			**3 138**
ExoplanetHuntingInDeepSpace	Classification	3 197	2	0,53	0,35	0,67	64 644	180	359
AntennaPower	Regression	10	3	1,92	0,08	0,04	994 363	114	8 722
CombinedCyclePowerPlant	Classification	4	1	0,88	0,81	0,92	10 289	282	36
Add10	Regression	10	1	7,73	6,61	0,85	516 781	59	8 759
ElectricalGridStability	Classification	13	2	0,40	0,35	0,88	2 192	863	3
FEMSimulations	Regression	9	4	5,68	5,06	0,89	108 794	428	254
...	...	...	...	...	...	...	...	...	...

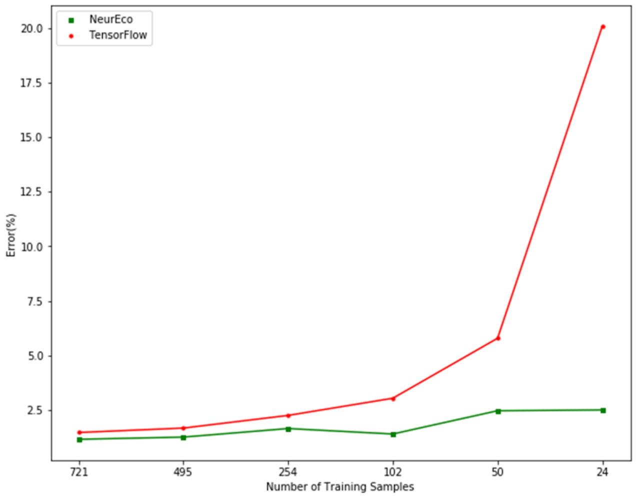
(*) We took the best error for TensorFlow after at least 10 tries

(**) Using only NeurEco default settings

NeurEco provides robust responses even with small datasets

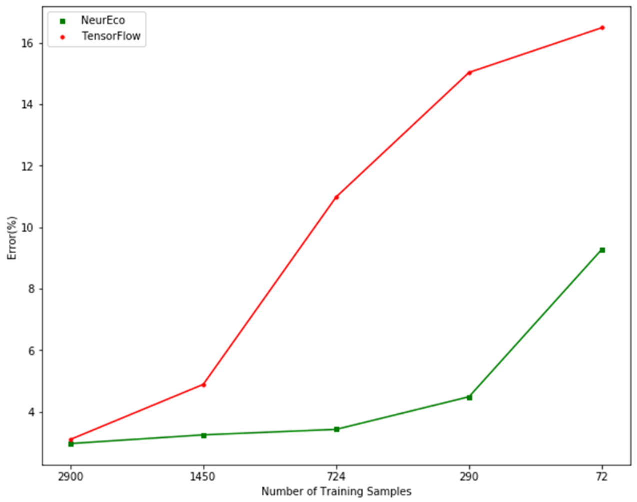
- We use the full dataset (to the left of the x axis) and we reduce it (to the right of x axis)
- Reducing the amount of training data has a limited impact on the accuracy of the NeurEco model

Atomic coordinate prediction of carbon nanotubes



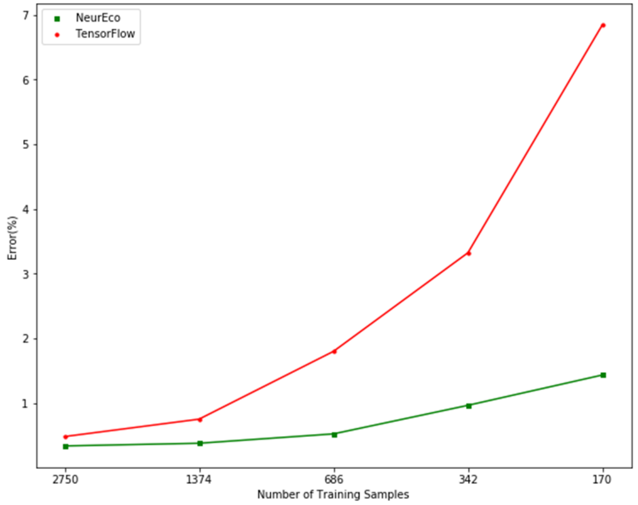
Regression
from 5 inputs to 3 outputs

CPU runtime prediction based on user tasks

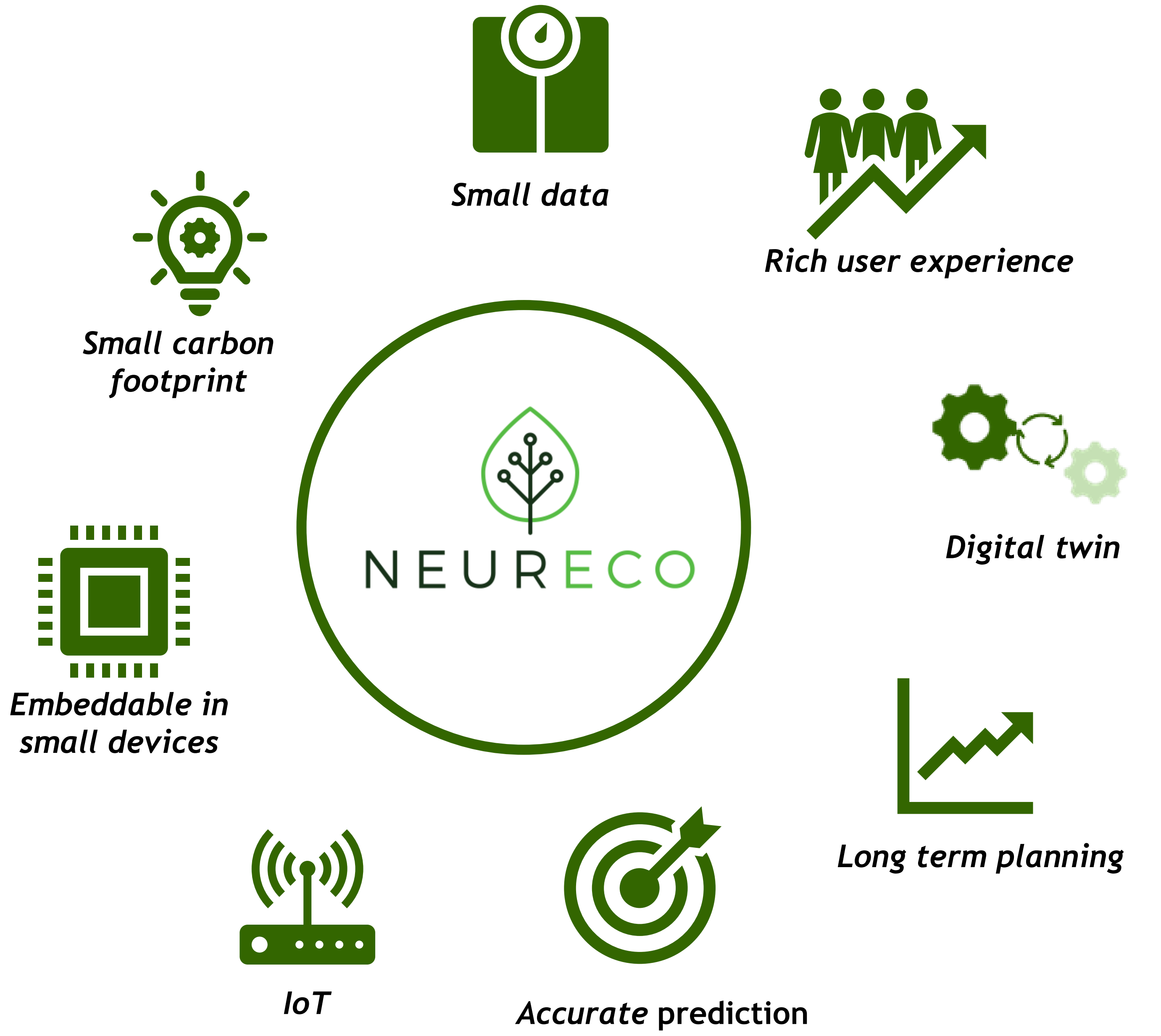


Regression
from 21 inputs to 1 output

Determining the appropriate action based on shuttle flight conditions



Classification
from 8 inputs to 7 outputs


Small data
Rich user experience
Small carbon footprint
NEURECO
Digital twin
Embeddable in small devices
Long term planning
IoT
Accurate prediction

Conclusion

Beyond learning the data,

NeurEco learns the underlying models

Parsimony forces the learning process to extract the model from the data

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Embedded automotive applications

Real-time combustion control model

Real-time turbocharger control model

Real-time engine shaft control model

Embedded AI for autonomous driving

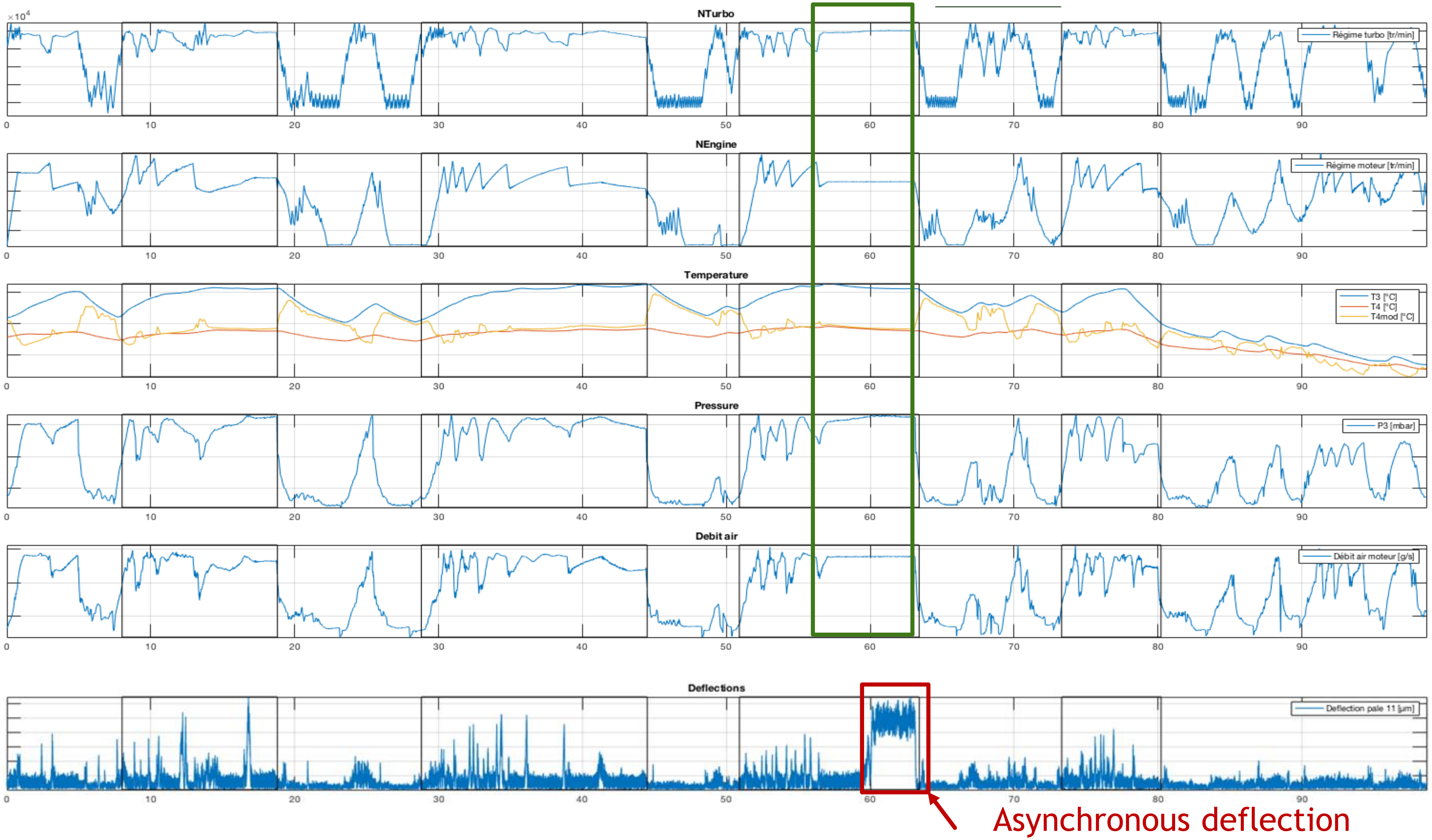
Embedded model for road surface prediction

Turbocharger deflection

The input data preceding the asynchronous deflection is flat
$\Rightarrow$ **A long term memory is needed**

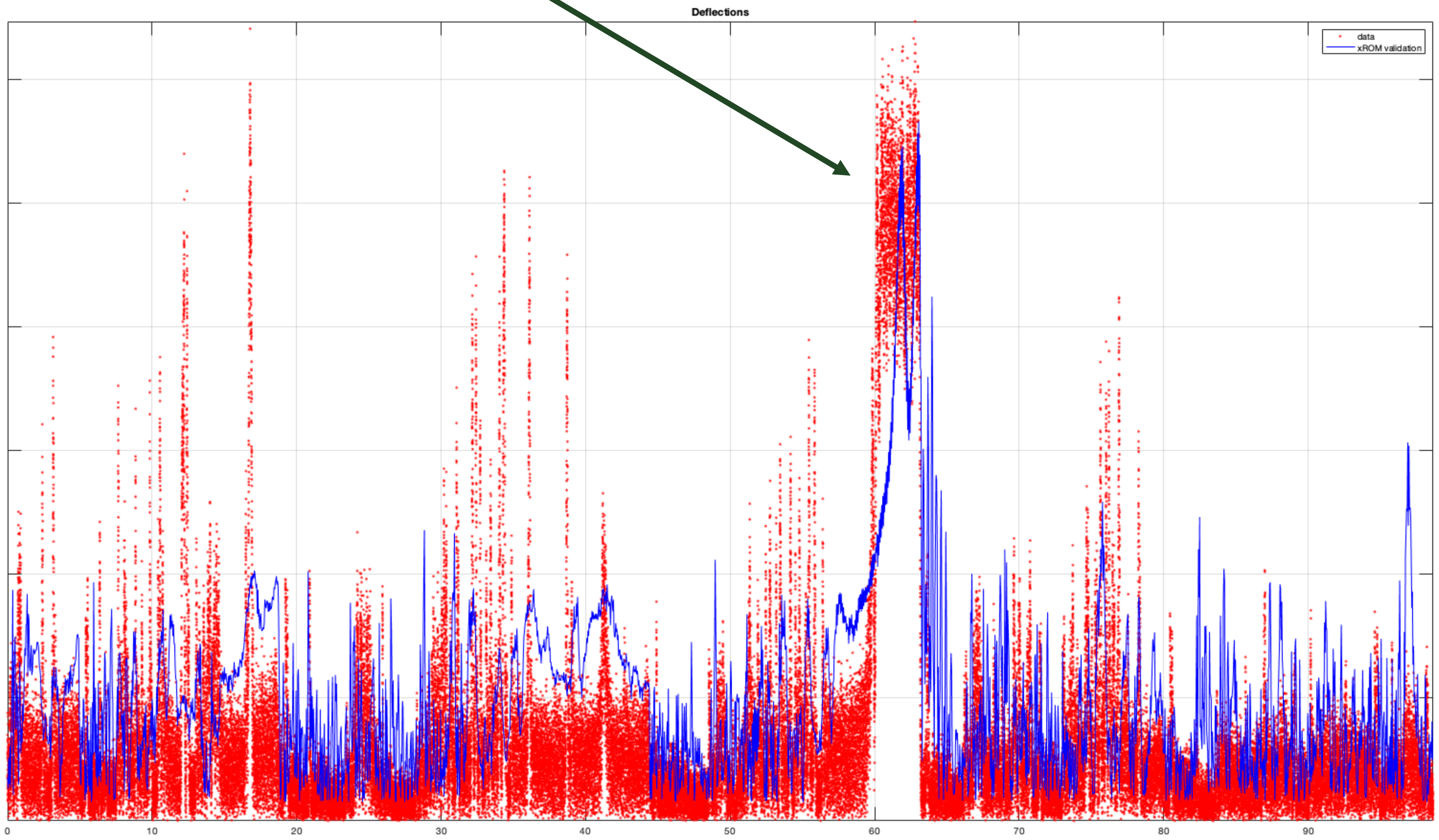
Engine parameters (Inputs)

Deflection (target)



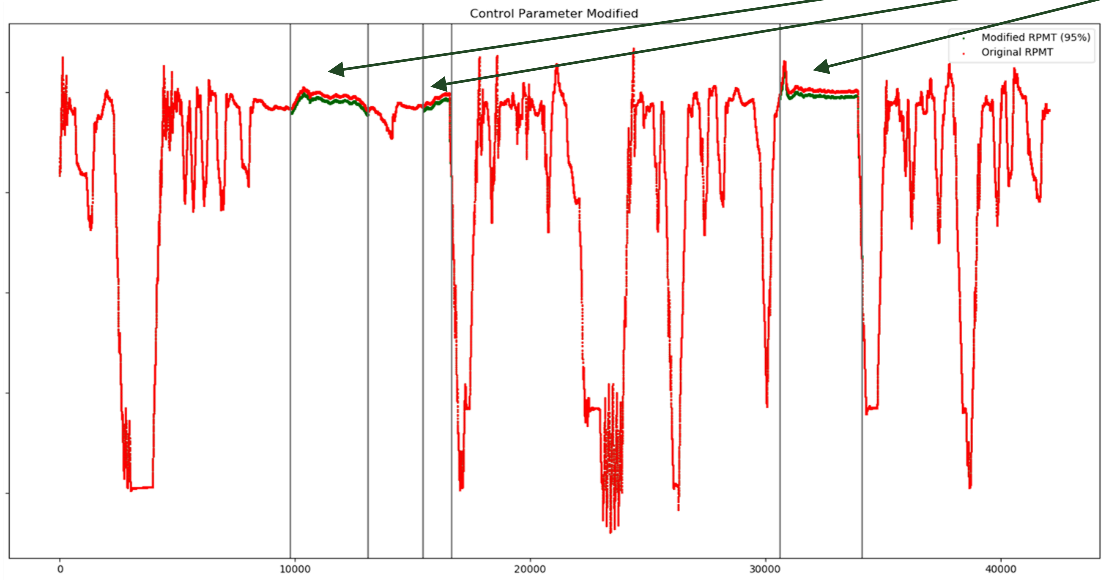
Turbocharger deflection

Asynchronous deflection

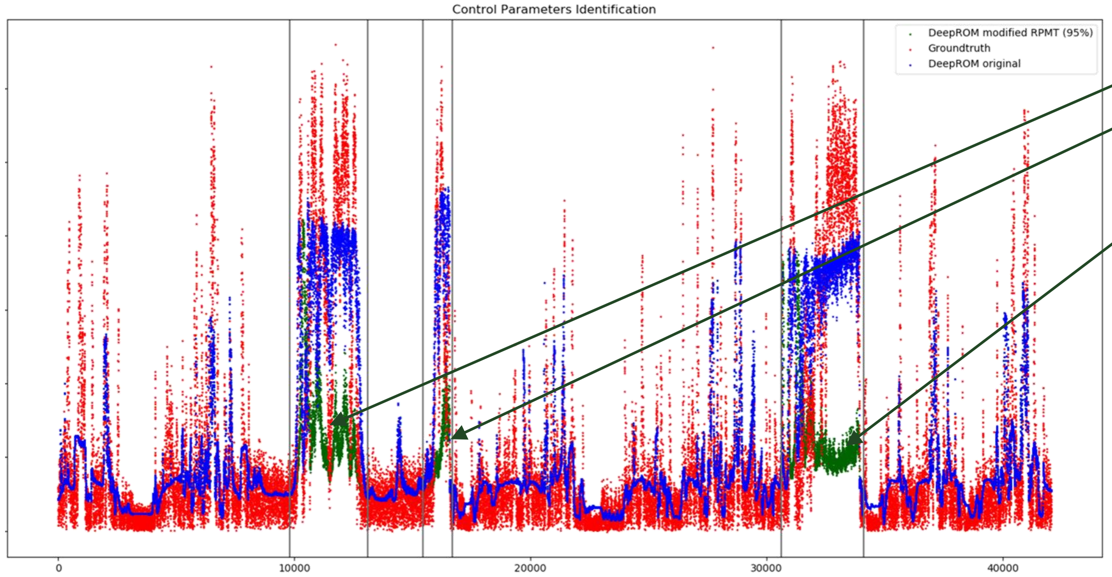


Turbocharger deflection

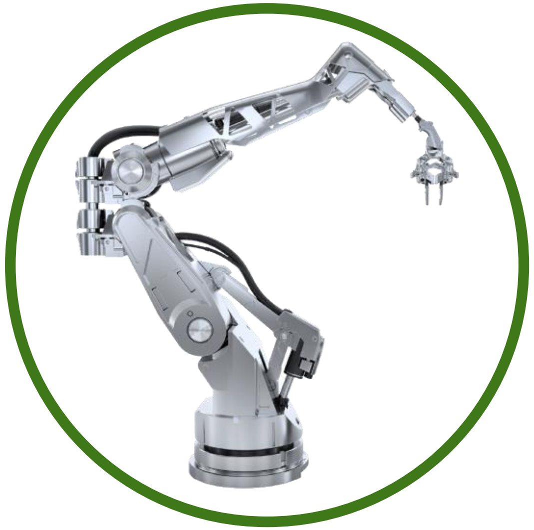
Control of the turbo rpm



Controlled asynchronous deflections



Embedded applications on STM32 microcontroller

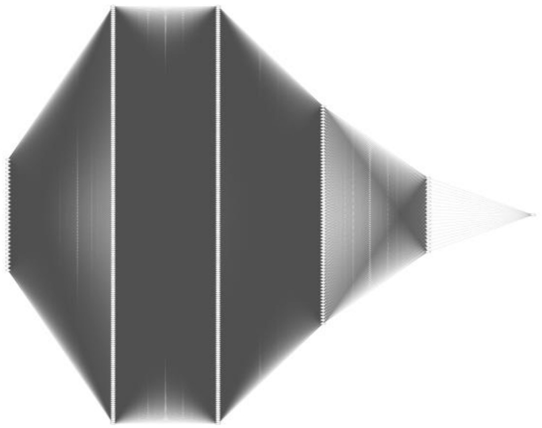


Robot grasping quality

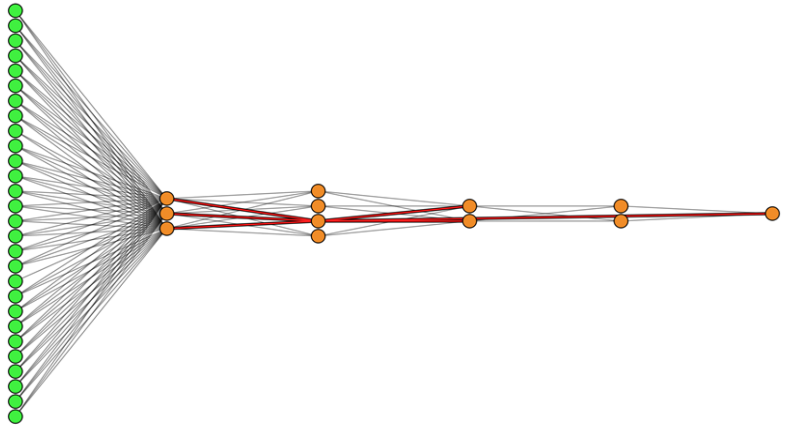
Motor vibration classification

Regression grasping study

- Embed IA algorithm on STM32 NUCLEO-L476RG, provided by STMicroelectronics
- The study: Predict robotic hand's grasp stability
  - 28 input parameters
  - Output: grasp stability



Tensorflow neural network
Relative Testing Error: 24.2%
Links Number: 121,511



NeurEco neural network
Relative Testing Error: 22.5%
Links Number: 120

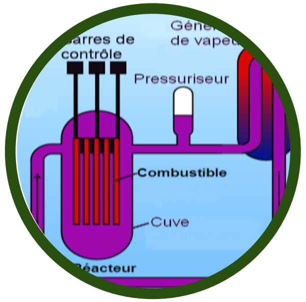
Regression grasping study
Results

Battery life in standby: 8 months, 3 days and 12 hours

	Tensorflow Redundant	Tensorflow Redundant	NeurEco© Parsimonious
CPU Frequency (Mhz)	4	80	4
Duration (ms)*	203.92	13.12	1.30
CPU cycles*	815,715	1,050,346	5,222
Used flash memory (Kb)	537.57	537.57	69.69
Battery life (one test every 50 ms)	Not applicable (computation too long)	10 days and 20 hours	7 months, 22 days and 8 hours

* average values (16 tries)

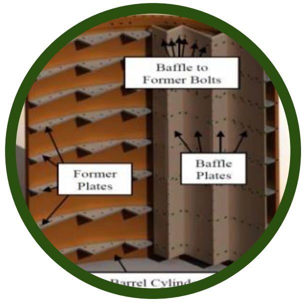
Energy



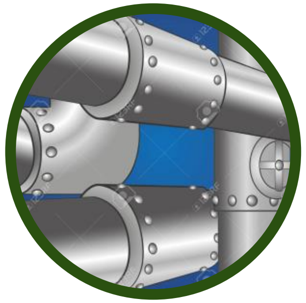
Nuclear core cooling system simulatin

Predicting the production of a wind farm

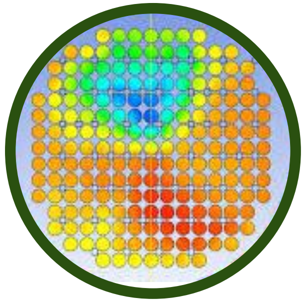
Pellet Clad Interaction Stress Corrosion Cracking



Structural Analysis for Baffle Former Bolt Asset Management



Digital twin of a gas network



Prediction of neutronic fluxes

Digital twin of gas network

Context and objective:

- Existing simulation tools aren't satisfactory (PSI)
- The real state of the network (measurements) is not taken into account properly

The objective is to create a **digital twin** of the Network

Our objective is to deploy this solution by February 2022 on the Teréga network

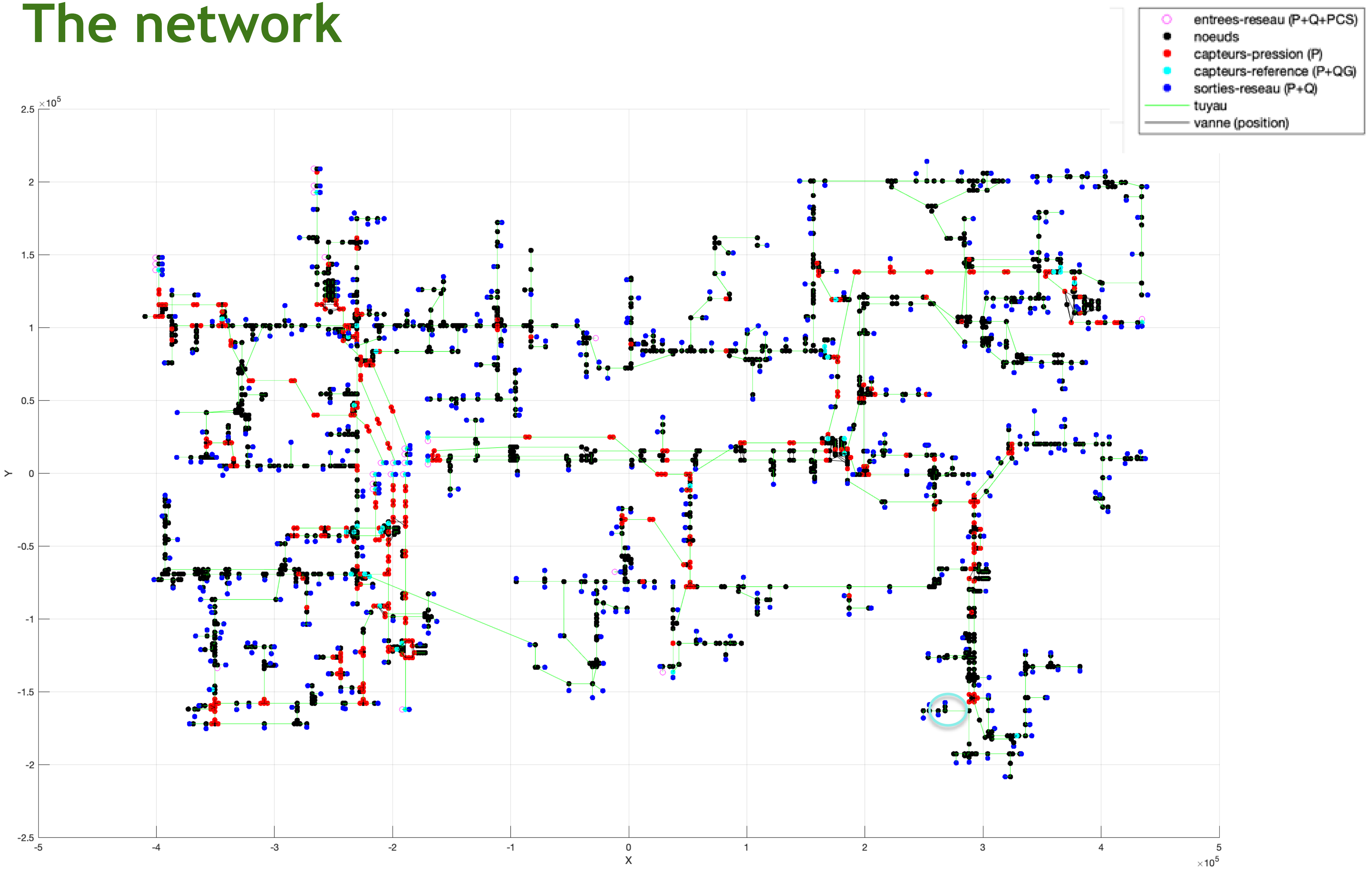
Model input:

- Topology and geometry of the gas network
- History of flow and pressure measures for several nodes of the network
- Altitude of the network nodes

Model output:

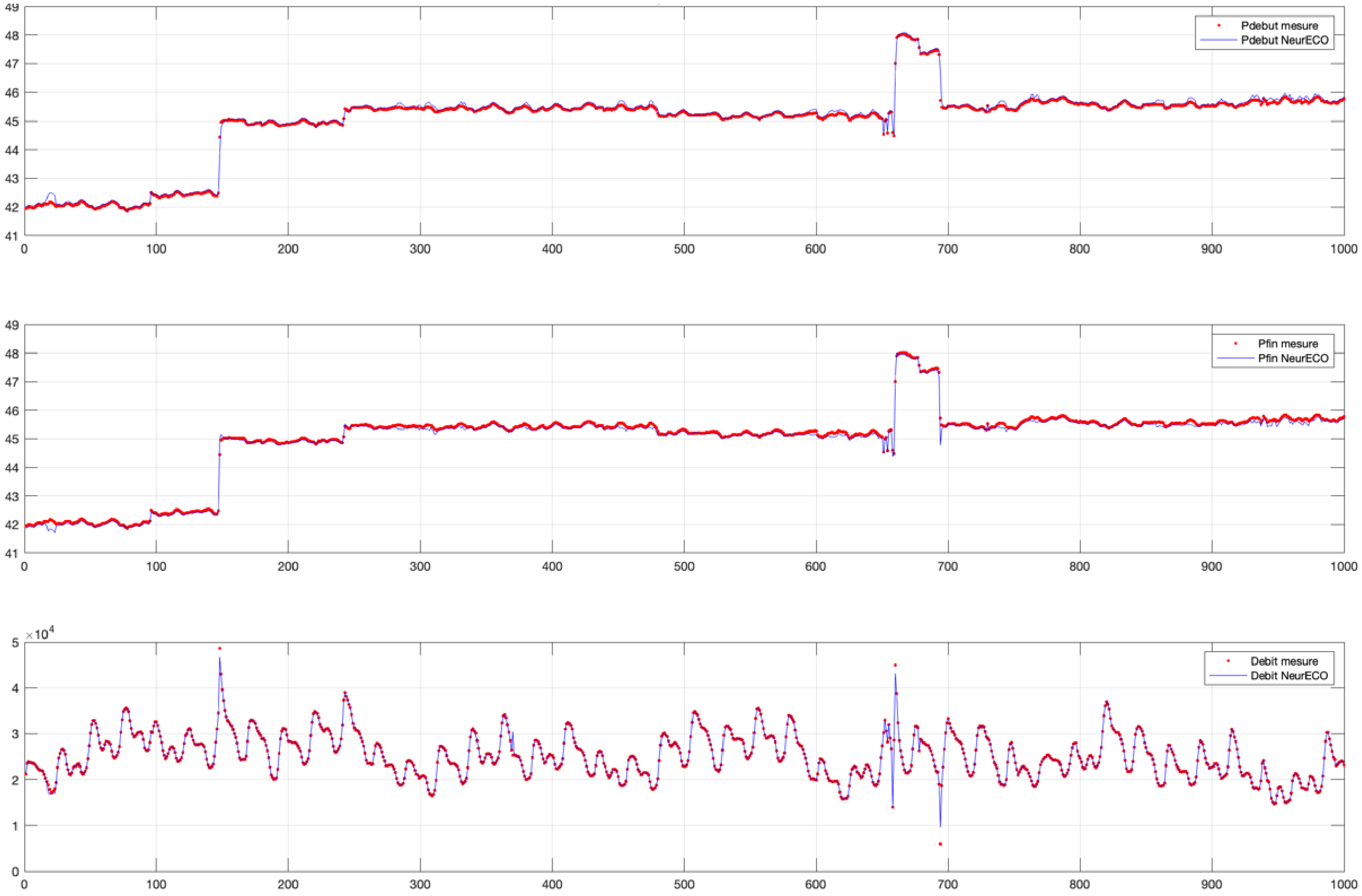
- Flow and pressure at several nodes, every 3 minutes

The network

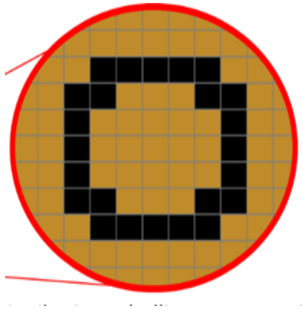


entrees-reseau (P+Q+PCS)
noeuds
capteurs-pression (P)
capteurs-reference (P+QG)
sorties-reseau (P+Q)
tuyau
vanne (position)
X
Y
×10^5
×10^5

Results obtained on some fragments of the network

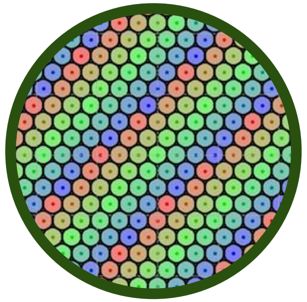


Spatial applications



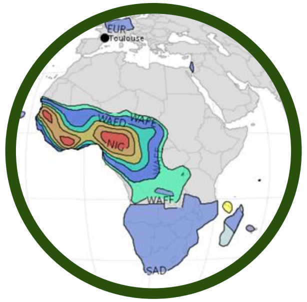
Surface frequency selection

Antenna diagnosis



Real time beam forming of an array antenna

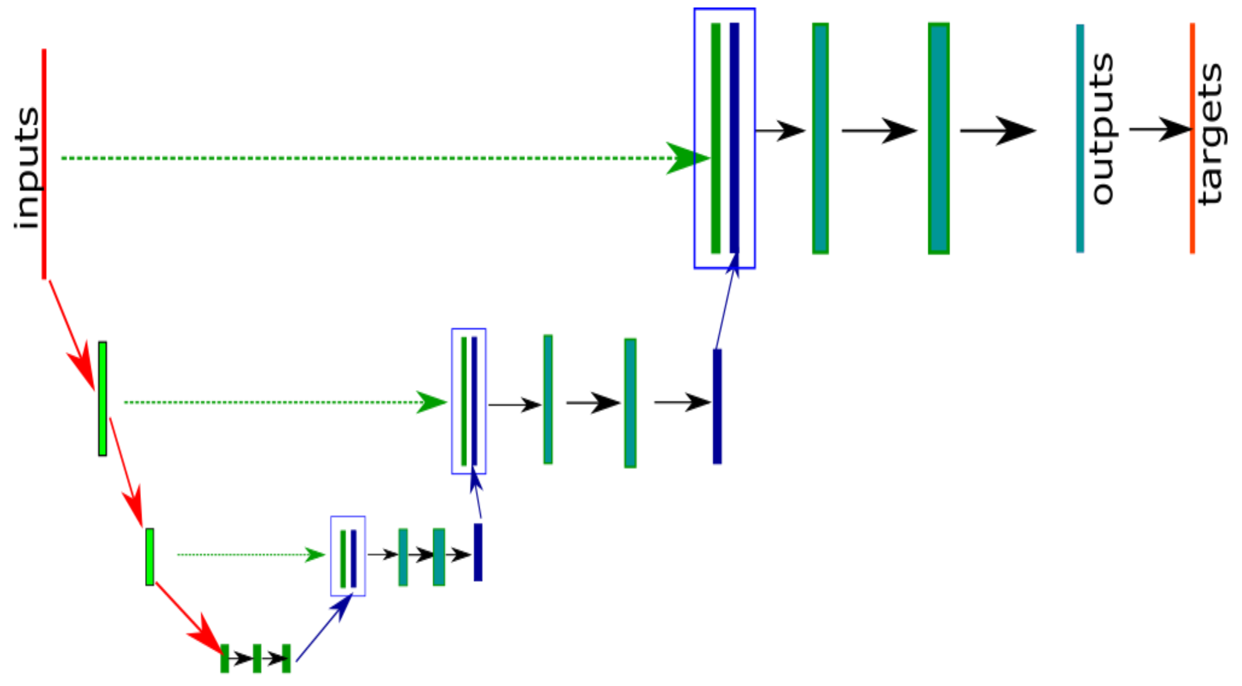
Satellite image processing



Design: optimal parameters of an antenna from its mission specification

Antenna surface frequency selection

Making a real-time copy of a complex solver



Convolutions with 3x3xd kernels, stride=1, preserves shape

Parallel propagation of information (no calculations)

Concatenation

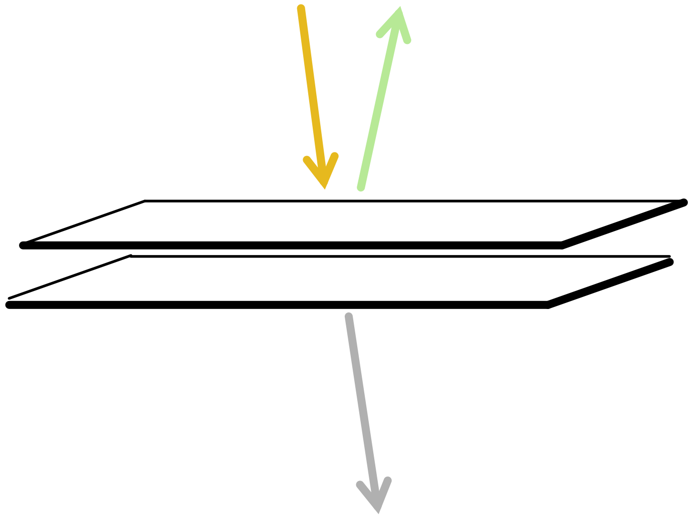
Compression. Wavelets constructions. For enrichment convolutions with 3x3xd kernels, stride=2, divides each spatial dimension size by two

Decompression, upconvolutions with 3x3xd kernels, stride=2, multiplies each spatial dimension size by two

- The input is one or several grids representing the material properties and the geometry
- The output is one or several grids representing the solutions

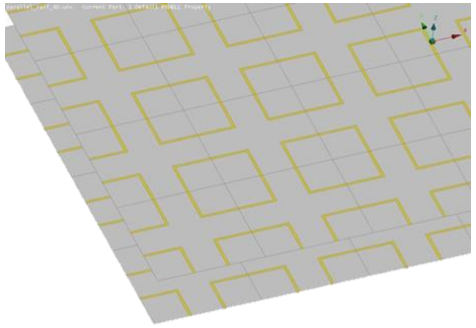
Antenna surface frequency selection

Making a real-time copy of a complex solver

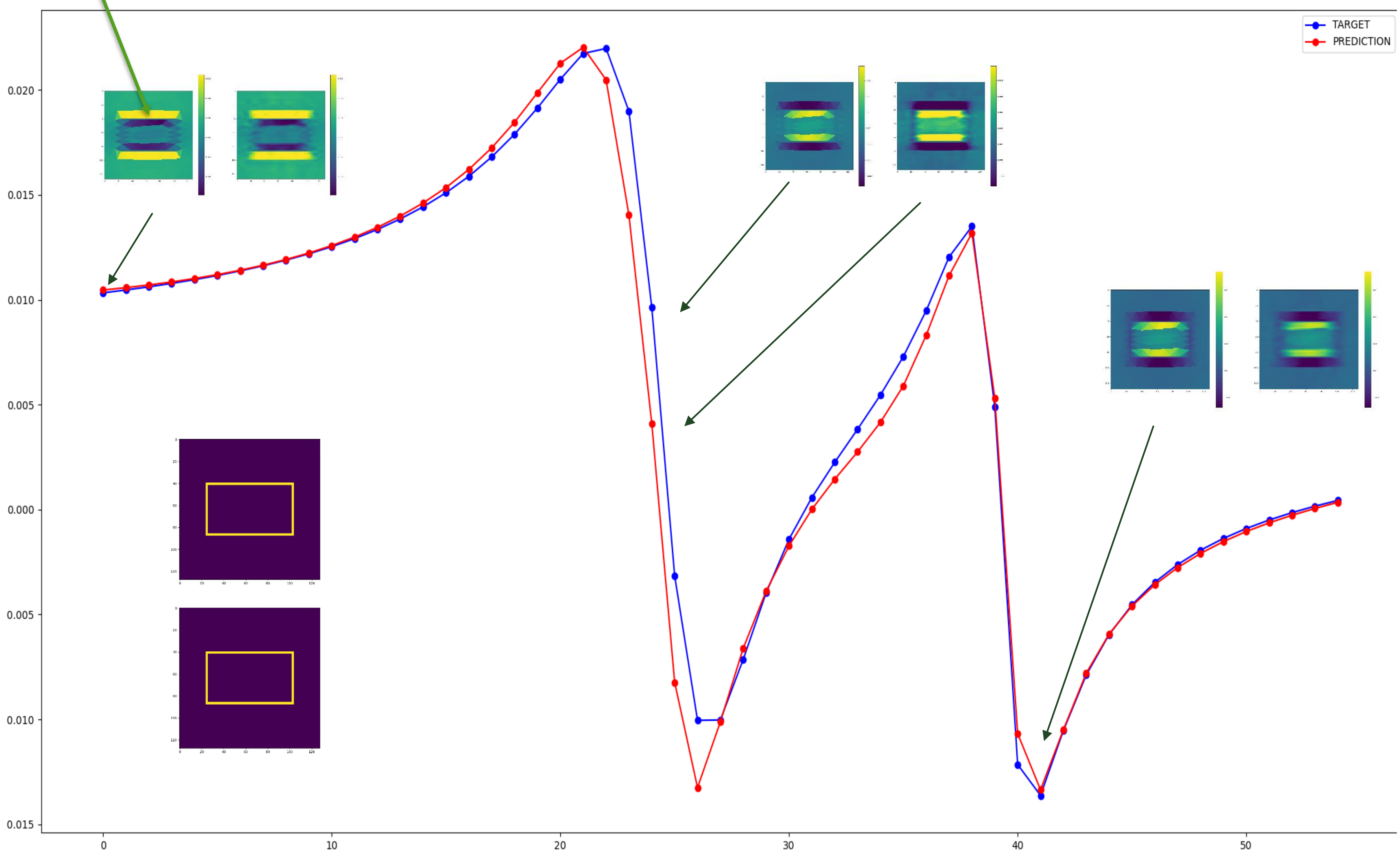


- **Input:** geometry - 128x128 binary grids: metallic-non metallic cells
- **Output:** the electrical current

- **Global dataset:** 200 geometries (128x128 grids) and 55 frequencies for each geometry
- **Learning dataset:** 180 geometries and only 12 frequencies over 55
- **Testing dataset:** the remaining 20 geometries



GEOMETRY 96: DOF OF THE ELECTRICAL CURRENT



NEURECO

GEOMETRY 140: DOF OF THE ELECTRICAL CURRENT