ADAGOS

NEURECO

Parsimonious Neural Networks

October 2020

What is NeurEco ?

The first automatic parsimonious neural networks factory

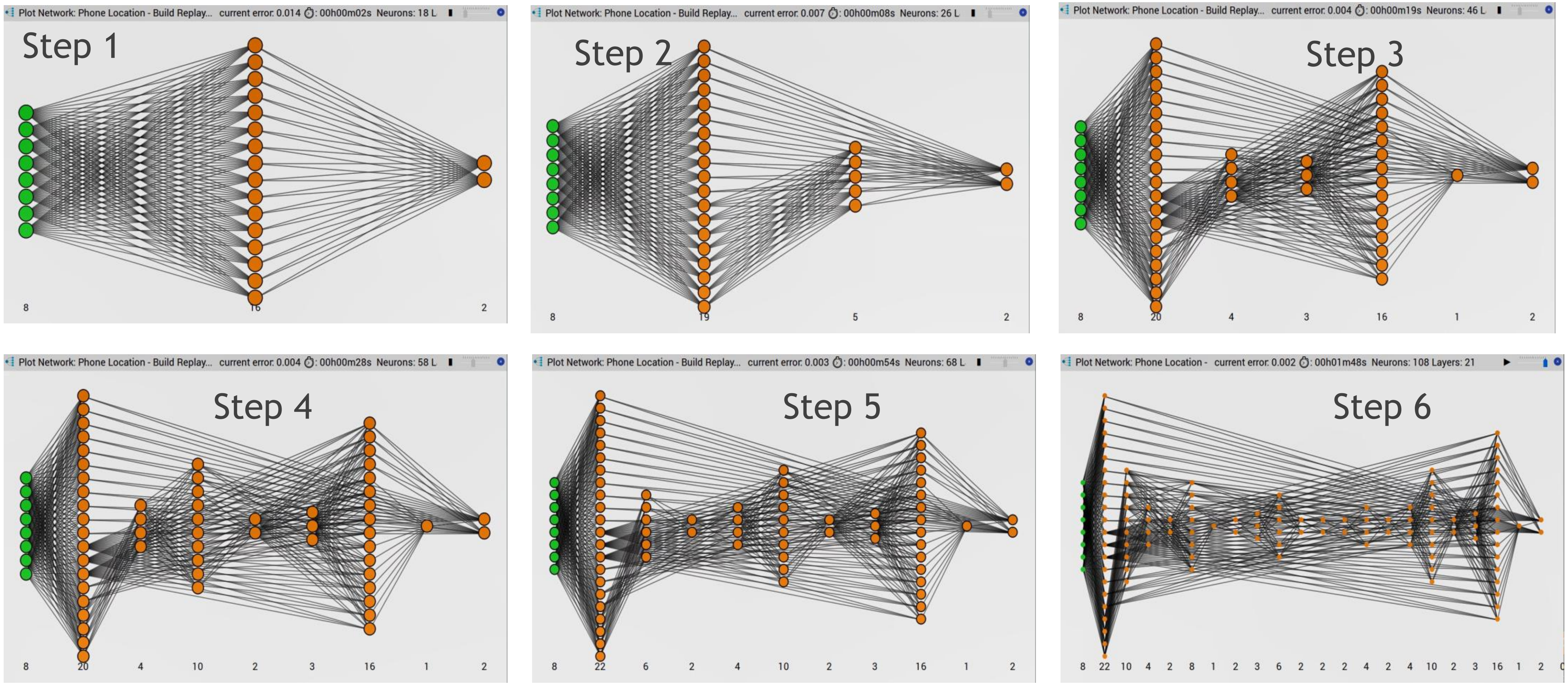
- Based on the fundamental **scientific principle of parsimony** that dates back to the 14th century.
- Based on the **theory of topological gradient**
  - Pr Mohamed Masmoudi, founder of ADAGOS, is one of its major contributor
  - ADAGOS is a **spinoff** of the **IMT** (Institute of Mathematics of Toulouse), founded in 2011
- Developed thanks to the support of **major partners:**
  - FRAMATOME
  - ANSYS- ESTEREL TECHNOLOGIES
  - RENAULT SPORT RACING

NEURECO

Topological Optimization

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

[View online video]



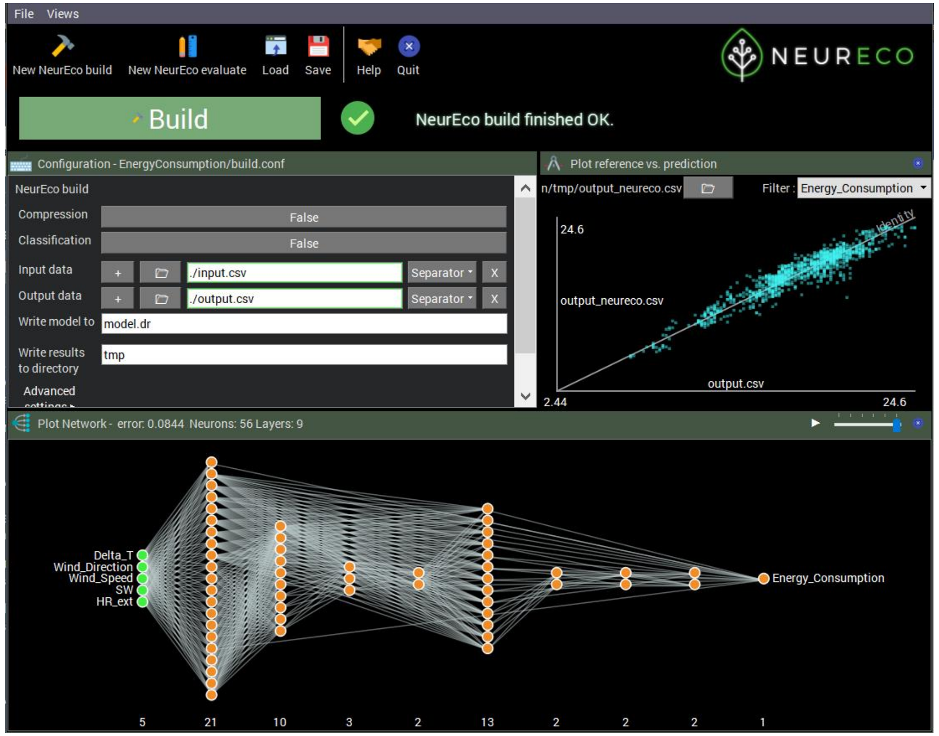
Impact of parsimony

It opens new horizons for AI

- Increases AI performance
  - Learn from **small sets of data**
  - Reduce the **computing resources of AI**
  - Allow **incremental or continuous** learning
  - Embed AI algorithms on **small devices** and **extend the battery life**
- Opens new horizons for AI
  - **Extend the scope of AI to continuous phenomena**
  - **Predict** the response of **almost chaotic systems**
  - Build **explainable** neural networks
  - **Resist** against attacks

Impact of automatic creation of NN

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



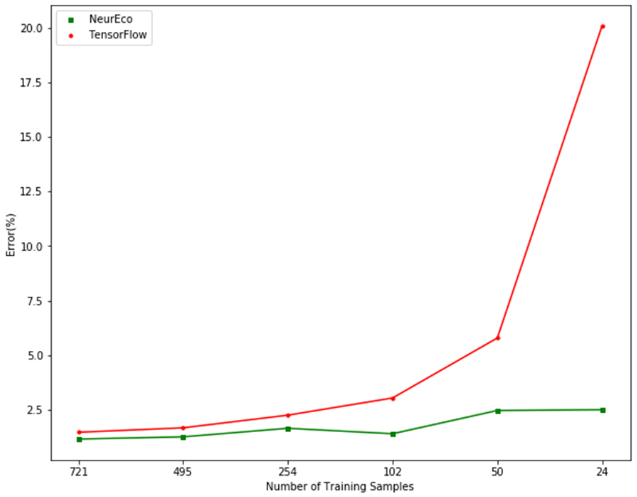
- **And if you are familiar with AI**
  - NeurEco is interfaced with standard AI environments
  - Compatible with Google, Azure, AWS
  - NeurEco adapts to your way of working
  - NeurEco lets you focus on your core business and helps you to reach efficiently your objective

NEURECO

NeurEco provides robust responses even with small datasets

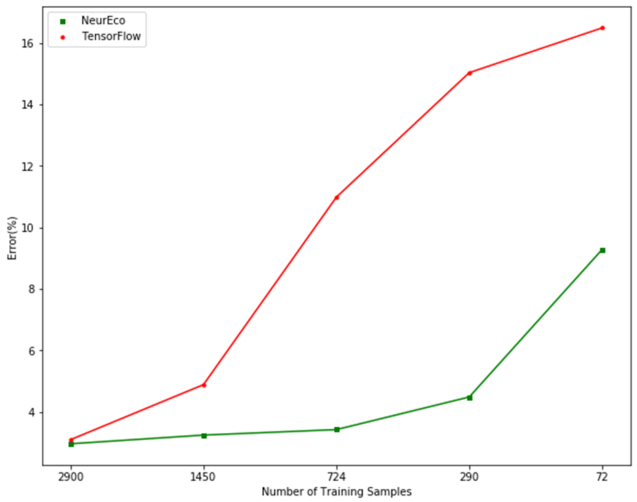
Reducing the amount of training data has a limited impact on the accuracy of the NeurEco model

Atomic coordinate prediction of carbon nanotubes



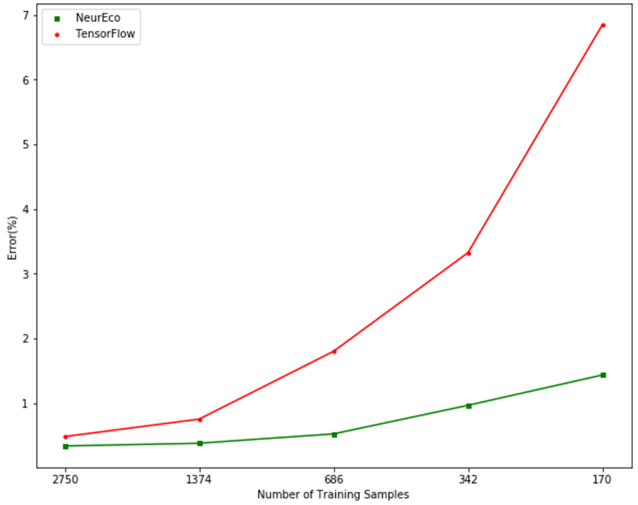
Regression
from 5 inputs to 3 outputs

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

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/

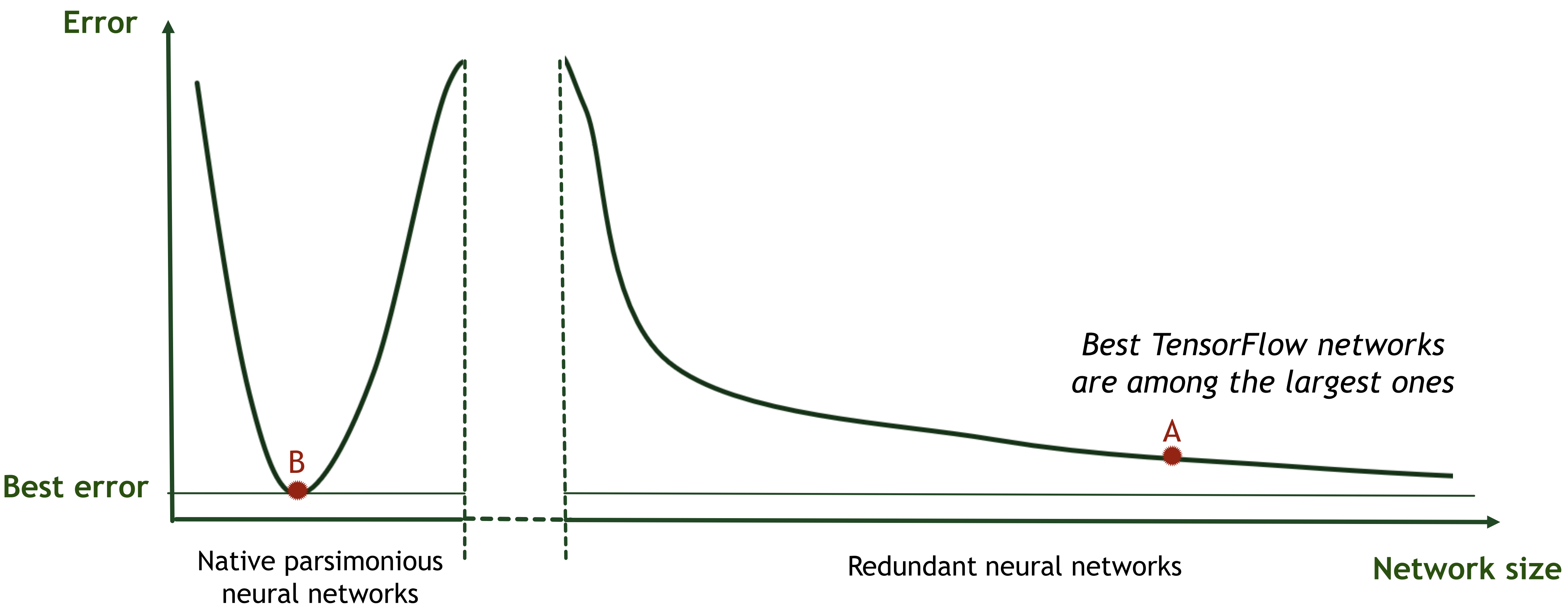
Test Case	Task	Number of inputs	Number of outputs	TF Test Error *	NeurEco Test Error **	Error NeurEco / Error TF	TF Total Parameters	NeurEco Total Parameters	Size TF / Size NeurEco
Mean						**0,93**			**3 138**
ExoplanetHuntingInDeepSpace	Classification	3 197	2	0,53	0,35	0,67	64 644	180	359
AntennaPower	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

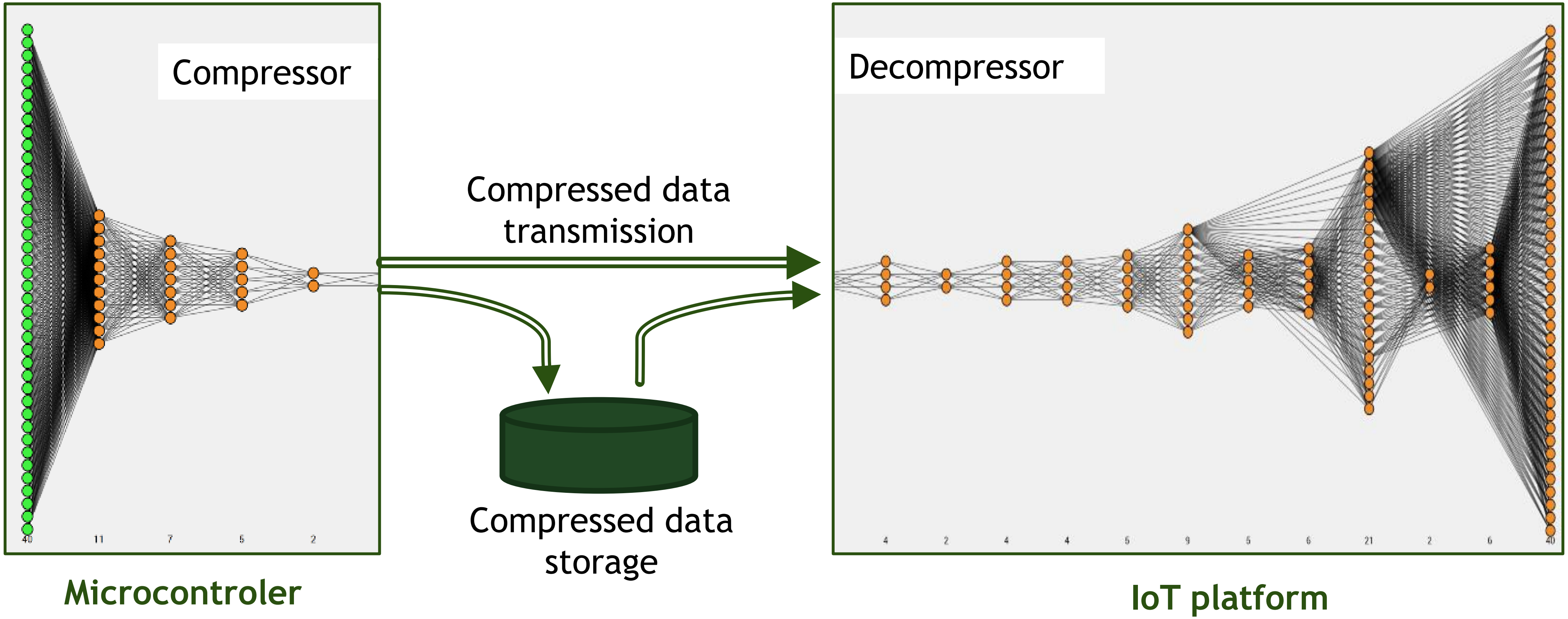
NeurEco models are much smaller and more accurate

There is no way going from point A to point B using a simplification process

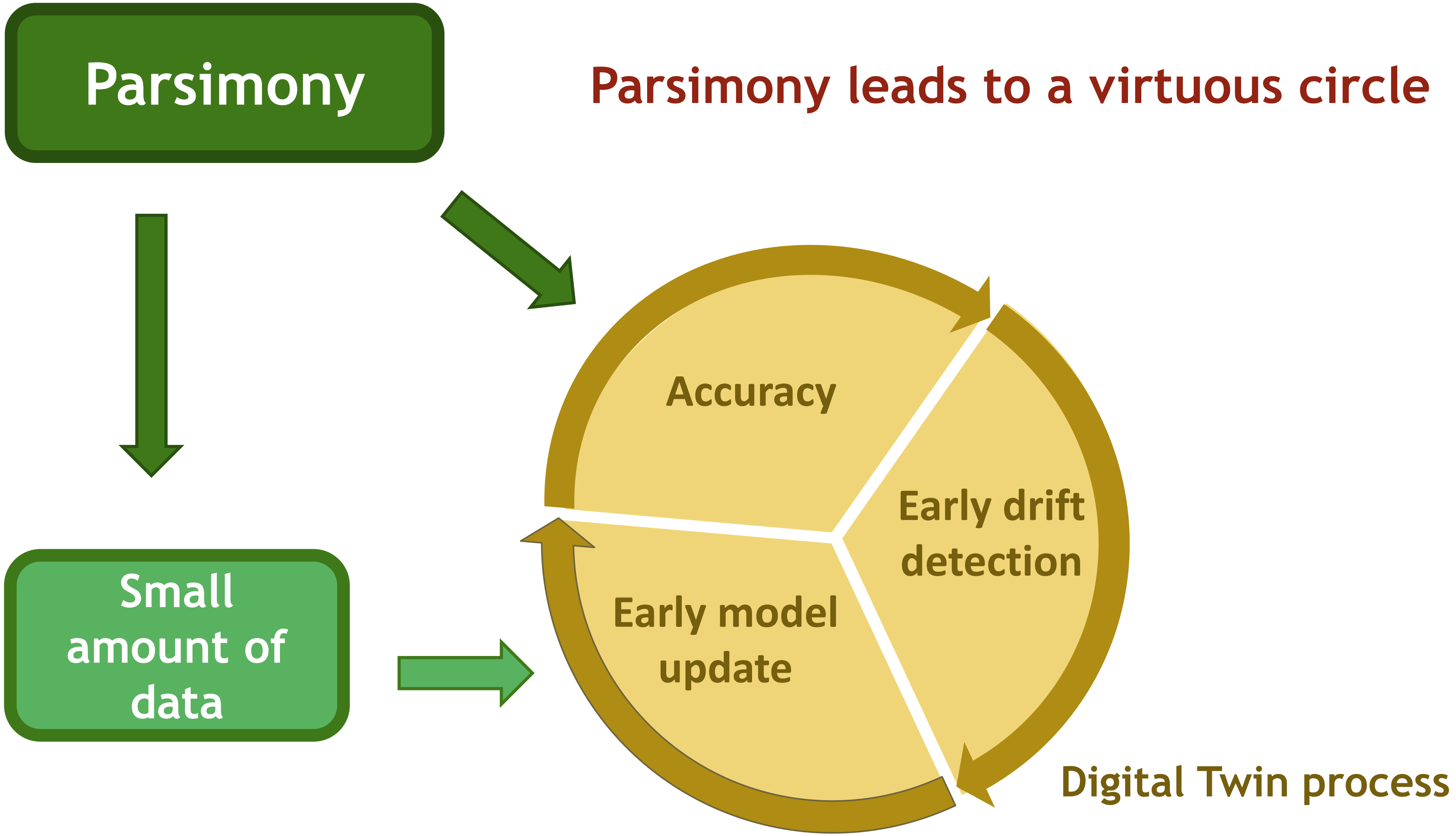


Parsimony: a solution to reduce connectivity needs

Data is restored by the decompressor with very good accuracy



Parsimony: an asset for Digital Twin prediction



Main industrial references

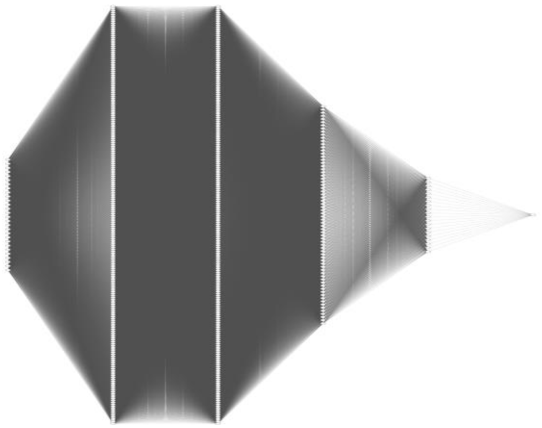
- **ANSYS:** The ANSYS Twin Builder product is based on our technology
- **CONTINENTAL:** Models for autonomous driving, real-time combustion control model
- **FRAMATOME:** Reliability models based on hybrid data processing
- **MBDA:** Reduced order models for thermal engineering.
- **MICHELIN:** Factory load planning model. Aircraft tire wear prediction model
- **RENAULT SPORT RACING:** On-board models for real-time control of engine components
- **STMicroelectronics:** Solutions for smart connected objects
- **TEREGA:** Gas consumption forecast model. Gas network simulation tool
- **THALES:** Complex antenna design and calibration tools

Embed AI algorithms on small devices

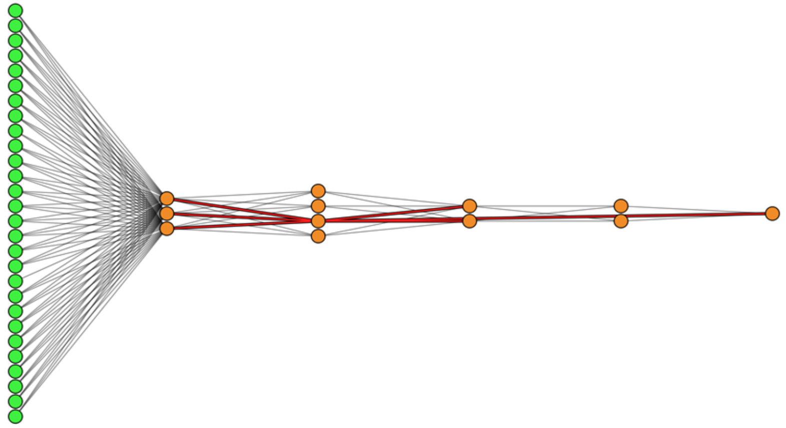
Embed AI algorithms on small devices

Grasping test case: Introduction

- Embed IA algorithm on STM32 NUCLEO-L476RG, provided by STMicroelectronics
- Test case: Predicting robotic hand's grasp stability
  - 28 input parameter
  - Output: grasp stability



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



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

Grasping test case: Keras versus NeurEco

Grasping test case: Results

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

	Keras Redundant	Keras 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)

Turbo Blade Deflection

Prediction / Control

Prediction of turbo blade deflection

Context and objective:

A significant asynchronous deflection of the blade causes bending stresses and strong vibrations which can eventually damage the turbo. This phenomenon, due to strong nonlinear fluid/solid interaction, is almost chaotic.

⇨ **Predict** the blade deflection and define an engine control strategy that avoids damage to turbine blades

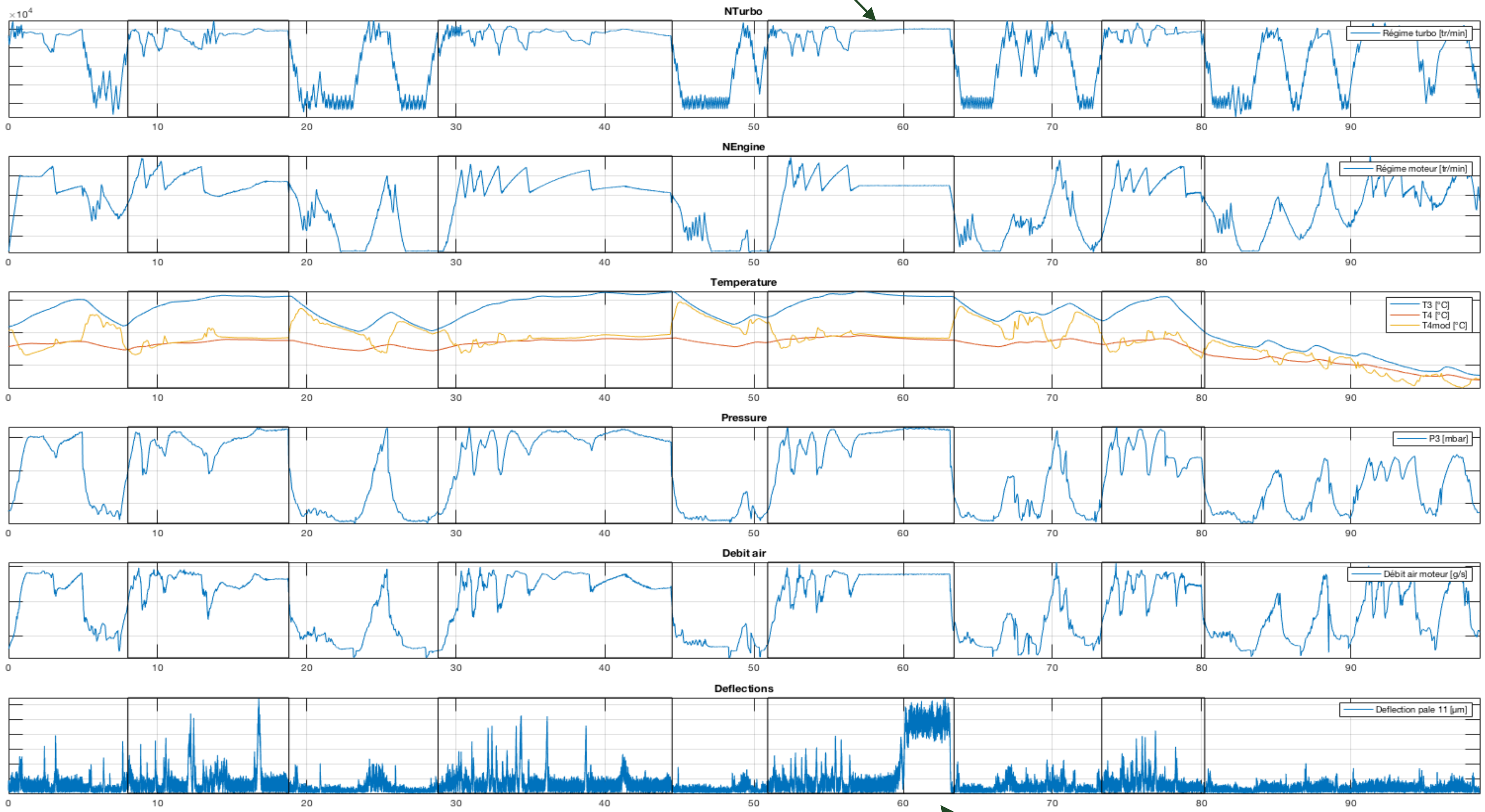
⇨ **Dynamic modelling is needed** to catch asynchronous deflections

Data available for the creation and validation of the model:

- Engine RPM, Turbo RPM, Air temperature, Air pressure
- Turbo blade deflection

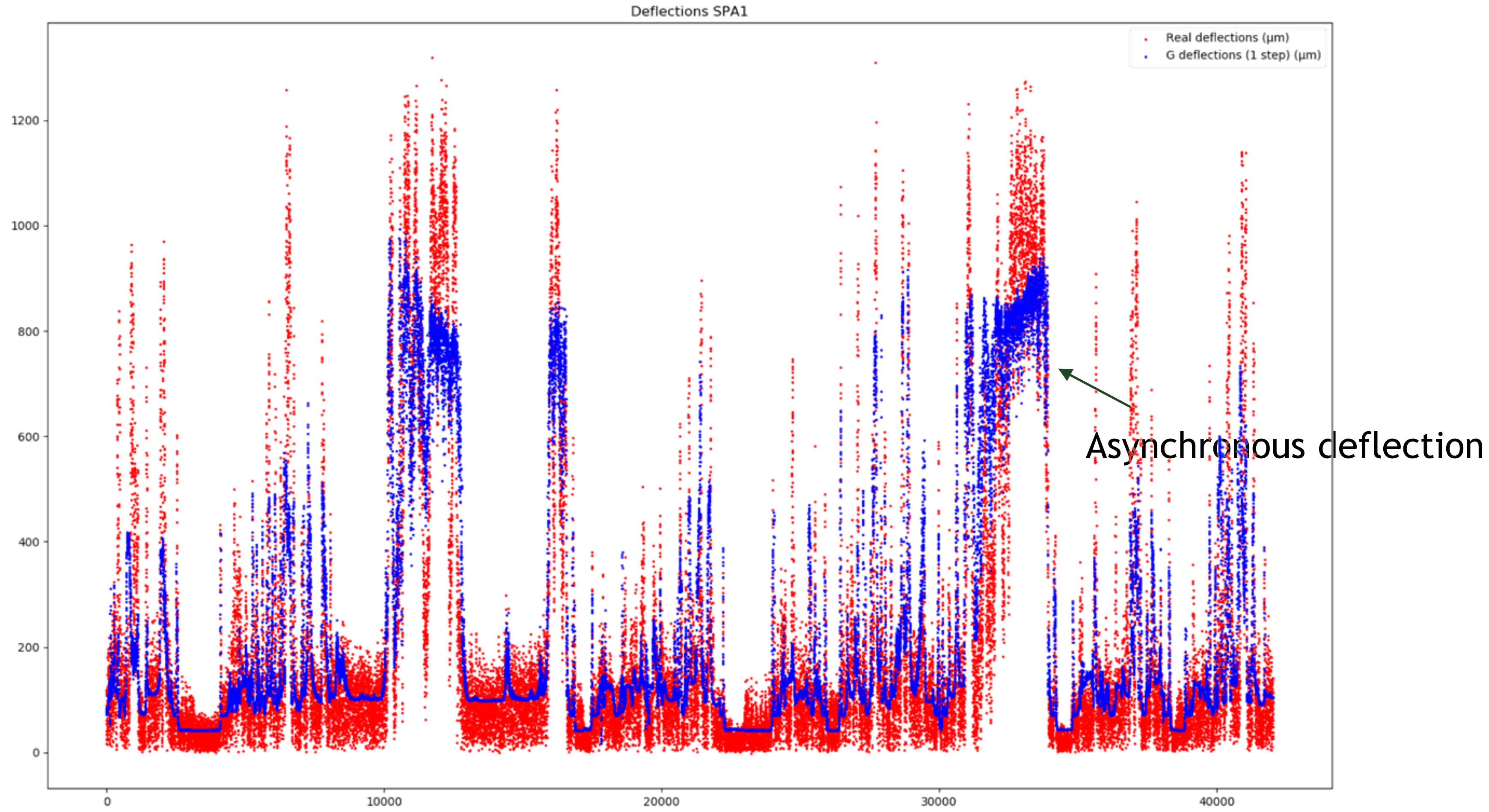
PREDICTION OF TURBO BLADE DEFLECTION

Prior to asynchronous deflection excitations are flat



Asynchronous deflection

PREDICTION OF TURBO BLADE DEFLECTION



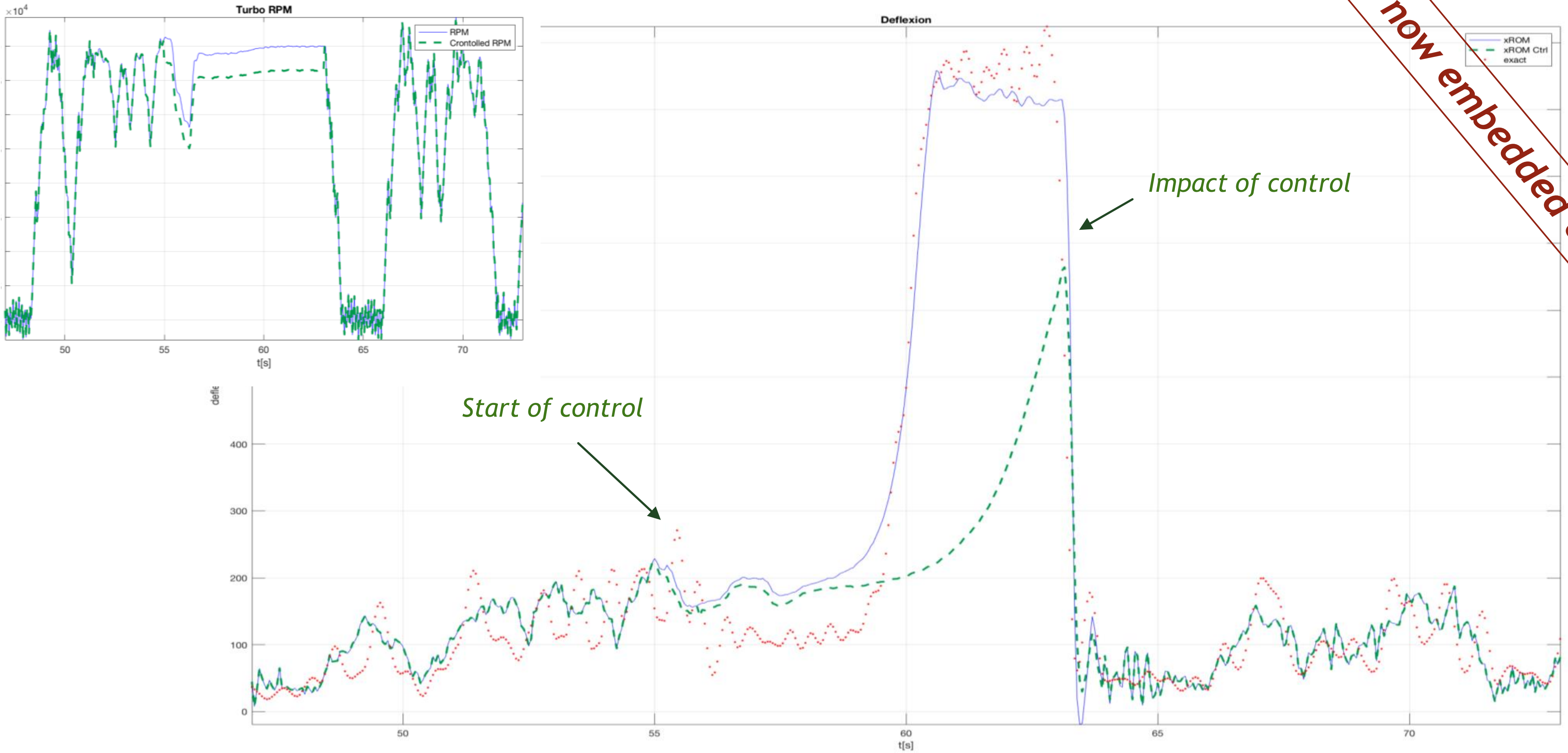
This model is embedded to control large blade deflection

EXAMPLE OF CONTROL TURBO BLADE DEFLECTION

3% reduction of the turbocharger rpm during few seconds, attenuates large deflections.

Now, Renault F1 has a strategy to avoid completely the deflections.

Model now embedded on vehicle



COMBUSTION CONTROL

COMBUSTION CONTROL

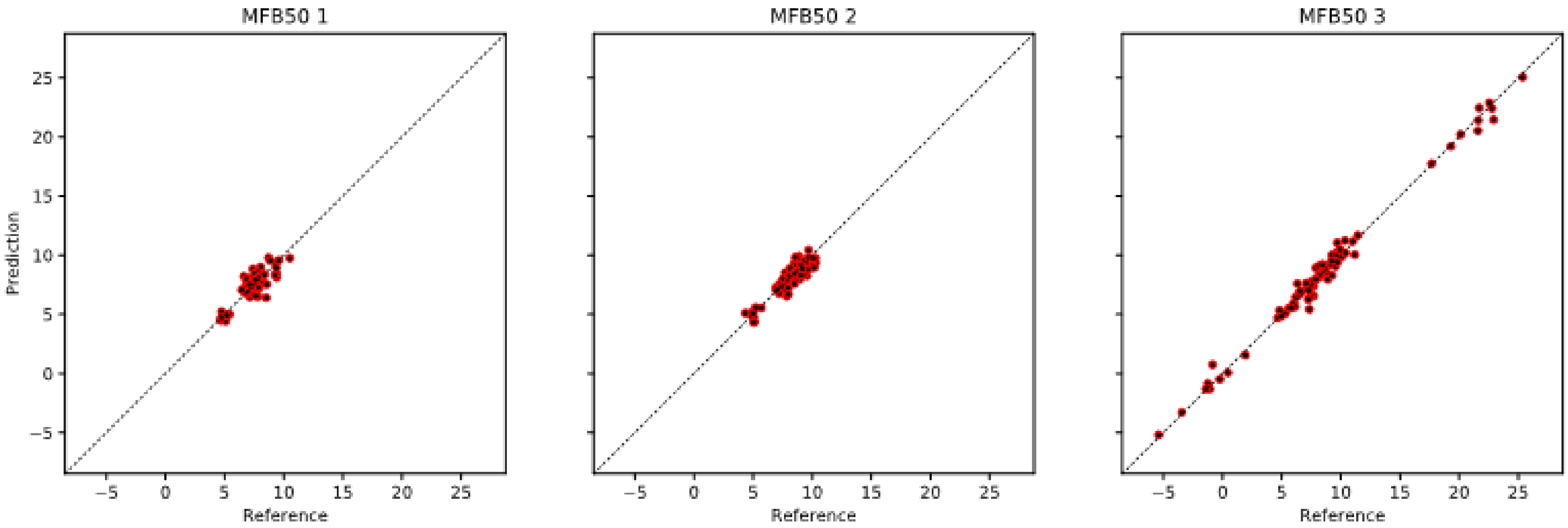
Context and objective:

The quality of the combustion can be analysed thanks to two important parameters

- Mass Fraction Burned 50 % (**MFB50**) ;
- Indicative Mean Effective Pressure (**IMEP**).
- Goal: predict the **average MFB50**, **IMEP standard deviation, the pressions and the air-fuel ratio (AFR)** from the **crankshaft angular velocity/acceleration** for various engine speeds and ignition advances (IGA).
- We have 250 cycles of data.

MFB50 MEANS PREDICTION

Predictions based on 50 cycles vs. References based on 200 cycles
(each red dot is an operating point)



	MFB50 1	MFB50 2	MFB50 3
Average error	**4,4 %**	**4,5 %**	**1,7 %**

Reduce Order Model (ROM)

Faithful copy of a physical simulation tool
allowing to evaluate in real time
any variation of input parameters

Predict the response of almost chaotic systems

Aorta simulation

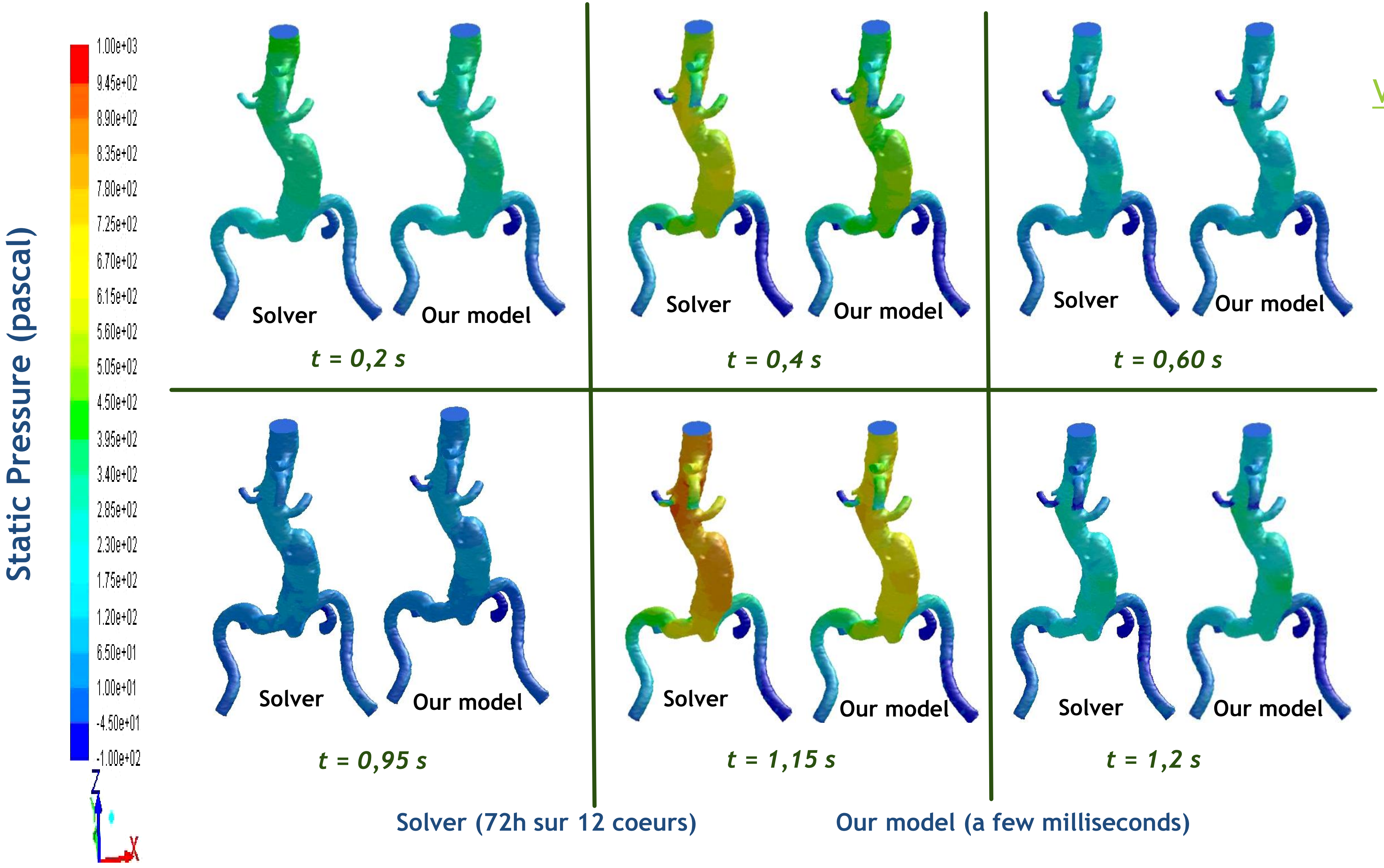
Dynamical parameters: flow velocity at the inlet of the aorta

1. Run ANSYS Fluent on a first boundary condition (blue curve)
2. Build a dynamic reduced order model form data generated by Fluent (learning data)
3. Run the model on a new flow profile (red curve)
4. Compare with the solution generated by Fluent for the same flow profile

Validation aorta simulation - Results

View online video
for pressure

View online video
for velocity



Solver (72h sur 12 coeurs) Our model (a few milliseconds)

Prediction of tires returns

Prediction

Prediction of tires returns

Context and objective:

Tires sold by Michelin to airlines are regularly returned for retreading. A good monthly forecast of the quantities of tires to be retreaded optimizes the supply and operation of retreading plants

⇨ **Predict** the number of tires **returned over the next 12 months** based on **past sales**.

Data available for the creation and validation of the model:

- 49 customers (airlines) and 25 products (tires)
- Sales and returns histories of 149 customer-product pairs (customers have different products)
- 55 months of learning data (from January 2014 to July 2018)
- 12 months of validation data (from August 2018 to July 2019)

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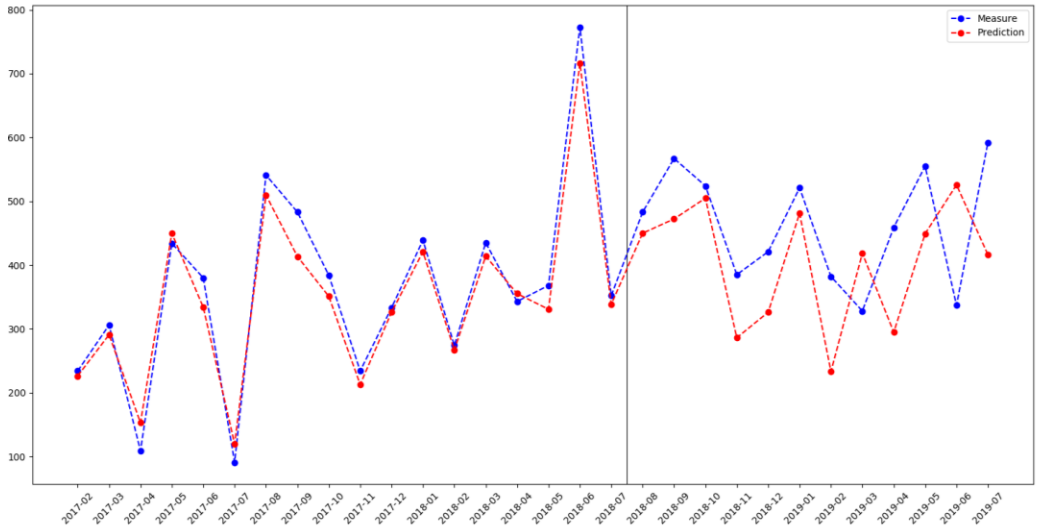
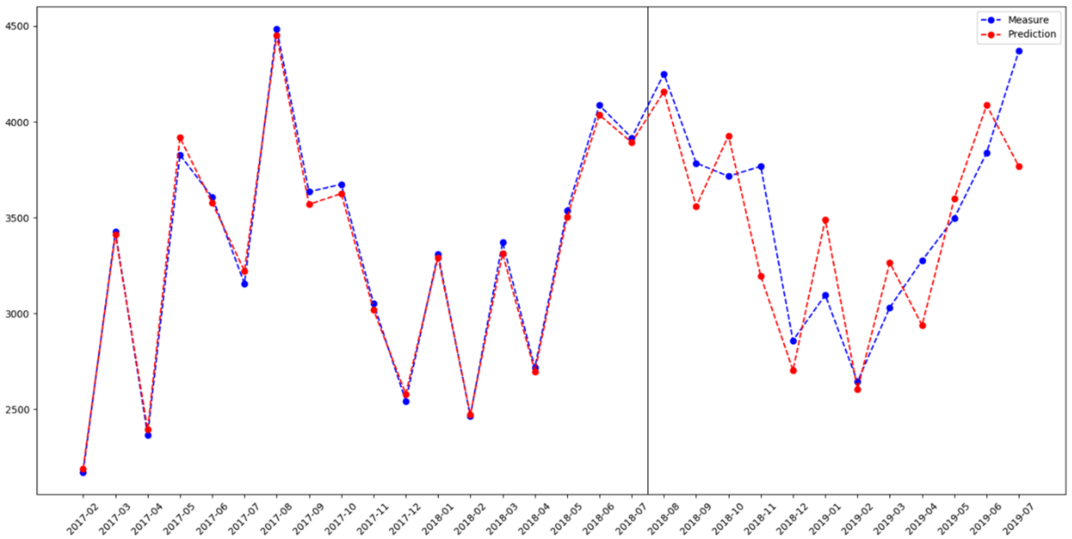
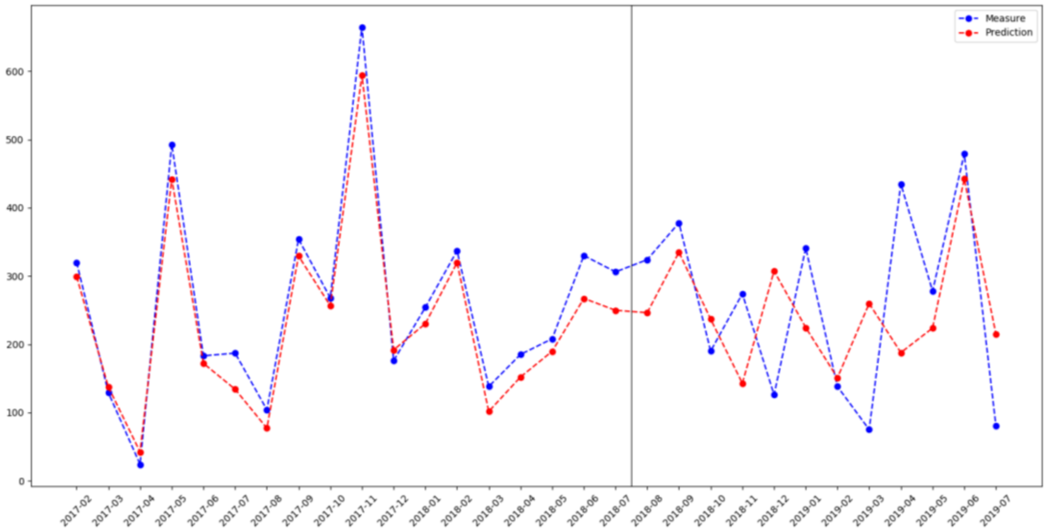
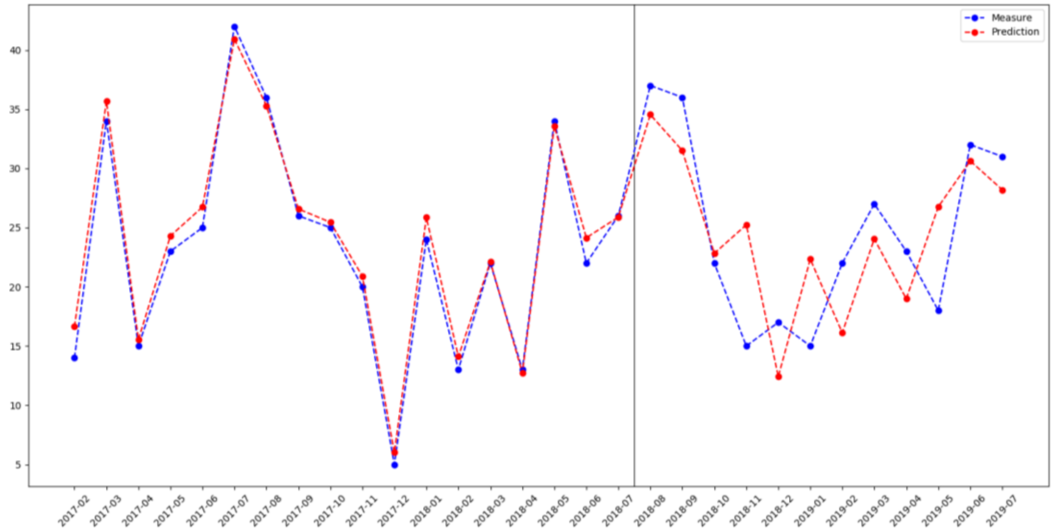
Results - Validation data









Error indicator

Bias

$$\frac{\sum_{PN}\sum_{Cust}\sum_{12\ mois} Forecast - \sum_{PN}\sum_{Cust}\sum_{12\ mois} Reel}{\sum_{PN}\sum_{Cust}\sum_{12\ mois} Forecast} = -1{,}61\%$$

MAPE_PN

$$\frac{\sum_{PN}\left|\sum_{Cust}\sum_{12mois} Forecast - \sum_{Cust}\sum_{12mois} Reel\right|}{\sum_{PN}\sum_{Cust}\sum_{12mois} Forecast} = 5{,}42\%$$

MAPE_PN_Cust

$$\frac{\sum_{PN}\sum_{Cust}\left|\sum_{12mois} Forecast - \sum_{12\ mois} Reel\right|}{\sum_{PN}\sum_{Cust}\sum_{12mois} Forecast} = 11{,}91\%$$

MAPE = Mean Absolute Percentage Error

An error reduced by 50% compared to existing models

GAS CONSUMPTION

PREDICTION

PREDICTION OF GAS CONSUMPTION

Context and objective:

Terega is in charge of the gas distribution in the quarter southwest of France. Terega needs to know precisely the consumptions of their 450 distribution stations in this region.

⇨ **Predict** the gas consumption of 450 distribution stations every hour with a NeurEco model.

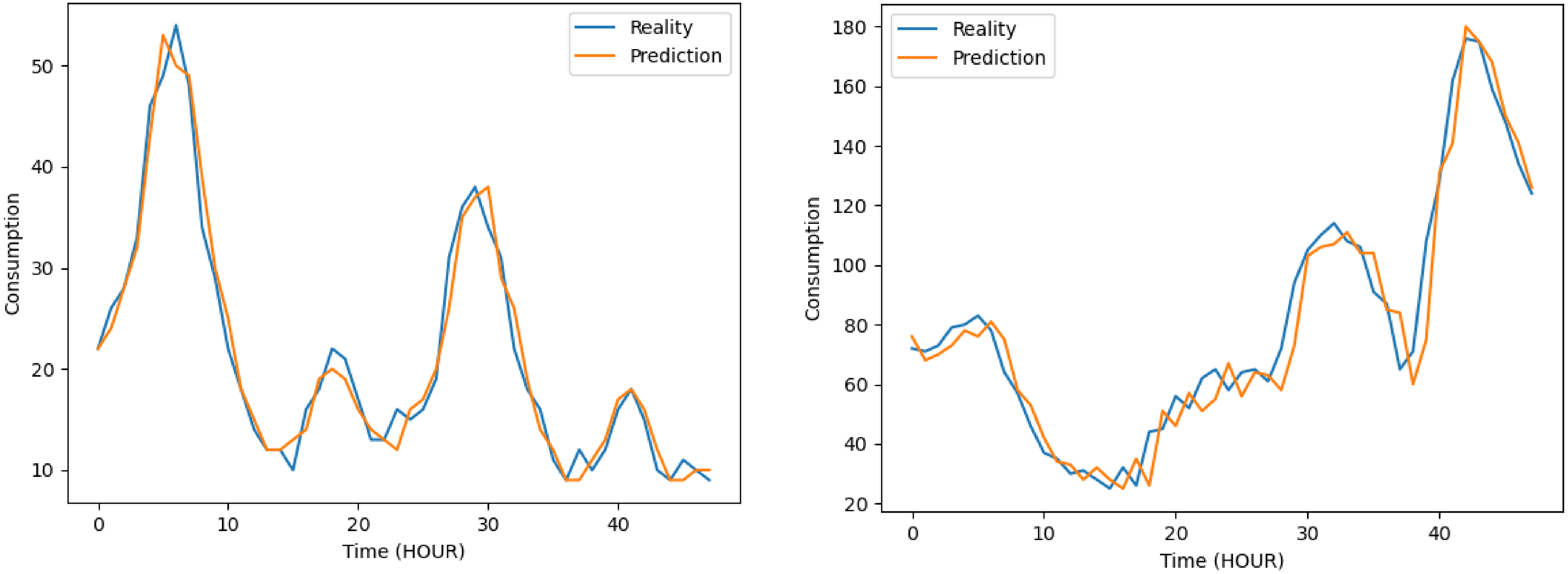
Data available for the creation and validation of the model:

- 42 months of gas consumption for each station.
- Meteo data (humidity, rain, temperature, wind).

Two types of station:

- Several stations are meteo-dependent and the others are linked with industrial processes.

RESULTS – VALIDATION DATA (TWO EXAMPLES)



Two stations are considered here : a meteo-dependent station (left) and an industrial station (right) with 48 hours of prediction.

Error computed : Relative error between the real consumption and the prediction at each hour.

MODELIZATION OF GAS NETWORK

Prediction / Control

ADAGOS SAS - 9 avenue de l'Europe - 31520 Ramonville-Saint-Agne

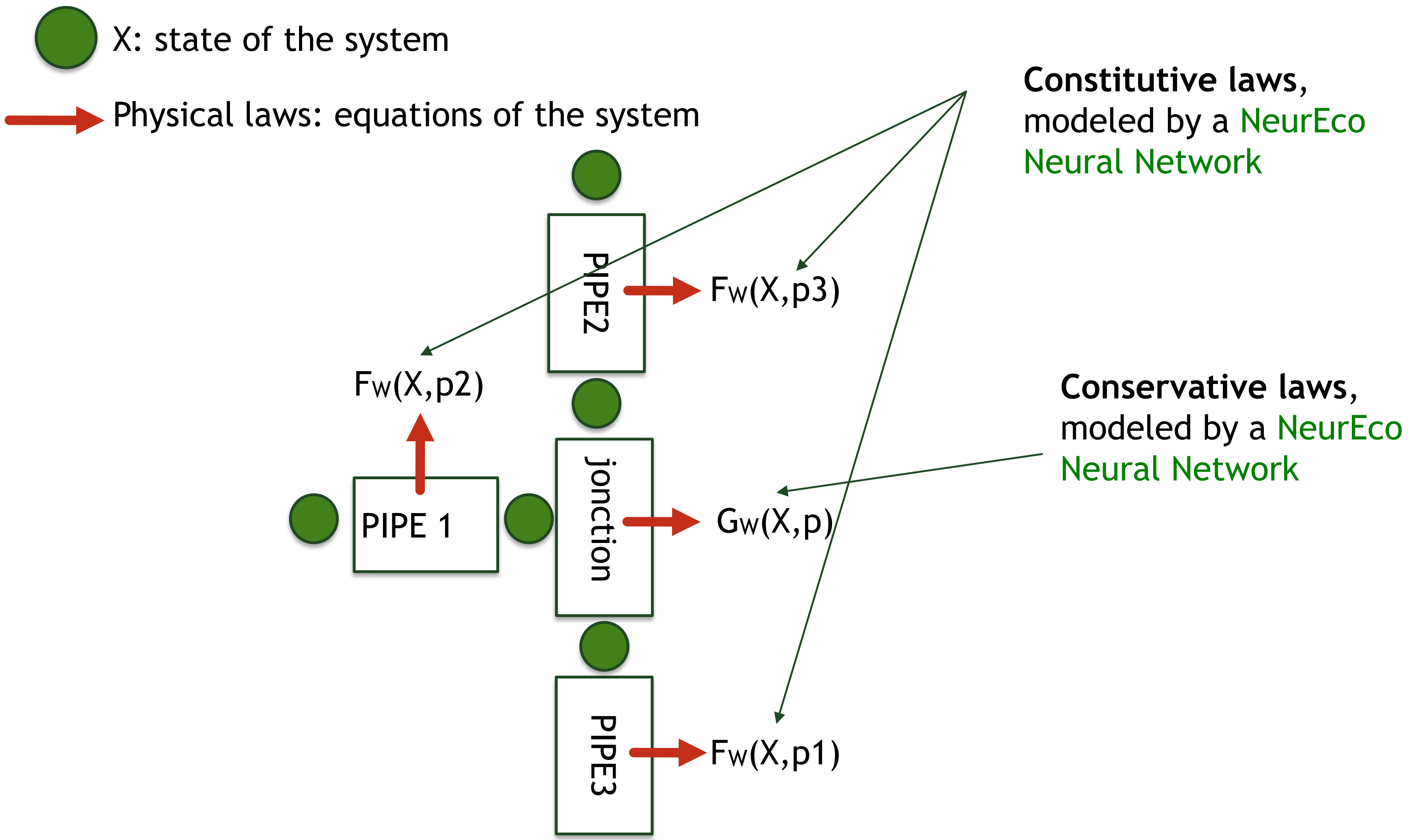
MODELIZATION OF GAS NETWORK

Context and objective:

The simulation tools are inadequate to describe in a satisfactory manner the state of the gas network supervised by Terega. For example, the state of the compressors are not taken into account.

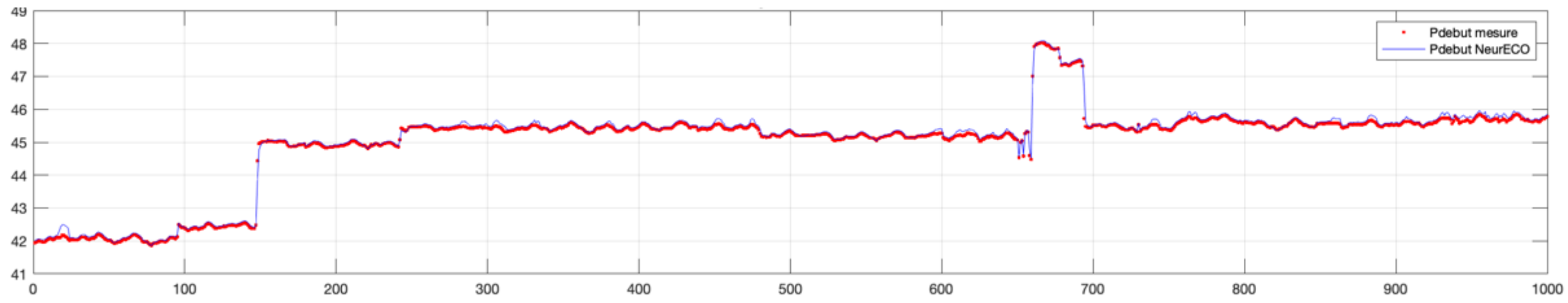
- ⇨ Create a digital twin of the gas network to overcome these inadequacies.
- ⇨ Propose a new tool which is able to use the operational measures and not only the simulated data.
- ⇨ This tool has to permit a robust supervision of the gas network.

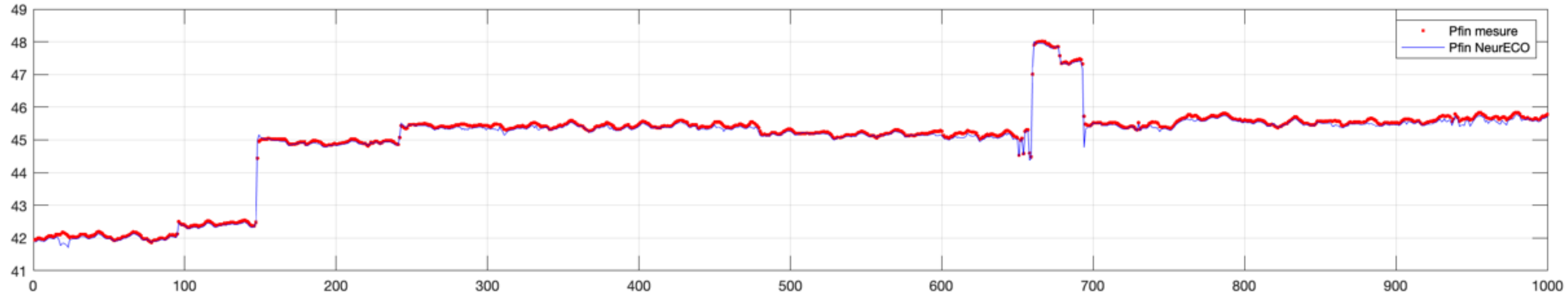
MODELIZATION OF THE GAS NETWORK

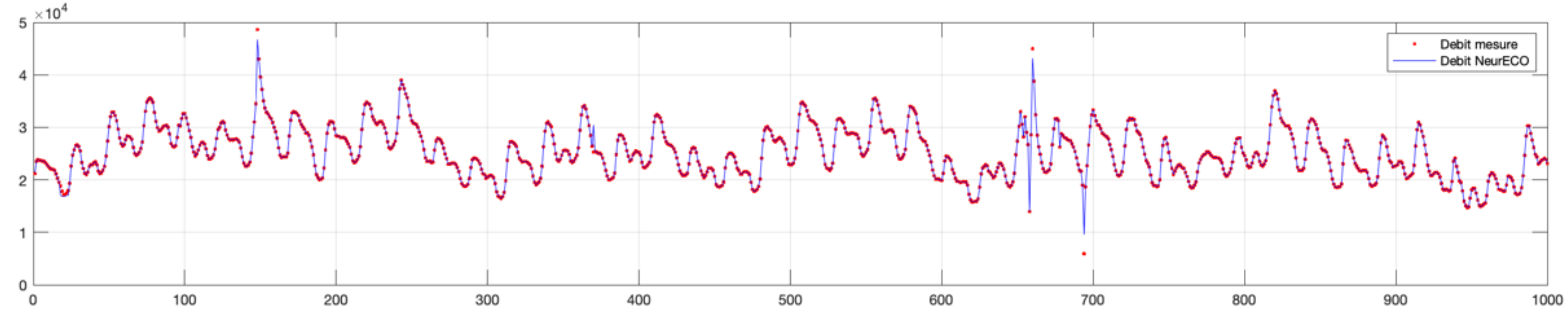


RESULTS –VALIDATION DATA

We validate on 20% of temporal data. We show the results for one pipe. A good correlation between the measured data and the prediction data is observed.



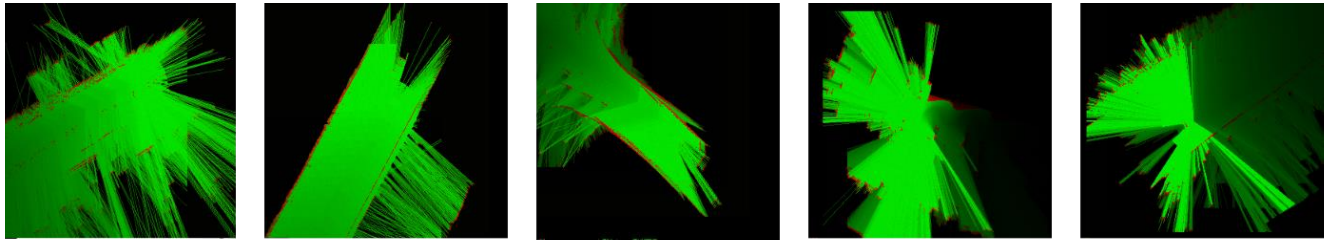


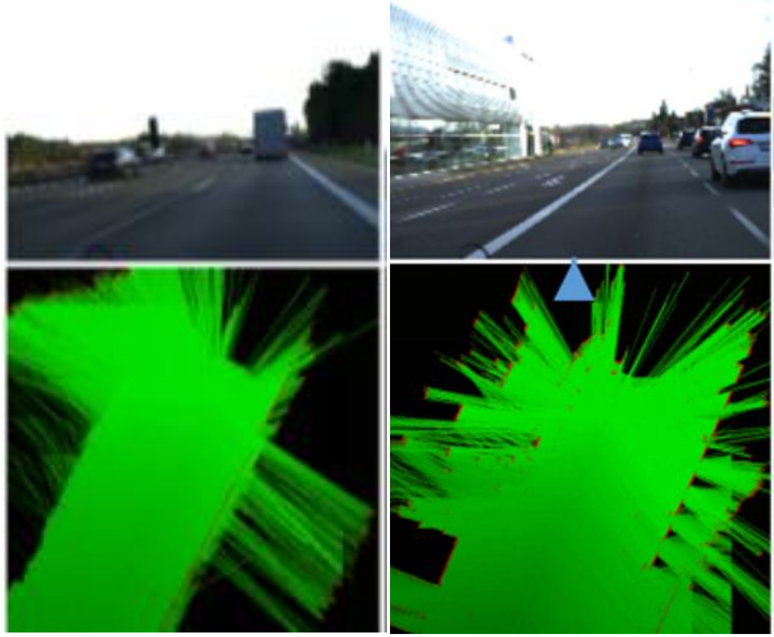


Toward embedded image recognition

Toward embedded image recognition: Continental Start-up Challenge 2019

Given an image of lidar measurements, the model should determine the driving context (city, highway, countryside, parking, traffic jam)





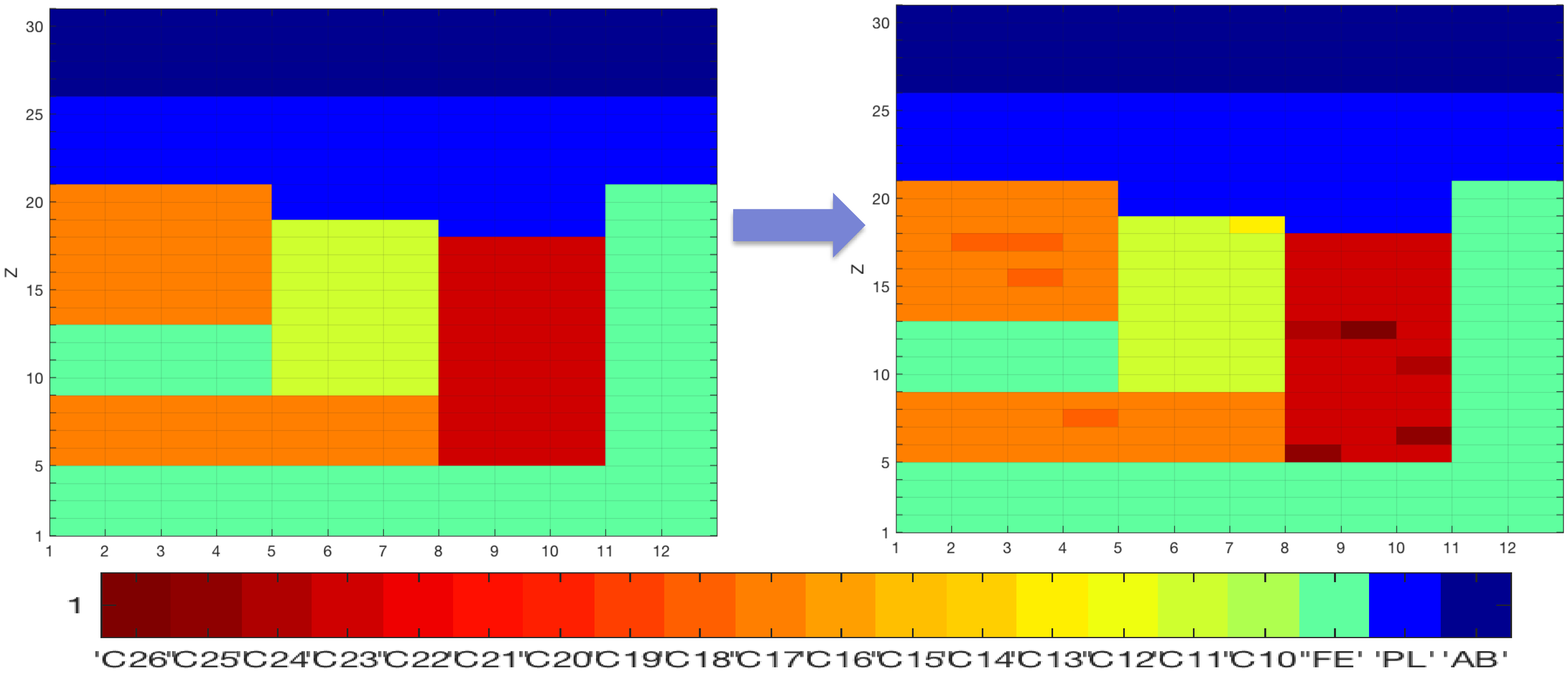
Results

	NeurEco (CNN)	Keras
Accuracy	99.7%	96%
Number of trainable parameters	1 719	127 301
Size on the disk	172 KB	1 568 KB
RAM usage of the model	~4MiB	~40MiB

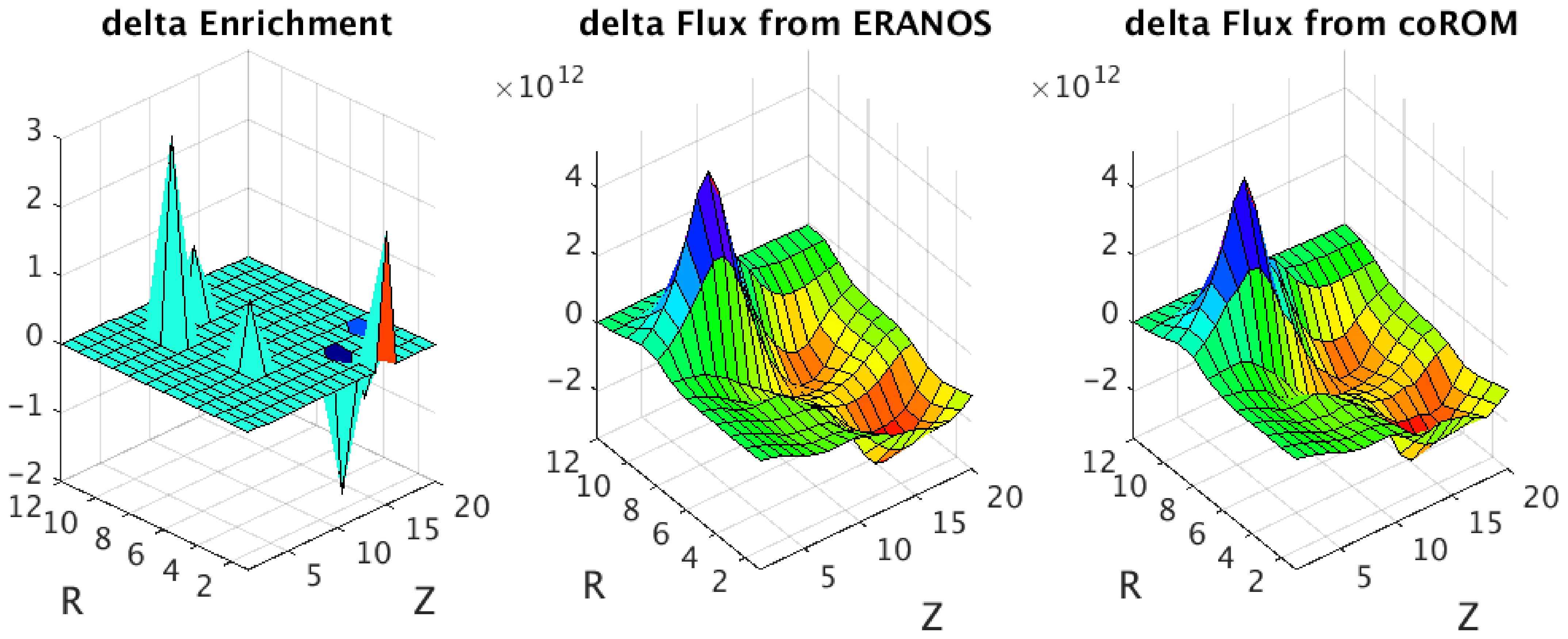
Variation of the neutron flux

Prediction of the variation of the neutron flux created by a given variation of the enrichment inside the reactor core

- The percentage of enrichment can vary in 240 cells of the reactor core.
- The model was built by learning from 40 examples, which is considerably smaller than number of parameters.



Validation example



Weather forecast applications

&

Wind farm power prediction

Wind farm power prediction

We proceed in three steps:

1. First, we build a **predictive model of the local wind speed**, exactly at the coordinates of the given wind turbines

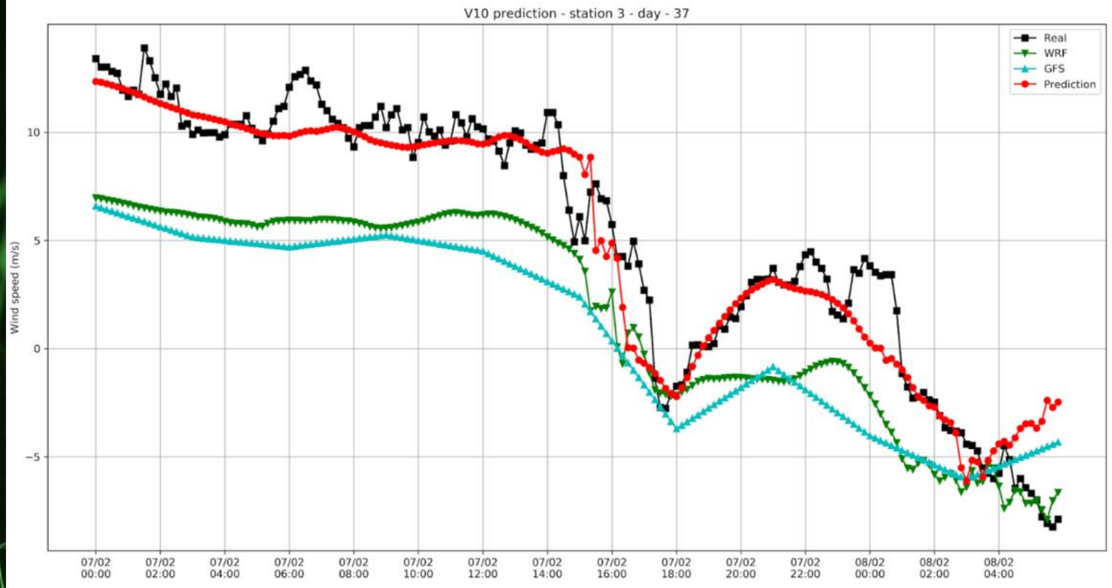
2. Then, for each turbine, we build a **predictive model of the power generated** according to the wind speed

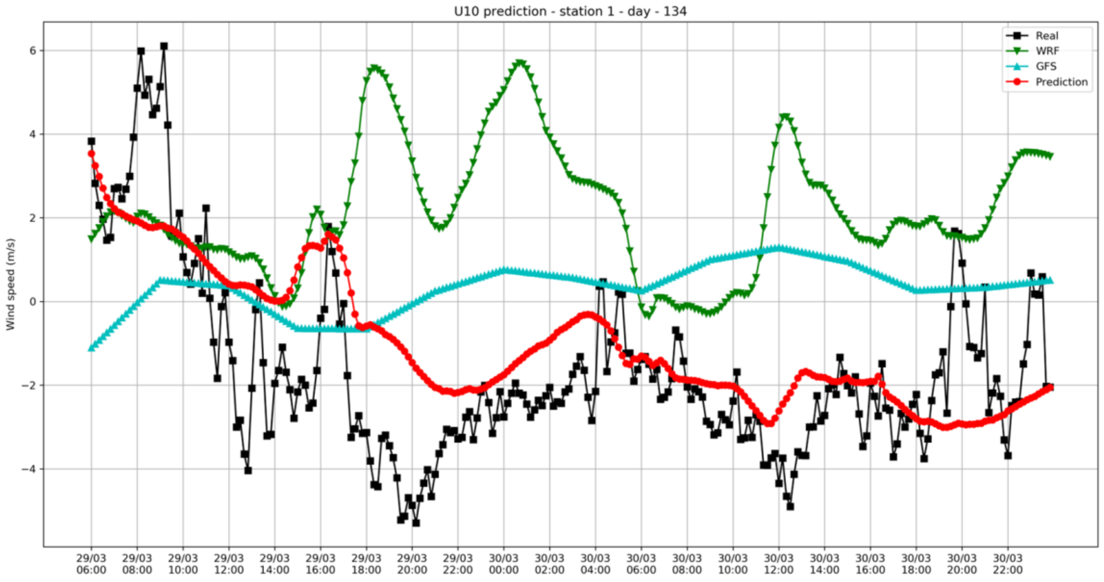
3. Finally, we **couple these different models** to predict the global farm production

1. Predictive model of the local wind speed - Results

We extract from a global weather model (such as GFS, WRF or ECMWF) information on the evolution of all meteorological variables on a starting grid of 253 x 253 km² centered on the position of the wind turbine.

The results are given for a long period of time (30 hours in advance).



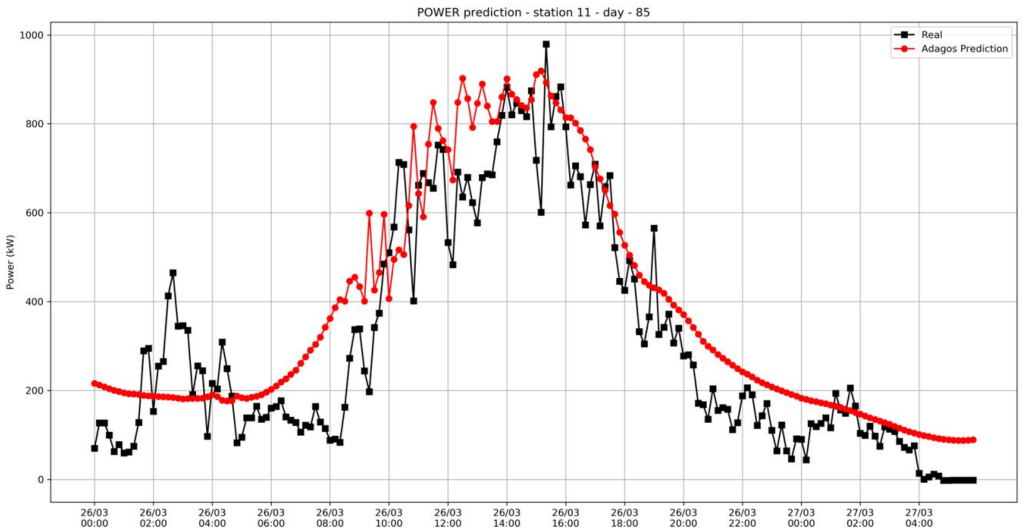


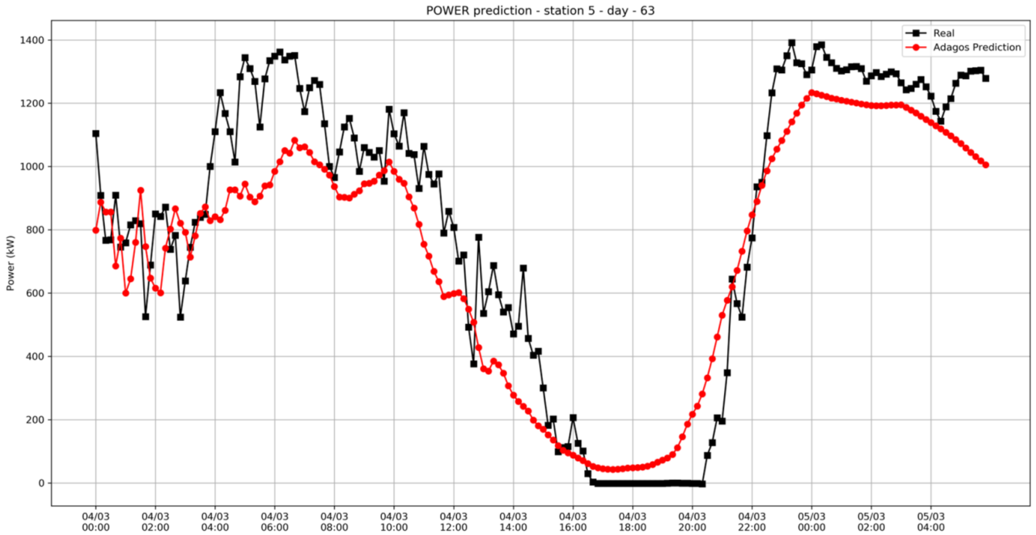
2. Predictive model of the power production of a single wind turbine

By considering historical data of electricity production of a wind turbine according to the observed wind speed, our tool builds a model of production of the considered turbine.

Then by coupling this model with the local speed wind forecasting model obtained previously, we are able to **predict with great accuracy the wind production forecast over a period of 30 hours**.

The following results show a comparison between the power prediction given by our solution and the power measured.





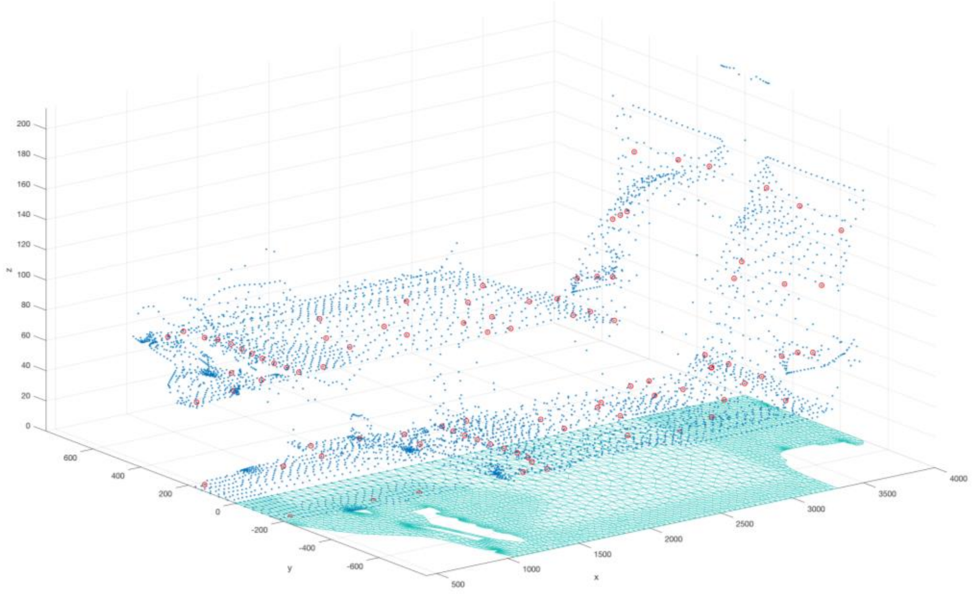
Management of missing data

Management of missing data

Wind tunnel test case presentation

PRESSURE FIELD:

- Simulation : 4816 DOF (blue dots) – 24 experiments
- Wind tunnel test : 94 measurements (red dots) – 2 experiments

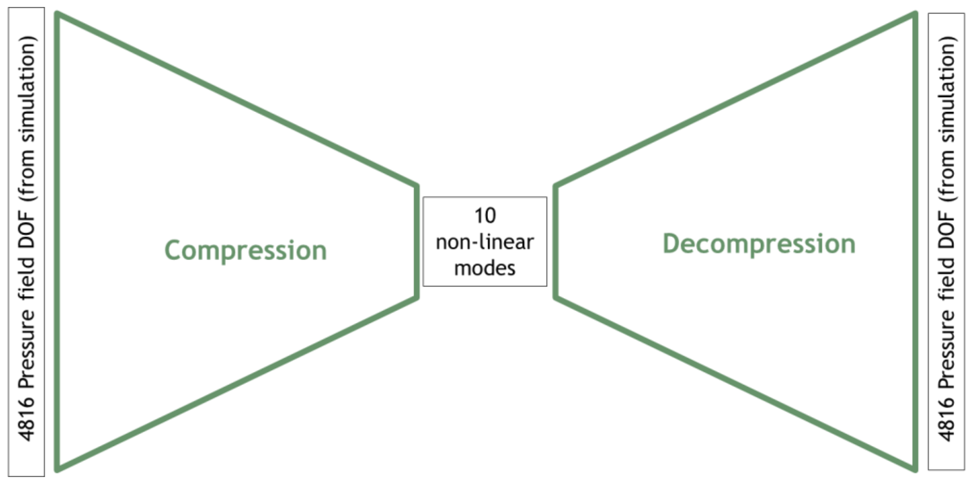


OBJECTIVE: Use NeurEco™ non linear compression capability to:

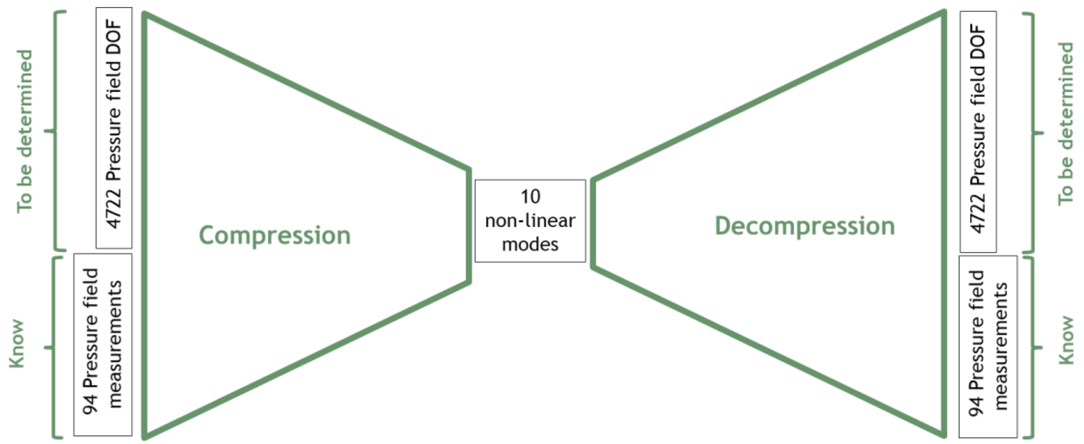
- Perform the entire pressure field reconstruction from measurements
- Reduce the number of sensors to be positioned for effective pressure field reconstruction across the entire vehicle

Management of missing data

Strategy implemented



Create the model from simulation data

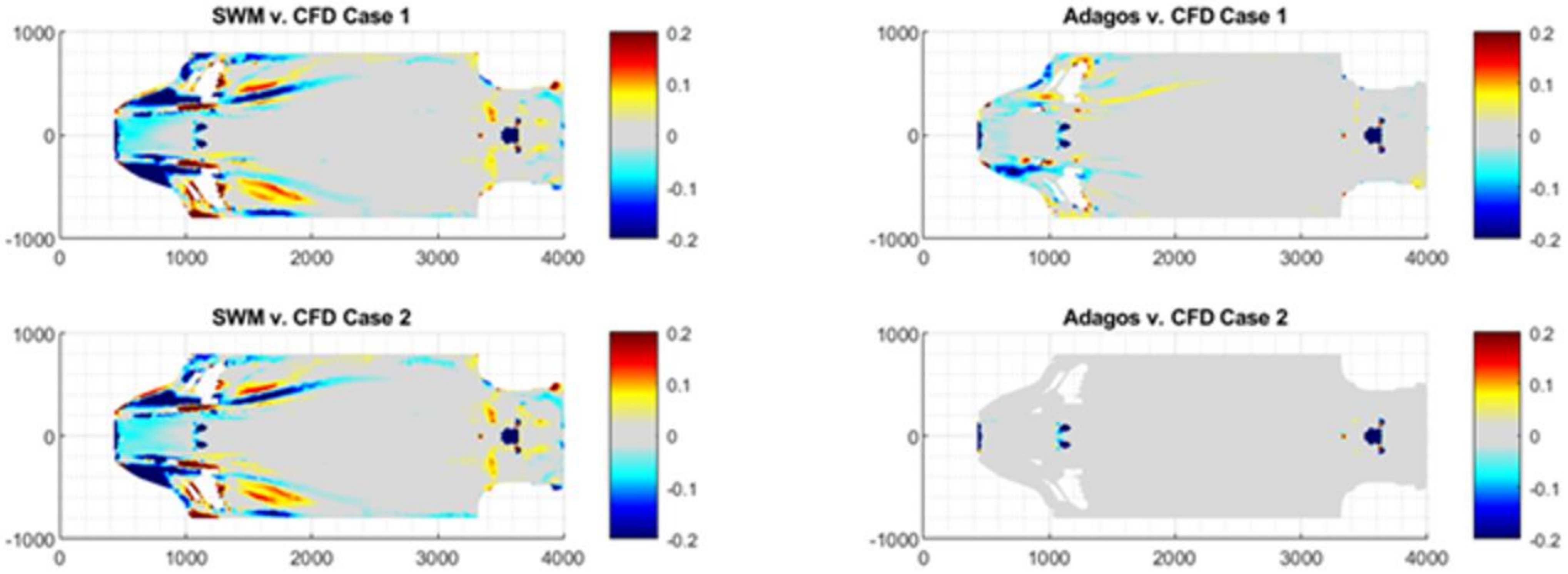


Use de model to :

1. Computed the 10 non-linear modes using the 94 measurements
2. Apply the model to determine the 4722 missing data to obtain the complete field

Management of missing data

Entire pressure field reconstruction from measurements



Error obtained with state-of-the-art method

Error obtained by ADAGOS