An incomplete overview of hybrid physics/machine learning modelling at Michelin

Focus on Physics-Informed Neural Networks applications

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Contents

PINNs: Physics-Informed Neural Networks

Helicopter overview

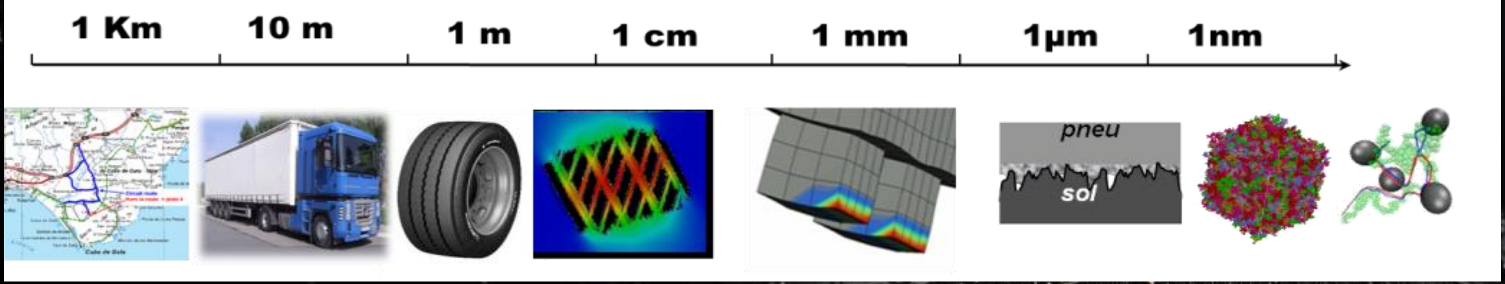
SIMULATION & DATA: FROM MOLECULE TO VEHICLE

Product performance

- virtual submission & virtual tire

Material conception levers

- optimize material recipe
- virtual material for simulation



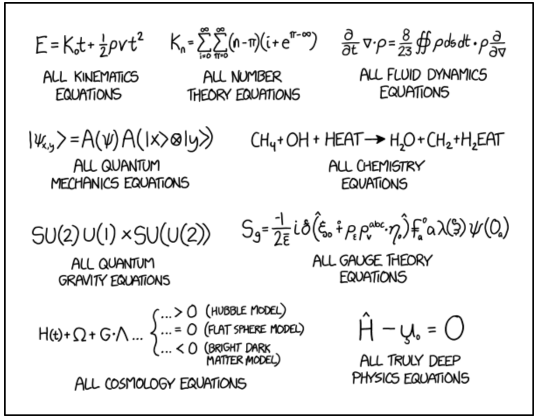
Services & usage

- predictive maintenance
- real time condition assessment

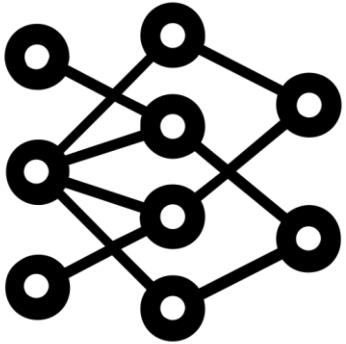
Tire conception levers

Models in engineering

Physics-based



Machine learning



Complex phenomena

Laws of physics

High cost (time & expertise)

Still unknown physics

Impressive results in various fields

No need to understand physics

Need data

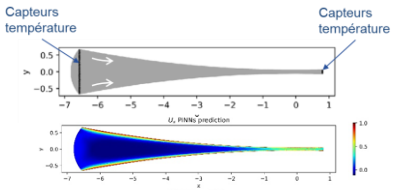
Generalization

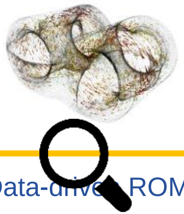
Research work at Michelin

- **Applied research: combining physics-based & machine learning**
  - **Combine state of the art methods** in industrial context
  - **Partnerships** to reinforce our innovation capabilities
  - **Maintain link** between **academia** & **methods industrialization**

- **Industrial stakes**
  - **Take better decision**: quality, certification, optimal design generation…
  - **Reduce time-to-market**: early design rules, solution assessment, real time actuation…

General context : hybrid modelling





System models & sequential data assimilation (Kalman)

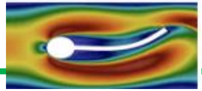
Fidelity -

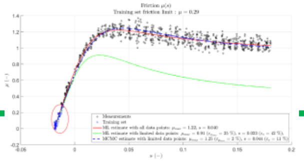
Fidelity +

Data assimilation with PINNs

ROM/FOM coupling

Data-driven ROM





Cost -

Cost +

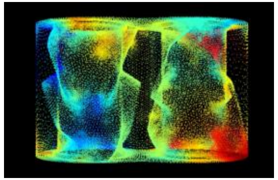
PINNs : Physics Informed Neural Networks
ROM: Reduced Order Model
FOM: Full Order Model

MIMO: a simulation-based **decision making assistant** for **mixing line process**

Choose *a factory ;* ***Define*** *process parameters ;* ***Analyse*** *mix. properties*

≈ 100 mix **designers** & **industrializers** users WW

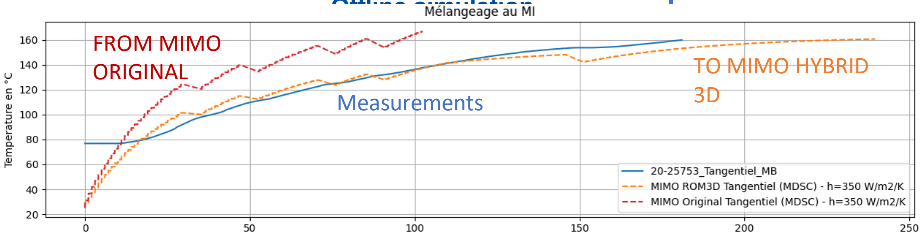
Modelling of rubber internal mixer is inaccurate but fast (minutes)

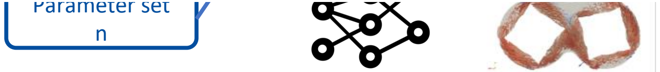


3D physics-based simulations are accurate but slow (days)

Modelling trade-off: use **3D simulation** as a **data generator** for **machine learning**

New parameter set

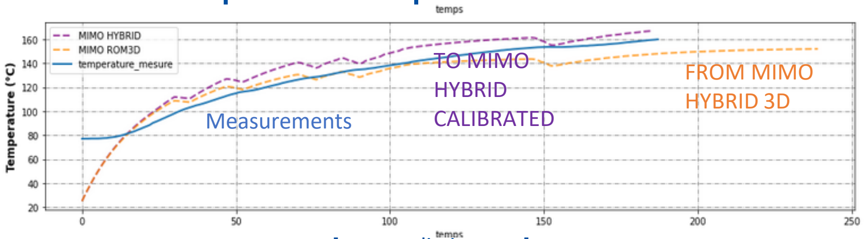




Reduce cost and industrialization delays with machine learning augmented by simulation

Still possible to improve modelling using **process measurements**

New

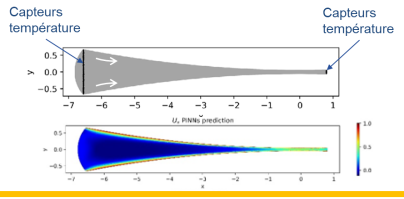


prediction

Advanced research (3 last years) opens the way to **MIMOV2**

- 3D hybrid models to assess the **impact of rotor geometry** and define accurate **mixing criteria**”
- **Prediction time compatible** with the needs of MIMO’s user community

General context : hybrid modelling



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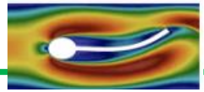
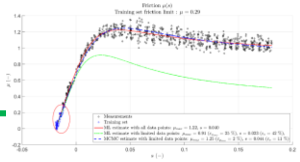


Data-driven ROM



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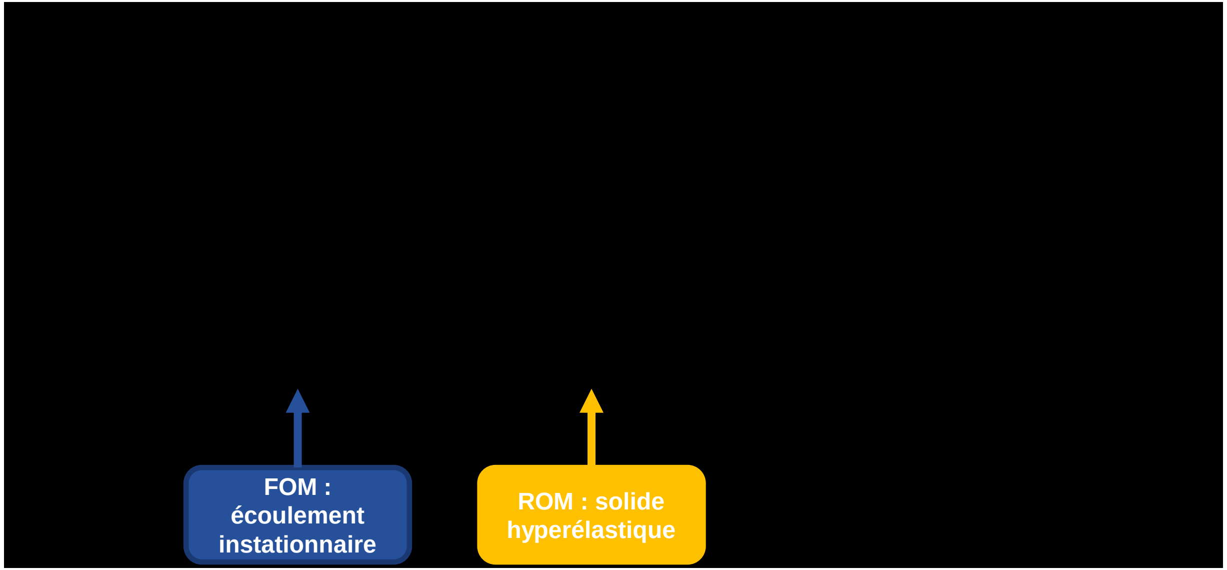
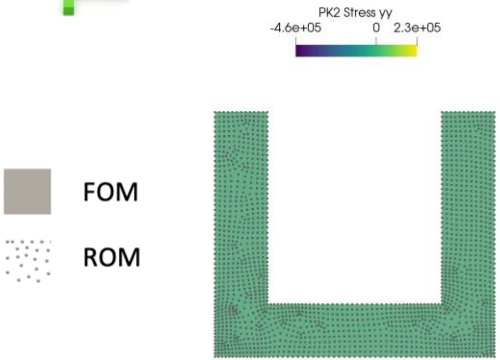
Couplage ROM-FOM pour l'interaction fluide structure



Speedup total ≈ 1.8



Tiba *et al.* submitted to JFS 2024

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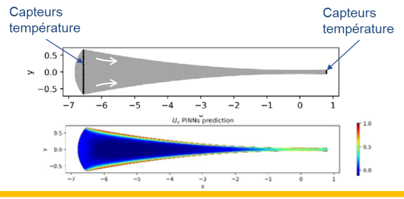
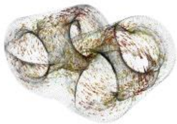
General context : hybrid modelling





System models &
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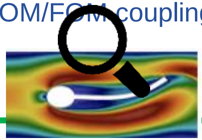
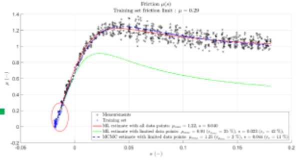


Data-driven ROM



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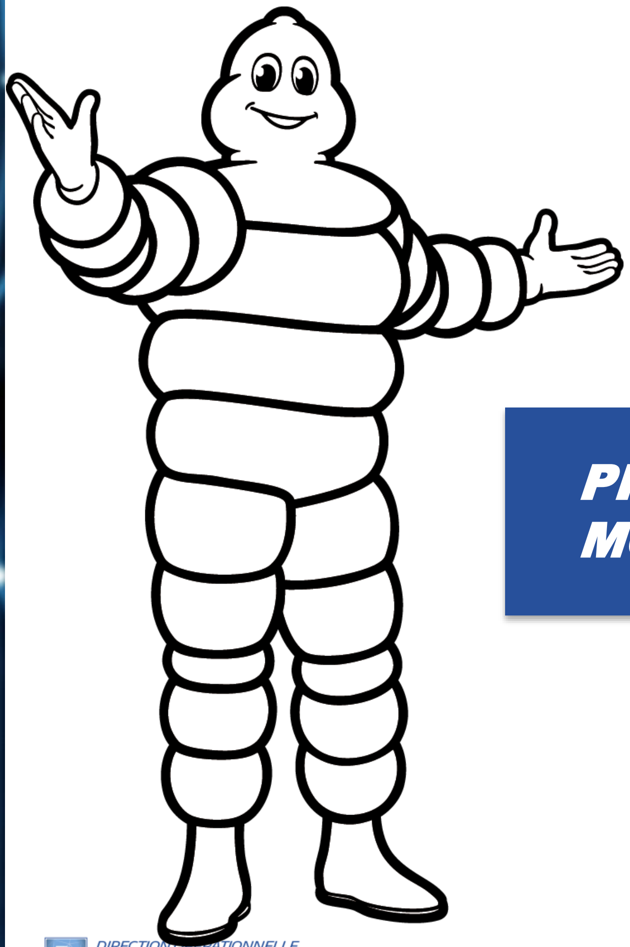


PINNs FOR CALENDERING PROCESS MODELLING

Apprentissage physiquement informé : contexte

- **Travaux de thèse de Khoa Nguyen** débutés en Septembre 2021 en co-encadrement avec M. Mougeot (ENS Saclay), C. Millet (CEA) & R. Meunier (Michelin)

- **Objectifs**

  - Evaluer l'**intérêt des méthodes d'apprentissage physiquement informé** dans un contexte industriel

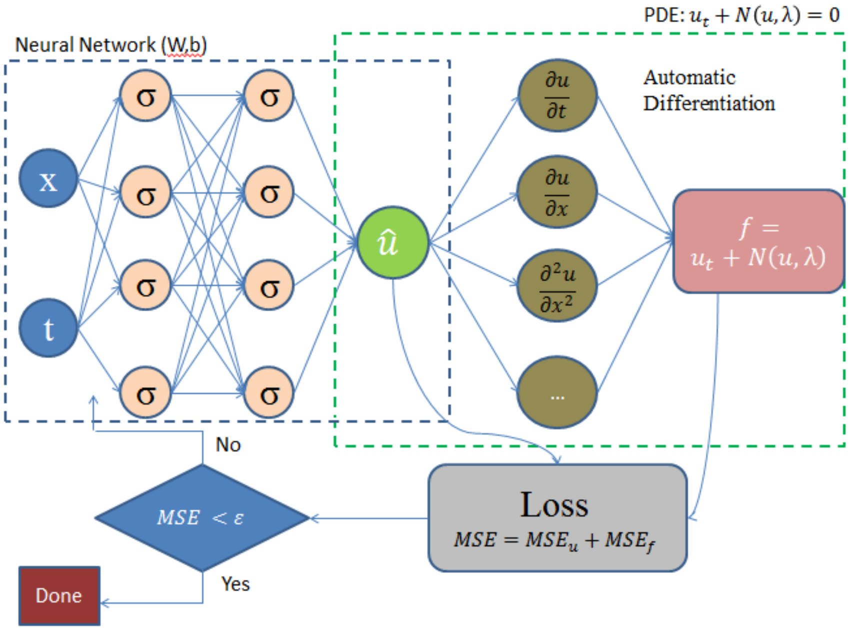
    Raissi *et al.* JCP 2019 ; **Karniadakis** Nature Reviews Physics 2021

  - **Problèmes couplés** et souvent **multi-échelles** régis par des EDPs
    - Résolution de **problèmes inverses** et **assimilation de données** pour reconstruire des champs à partir de **données parcellaires**

    - Résolution de **problèmes directs paramétriques**

Apprentissage physiquement informé : méthode

Méthode PINNs



Raissi *et al.* JCP 2019

- **EDP générique**

$$\boldsymbol{u}_t + \boldsymbol{N}(\boldsymbol{u},\boldsymbol{\lambda}) = \boldsymbol{0}, \boldsymbol{x} \in \Omega, \mathrm{t} \in]0,T]$$
$$\boldsymbol{B}(\boldsymbol{u},\boldsymbol{x},t) = \boldsymbol{0}, \boldsymbol{x} \in \partial\Omega$$
$$\boldsymbol{u}(\boldsymbol{x},0) = \boldsymbol{g}(\boldsymbol{x}), \boldsymbol{x} \in \Omega$$

- Approcher $\boldsymbol{u}$ par un réseau de neurones

$$\boldsymbol{u} \approx \hat{\boldsymbol{u}} = NN(\boldsymbol{x},t,\boldsymbol{\theta})$$

- Points **supervisés** $\{\boldsymbol{x}_i^{\boldsymbol{u}}, t_i^u, \boldsymbol{u}_i\}_{i=1}^{N_{data}}$
- Points de **collocation** $\left\{\boldsymbol{x}_i^f, t_i^f\right\}_{i=1}^{N_{edp}}$
- **Fonction coût**

$$L = L_{pde} + L_{data}$$

$$L_{edp} = \frac{1}{N_{edp}} \sum_{i=1}^{N_{edp}} \left|\hat{\boldsymbol{u}}_t\left(\boldsymbol{x}_i^{\boldsymbol{f}}, t_i^f\right) + \boldsymbol{N}\left(\hat{\boldsymbol{u}}\left(\boldsymbol{x}_i^{\boldsymbol{f}}, t_i^f\right), \boldsymbol{\lambda}\right)\right|^2$$

$$L_{data} = \frac{1}{N_{data}} \sum_{i=1}^{N_{data}} |\hat{\boldsymbol{u}}(\boldsymbol{x}_i^{\boldsymbol{u}}, t_i^u) - \boldsymbol{u}(\boldsymbol{x}_i^{\boldsymbol{u}}, t_i^u)|^2$$

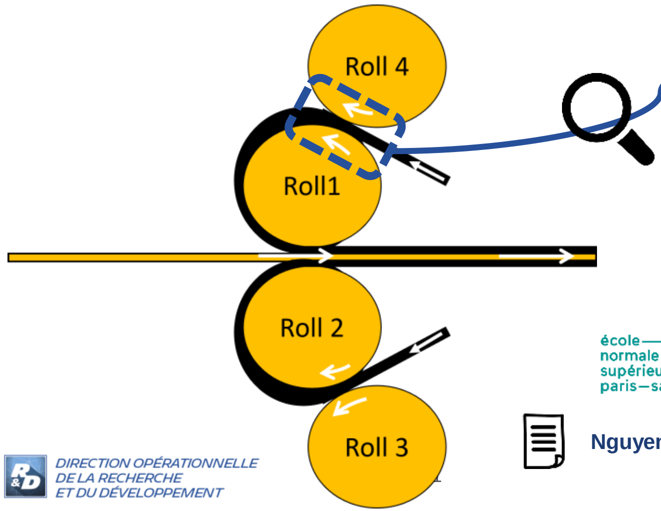
Estimation of physical fields of interest from sensors measurements (1)

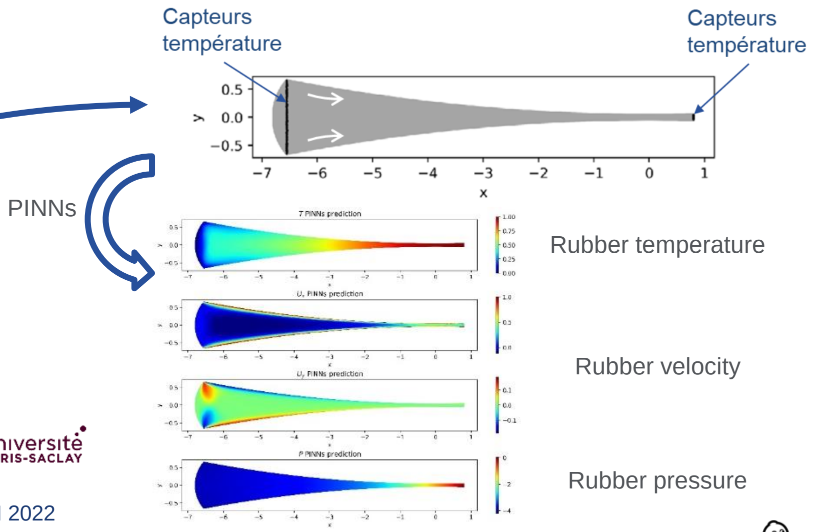
- **Rubber calendering : process manufacturing**

Non-Newtonian fluid with **thermo-mechanical** coupling

- **Generalized Stokes** eq. for mechanics
- **Convection/diffusion** with nonlinear **source term** for heat transfer

- **High Fidelity simulation** with internal solver

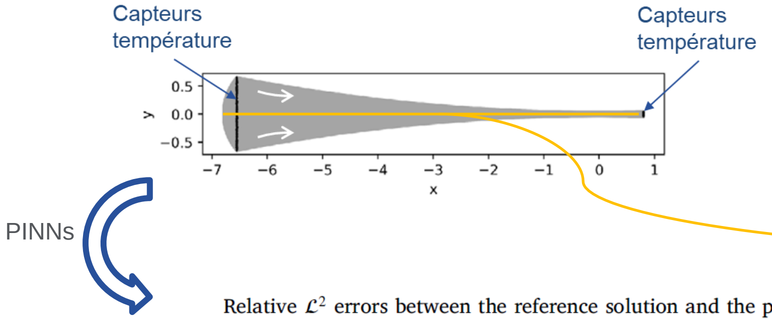




Nguyen *et al.* EAAI 2022

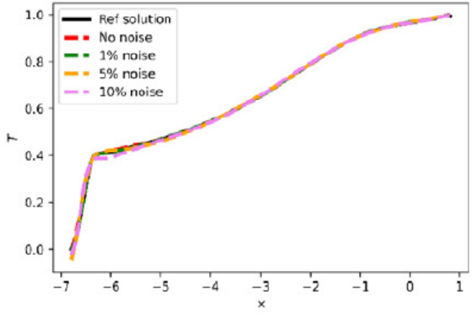
Estimation of physical fields of interest from sensors measurements (2)

- **Adding Gaussian noise on the sensors data**

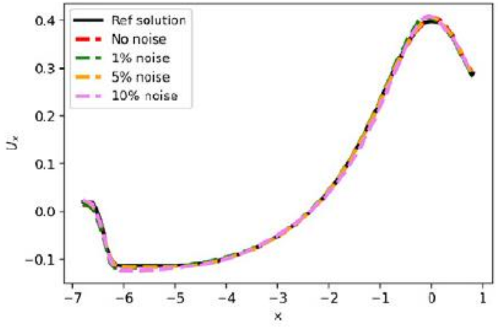


Relative $\mathcal{L}^2$ errors between the reference solution and the predictions by PINNs with different level of noise.

	ϵ_T	ϵ_{u_x}	ϵ_{u_y}	ϵ_p
0% noise	3.24	4.63	4.87	0.83
1% noise	4.16	5.73	6.16	1.07
5% noise	4.55	6.94	6.57	1.64
10% noise	5.60	7.21	7.16	1.69



(a) T



(b) u_x

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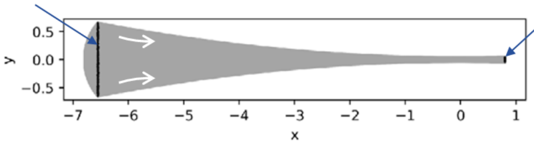
Identification of unknown physical parameters

- **Identify rubber thermal conductivity λ from sensors measurements**

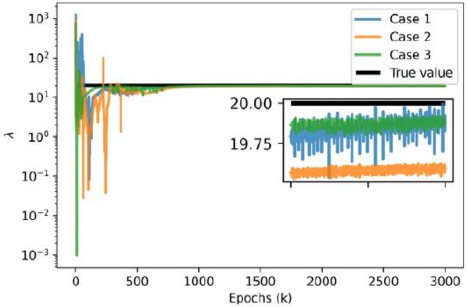
Temperature & Velocity sensors

Temperature & Velocity sensors



$$\boldsymbol{u}.\boldsymbol{\nabla}T = \frac{\lambda}{\rho C_p}\nabla^2 T + \frac{1}{\rho C_p}\eta(\boldsymbol{u},T)\gamma^2(\boldsymbol{u})$$

PINNs



(c) λ

	$1/Pe$	Br/Pe	λ
High-fidelity model	4.00e−03	1.20e−01	2.00e+01
0% noise	3.94e−03	1.19e−01	1.98e+01
1% noise	3.89e−03	1.18e−01	1.97e+01
5% noise	3.81e−03	1.16e−01	1.96e+01
10% noise	3.77e−03	1.16e−01	1.94e+01

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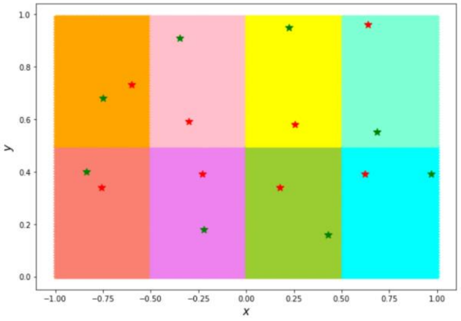
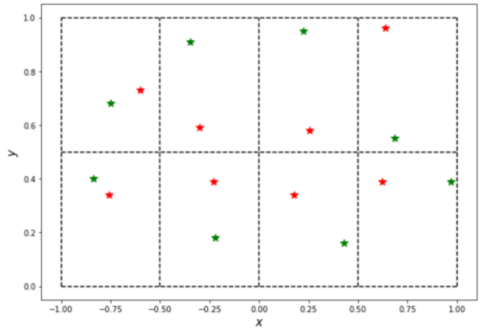
Fixed-Budget Online Adaptive Learning (FBOAL) for collocation points

- PDEs residuals calculated on a set of collocation points (unsupervised points).
  - The position of these collocation points has a huge impact on PINNs performance.
  - Adaptive strategy to infer the best locations for these collocation points based on the PDEs residuals during the training.
- **Fixed-budget online adaptive learning (FBOAL): every k learning iterations**



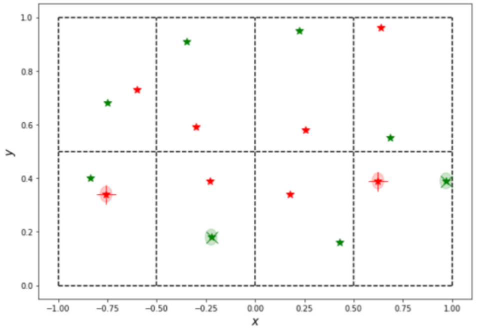
(a) Step 1

1. Divide the spatial domain in d subdomains
2. In each subdomains
   - Compute the smallest residual on the set of collocation points C (green points)
   - Compute the largest residual on a new random set C' (red points)



(b) Step 2

1. Gather and sort all the green points into a set R
2. Gather and sort all the red points into a set A



(c) Step 3

1. Remove m points of the set R
2. Add m points of the set A

to the set C of collocation points

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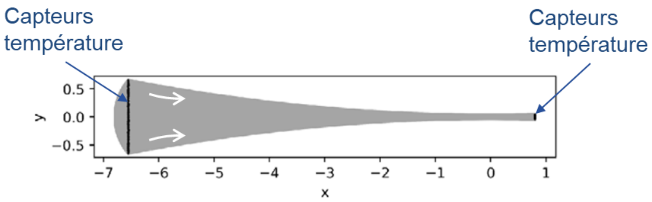
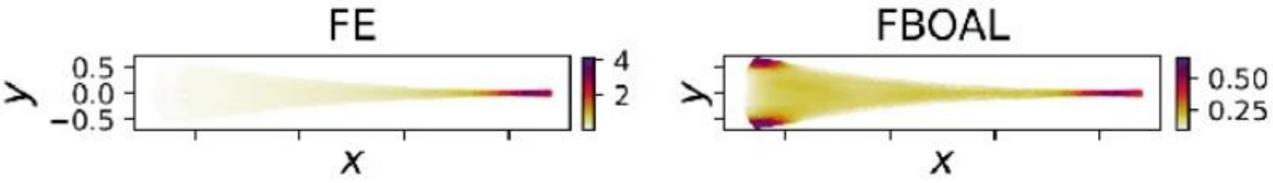
Fixed-Budget Online Adaptive Learning (FBOAL) for collocation points (2)

- **Rubber calendering: going back to the estimation of physical fields of interest from sensors measurements**



Density of collocation points



Relative errors

	ϵ_T	ϵ_{u_x}	ϵ_{u_y}	ϵ_P
Random mesh	13.6 ± 1.17	24.1 ± 3.77	15.6 ± 2.73	11.9 ± 1.33
FE mesh	$\mathbf{8.54 \pm 1.39}$	$\mathbf{14.7 \pm 2.49}$	18.0 ± 2.61	$\mathbf{1.41 \pm 0.17}$
FBOAL	10.5 ± 1.82	19.3 ± 1.85	$\mathbf{9.63 \pm 3.24}$	5.13 ± 0.72

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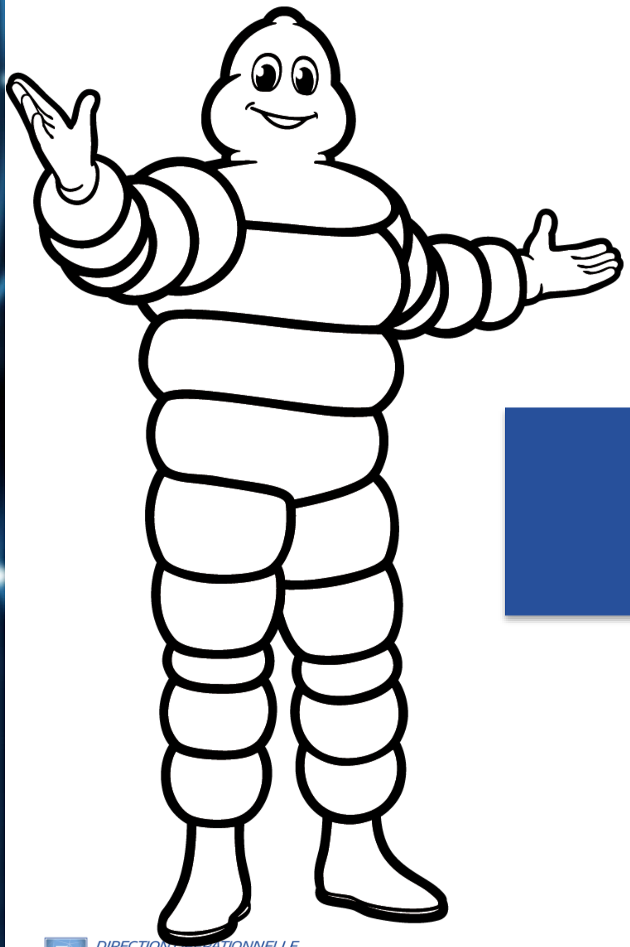
CONCLUSION

- **Travaux encore (très) exploratoires sur l'utilisation de PINNs dans un contexte industriel**
  - Estimer des champs physiques à partir de données disponibles sur des capteurs
  - Identifier des paramètres inconnus dans un problème régi par des EDPs
  - **Inférer des solutions dans le cas de problèmes paramétriques régis par des EDPs**

Présentation Khoa Nguyen juste après!

- **Quelques pistes en cours d'étude**
  - **Stage Rémy Vallot** (Michelin/ENS PS/UTC) : PINNs & co pour accélérer un solveur non linéaire → aider la simulation traditionnelle sans la remplacer
  - **Stage Antoine Corduant** (Michelin/ENS PS/Univ. Poitiers) : PINNs & co pour l'estimation d'état non linéaire → comparaison et lien avec le filtrage de Kalman

- **Travailler en étroite collaboration avec le monde académique**
  - Un domaine de recherche **très large** → besoin d'**expertises multidisciplinaires**
  - Un domaine de recherche en **évolution très (trop) rapide** → besoin de liens **robustes** et de **long terme** entre académiques et industriels



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