





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

from rubber manufacturing simulation to real-time tire performance prediction opportunities

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Raphaël Meunier



- ✓ Senior Numerical Engineer
- ✓ Product Owner « AI4Eng »

I am involved in the development and spread of a wide range of subject ranging from optimization, sensitivity analysis, coupling physical models with machine learning (so called hybrid models), generative design...

Numerical methods are evolving every day, getting better and better (boosted by AI), I am always looking for breakthroughs.

Some background:

- ✓ 2012-2017: Master's Degree in Applied Mathematics from INSA Toulouse
- ✓ Since 2017: at Michelin ! Project contribution, expertise management, students tutoring, scientific collaborations with external partners

Contents

I. **Michelin R&D in a nutshell**

II. **Overview of numerical methods**

III. **Let's have a look at the applications**

A Research and Development Direction globalized at a worldwide level

It gathers the activities of:

ADVANCED RESEARCH

PRE-development

development



Innovation at Michelin



PART OF
OUR DNA

OVER 130 YEARS
OF INNOVATION

CONTRIBUTES TO
HUMAN PROGRESS
AND A MORE
SUSTAINABLE WORLD

LEVERAGE FOR
DIFFERENTIATION AND
SUSTAINABLE GROWTH

MICHELIN

Over 130 years of innovation
Breakthrough innovations transforming the mobility market

40% renewable and recycled materials in our tires by 2030

RADIAL TIRE
1946



GREEN TIRE
1992



MICHELIN CROSSCLIMATE
2015



THE AIRLESS TIRE UPTIS
2019



TOTEM &DEMOS
2022



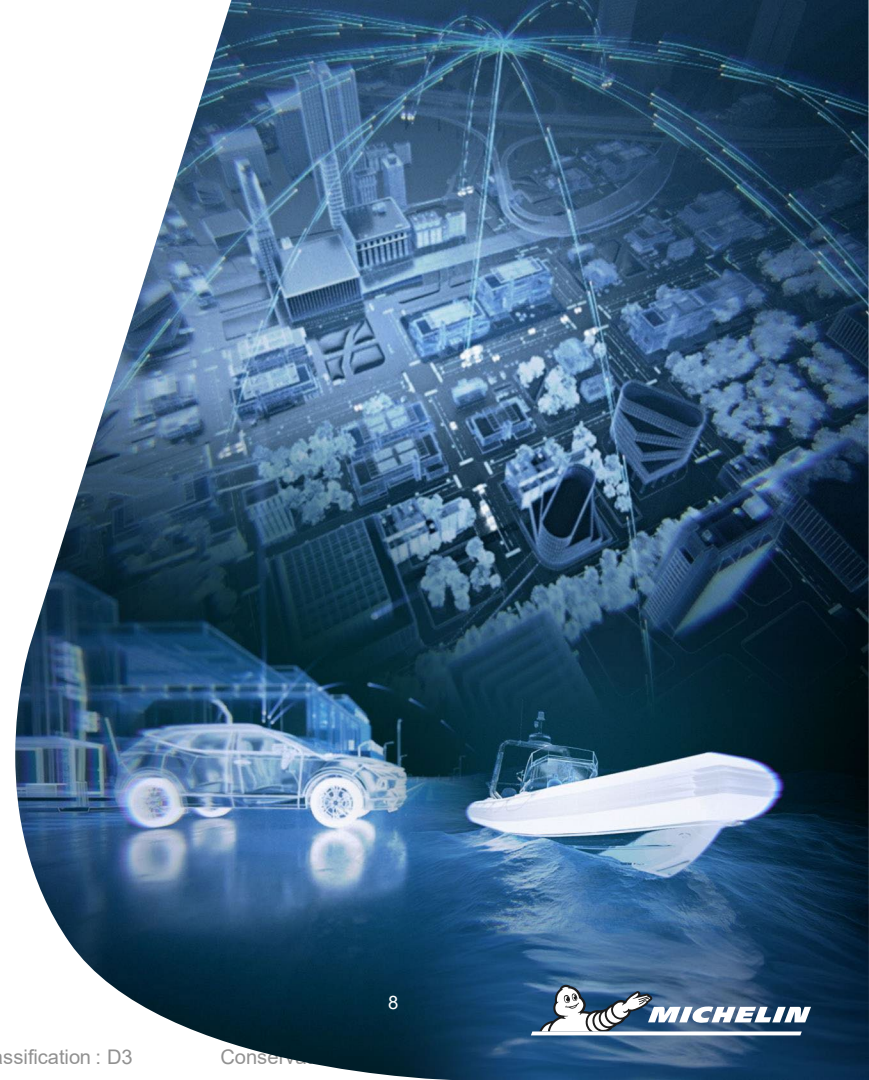


Other composites
Examples of our latest innovations

1. Eagle XLD bimodulus O-Ring belt
2. Retractable inflatable sail
3. Inflatable structures
4. Non-toxic adhesive resin
5. ICE ARROWHEAD 130 tracks
6. Michelin EFFILINER® bandage

Open innovation: 4 domains

- composites
- hydrogen
- Renewable or recycled materials
- Simulation & data



Open innovation: using data to improve performance

Multiphysics solver
Simulation and optimization of the manufacturing process and the performance of our products

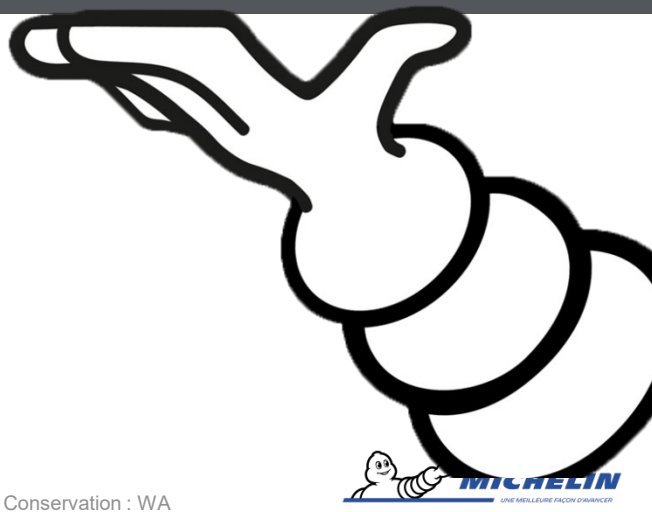
High performance computing
Developing the use of computing for simulation and AI

Simulation & data

AI for engineering
Combining simulation and data for precision and performance

AI for connected
Data for fast, robust engineering decisions

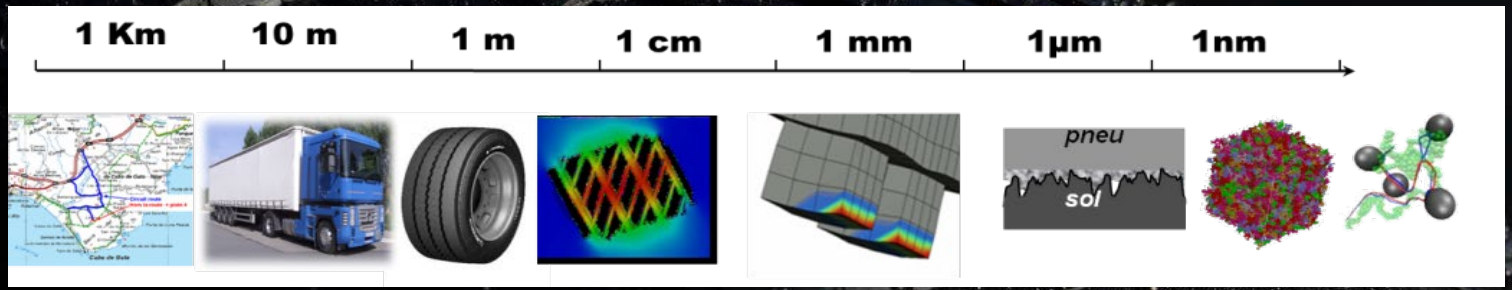
Modelling methods overview



SIMULATION & DATA: FROM MOLECULE TO VEHICLE

Material conception levers
- optimize material recipe
- virtual material for simulation

Product performance
- virtual submission & virtual tire

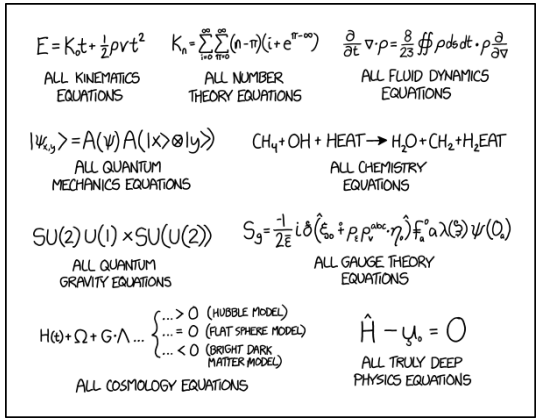


Services & usage
- predictive maintenance
- real time condition assessment

Tire conception levers

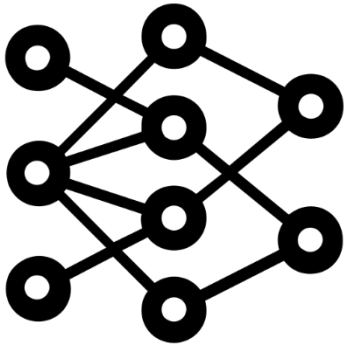
Models in engineering

Physics-based





Machine learning





Complex phenomena

Laws of physics



Impressive results in various fields

No need to understand physics



High cost (time & expertise)

Still unknown physics



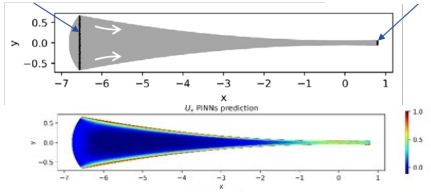
Need data

Generalization

A panorama of modelling methods towards digital twinning

Temperature & Velocity sensors

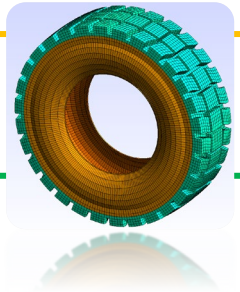
Temperature & Velocity sensors

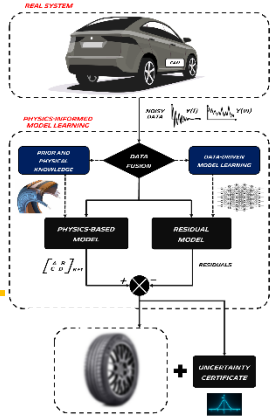


Physics +

Data assimilation with PINNs

Data-driven ROM
ROM/FOM Coupling





Physics -

Cost +

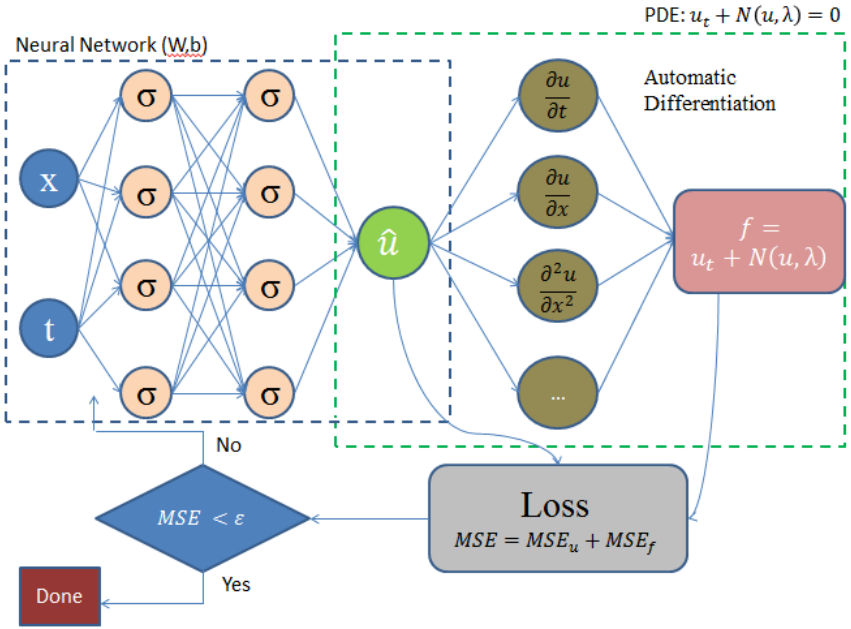
Cost -

System models & sequential data assimilation (Kalman like)

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

Data-assimilation with Physics-Informed Neural-Networks

PINNs method



Raissi *et al.* JCP 2019

- **Take a generic PDE**

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

- Approximate $\boldsymbol{u}$ with a NN

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

- **Supervised** data $\{\boldsymbol{x}_i^{\boldsymbol{u}}, t_i^u, \boldsymbol{u}_i\}_{i=1}^{N_{data}}$
- **Unsupervised collocation points** $\left\{\boldsymbol{x}_i^f, t_i^f\right\}_{i=1}^{N_{edp}}$
- **Loss function**

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

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

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

Data-driven ROM methods (1)

- Let's consider N observations of a **state vector** $\boldsymbol{x}(\mu) \in \mathbb{R}^m$ with μ a scalar **parameter** (m usually large)

$$\boldsymbol{A} = (\boldsymbol{x}(\mu_1) \quad \dots \quad \boldsymbol{x}(\mu_N)) \in \mathbb{R}^{\mathrm{m}\times\mathrm{N}} \textbf{ snapshot matrix}$$

- **To work in a smaller space**: perform a **dimensionality reduction step**

$$\boldsymbol{x}(\mu) \approx \hat{\boldsymbol{x}}(\mu) = \boldsymbol{\Gamma}\big(\boldsymbol{a}(\mu)\big)$$

$\boldsymbol{a} \in \mathbb{R}^r$ **reduced state** vector with $r \ll m$

$\boldsymbol{\Gamma}: \mathbb{R}^r \to \mathbb{R}^m$ **mapping function**

  - **Linear dimensionality reduction:** Proper Orthogonal Decomposition (POD)

$$\boldsymbol{\Gamma}\big(\boldsymbol{a}(\mu)\big) = \boldsymbol{U}\boldsymbol{a}(\mu) \text{ and } \boldsymbol{a}(\mu) = \boldsymbol{U}^T\boldsymbol{x}(\mu)$$

$\boldsymbol{U} \in \mathbb{R}^{m\times r}$ **POD modes** matrix obtained by SVD of ***A***



e.g. **Berkooz *et al.*** ARFM 1993
Chatterjee Current Science 2000
Bergmann *et al.* JCP 2009

  - **Nonlinear dimensionality reduction:** Data-driven quadratic solution-manifolds

$$\boldsymbol{\Gamma}\big(\boldsymbol{a}(\mu)\big) = \boldsymbol{U}\boldsymbol{a}(\mu) + \bar{\boldsymbol{U}}\big(\boldsymbol{a}(\mu) \otimes \boldsymbol{a}(\mu)\big)$$

$\bar{\boldsymbol{U}} \in \mathbb{R}^{m\times r^2}$ quadratic mapping operator

$$\bar{\boldsymbol{U}} = \arg\min_{\bar{\boldsymbol{U}} \in \mathbb{R}^{m\times r^2}} \sum_j^N \left\| \boldsymbol{x}(\mu_j) - \boldsymbol{U}\boldsymbol{a}(\mu_j) - \bar{\boldsymbol{U}}\left(\boldsymbol{a}(\mu_j) \otimes \boldsymbol{a}(\mu_j)\right) \right\|_2^2$$

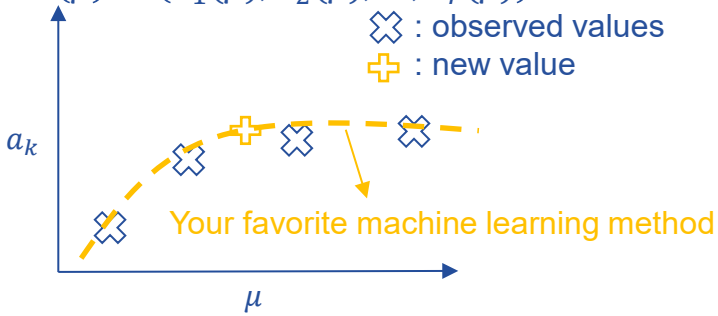


Geelen *et al.* CMAME 2023

Data-driven ROM methods (2)

- Now, it is possible to **interpolate/approximate between parameter values** in the **reduced space**

$$\boldsymbol{a}(\mu) = (a_1(\mu), a_2(\mu), \dots, a_r(\mu))^{\boldsymbol{T}}$$



e.g. **Audouze *et al.*** NMPDE 2013
Swischuk et al. C&F 2019

- And finally, the **full state solution** can be **approximated** by using either

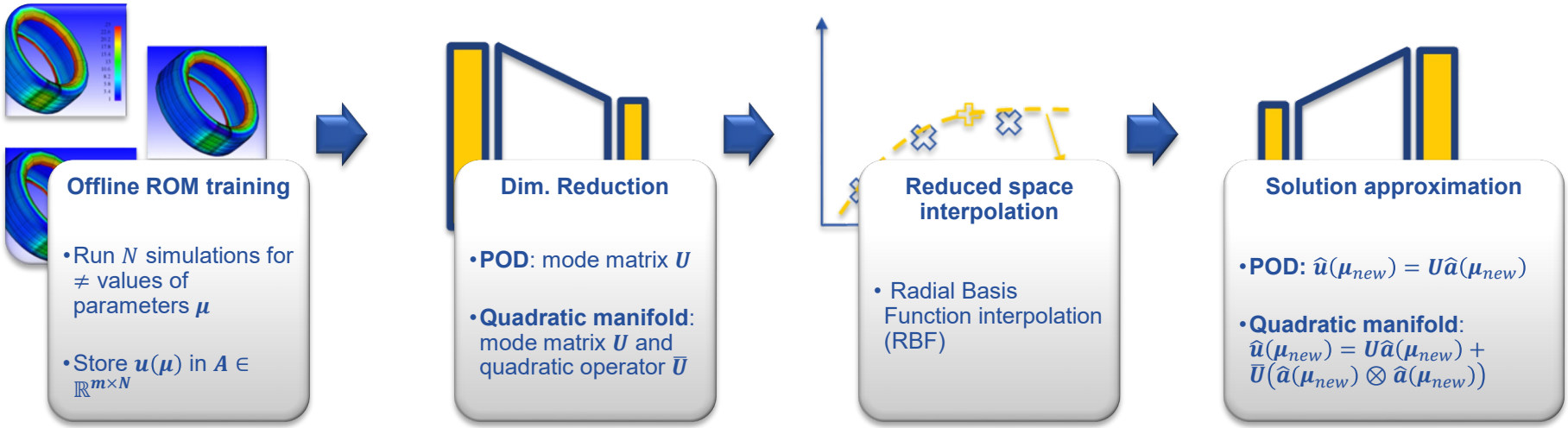
$$\hat{\boldsymbol{x}}(\mu_{new}) = \boldsymbol{U}\hat{\boldsymbol{a}}(\mu_{new}) \rightarrow \text{POD}$$

or

$$\hat{\boldsymbol{x}}(\mu_{new}) = \boldsymbol{U}\hat{\boldsymbol{a}}(\mu_{new}) + \bar{\boldsymbol{U}}\left(\hat{\boldsymbol{a}}(\mu_{new}) \otimes \hat{\boldsymbol{a}}(\mu_{new})\right) \rightarrow \text{Quadratic manifold}$$

Application of ROM methods for design space exploration

Goal: approximate a parametric field of interest in a known design space



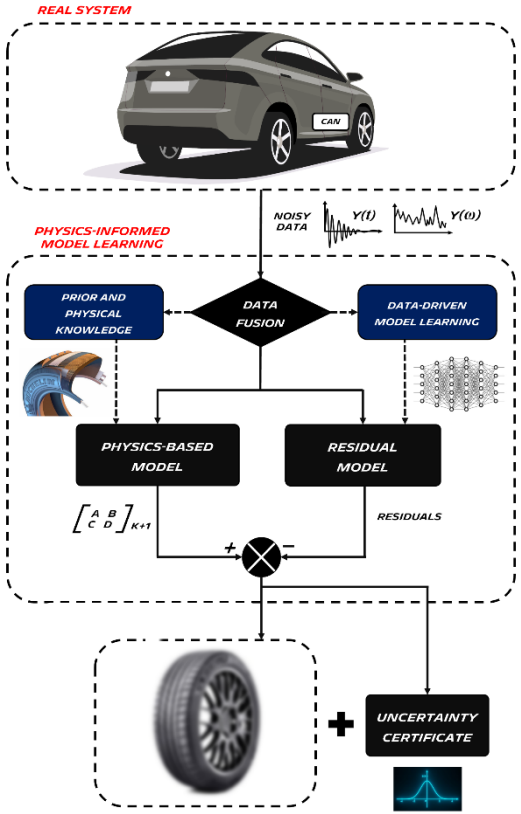
System models & sequential data assimilation

Combining sensors data

With physics knowledge

Thanks to data fusion and Kalman filtering

To estimate product state



Leveraging physics knowledge and databases

And data-driven model learning



From rubber manufufacturing to tire usage twinning



Molecule to Mat. Simulation

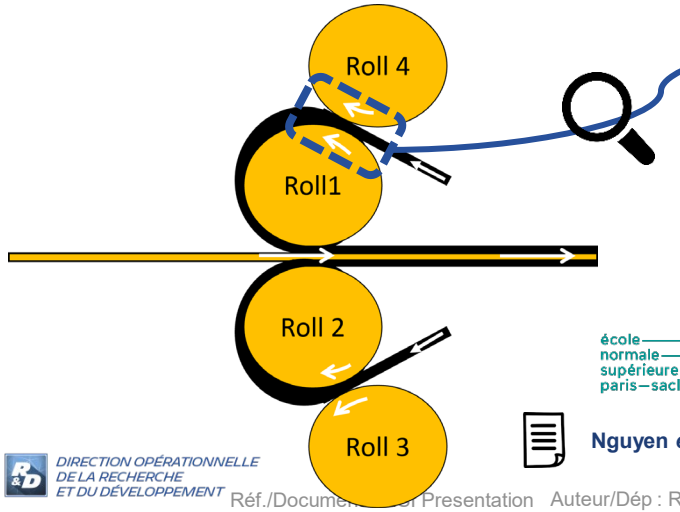
Tire & Vehicle Simulation

Embedded Tire Twin

PINNs virtual sensors for rubber calendering

- **Rubber calendering : process manufacturing**



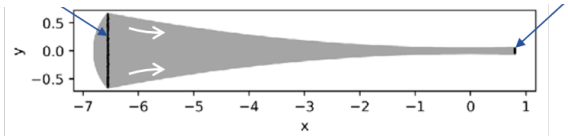


Non-Newtonian fluid with **thermo-mechanical** coupling

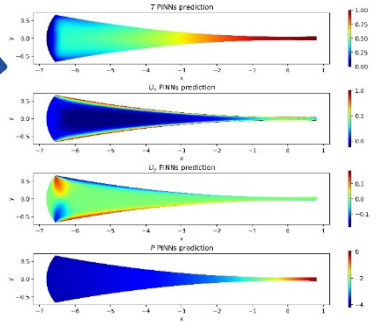
- **Generalized Stokes** eq. for mechanics
- **Convection/diffusion** with nonlinear **source term** for heat transfer
- **High Fidelity simulation** with internal solver

Temperature & Velocity sensors

Temperature & Velocity sensors



PINNs



Rubber temperature

Rubber velocity

Rubber pressure

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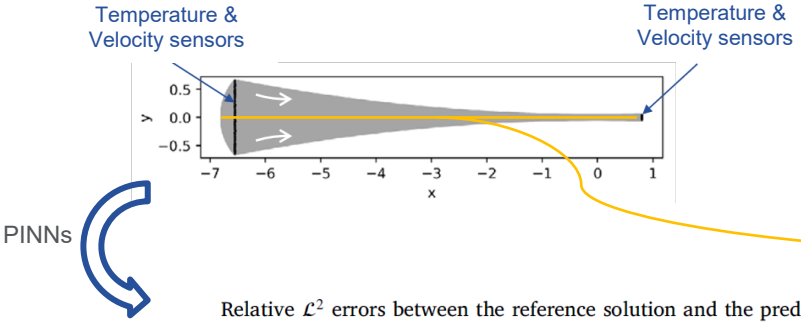
Nguyen *et al.* EAAI 2022

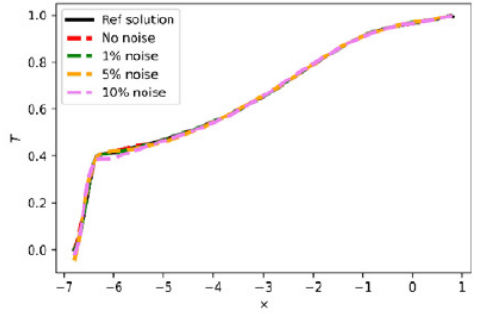
Estimation of physical fields of interest from sensors measurements (2)

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

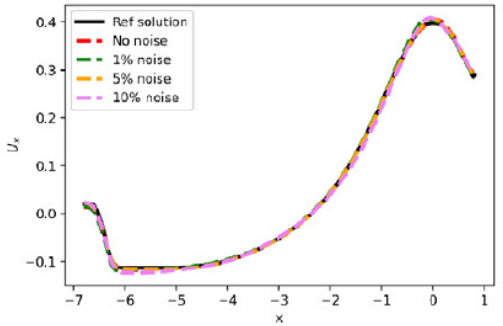


Relative $\mathcal{L}^2$ errors between the reference solution and the predictions by PINNs with different level of noise.

	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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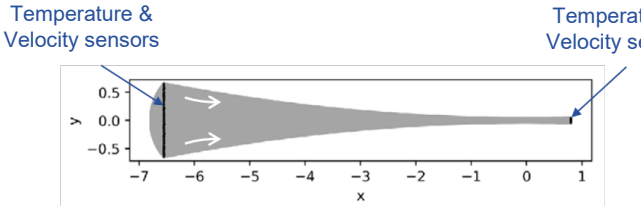
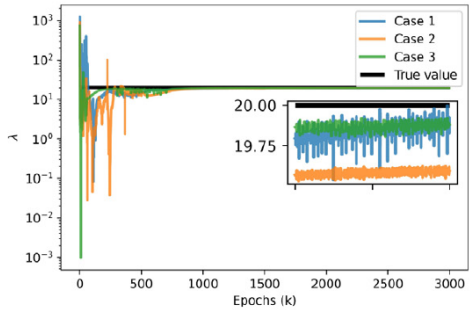
Identification of unknown physical parameters with PINNs

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



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

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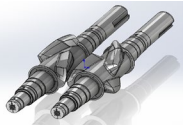
MIMO: a simulation-based **decision-making assistant** for **mixing line process**

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

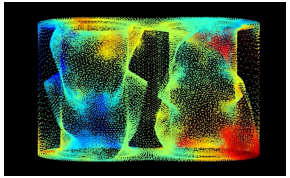




≈ 100 **mix designers** & **industrializers** users WW



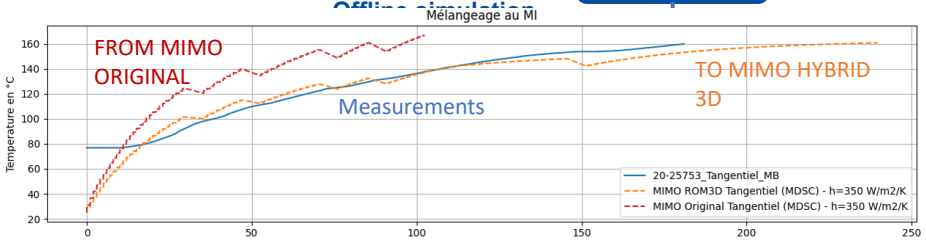
Modelling of rubber internal mixer is inaccurate but fast (minutes)



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

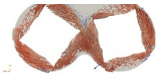
Modelling trade-off: use **3D simulation** as a **data generator** for **machine learning**

New parameter set



Parameter set n

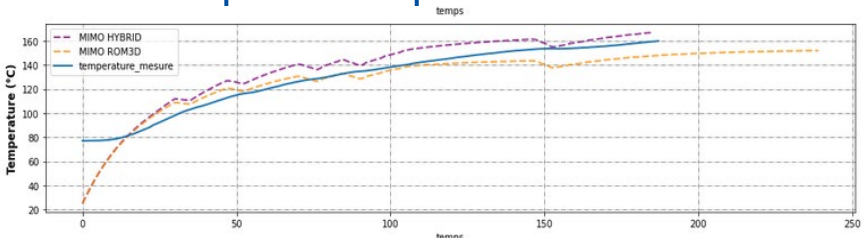




Reduce cost and industrialization delays with machine learning augmented by simulation

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

New



prediction

Advanced research 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

From rubber manufufacturing to tire usage twinning



Molecule to Mat. Simulation

Tire & Vehicle Simulation

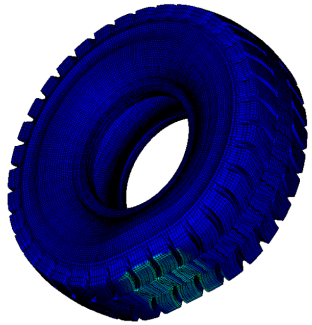
Embedded Tire Twin

Our usecase: 3D Rolling tire

Idealized straight rolling on an inderformable ground at constant speed

3 already existing **modeling approaches**:

- **3D mechanical**: accurate but time consuming
- **1D/0D functional**: fast but not very accurate
- **Pure data-driven based machine learning**: fast but lack generalization

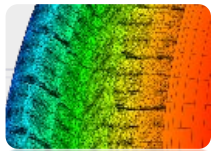


Objective

Propose a hybrid method coupling a mechanical model and a machine learning model to simulate a (3D) rolling tire.

Stakes

- Rolling simulations provides a lot of useful information (contact area, forces, contact pressure, moments…) but too expensive to be used in industrial applications
- Hybrid model would be a trade-off between computational time and accuracy
- It would democratize its usage



Hybridization

Bergmann, M., Ferrero, A., Iollo, A., Lombardi, E., Scardigli, A., & Telib, H. (2018). ***A zonal Galerkin-free POD model for incompressible flows***. *Journal of Computational Physics, 352, 301-325.*

High-fidelity zone

«Imaginary» Rim

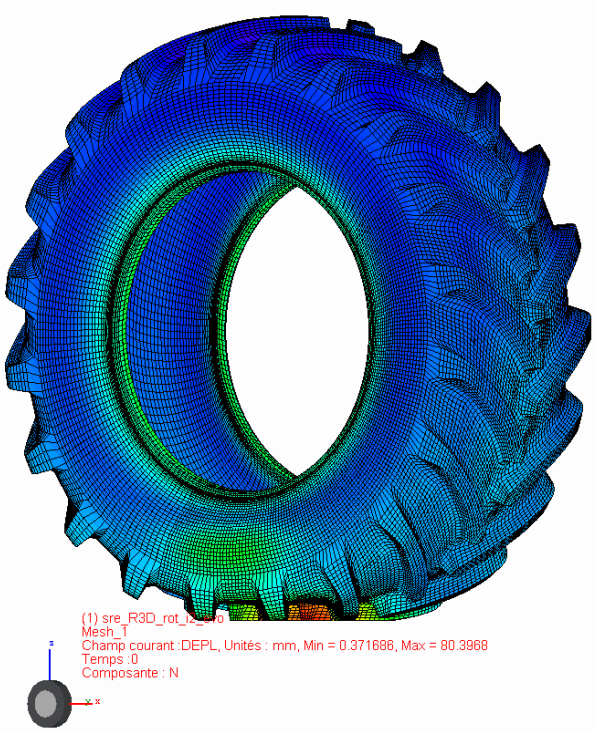
Domain decomposition

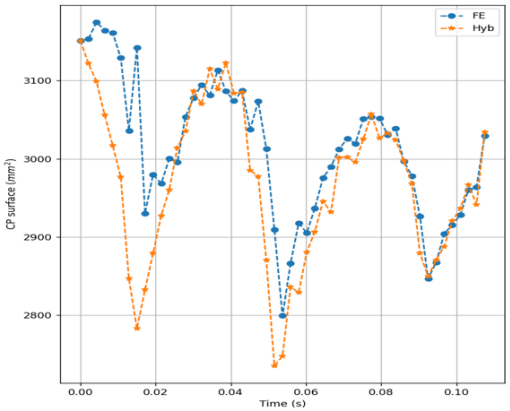
Numerical method	Computational time	Accuracy
Zonal ROM	++ **One way coupling**	--
Domain decomposition	--	++ **Feedback**

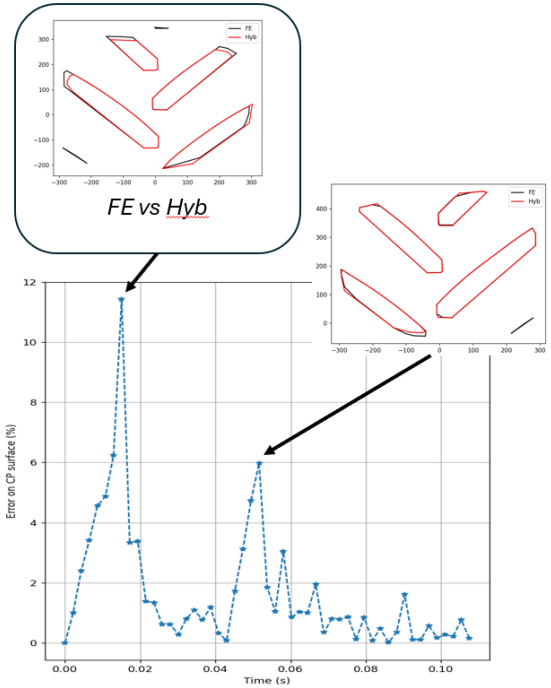
Ground

Rim

Integration into Michelin in-house solver: Validation







Conclusions & perspectives

- We adapted and implemented a reduced order model for 3D rolling simulation
  - The compromise between accuracy and speed is user defined
  - A first step towards a digital twin for tire design ?

- We will continue our integration of the method on Michelin in-house solver
  - Assess computational gain… While monitoring the error
  - Adapt to new ways of running the simulation
  - Métier criteria assesment

- Food for thoughts:
  - Could proposing an initial guess with a learning method save even more time?



From rubber manufufacturing to tire usage twinning



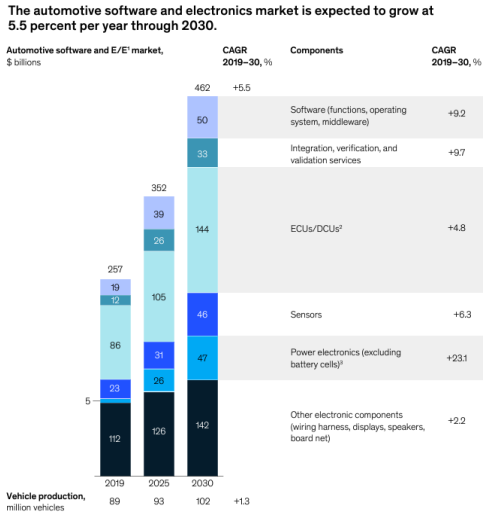
Molecule to Mat. Simulation

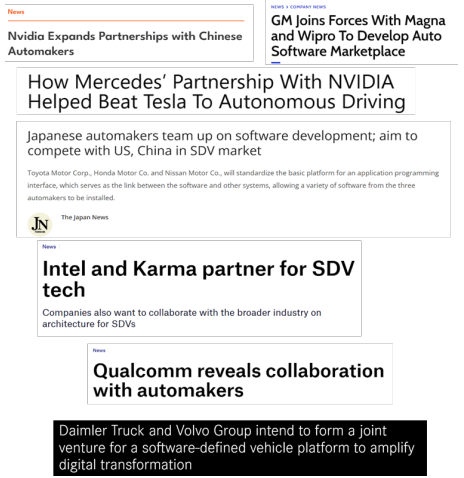
Tire & Vehicle Simulation

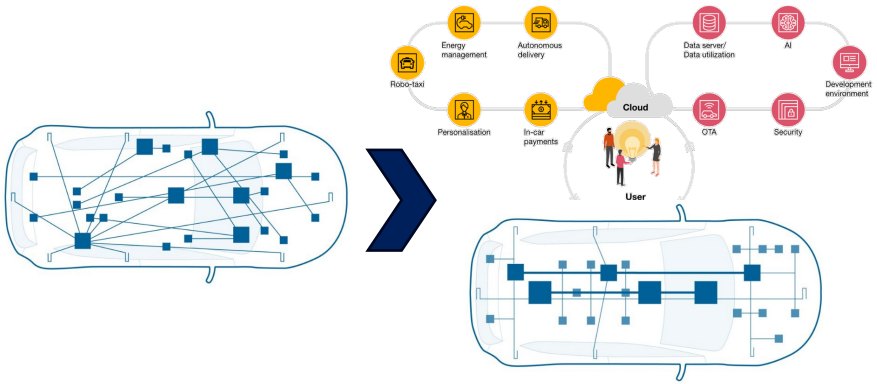
Embedded Tire Twin

SOFTWARE-DEFINED VEHICLE IS MUCH MORE THAN A NEW TECH ADD-ON

A complete reshuffle of the power map in transportation industry







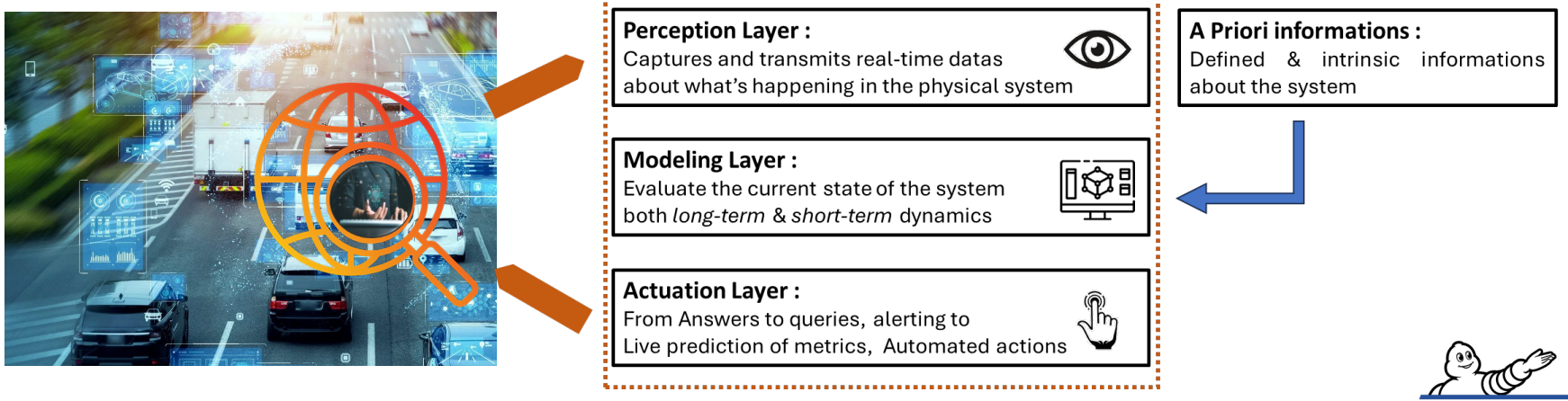
A holistic ecosystem providing new values & experiences to users by updating software from the cloud.

SDV NEEDS RELIABLE & REAL-TIME STATE ESTIMATION OF ITS COMPONENTS

As ground mobility is heading towards Software-Defined Vehicle, the nature of the interactions between physical subsystems in the vehicle and in the cloud will be significantly reshuffled.

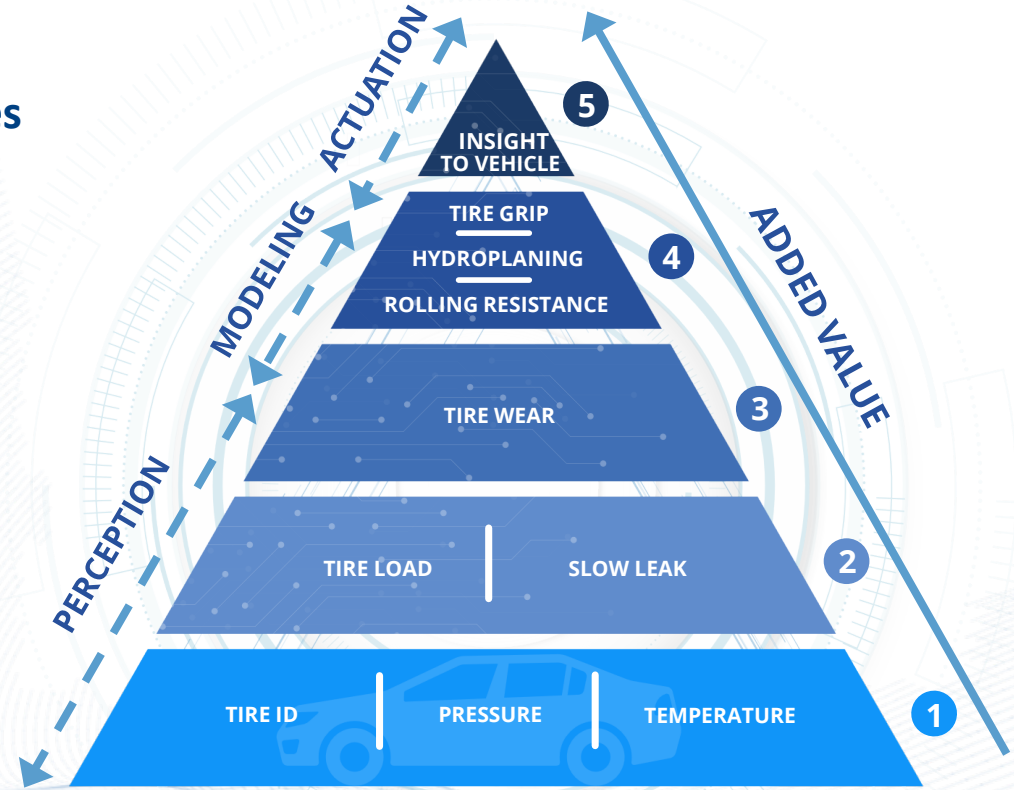
Embedded Digital Twin technology is both a need and an opportunity to operate those interactions.

It should not limit to mechatronics – but also extend to Tire and Tire+Road.



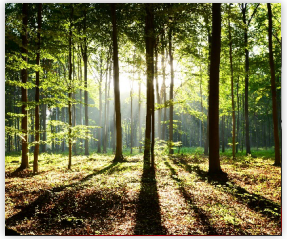
a tire digital twin
built from basic to advanced features

- Need for solid technical foundation
- A digital twin to bring more insights…
- …with higher technical challenge



Software solutions TO SUPPORT CAR safety, DRIVER EXPERIENCE & sustainability







MICHELIN

Differentiation factors

Several algorithms developed with same principles that ensures **consistency and easier deployment** of new features.

Our partners

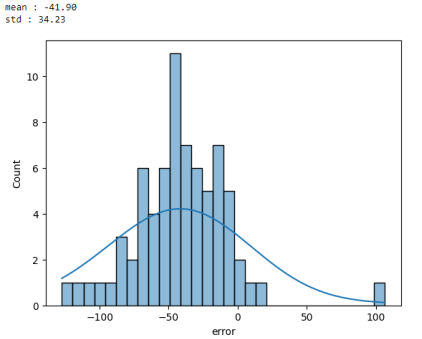
QNX eTAS brembo

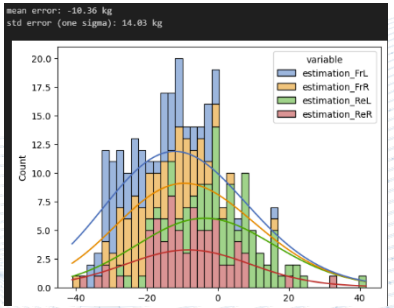
	Driver experience &Tire Predictive Maintenance	Tire Life Cycle Assessment	Vehicle safety & ADAS
SMARTWEAR READY — *Tire Wear monitoring & end of life prediction*	✓	✓	✓
SMARTLEAK READY — *Monitoring, early Leak detection & time to critical*	✓	✓	
SMARTLOAD READY — *Vehicle & tire Load estimation*			✓
SMARTGRIP 2026+ — *Max grip prediction & hydroplaning prevention*			✓
LIVE RR 2026+ — *Tire real RR input to the vehicle*	✓	✓	

Michelin SmartLoad: real-time accurate estimation of vehicle and tire load

Real time load estimation compared with measurement (Rear-Right wheel):

Test passenger car with 25 configurations tested
Error on total vehicle mass: -2% +/- 1,7% at 1σ (42 kg +/- 34 kg)
Error on tire load: -1,8% +/- 2,45% at 1σ (10,4 kg +/- 14 kg)



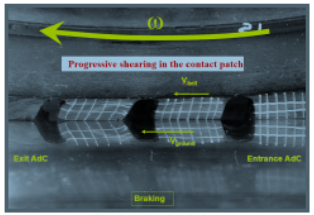


Video SmartLoad

Online Tire grip potential estimation

Tire grip potential

→ Advanced Driver Assistance Systems (ADAS) need to be aware of the environment of the vehicle to perform optimally.
→ Tire grip potential: maximum force the tire can develop with respect to the road surface.



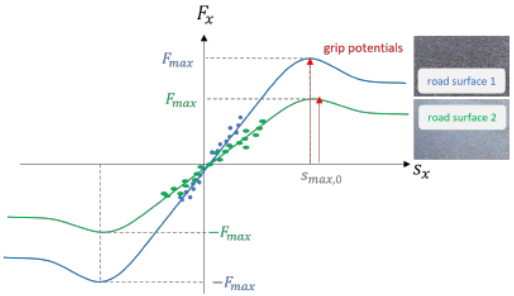
Tire longitudinal slip.

→ Tire slip-ratio is defined as;

$$s_x = \frac{R_e\omega - v_x}{v_x}. \quad (1)$$

→ Friction is a force that opposes the relative motion between two surfaces in contact:

$$\mu = \frac{F_x}{F_z}. \quad (2)$$

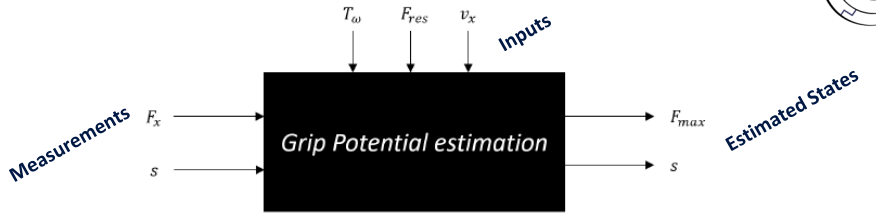


Longitudinal tire characteristics and slip-slope approach.

Estimate tire grip potential online, under standard driving conditions, in order to improve the vehicle dynamics control.

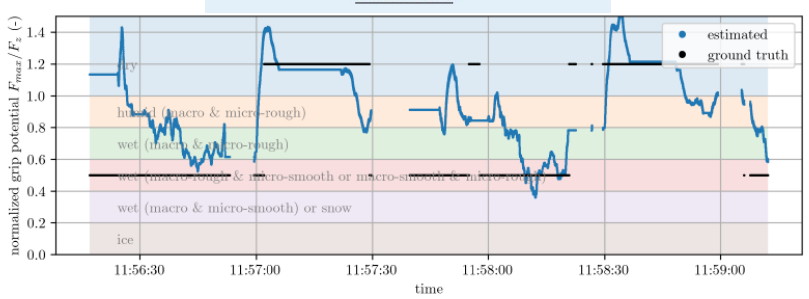
Constraints: The solution must be low-cost (no extra sensors, only CAN bus signals), applicable to any car and tire, and provide online estimation.
The vehicle is considered to be in standard driving conditions, i.e. the trajectory is longitudinal and tire grip consumption is lower than $\mu = 0.5$.

A state space estimation LPV observer is designed





Test vehicle.



Grip potential estimation and road classification with limited tire excitation ($|\mu(t)| < 0.5$). (Experiment)



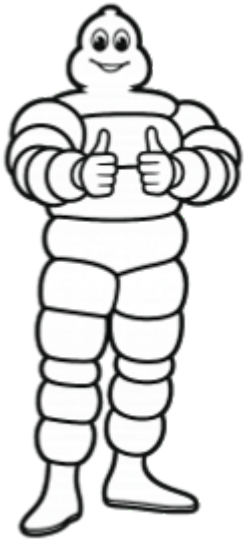




Conclusions

Conclusions and perspectives

- Innovation is at the heart of Michelin R&D
  - A special space is dedicated to simulation and data
- Digital twin is not an ambition anymore. It is real !
  - In the usage phase, the tire embedded twin is already providing first results
  - Process will come next
- Scale up:
  - Most of our methods are tried and tested (POD, Kalman filtering…)
  - There is still places where research is needed



THANK YOU