AN OVERVIEW OF HYBRID PHYSICS/MACHINE LEARNING MODELLING AT MICHELIN

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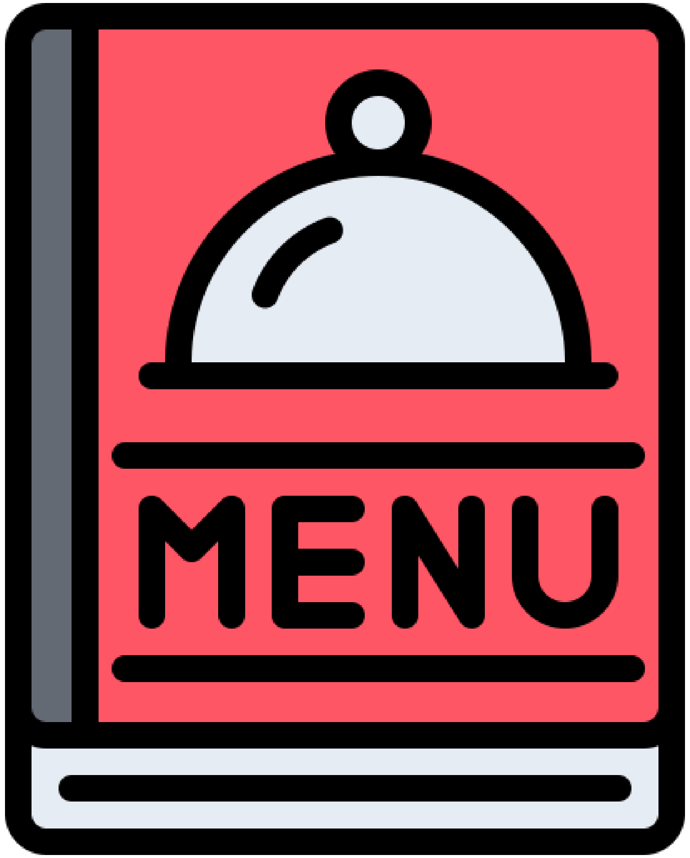
Simulation & Data Science Dept.

Michelin R&D

MICHELIN

OUTLINE



1. Simulation & AI @ Michelin R&D
2. Predict rubber mix behavior during the manufacturing phase
3. Accelerate tire rolling simulation during the design phase
4. Estimate real-time tire performance during the usage phase

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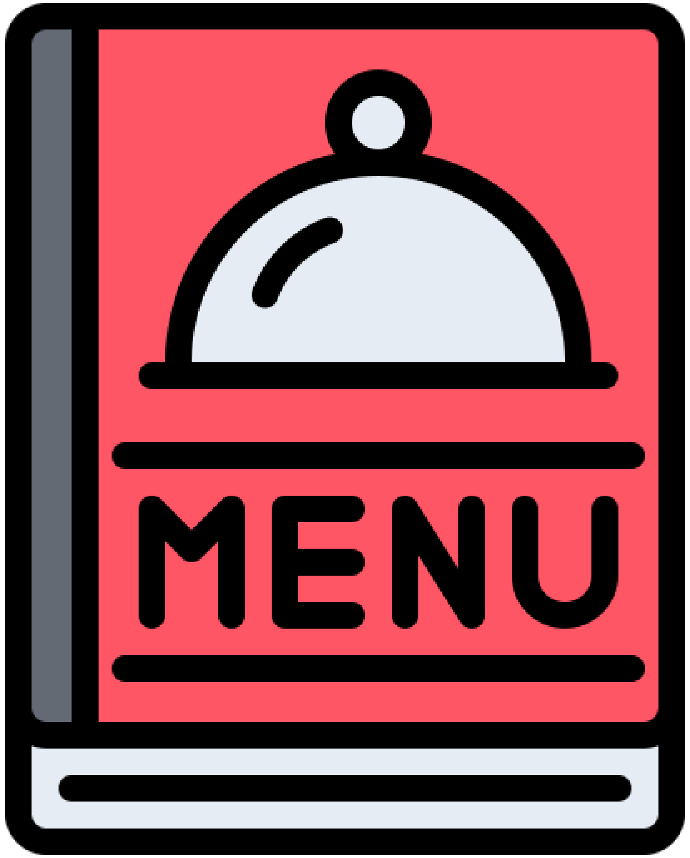

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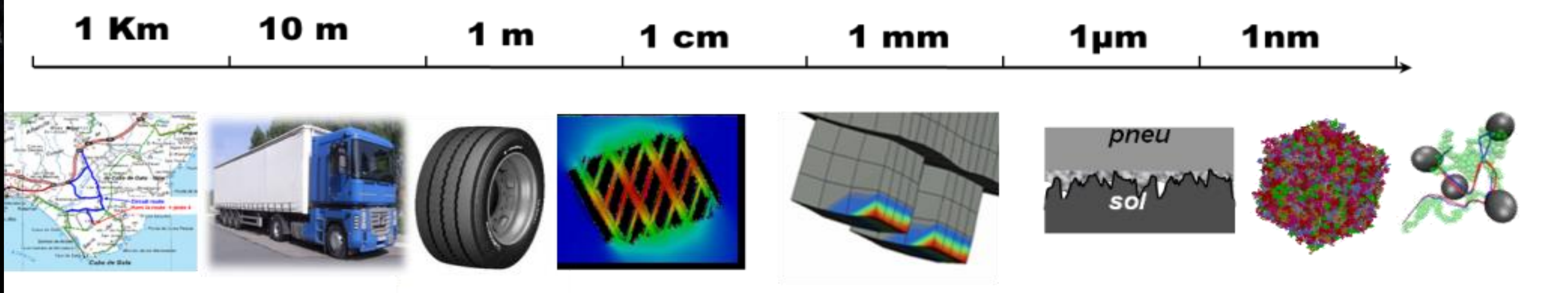
SIMULATION & DATA: FROM MOLECULE TO VEHICLE

Product performance

- virtual submission & virtual tire

Material conception levers

- optimize material recipe
- virtual material for simulation



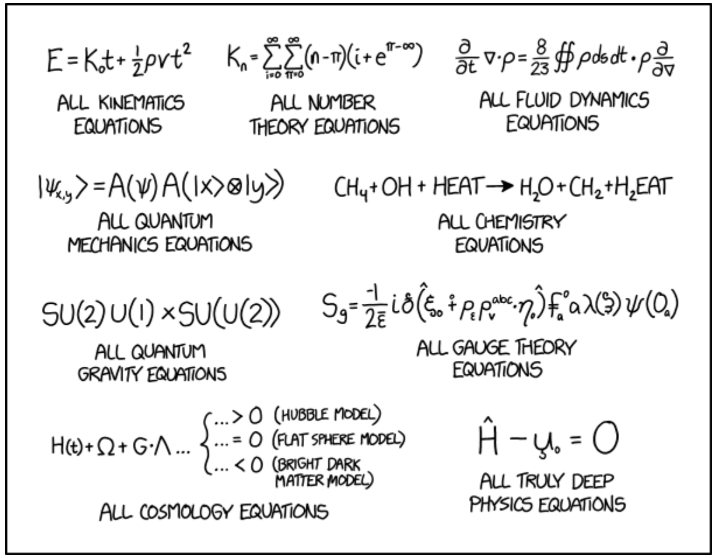
Services & usage

- predictive maintenance
- real time condition assessment

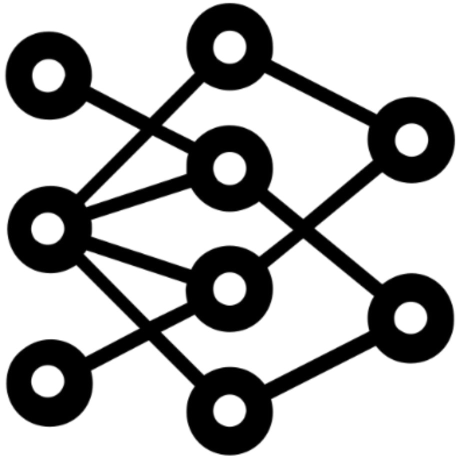
Tire conception levers

MODELS IN ENGINEERING

Physics-based



AI



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

ROM METHODS FOR DESIGN SPACE EXPLORATION

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

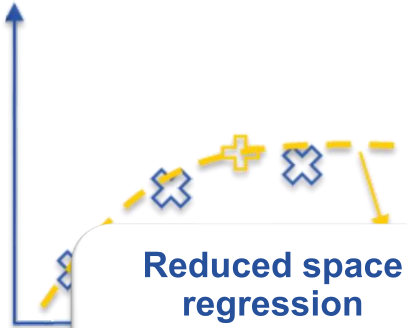
Offline ROM training

- Run N costly simulations for $\neq$ values of parameters $\boldsymbol{\mu}$
- Store $\boldsymbol{u}(\boldsymbol{\mu})$ in $\boldsymbol{A} \in \mathbb{R}^{m \times N}$

Dim. Reduction

- E.g. POD: mode matrix $\boldsymbol{U}$

$$\boldsymbol{a} = \boldsymbol{U}^T \boldsymbol{u}$$



Reduced space regression

- E.g. Radial Basis Function interpolation (RBF)

Solution approximation

- E.g. POD: $\hat{\boldsymbol{u}}(\boldsymbol{\mu}_{new}) = \boldsymbol{U}\hat{\boldsymbol{a}}(\boldsymbol{\mu}_{new})$

ROM: reduced order modelling

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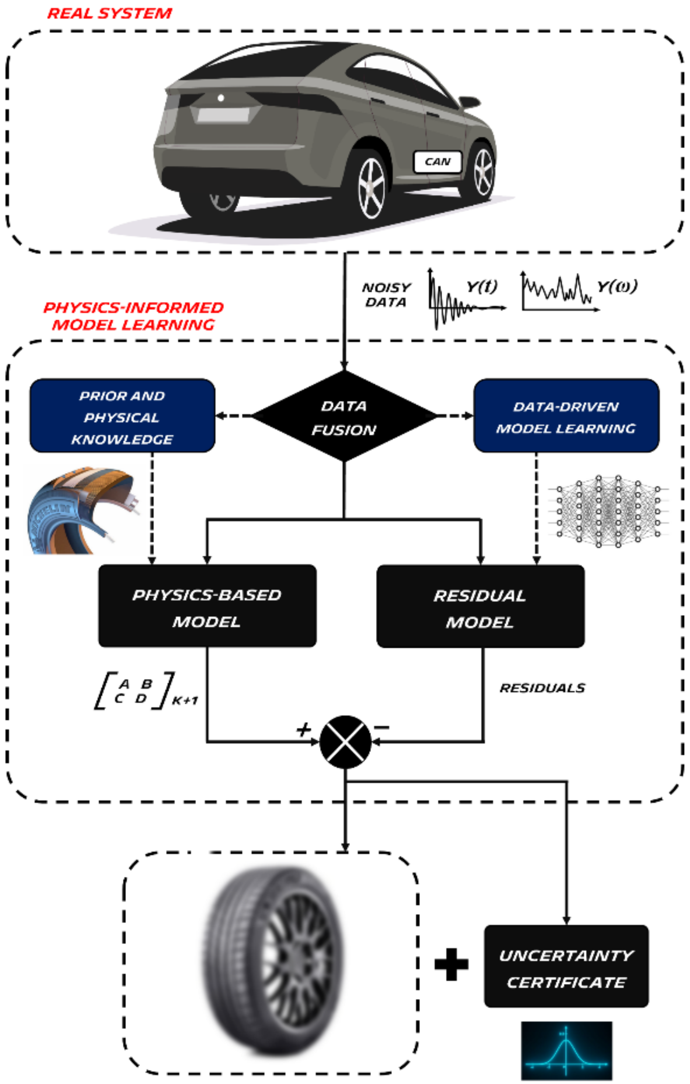
SYSTEM MODELS & SEQUENTIAL DATA ASSIMILATION

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

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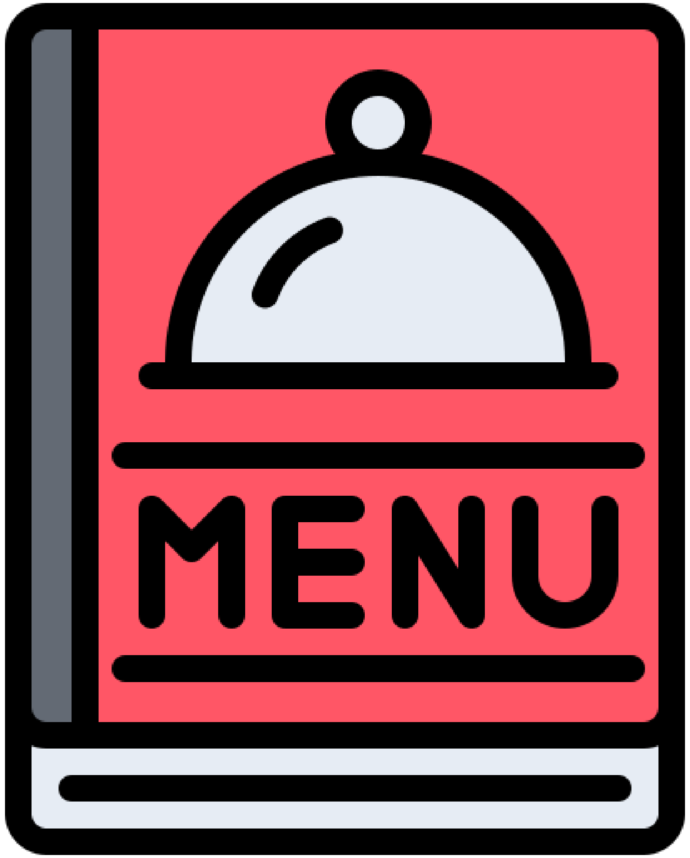
OUTLINE



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FROM RUBBER MANUFUFACTURING TO TIRE USAGE TWINNING

Molecule to Mat. Simulation

Tire & Vehicle Simulation

Embedded Tire Twin

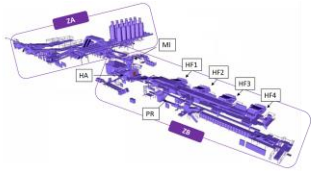
TRANSFORM PROCESS MANUFACTURING WITH SIMULATION & DIGITAL TWINS

Context

- Michelin ambition for 2030: **40% of renewable/recyclable materials** in all products

Stakes

- Allow the **industrialization** and **reduce the time-to-market** of our **new technologies**



Targeted domain

- **Material output** (metal, textile, rubber) dynamical control through continuous learning
- Production process maintenance and optimization with process line **Digital Twin**

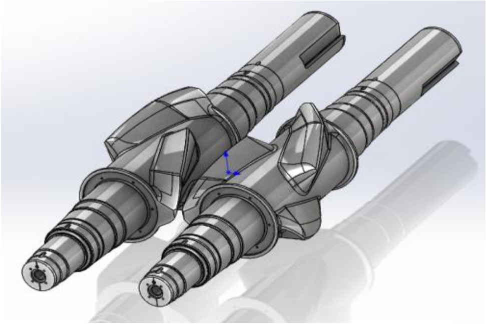
WHAT WE ARE TARGETING WITH DIGITAL TWINS

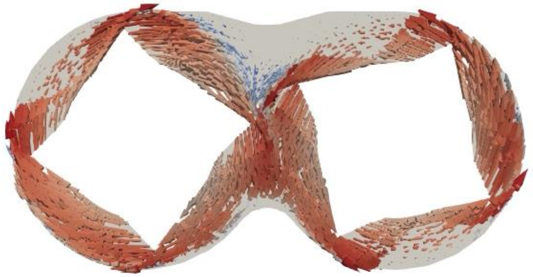
Real process

Sensors

Input command

A numerical version of the process





Virtual model of a physical process: leverage **real-time data and simulations** to analyze, **predict**, or optimize performance within an online **feedback loop**.

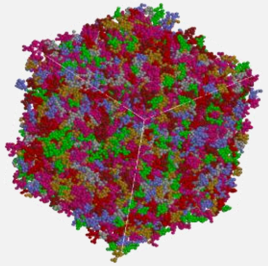
RUBBER MIX NUMERICAL MODELLING… NOT THAT EASY

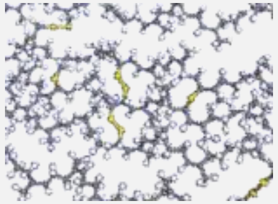
Multiple processes:

- Cylinder tools
- Calender
- Mixer
- Extruder
- Cooling belts
- …

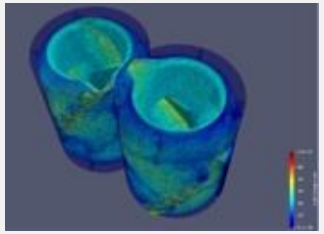
PHYSICS-BASED SIMULATION FOR RESEARCH & PRODUCT DESIGN

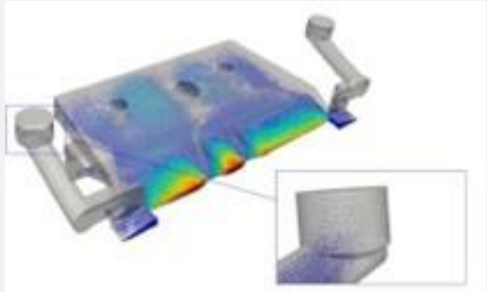
MATERIALS



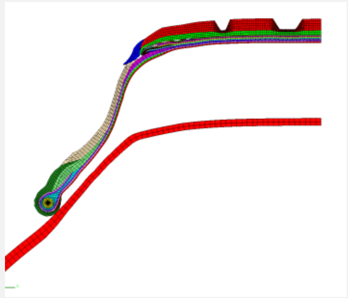


MANUFACTURING PROCESS

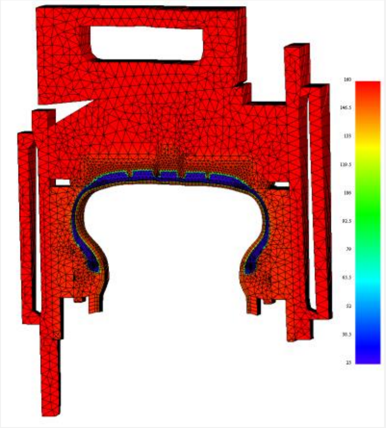


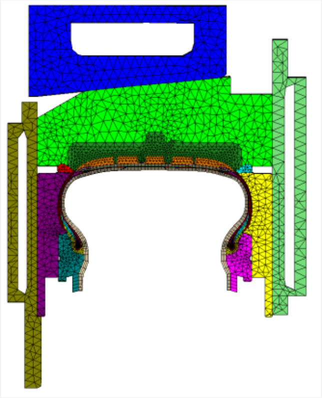


GREEN TIRE

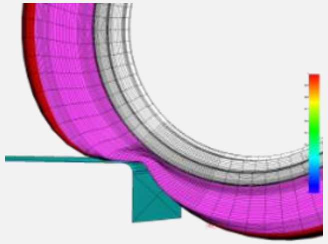


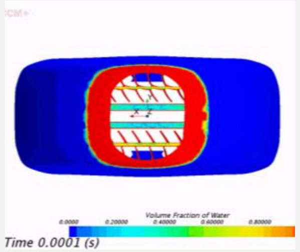
CURING

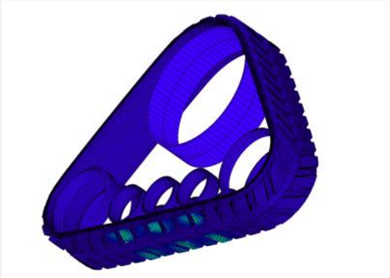




END PRODUCT PERFORMANCES

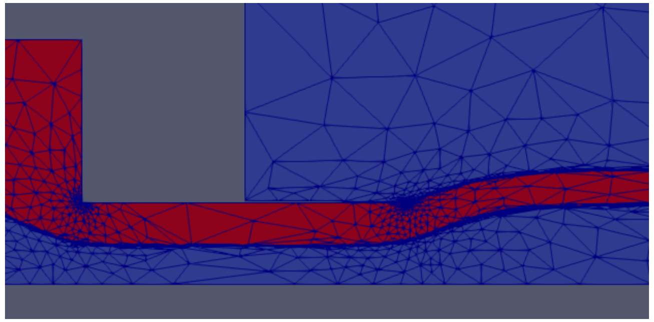


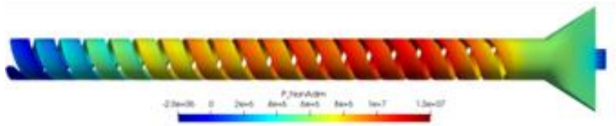


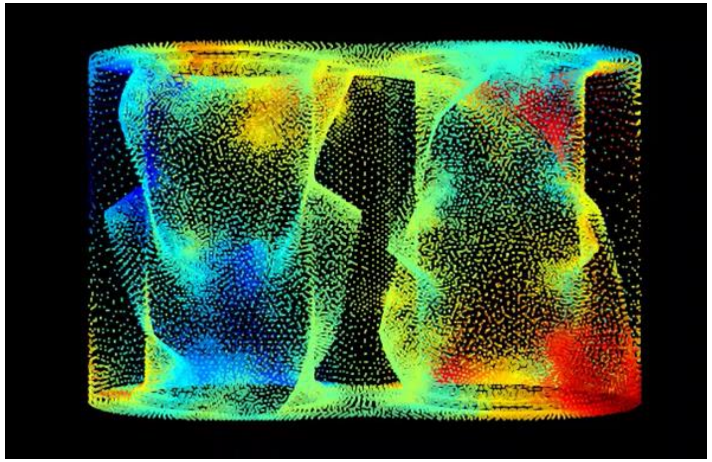


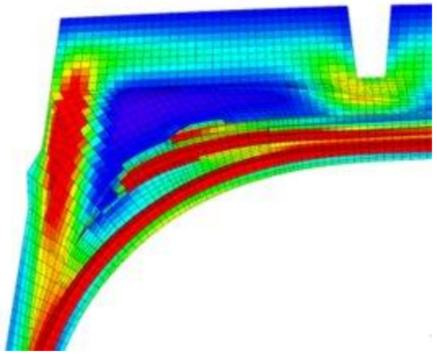
PHYSICS-BASED SIMULATION OF RUBBER MIX PROPERTIES INSIDE MANUFACTURING PROCESS

- **High Fidelity simulation** with in-house finite element solver
- **Non-Newtonian highly viscous** fluids
- **Generalized Stokes** eq. for mechanics
- **Non-linear temperature** eq. with viscous dissipation
- Non-linear **thermo-mechanical coupling**
- $O(10^6)$ nodes
- Quasi-static simulations









ROM-BASED DECISION-MAKING ASSISTANT FOR MIXING LINE PROCESS

Offline Simulation database

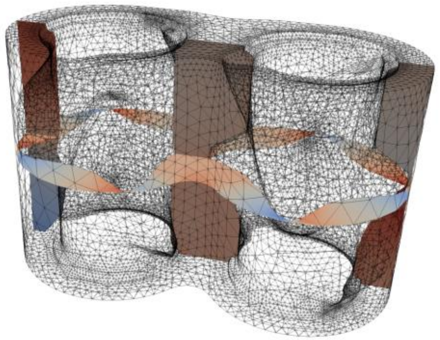
$\approx 10^3$ simulations

→ **Dimensionality reduction** → **Regression problem in the reduced space**

Inhouse FEM solver

Reduced basis

Predictions of physical fields

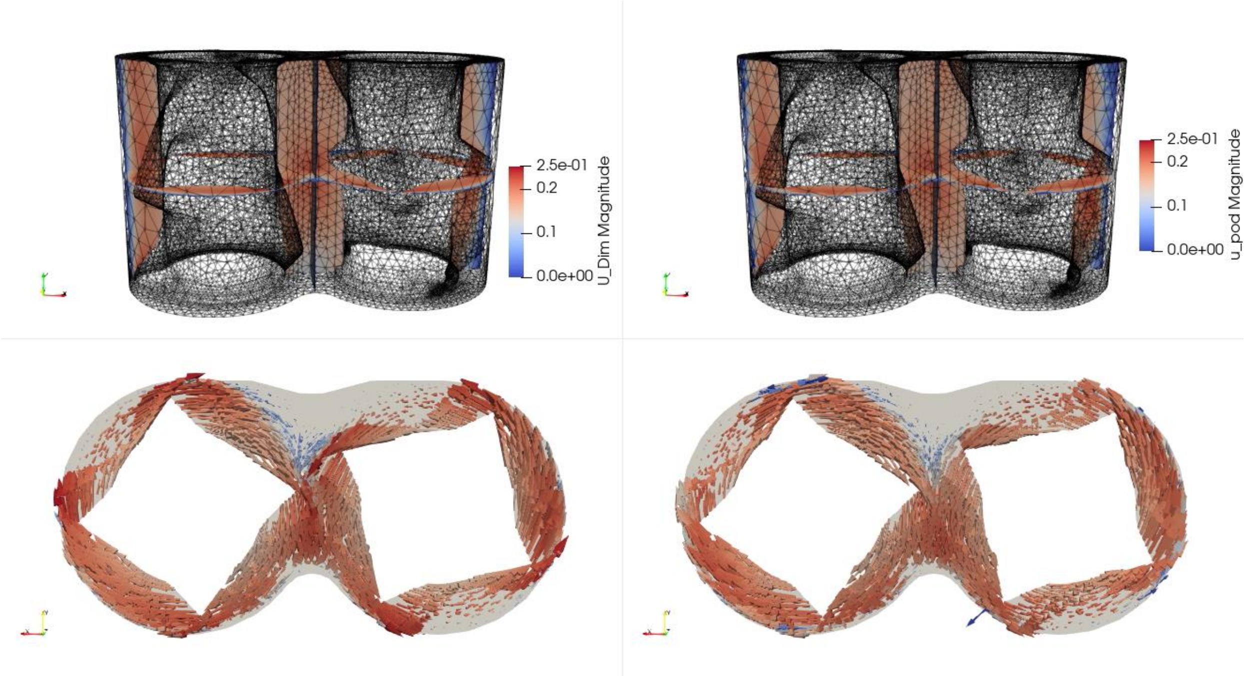


ROM-BASED DECISION-MAKING ASSISTANT FOR MIXING LINE PROCESS

Materials and process parameters → 3D mixer ROM → Physical Fields of Interest

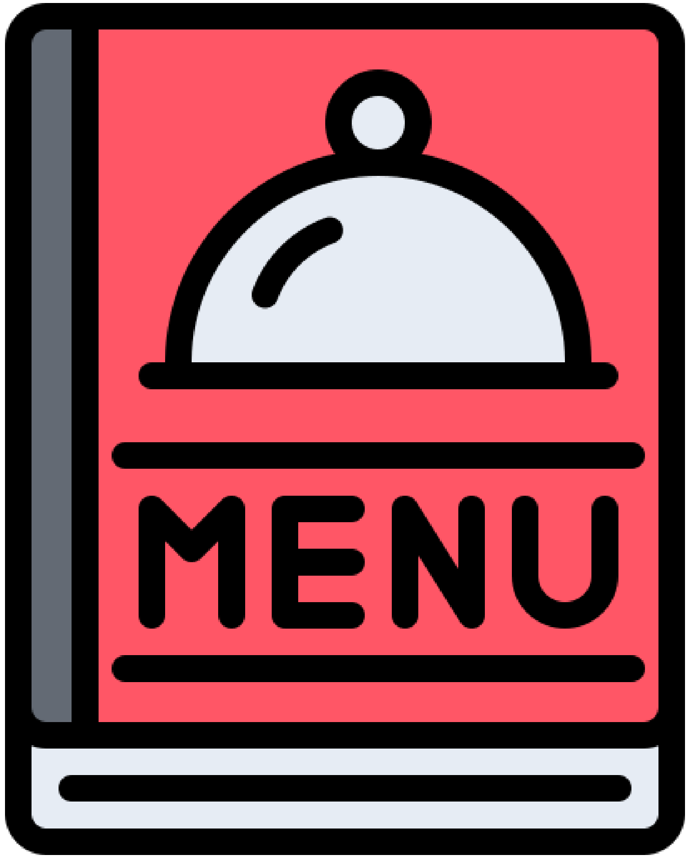
ONE ROTOR REVOLUTION

$$t_{FEM} = hours$$
$$t_{ROM} = seconds$$



Internal FEM solver

OUTLINE



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Embedded Tire Twin

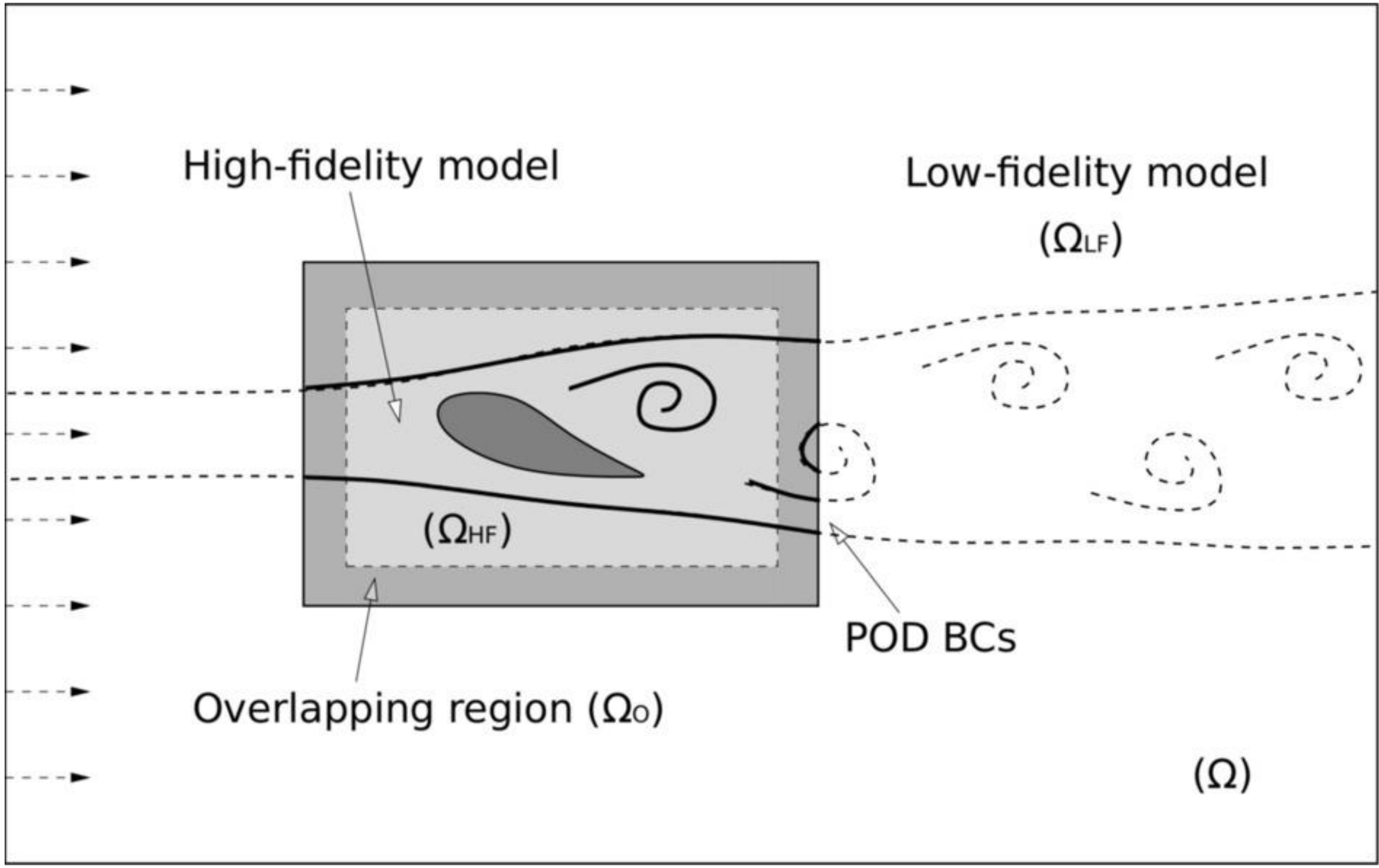
ZONAL ROM FOR 3D ROLLING

METHOD

- Our approach is inspired from Zonal ROMs for incompressible flows.

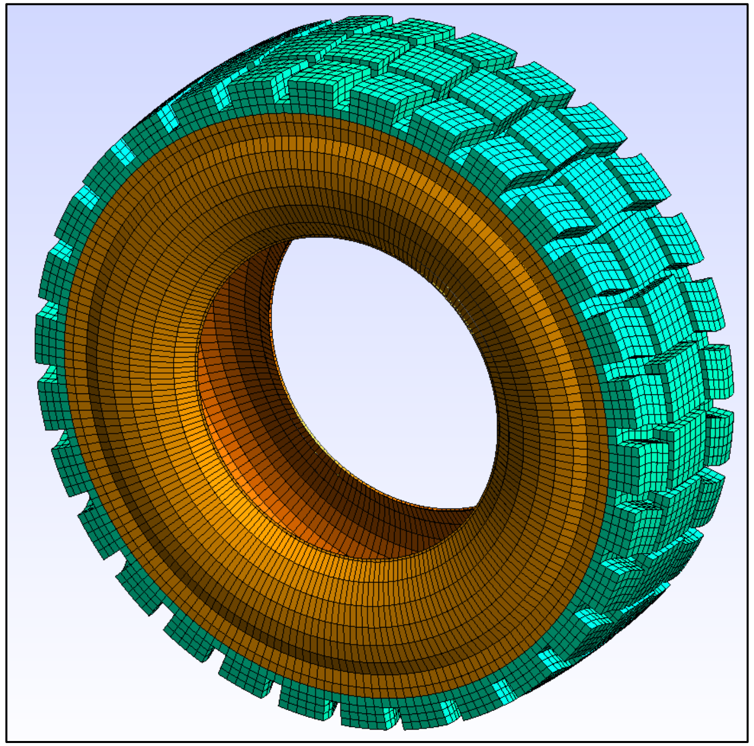
[Buffoni et al., Computs. Fl, 2009]
[Bergmann et al., JCP, 2018]

- The original approach couples a high-fidelity model with a low fidelity POD ROM.
  - The overlapping region is used to find the POD coefficients in the online phase.



ZONAL ROM FOR 3D ROLLING

CONTEXT



Constitutive law

$$\boxed{\mathbf{\Pi} = \partial_{\mathbf{F}} W(\mathbf{F}) \quad \text{in} \quad \Omega \times (0,T),} \tag{1}$$

Equations of motion

$$\boxed{-\rho \ddot{\boldsymbol{u}} + \operatorname{Div} \mathbf{\Pi} + \boldsymbol{f}_0 = \mathbf{0} \quad \text{in} \quad \Omega \times (0,T),} \tag{2}$$

Boundary conditions

$$\boldsymbol{u} = \boldsymbol{u}_d \quad \text{on} \quad \Gamma_1 \times (0,T), \tag{3}$$

$$\mathbf{\Pi}\boldsymbol{\nu} = \boldsymbol{f}_2 \quad \text{on} \quad \Gamma_2 \times (0,T), \tag{4}$$

$$u_\nu \le g, \quad \Pi_\nu \le 0, \quad (u_\nu - g)\Pi_\nu = 0 \quad \text{on} \quad \Gamma_3 \times (0,T), \tag{5}$$

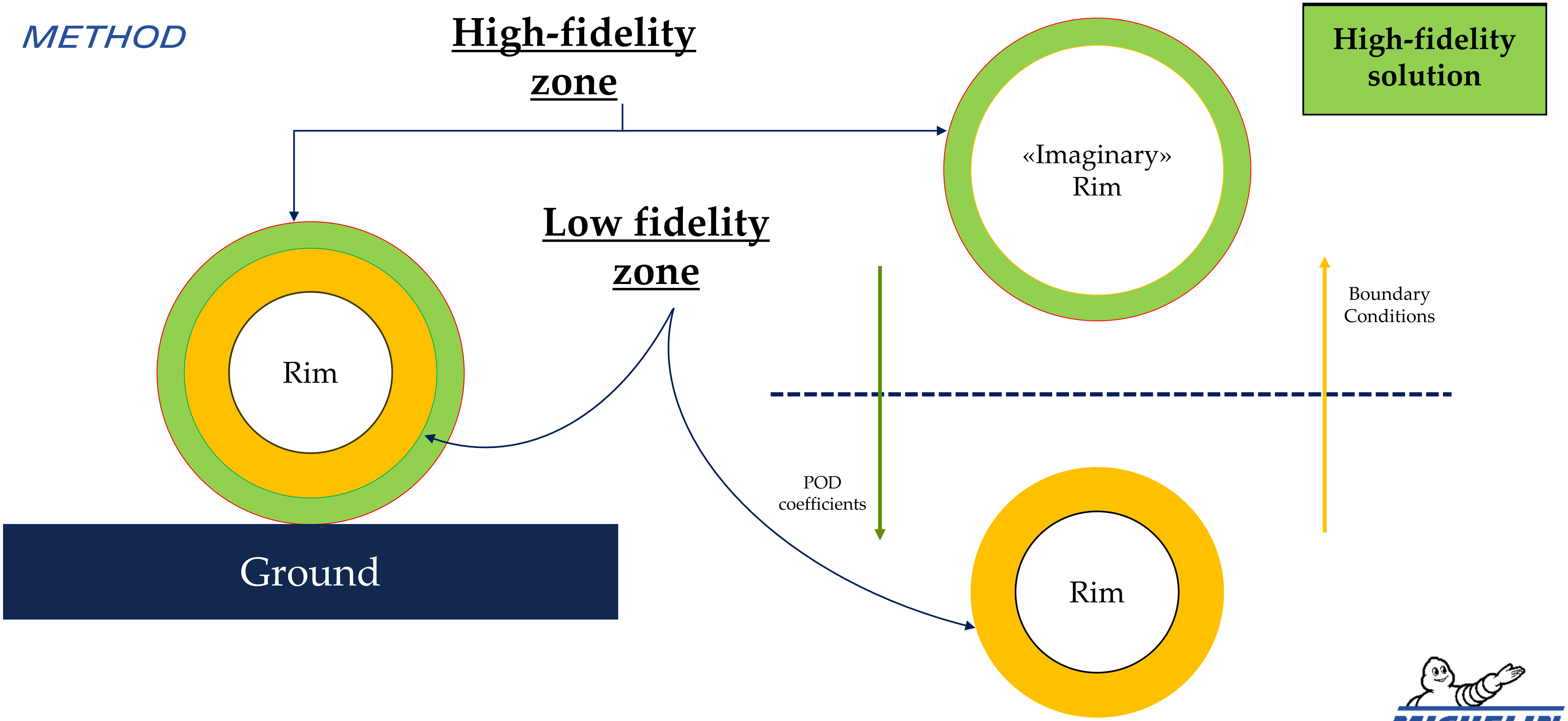
$$\begin{cases} \|\mathbf{\Pi}_\tau\| \le \mu\,|\Pi_\nu|, \\ -\mathbf{\Pi}_\tau = \mu\,|\Pi_\nu|\,\dfrac{\boldsymbol{u}_\tau}{\|\boldsymbol{u}_\tau\|} \ \text{ if } \ \boldsymbol{u}_\tau \neq \mathbf{0}. \end{cases} \quad \text{on} \quad \Gamma_3 \times (0,T), \tag{6}$$

Initial conditions

$$\boxed{\boldsymbol{u}(0) = \boldsymbol{u}_0, \quad \dot{\boldsymbol{u}}(0) = \boldsymbol{u}_1 \quad \text{in} \quad \Omega.} \tag{7}$$

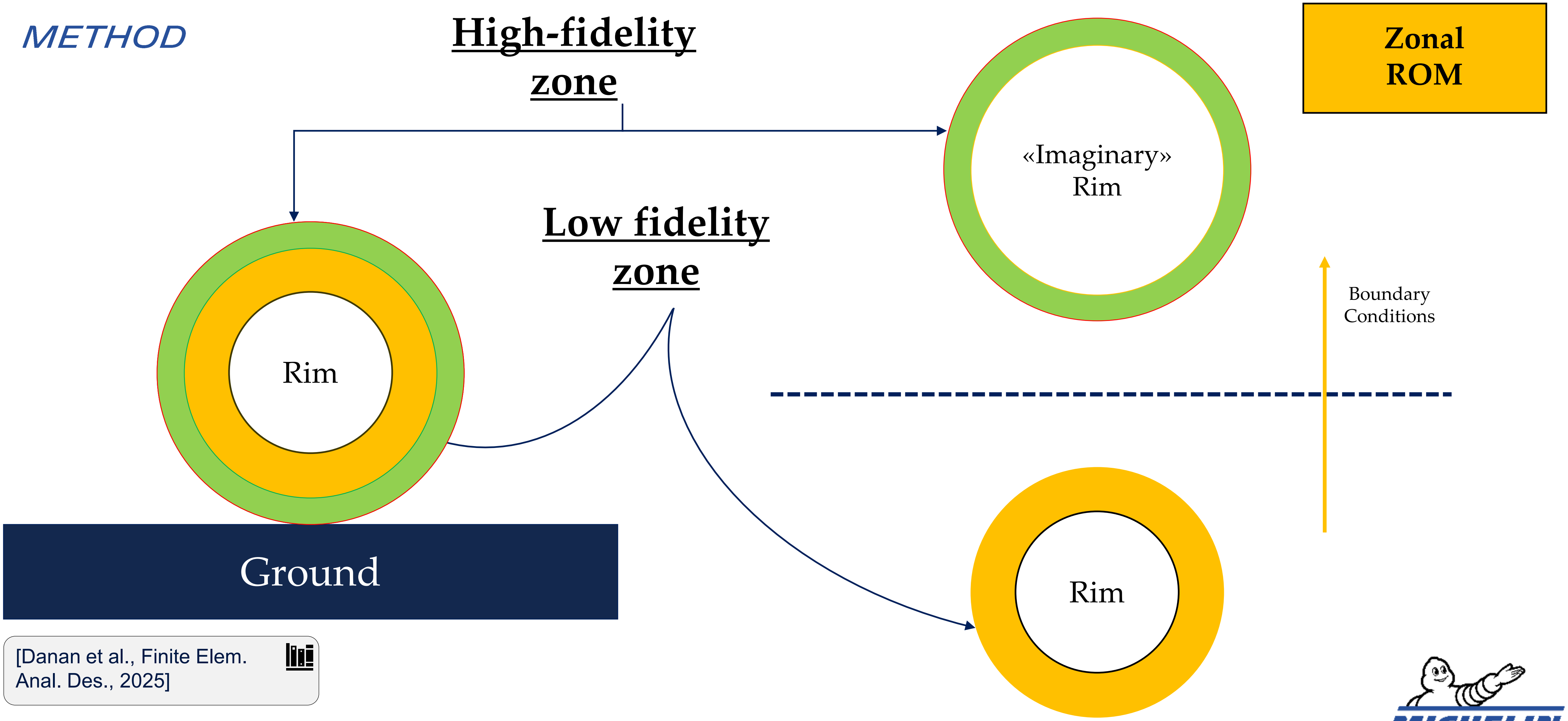
ZONAL ROM FOR 3D ROLLING

METHOD



ZONAL ROM FOR 3D ROLLING

METHOD



[Danan et al., Finite Elem. Anal. Des., 2025]

ZONAL ROM FOR 3D ROLLING

RESULTS (1/2)

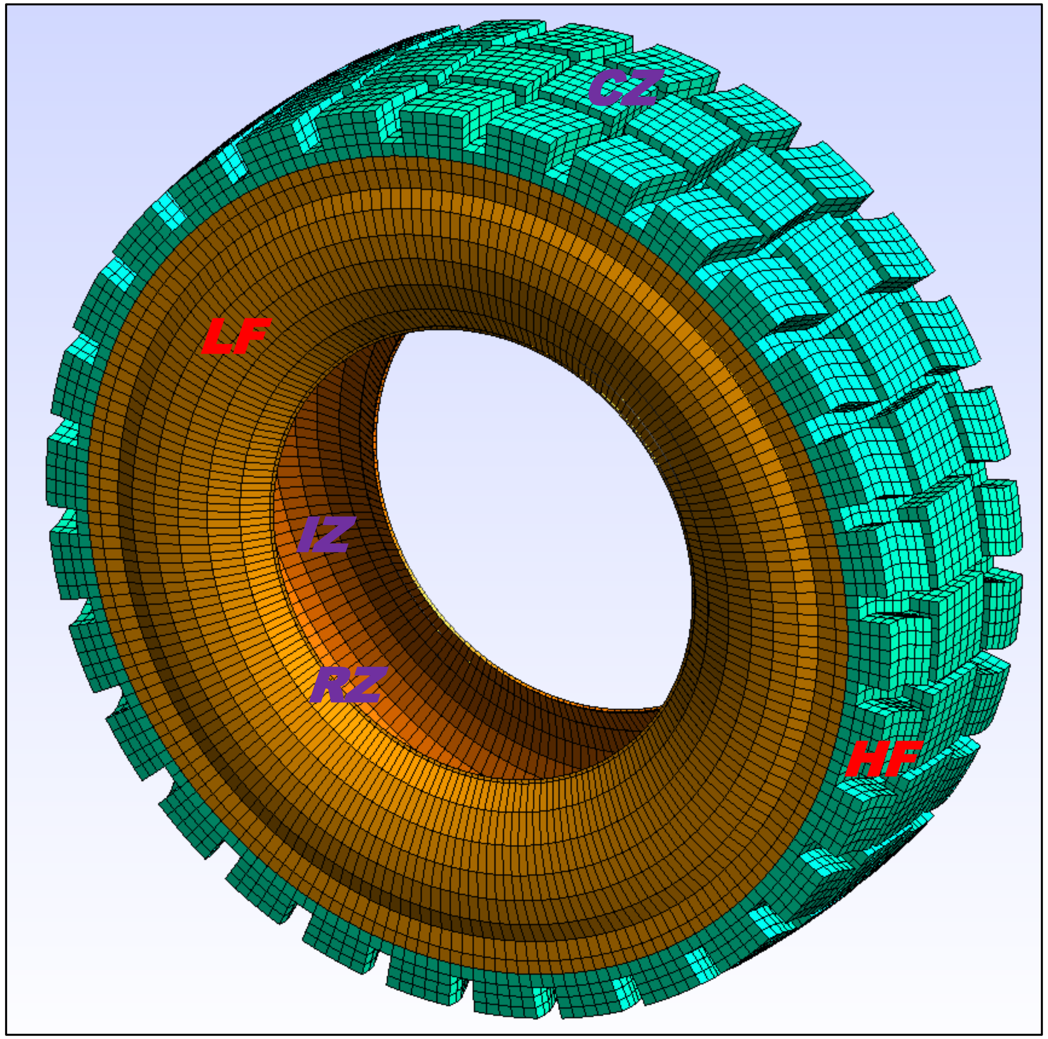
- **Behavior law: Mooney-Rivlin**
  Total Lagrangian Formulation

- **Boundary conditions:**
  - Angular velocity: 50 rad/s
  - Vertical displacement: 55 mm
  - Inflating pressure : 10^{-1} MPa
  - Friction coefficient: 0.1
  - Perfectly rigid ground

- **Time** related **parameters:**
  - Number of time steps: 130
  - Time step: 10^{-4} s

- **Number of DOF:**
  - Classical physical solver: 145,080
  - Physical solver within hybrid solver: 122,400 (radius filter=900)
    - 15% of the dofs are handled by the ROM

- **Zones:**
  - Volume: High fidelity (***HF***), low fidelity (***LF***)
  - Surface: rolling condition (***RZ***), Inflating (***IZ***), Contact (***CZ***)



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ZONAL ROM FOR 3D ROLLING

RESULTS (1/2)

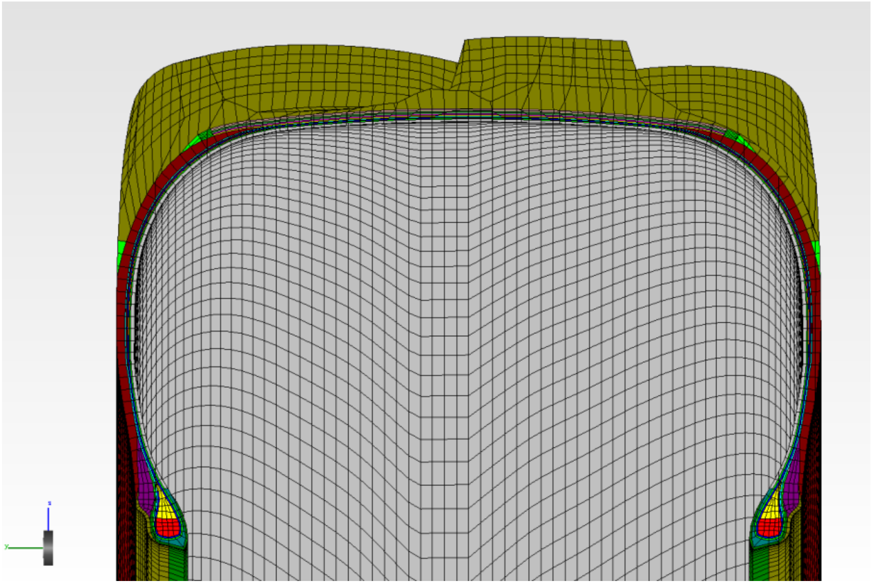
High fidelity FEM simulation
CPU Time: ~3h16mn

Fast-Zonal hybrid approach
(4 timesteps for online training)
CPU time: ~1h38mn

- Speedup ~50%
- Max relative errors:
  - longitudinal displacement: 0.11%
  - vertical displacement: 1.13%

ZONAL ROM FOR 3D ROLLING

RESULTS (2/2)

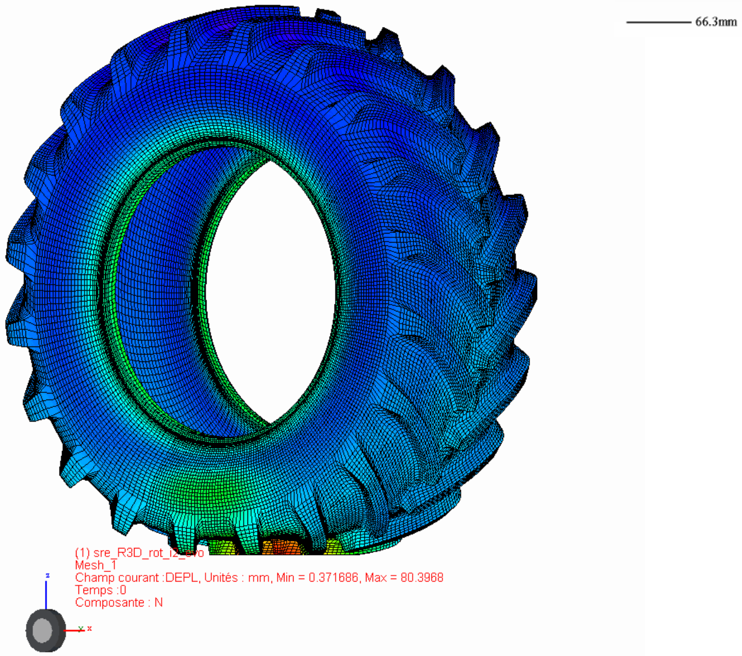


- **Different (visco) hyperelastic composite materials**
  Total Lagrangian Formulation

- **Boundary conditions:**
  - Vehicle velocity: 15 Km/h
  - Angular velocity: 4.15 rad/s
  - Vertical displacement: 80 mm
  - Inflating pressure : 0.18 MPa
  - Rough ground contact

- **Time** related **parameters:**
  - Number of time steps: 60
  - Time step: 2.10^{-3} s

- **Number of DOF:**
  - Classical physical solver: 397,058
  - Physical solver within hybrid solver: 66,000 (Tire tread only)
    - 83% of the dofs are handled by the ROM

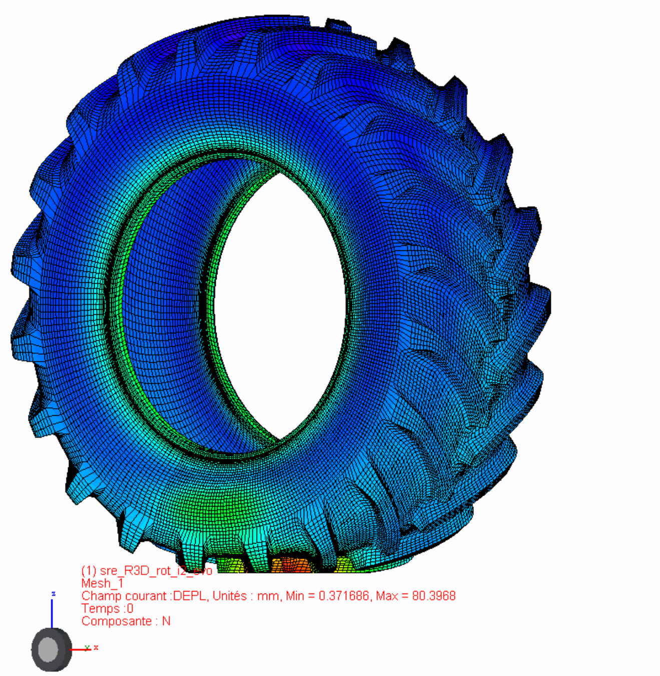


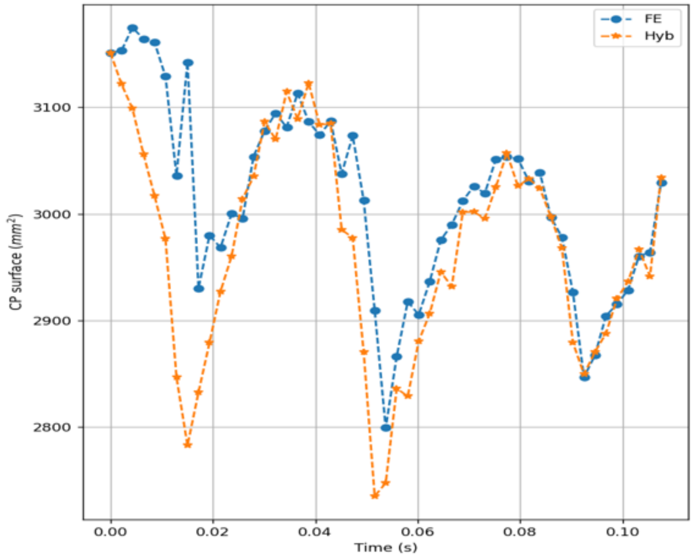
MICHELIN

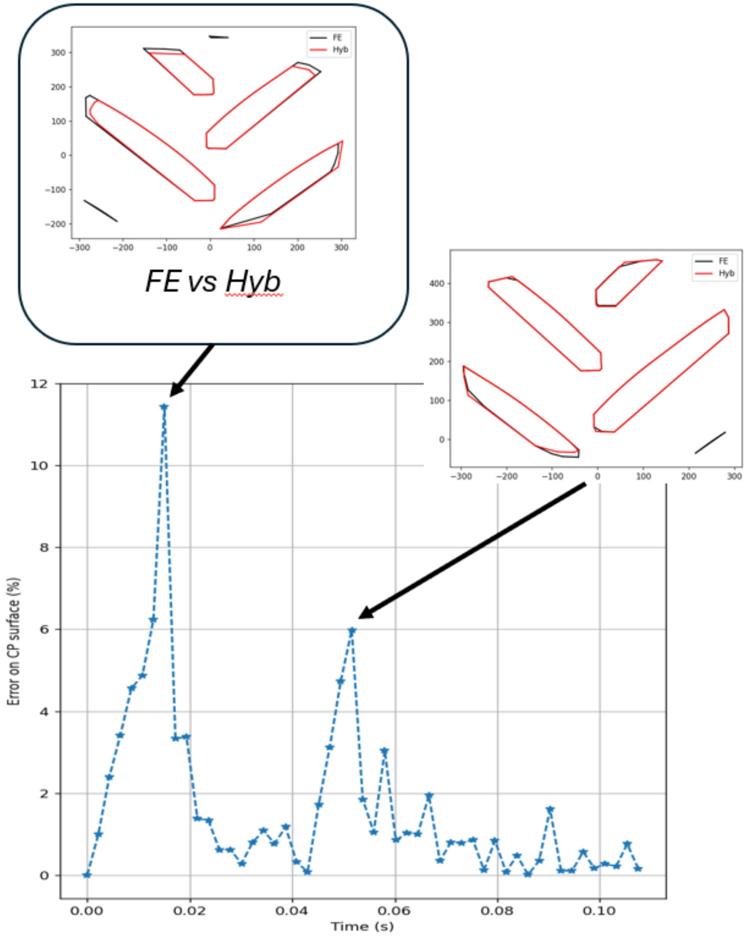
ZONAL ROM FOR 3D ROLLING

RESULTS (2/2)

- Good prediction of the contact area, a crucial quantity for performance criteria.







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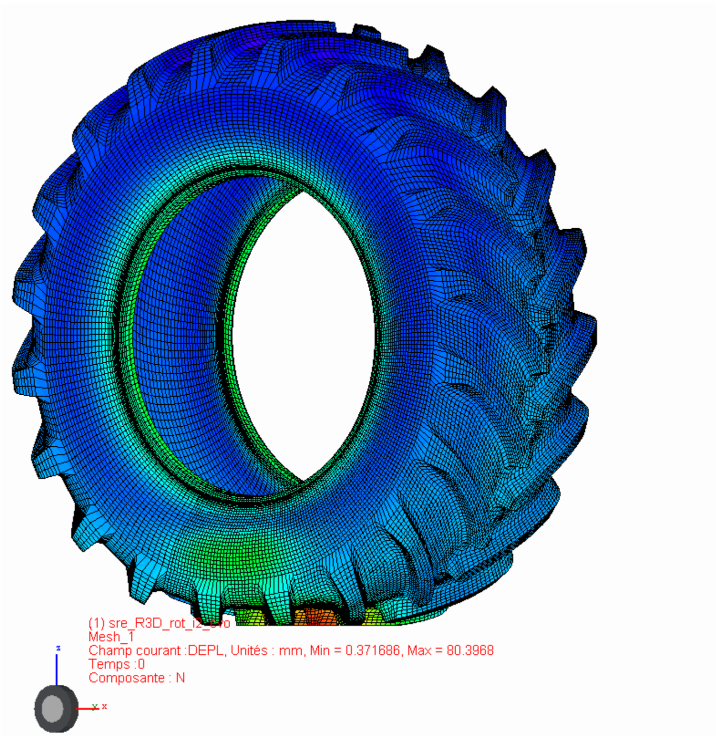
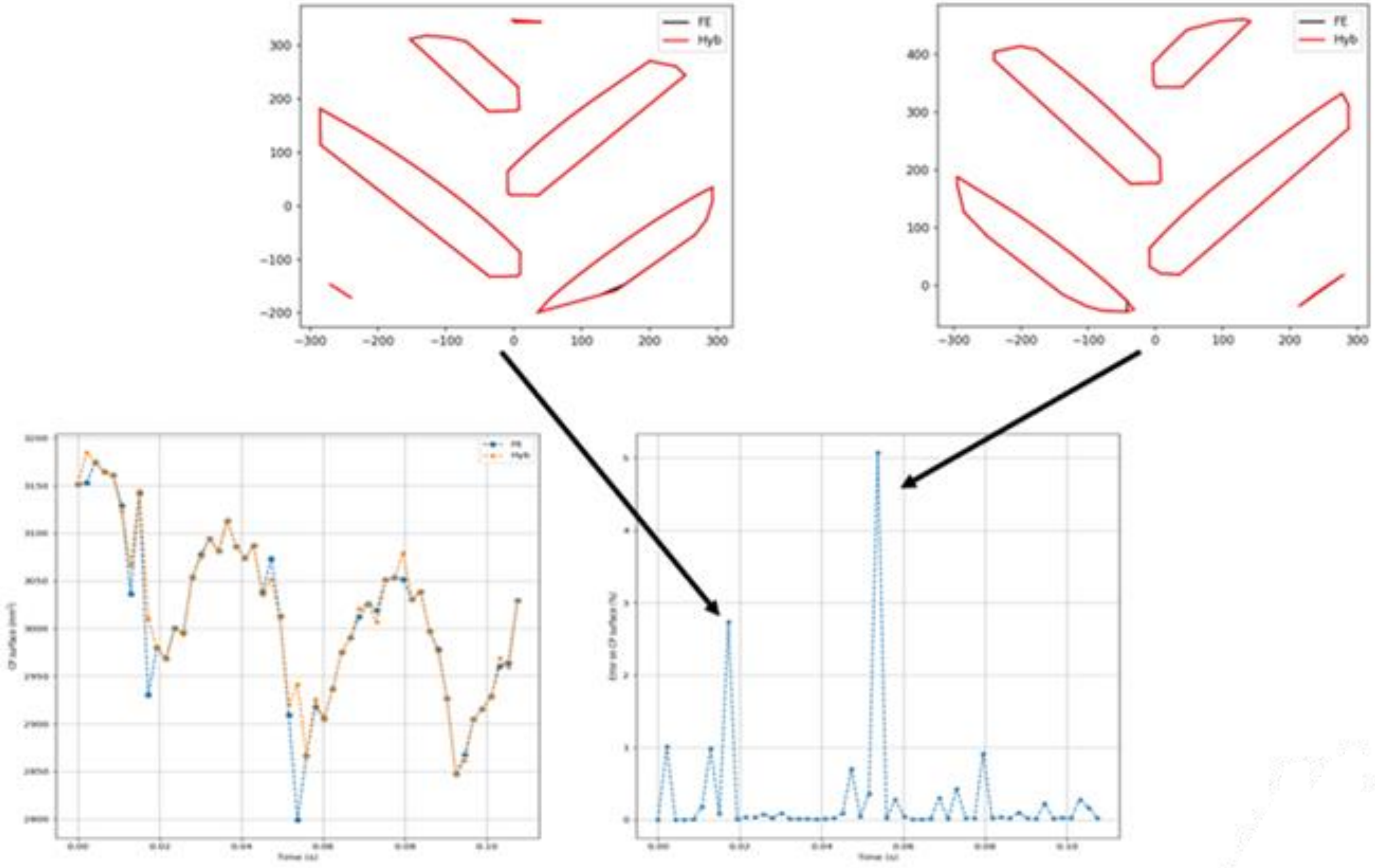
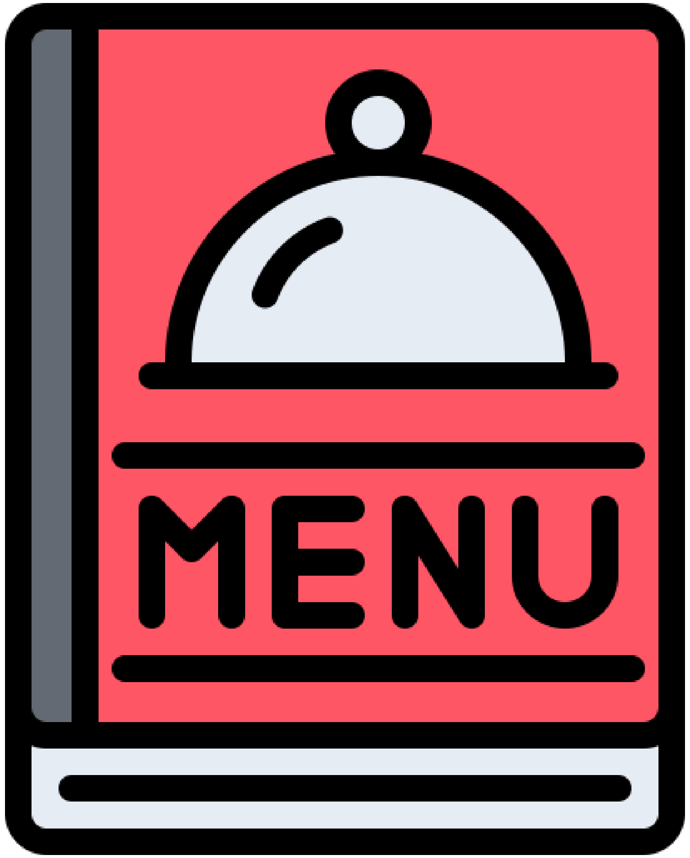
INTEGRATION INTO MICHELIN IN-HOUSE SOLVER: VALIDATION (INITIAL GUESS ONLY)





OUTLINE



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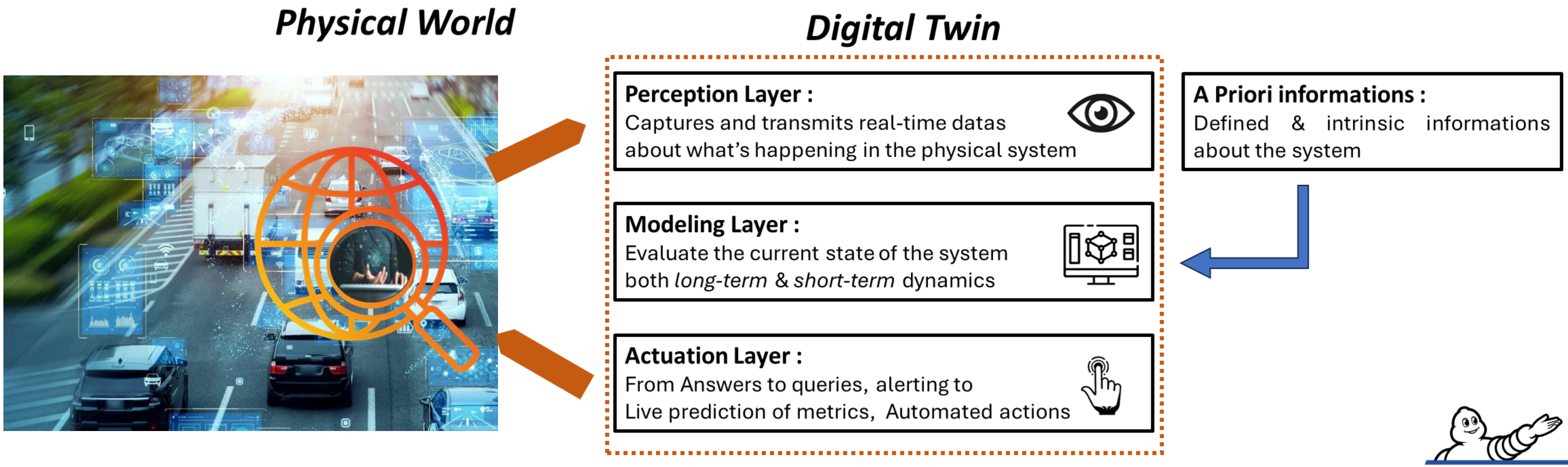
SDV NEEDS RELIABLE & REAL-TIME STATE ESTIMATION OF ITS COMPONENTS

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.



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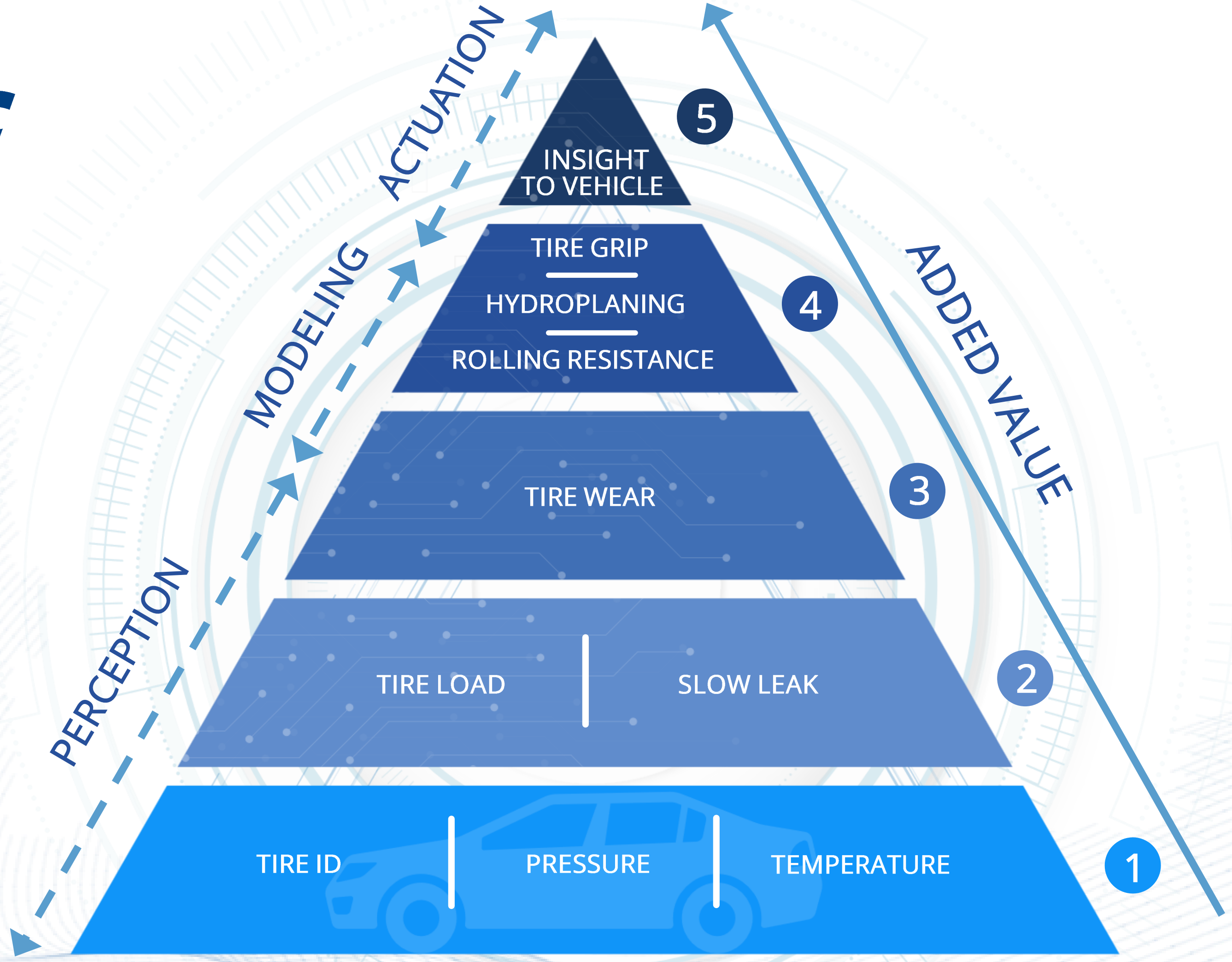
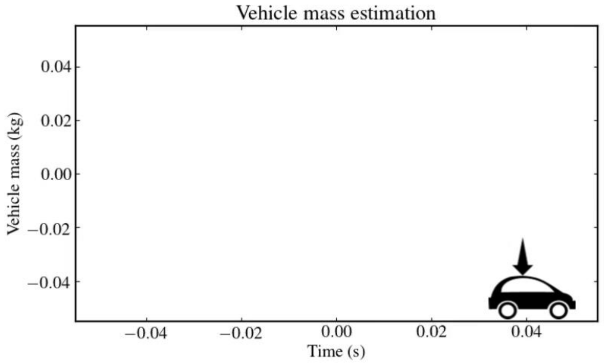
A TIRE DIGITAL TWIN BUILT FROM BASIC TO ADVANCED FEATURES

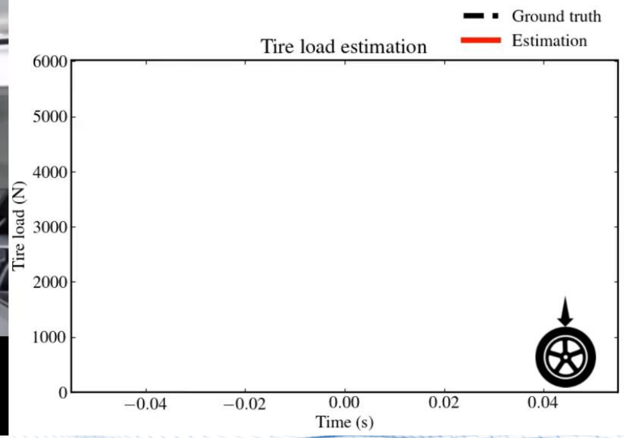
- Need for solid technical foundation
- A digital twin to bring more insights…
- …with higher technical challenge



MICHELIN SMARTLOAD: REAL-TIME ACCURATE ESTIMATION OF VEHICLE AND TIRE LOAD

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

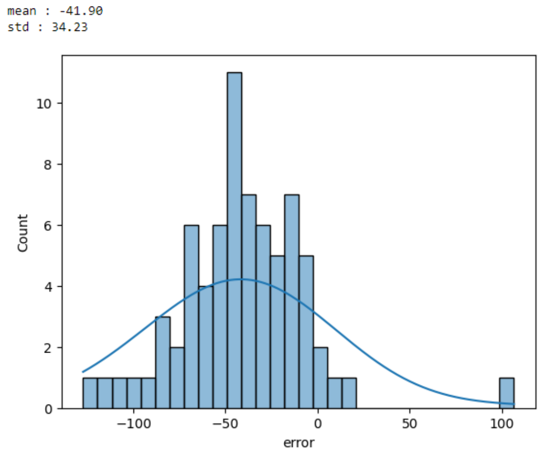


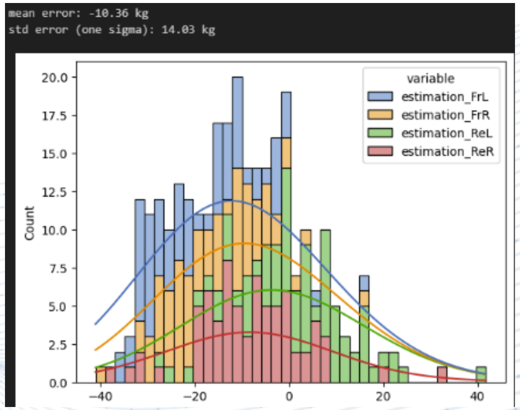


Test passenger car with 25 configurations tested

Error on total vehicle mass: -2% +/- 1,7% at 1σ (42 kg +/- 34 kg)

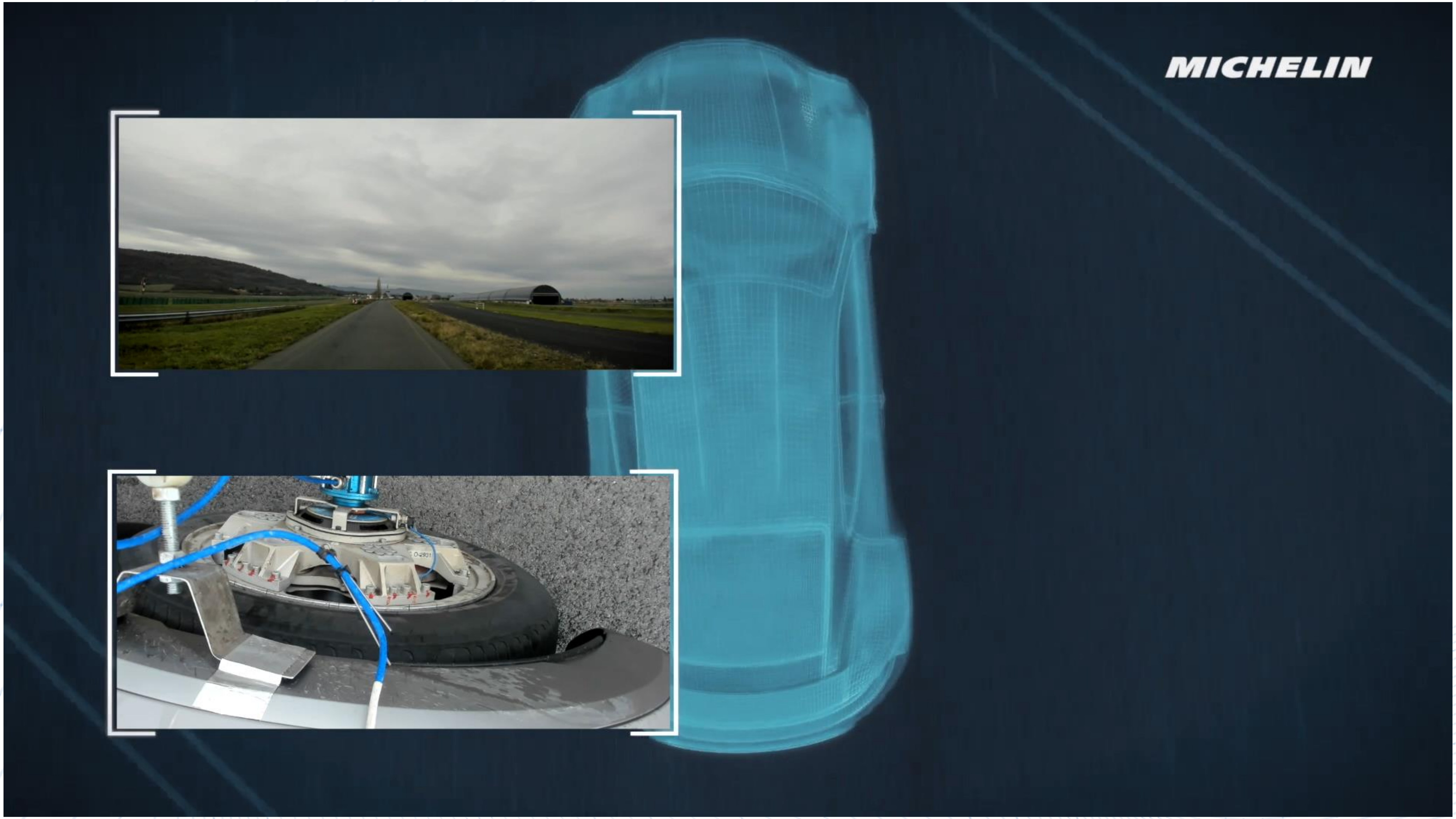
Error on tire load: -1,8% +/- 2,45% at 1σ (10,4 kg +/- 14 kg)





[Video SmartLoad]

ONLINE HYDRO STATUS MONITORING



FROM PHYSICS-BASED SIMULATION TO DIGITAL TWINS ? SOME TAKE AWAYS

Create Tangible Value(s)

- ✓ ***Onboard*** *end-users during dev phase to facilitate UX*
- ✓ ***Deploy*** *Minimum Valuable Product to quickly assess value*

Leverage Relevant Data

- ✓ *Realistic accessibility of data and, above all,* ***relevancy for model training***

Combine with Physics: maturity and relevancy of physics understanding and models

- ✓ *Powerful* ***physics-based models*** *are essential to complement AI*
- ✓ ***Multi-skills*** *teams and teamates: tire, process, materials, datascience, physics, applied maths, scientific computing, signal processing*

Adapt Methodology to the Use Case

- ✓ *From pushed cutting-edge methods to simple yet* ***robust approaches***

THANK YOU