TWINS

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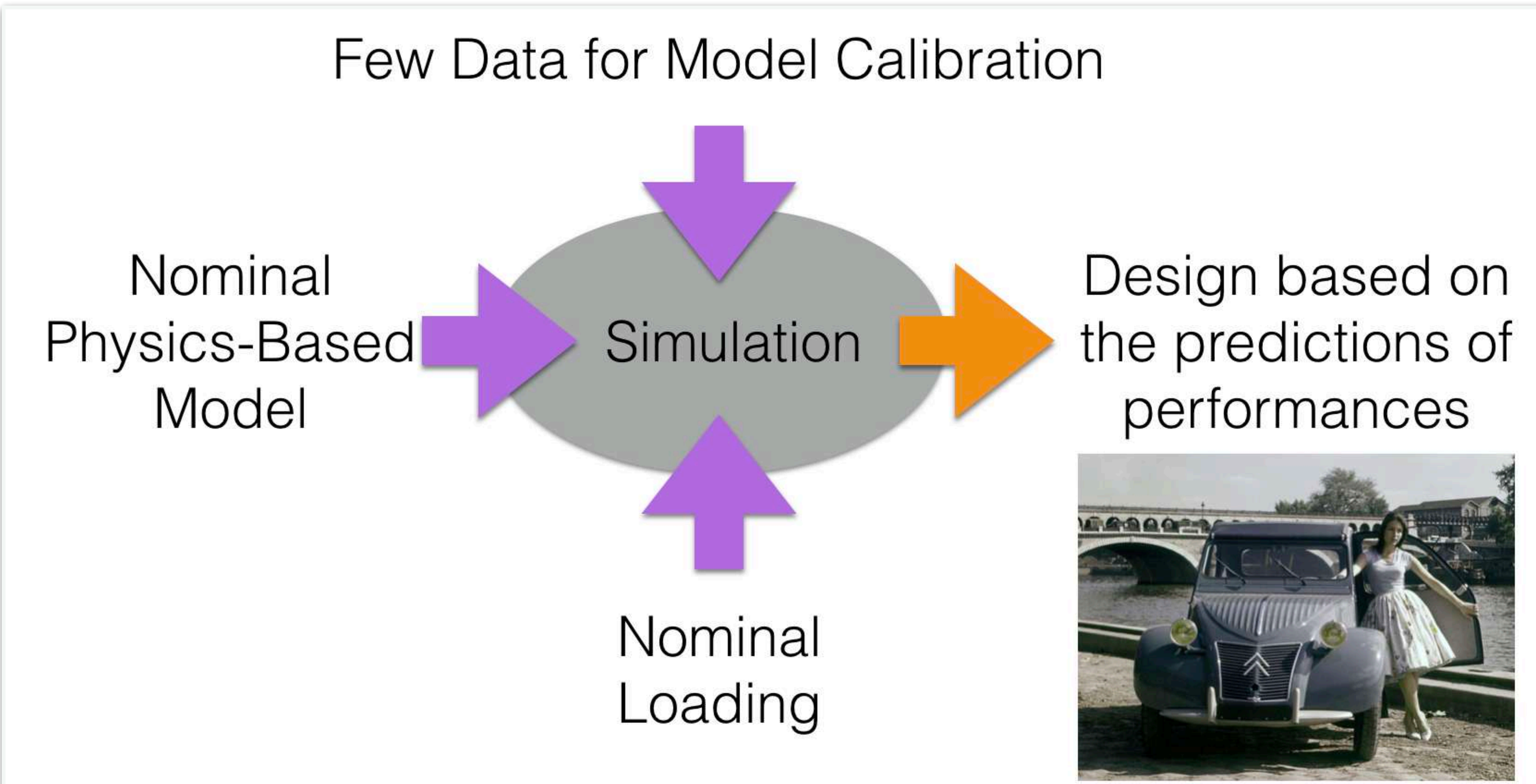
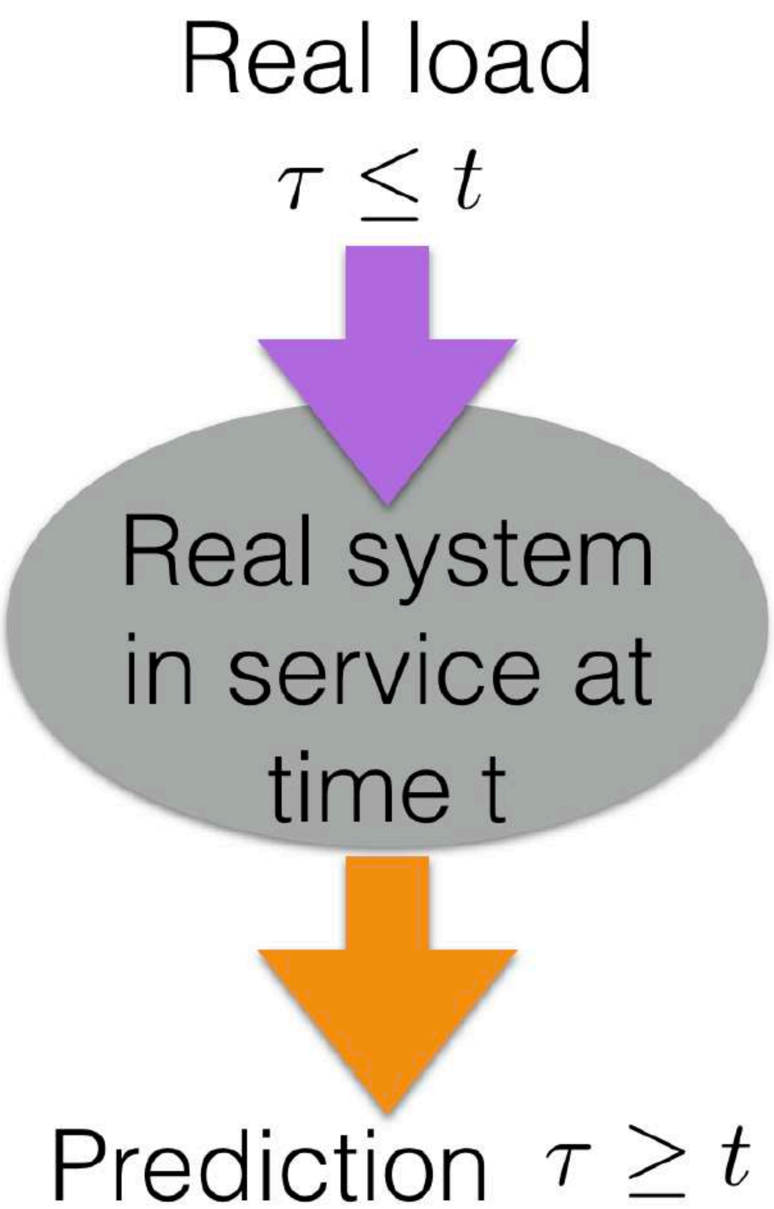

Few Data for Model Calibration
Nominal
Physics-Based
Model
Simulation
Design based on
the predictions of
performances
Nominal
Loading

SBE@XXI



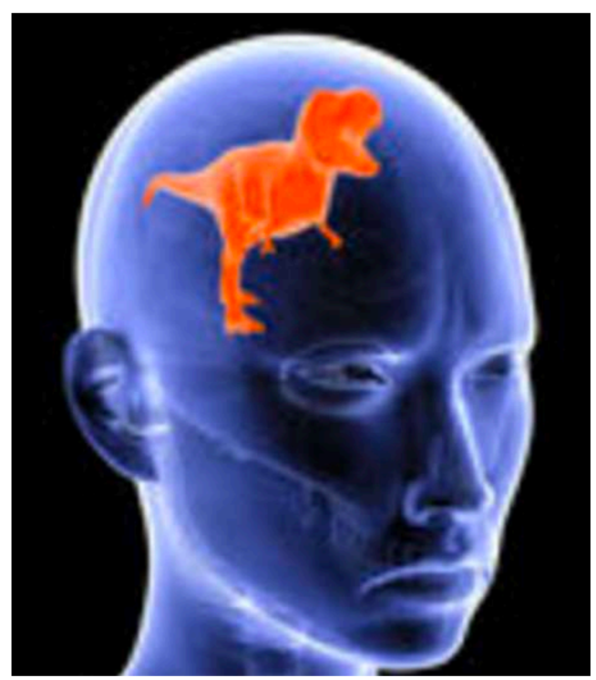
World is changing. Today we do not sell aircraft engines, but hours of flight, we do not sell electric drills but good quality holes, … We are nowadays more concerned by the performance management than by the products themselves …

A Twin is not

A **monitored and controled**
material, process, structure or system

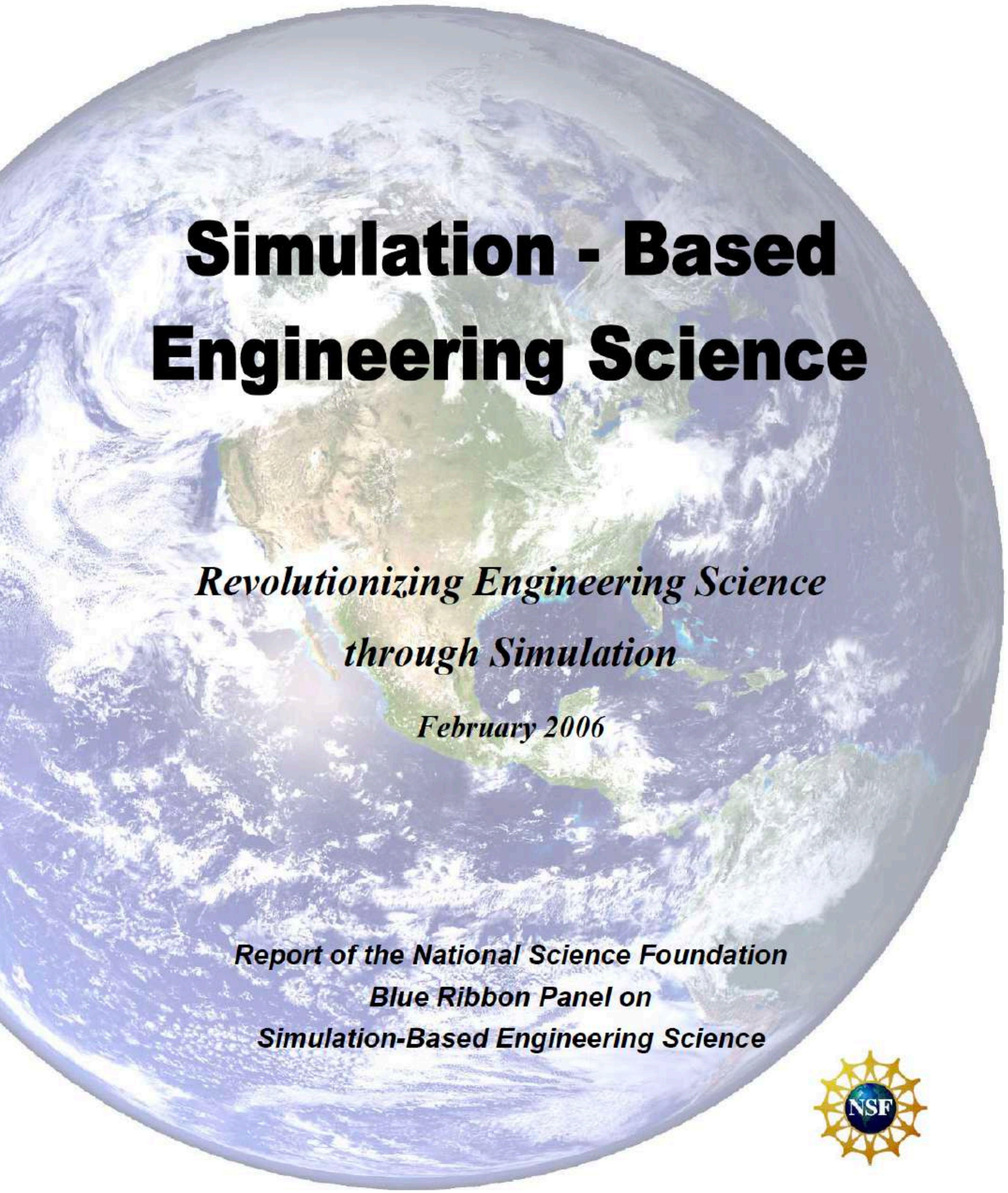
Automation was the 3rd industrial revolution

Model-based or Data-Driven
Transfer Function

Data →  → Decision

Pattern recognition

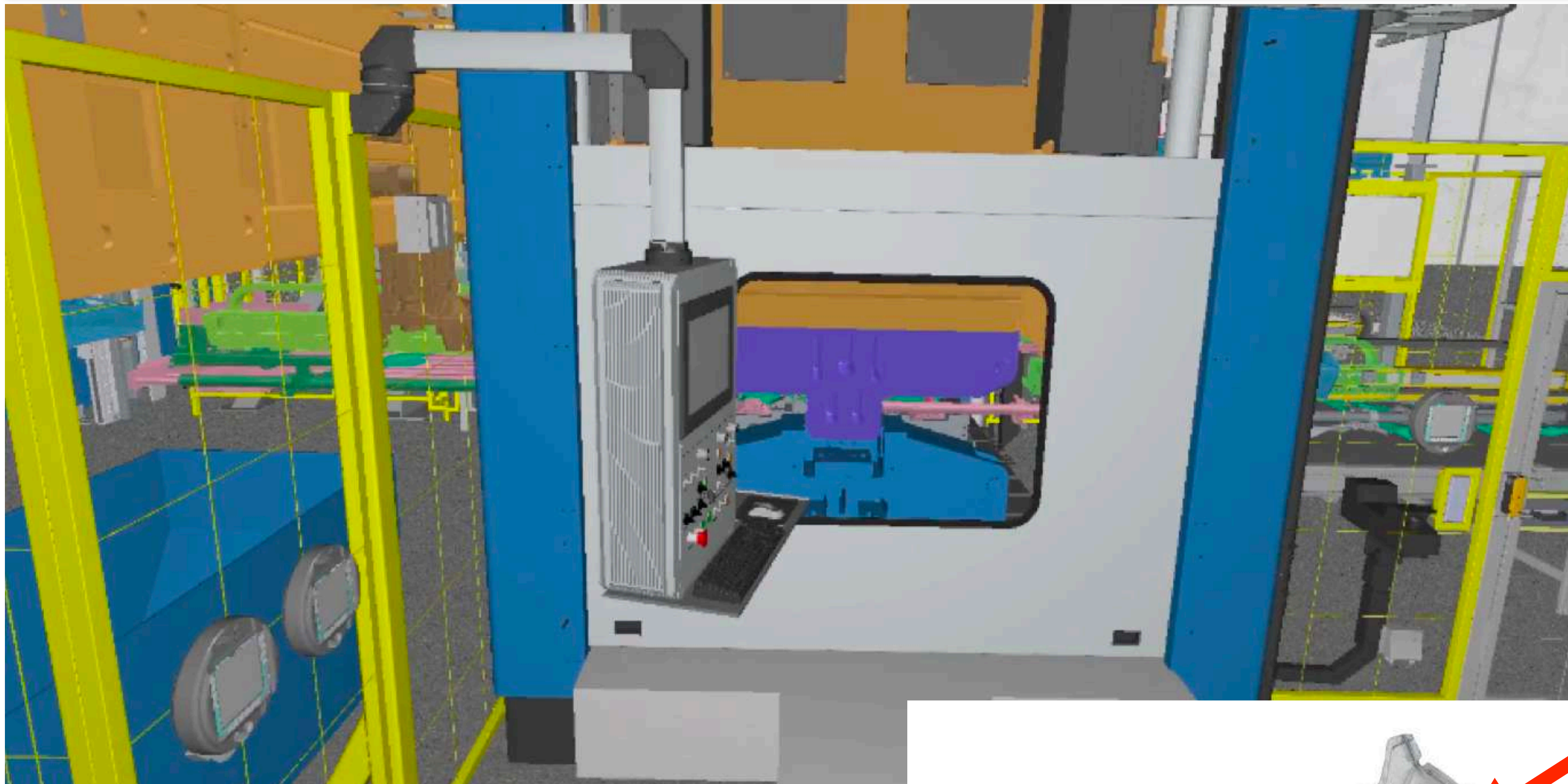
A Twin is not

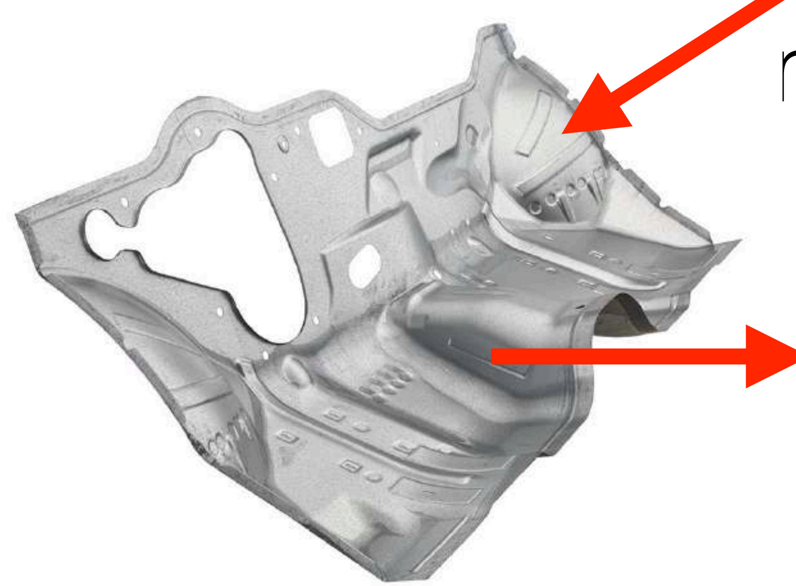


A simply **DDDAS**
-Dynamic Data Driven Application Systems-

Models, even when calibrated (data-assimilation) rarely represent accurately the reality, in particular when addressig systems of systems combining complexity, size and uncertainty …

A Twin should be



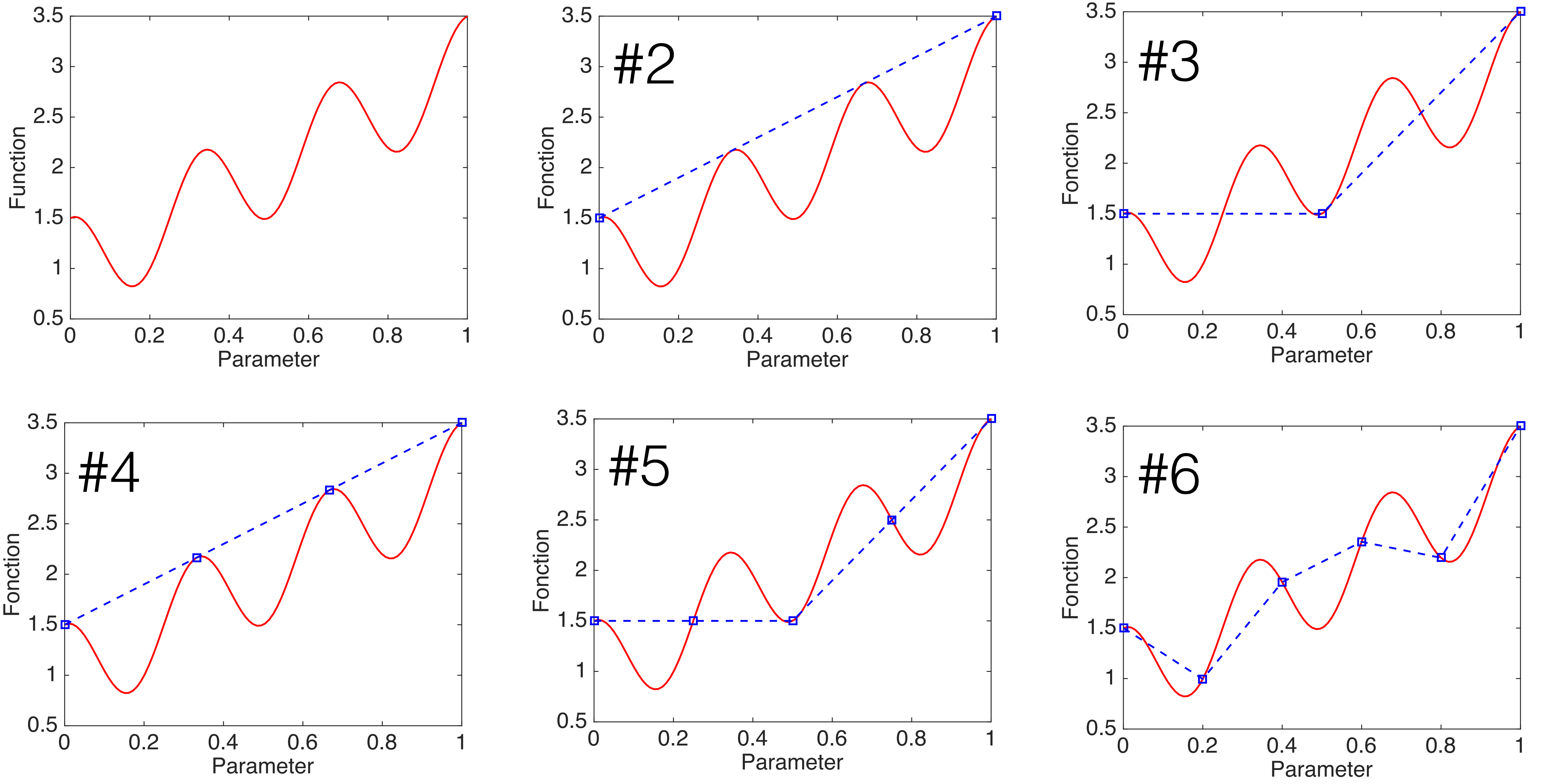


Thickness measurement

Infered residual stress

Frugal, Intrinsic, Holistic, Fast, Accurate, Explanaible, Certifiable & Usable

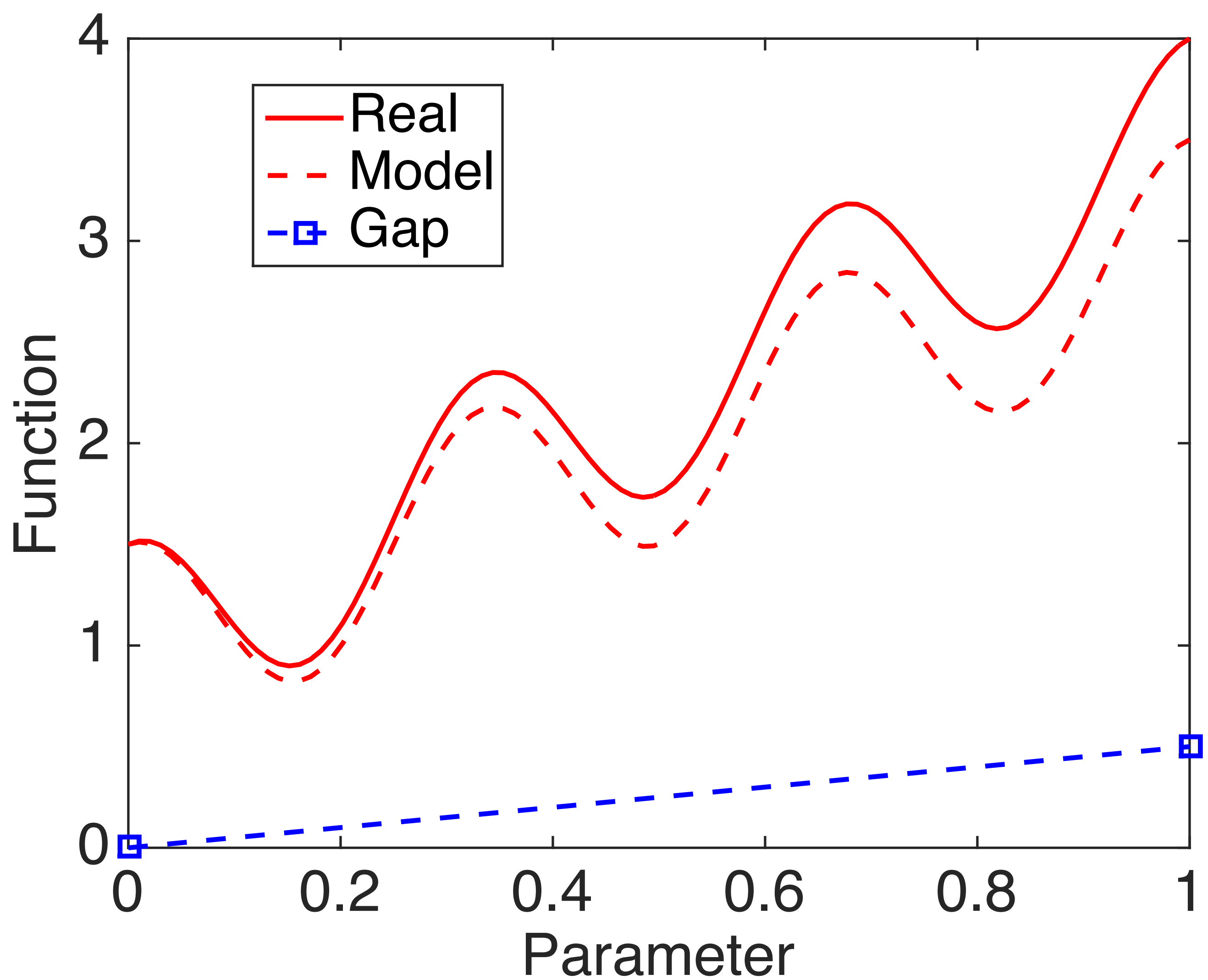
Data-Based Representation



Enormous amounts of data are compulsory for representing strongly nonlinear functions

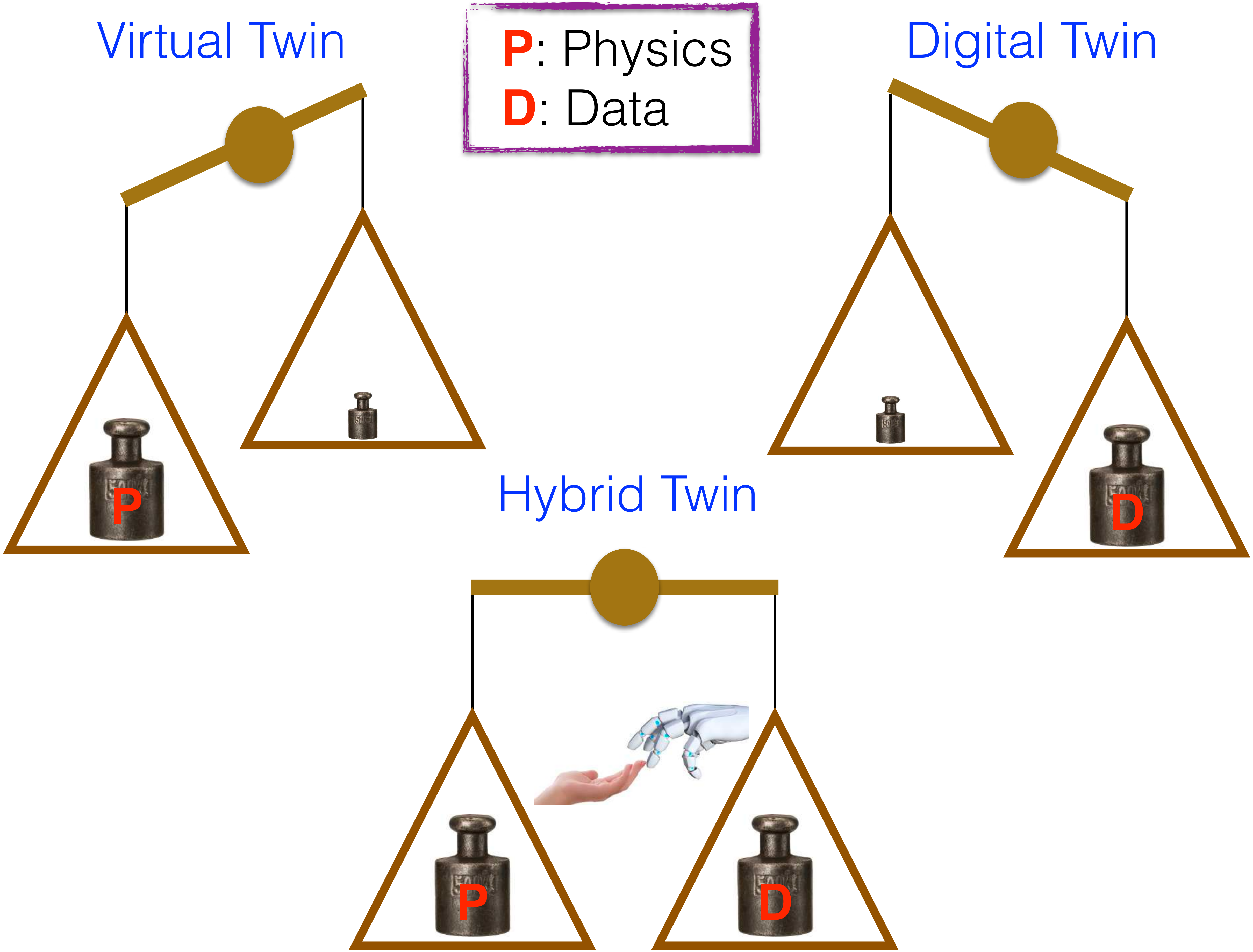
The Hybrid Paradigm

Behavior = Model + Deviation (Ignorance)



In this example the deviation being lineal it is accurately approximated with only two data

In the general case, being the deviation much less nonlinear, its approximation requires much less data



Virtual Twin
P: Physics
D: Data
Digital Twin
P
D
Hybrid Twin
P
D

PROS

The Physics-Based Model reduces the data needs

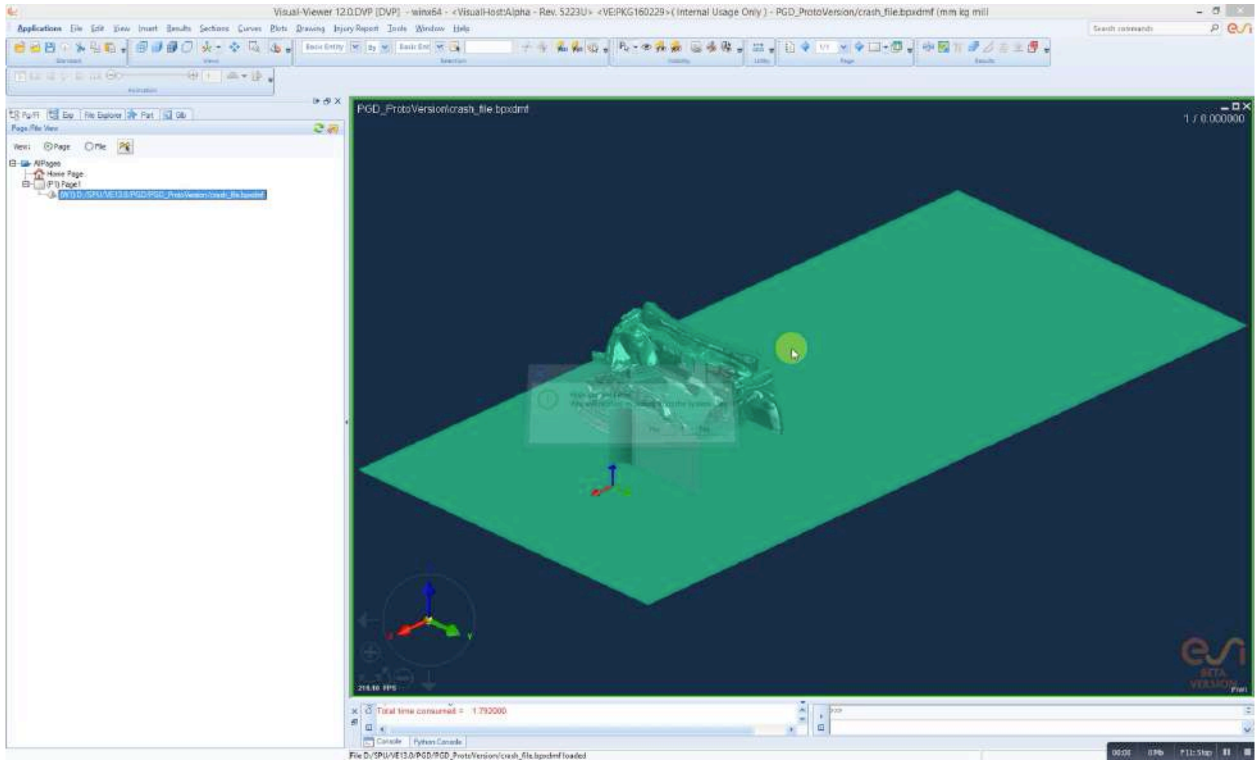
The Physics-Based Model enables certification

Issues = Opportunities

The Physics-Based Model must be solved in real-time

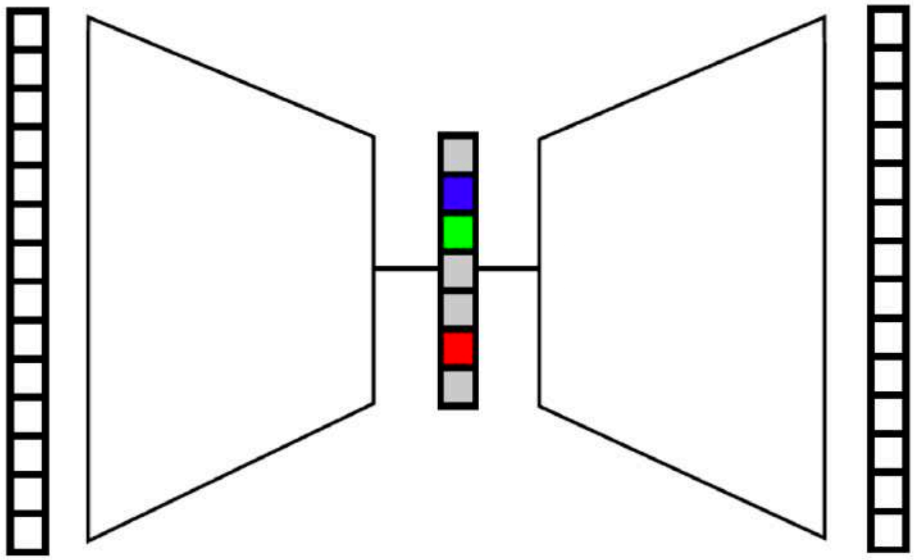
The Data-Driven Model must be learned in-the-fly while using few amount of data

What is needed



Real-Time Physics +

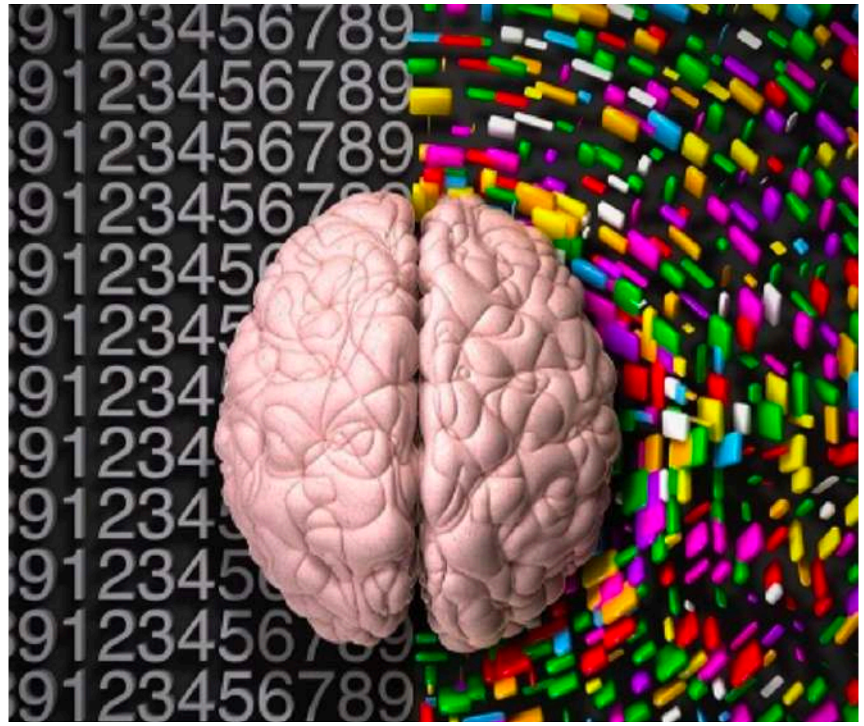
Physics aware AI

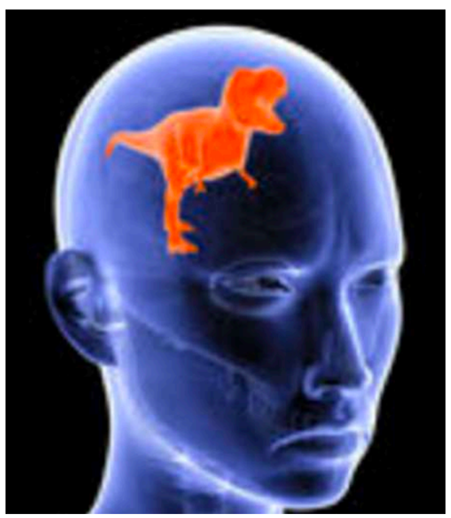


to model the gap between model & measurements

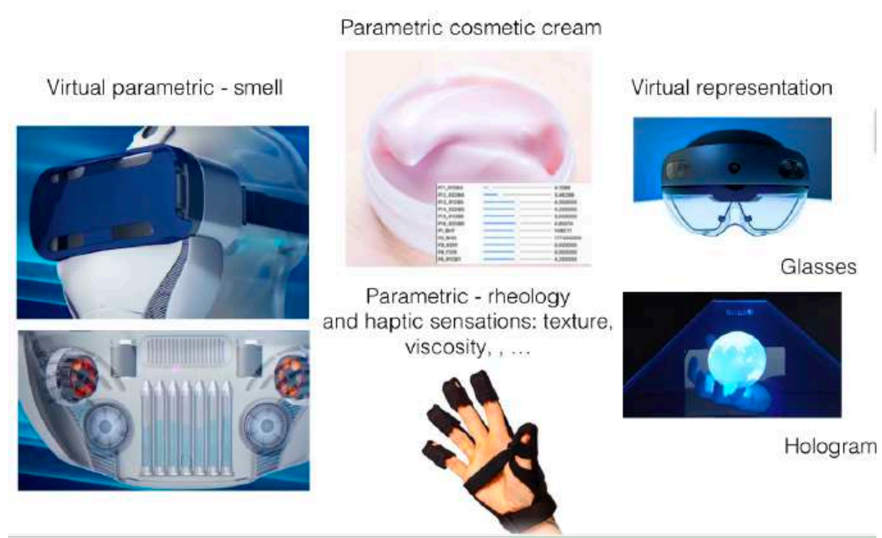
and human centric

Hybrid modeling
physics-based
and data-driven

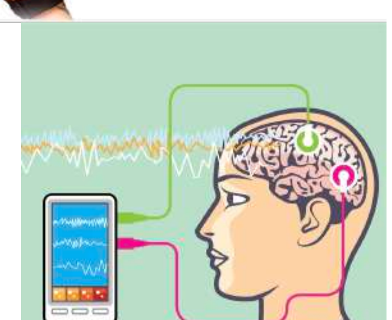




Control, pattern recognition and decision making

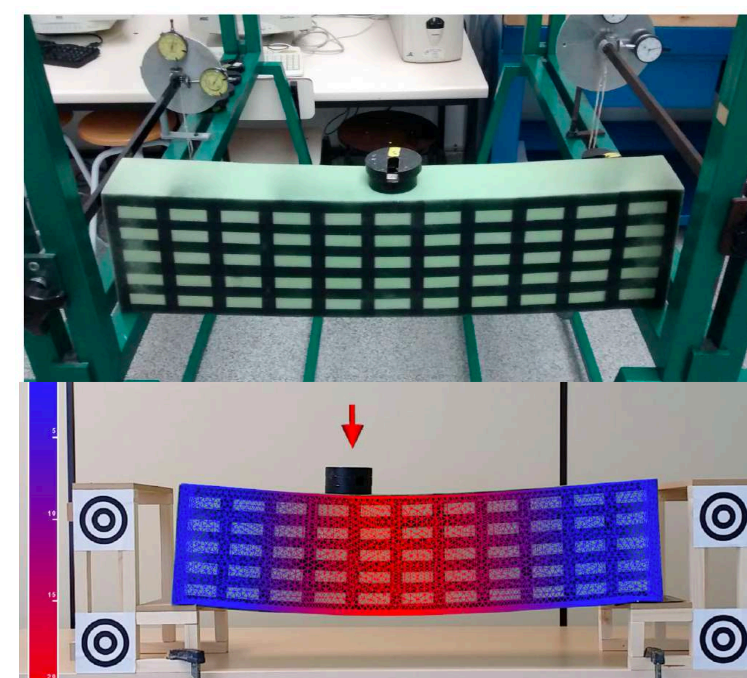


Multisensorial & Emotionnal

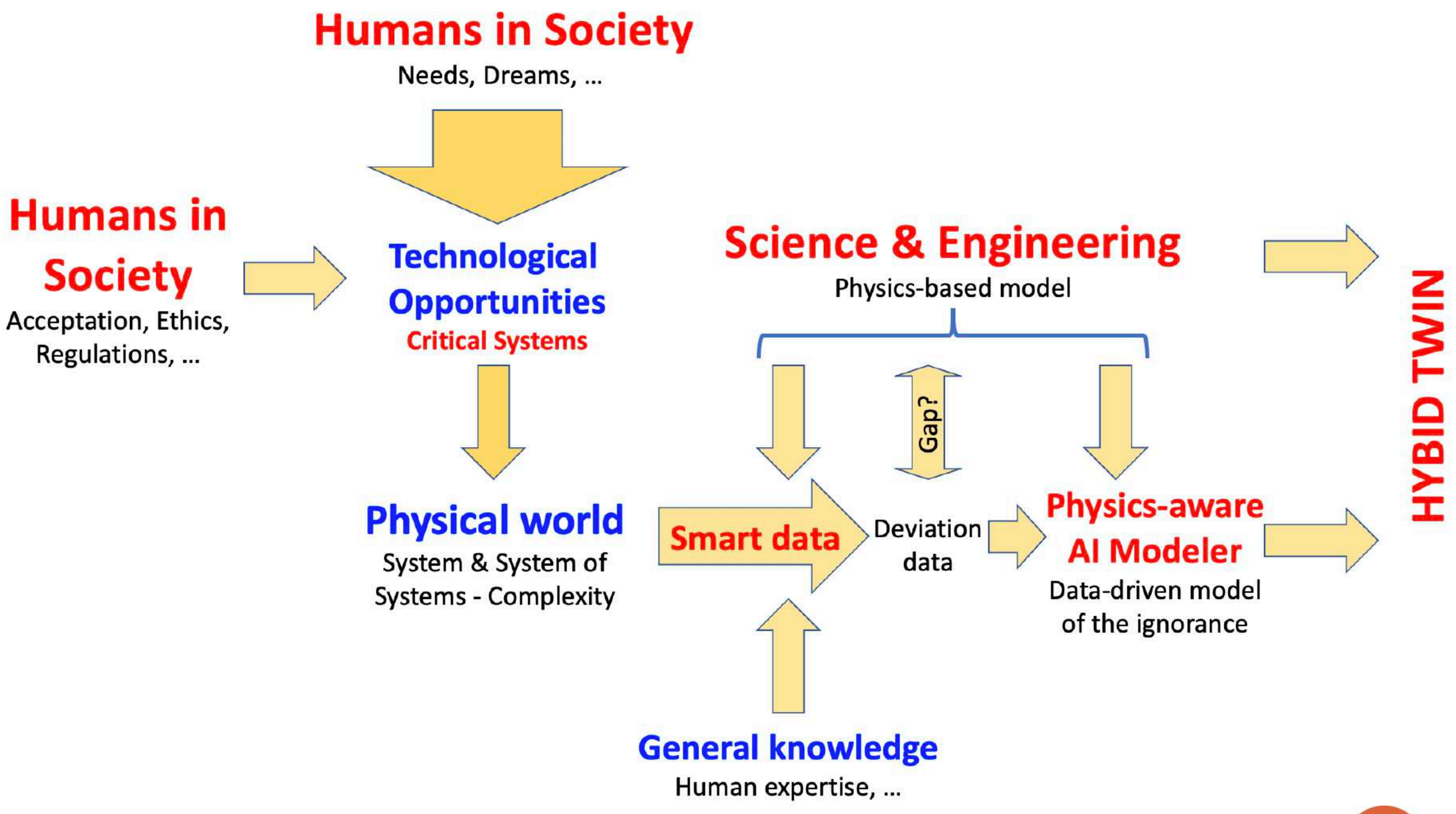


Virtual, augmented & hybrid reality

DT that learns theirselves

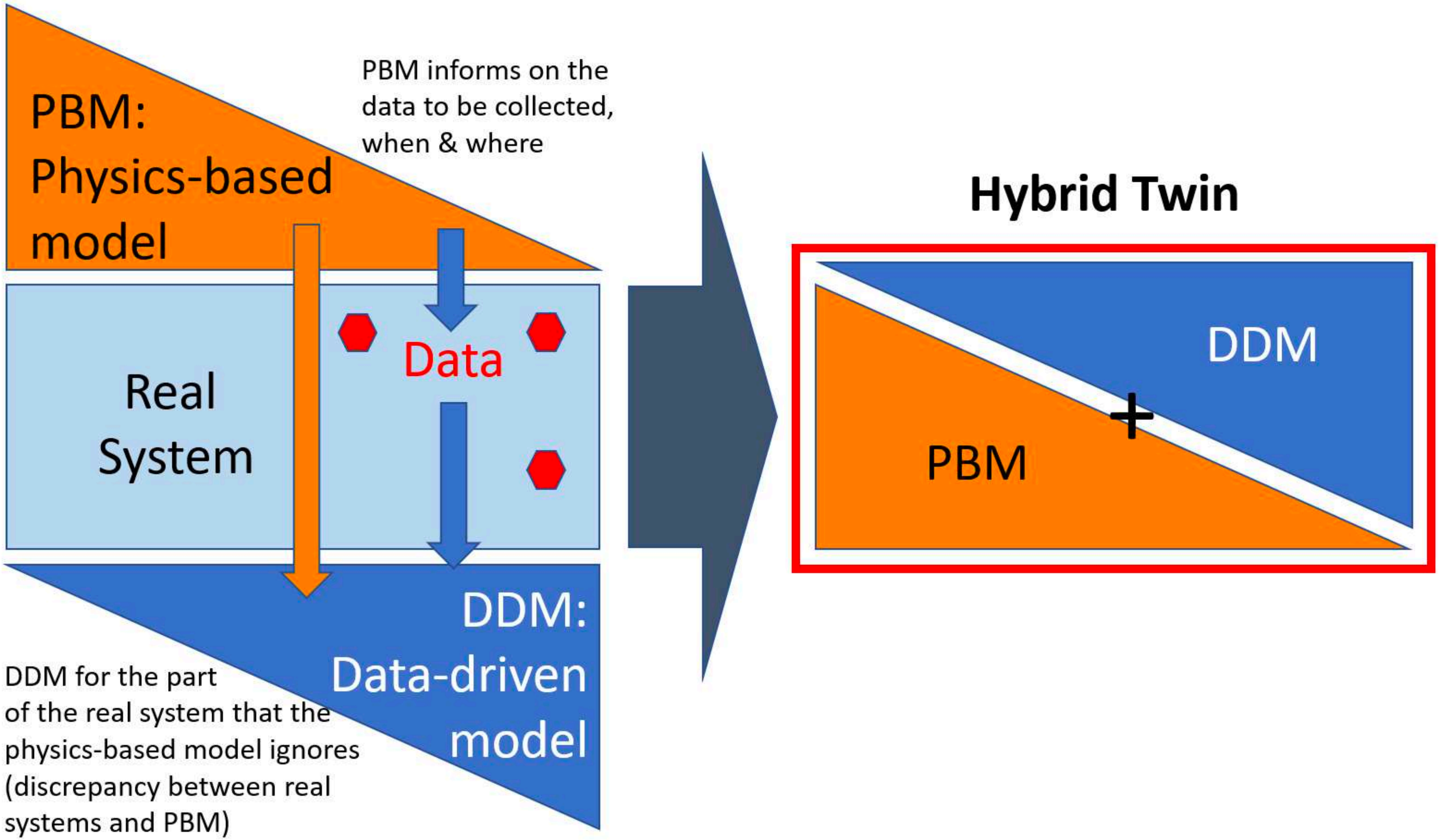


The HT Platform



get it right®

The HT Platform



Real-time simulation via MOR

FEM

$$u(x,t) \approx \sum_{i=1}^{\mathtt{N}} U_i(t) N_i(x)$$

$$\mathbf{KU} = \mathbf{F}$$

POD

learning $\longrightarrow$ $\phi_i(x), \; i = 1, \cdots, \mathtt{R}$

$$u(x,t) \approx \sum_{i=1}^{\mathtt{R}} u_i(t) \phi_i(x)$$

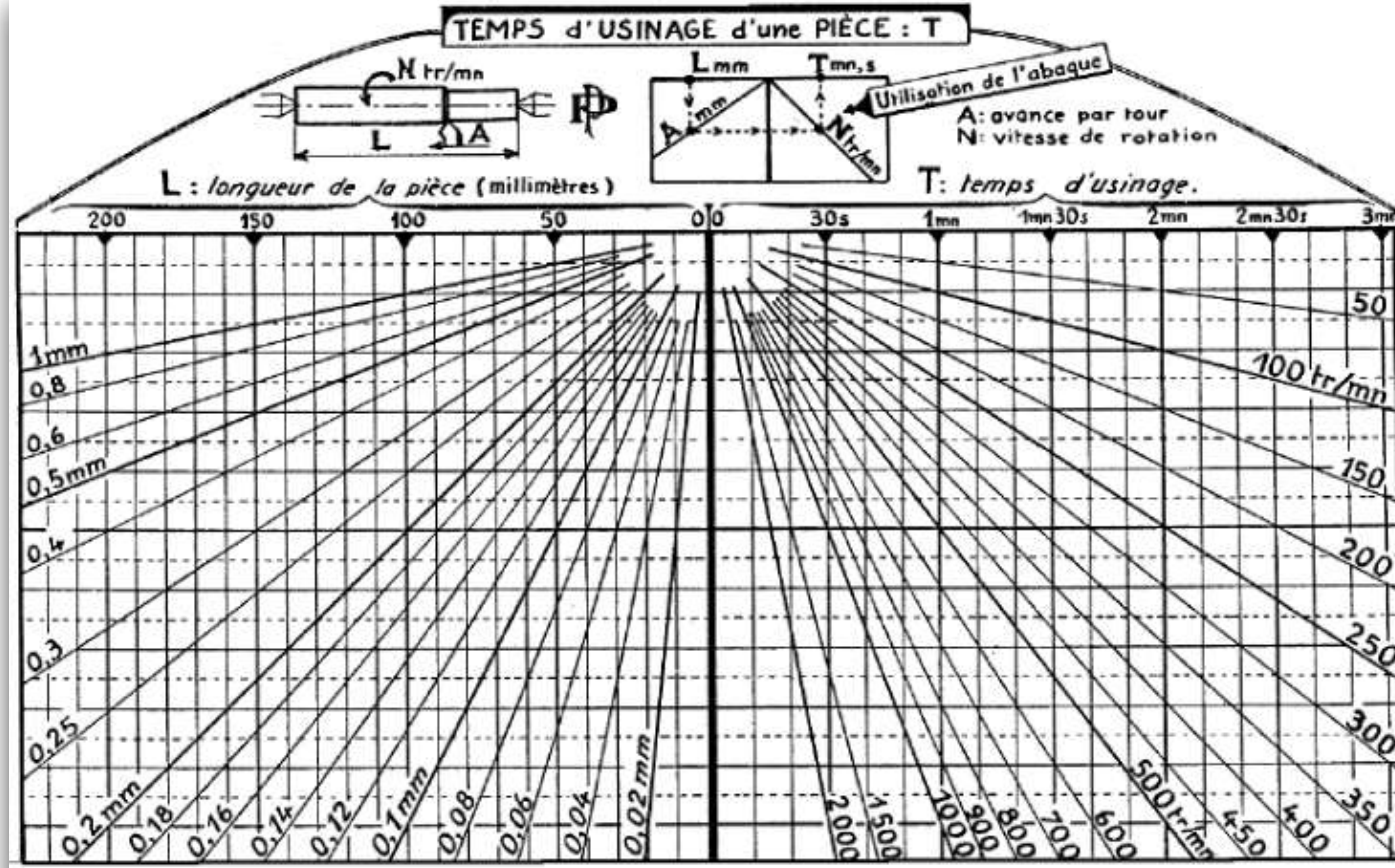
$$\mathbf{ku} = \mathbf{f}$$

PGD

$$u(x,t) \approx \sum_{i=1}^{\mathtt{M}} T_i(t) X_i(x)$$

Vademecum $u(x,t,p) \approx \sum_{i=1}^{\mathtt{M}} T_i(t) X_i(x) P_i(p)$

Machining vademecum



Parametric solutions in action

$$u(x,t,p) \approx \sum_{i=1}^{M} T_i(t) X_i(x) P_i(p)$$

Almost

- Real-time simulation
- Real-time optimization
- Real-time inverse analysis
- Real-time uncertainty propagation
- Real-time control

Non-Intrusive PGD-based meta-modeling

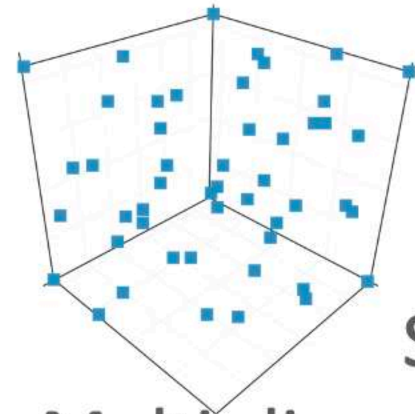
Commercial software

SSL, sPGD, …

Parametric solutions

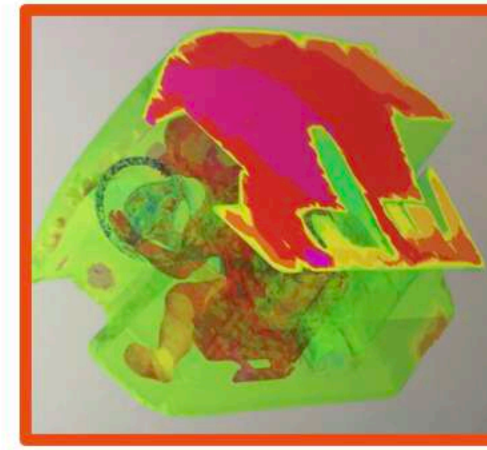
$$u(x,t,p) \approx \sum_{i=1}^{\mathtt{M}} T_i(t) X_i(x) P_i(p)$$

Vademecum



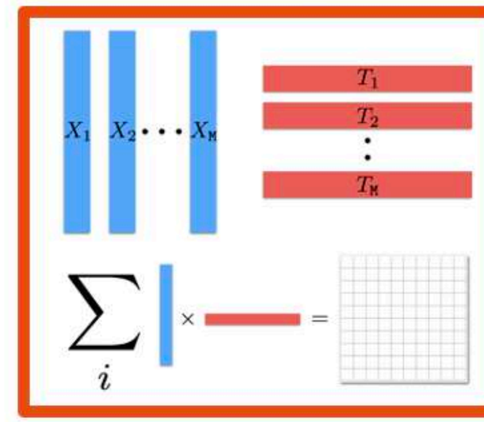
Sparse Multi-dimensional DOE

Runs of the HF solver



Solution compression (RB):

POD, PGD, CUR, EIM, Cross, …



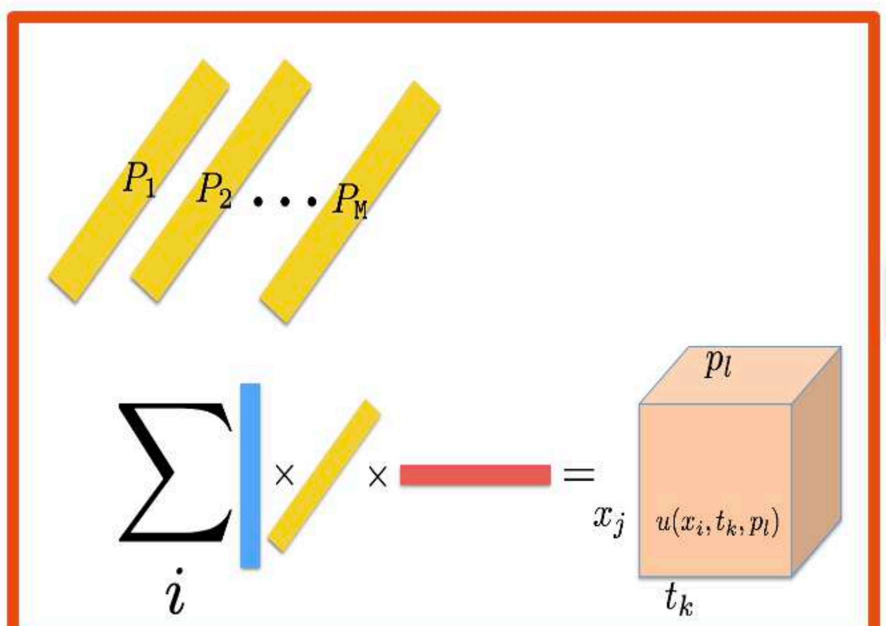
SSL,

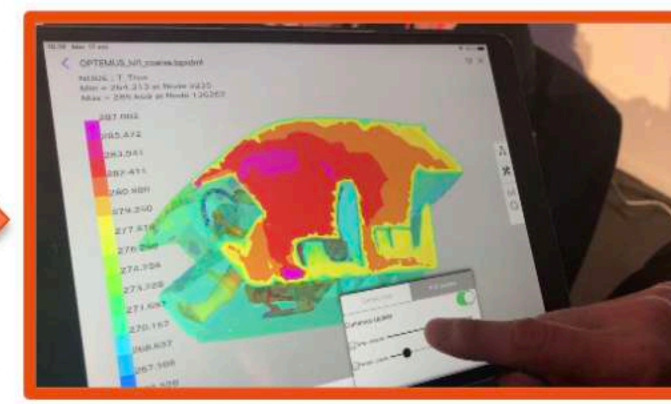
sPGS,

msPGD,

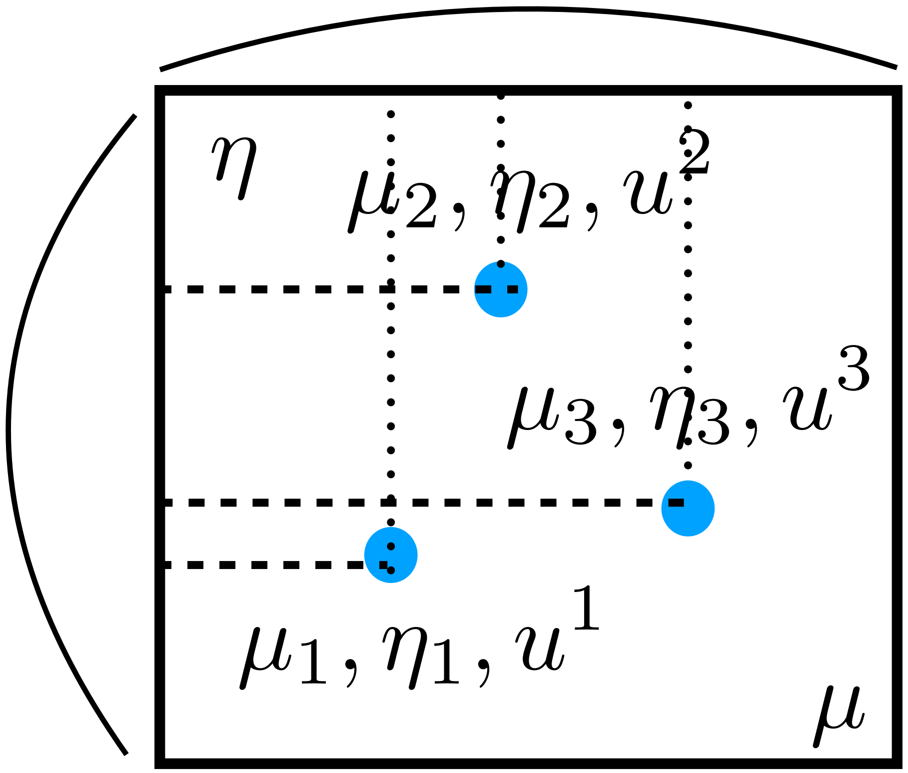
s2PGD,

ANOVA-PGD, …





sPGD



Linear regression

$$u(\mu, \eta) = a + b\mu + c\eta$$

sPGD

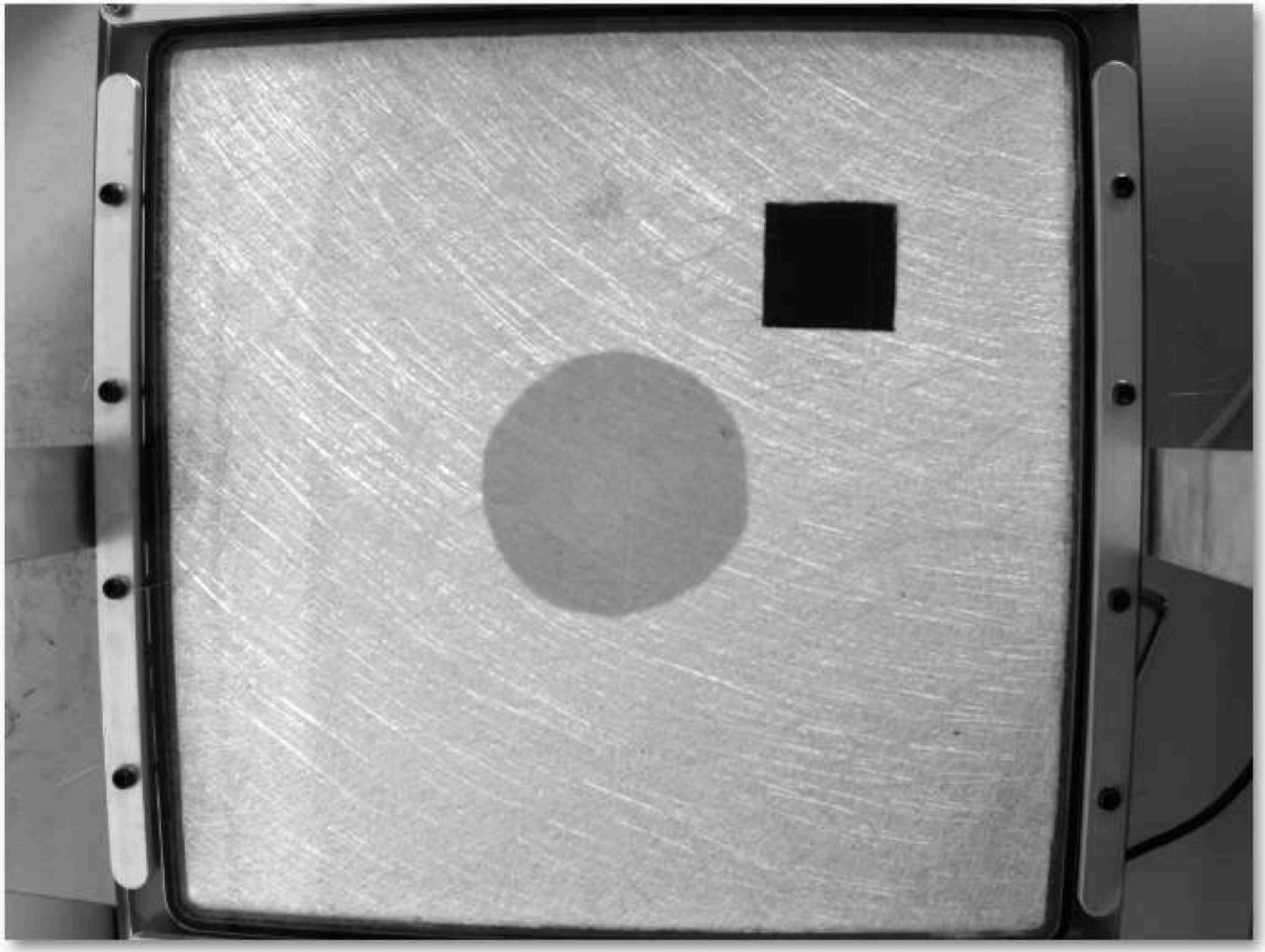
$$u(\mu, \eta) = \sum_i M_i(\mu) E_i(\eta)$$

$$[1, \mu, \eta, \mu^2, \mu\eta, \eta^2, \mu^2\eta, \mu^2\eta^2, \mu\eta^2]$$

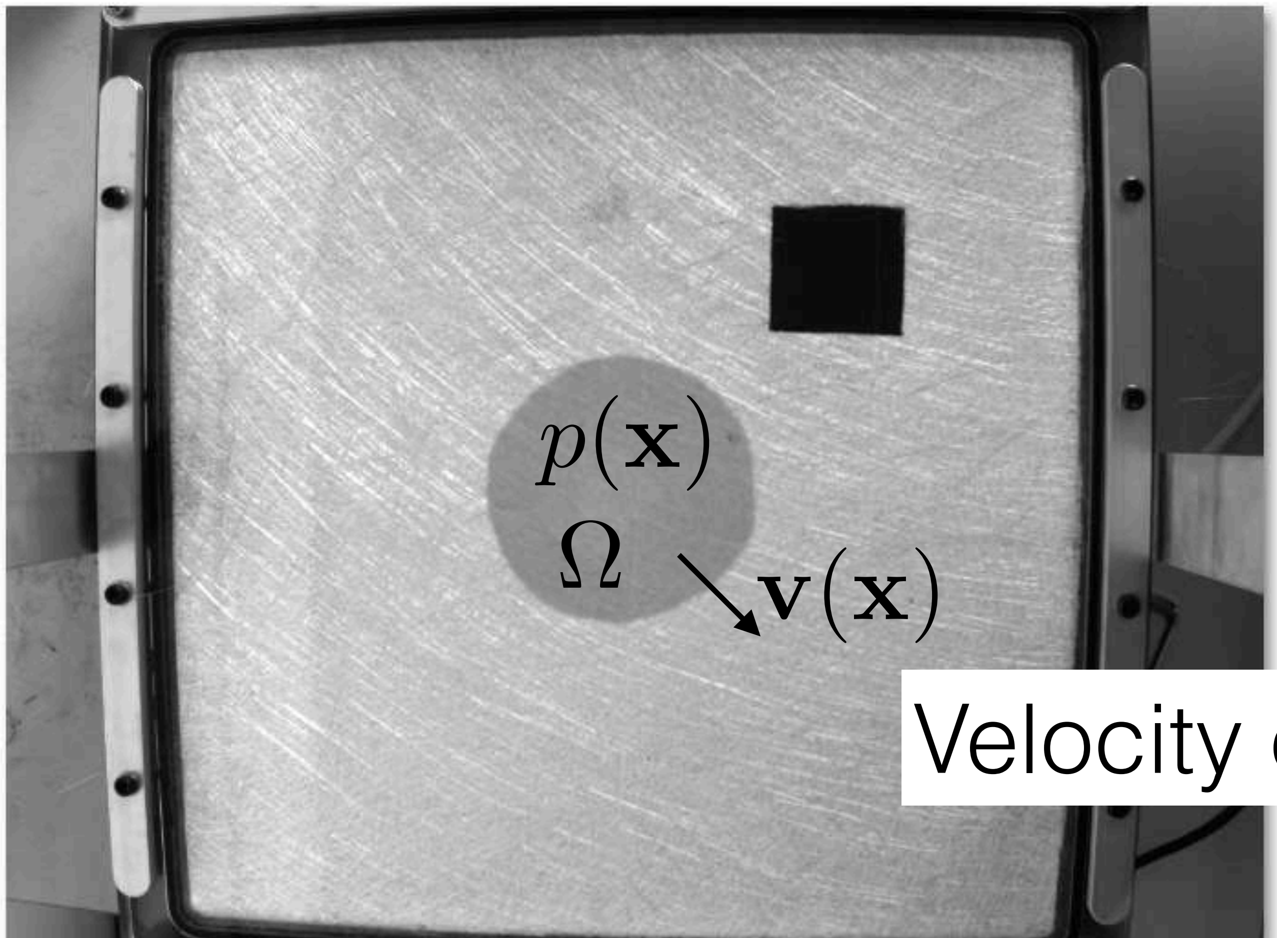
specially adapted for addressing nonlinear regression in multi-parametric settings in the low data limit

Example

The system & the goal



The existing knowledge



Fluid domain Ω

Point in the fluid domain $\mathbf{x}$

Pressure in the fluid $p(\mathbf{x})$

Velocity of each point in the fluid $\mathbf{v}(\mathbf{x})$

Fluid behavior $\mathbf{v}(\mathbf{x}) = -\mathbf{K} \cdot \nabla p(\mathbf{x})$

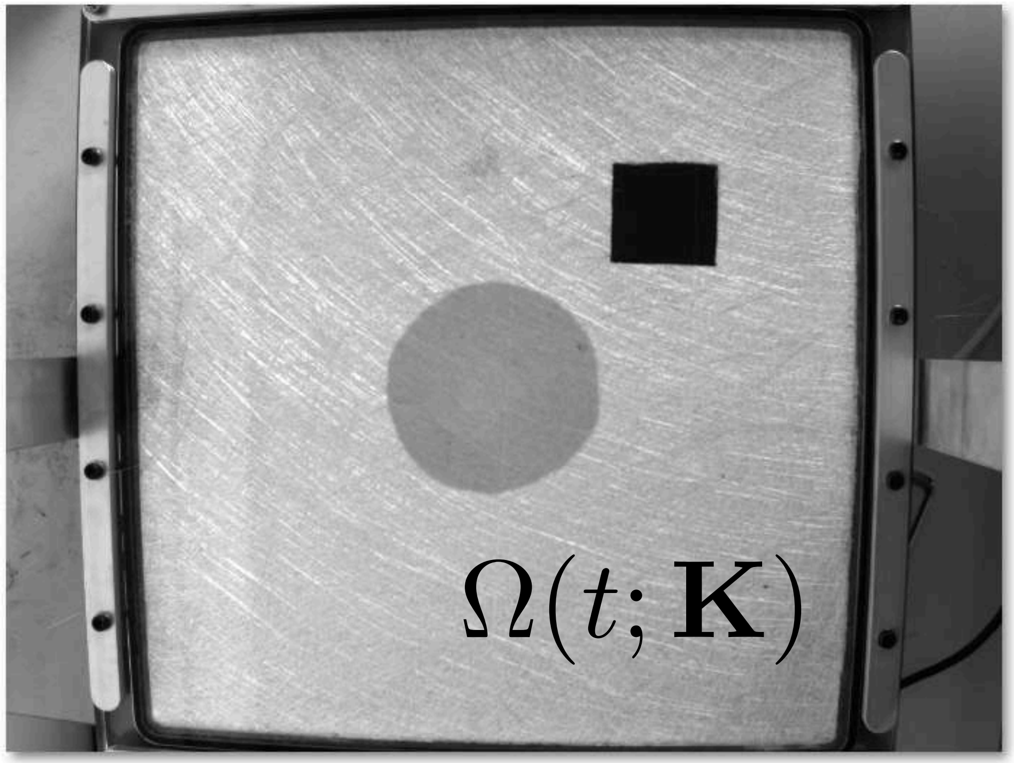
Fluid conservation $\nabla \cdot \mathbf{v}(\mathbf{x}) = 0$

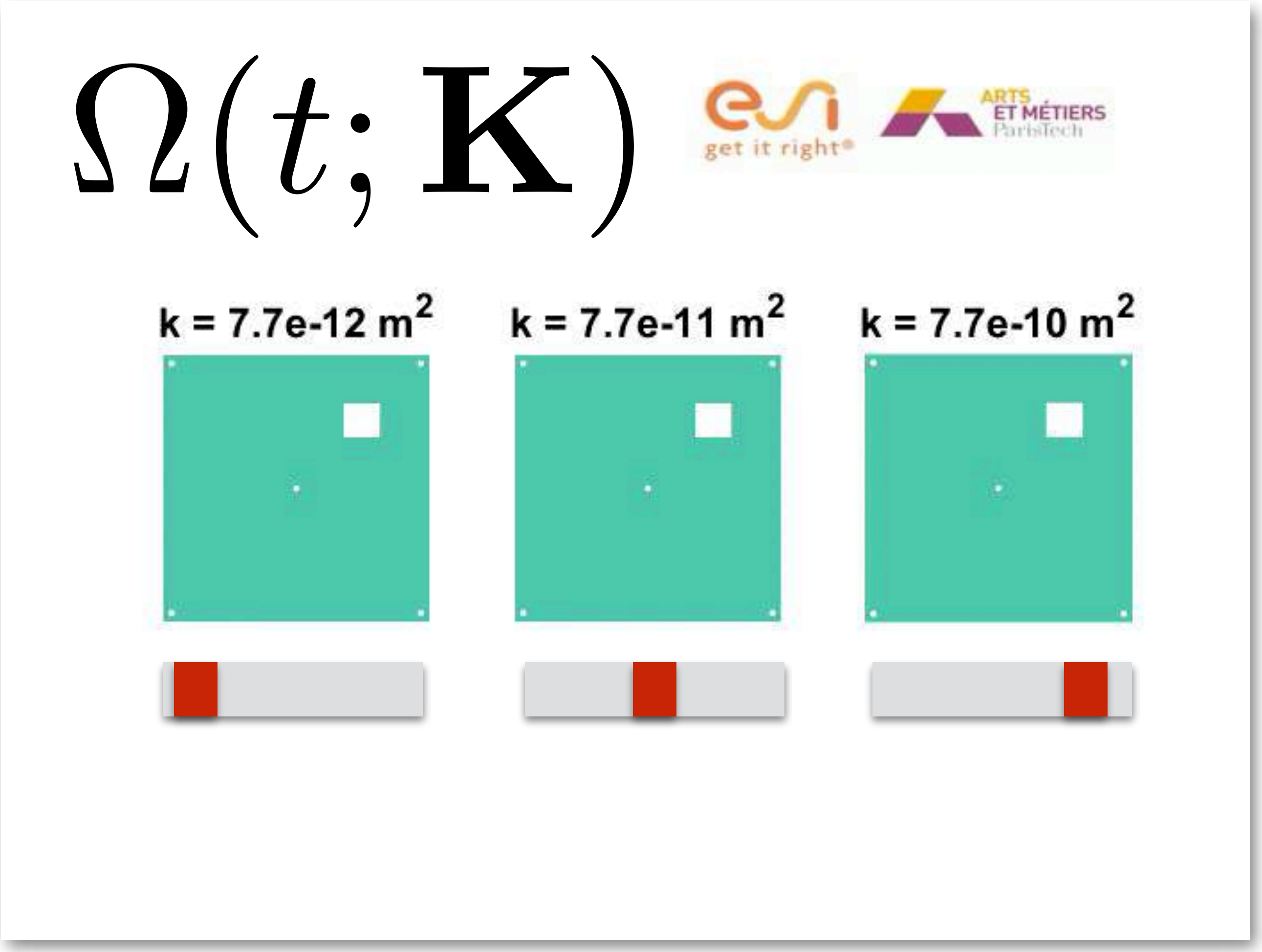
$$\nabla \cdot \{\mathbf{K} \cdot \nabla p(\mathbf{x})\} = 0$$

Physics in real time

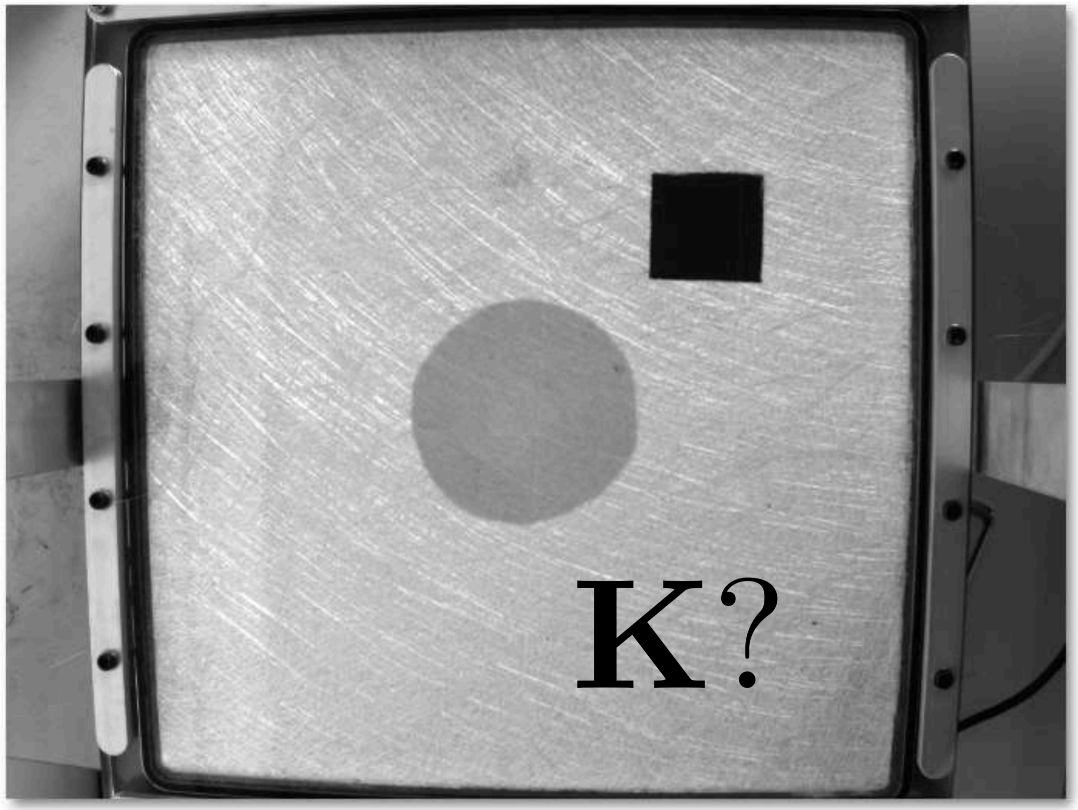
$$\nabla \cdot \{\mathbf{K} \cdot \nabla p(\mathbf{x})\} = 0$$

Commercial Software &
Model Order Reduction

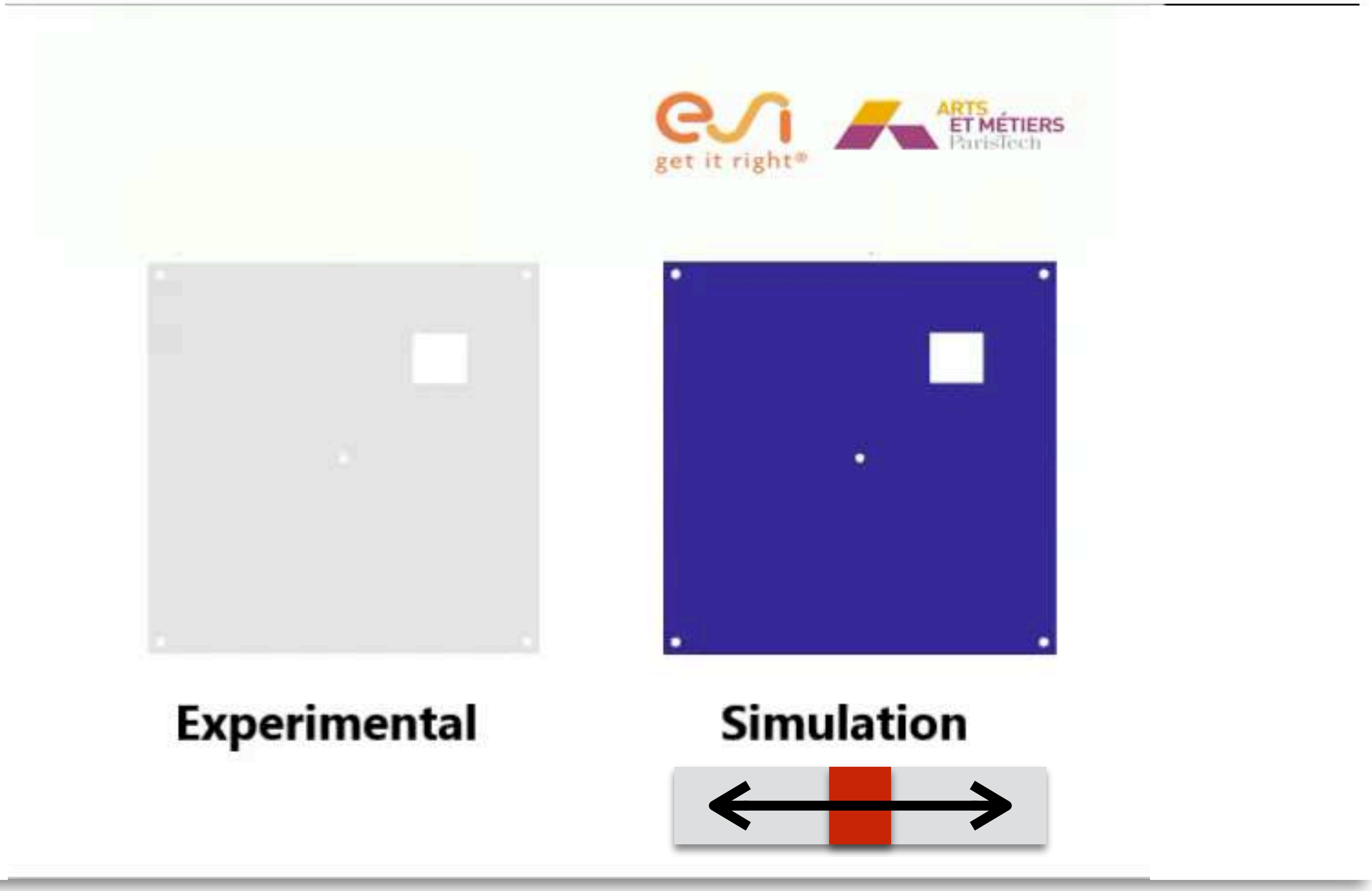




Real time model calibration

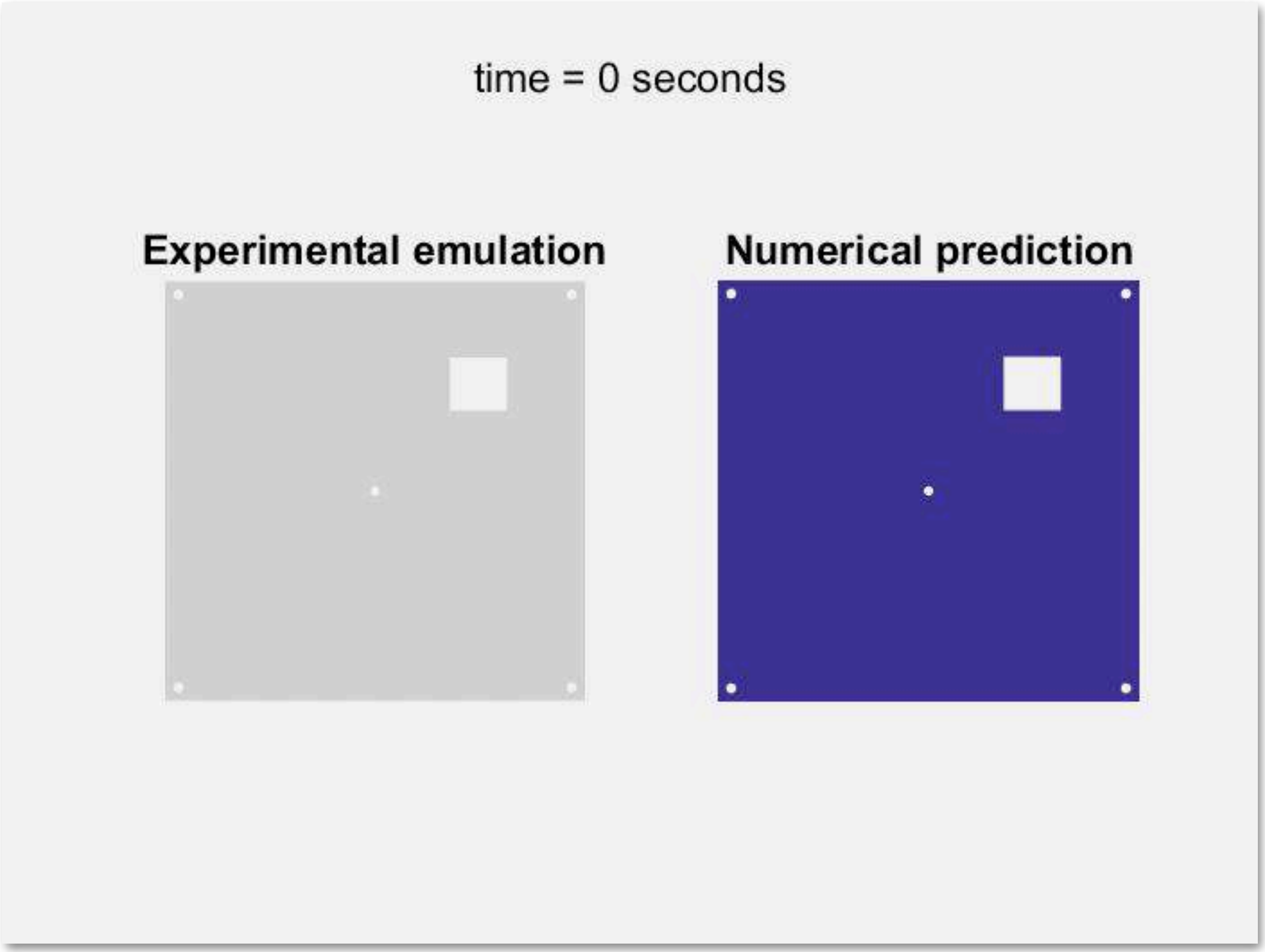


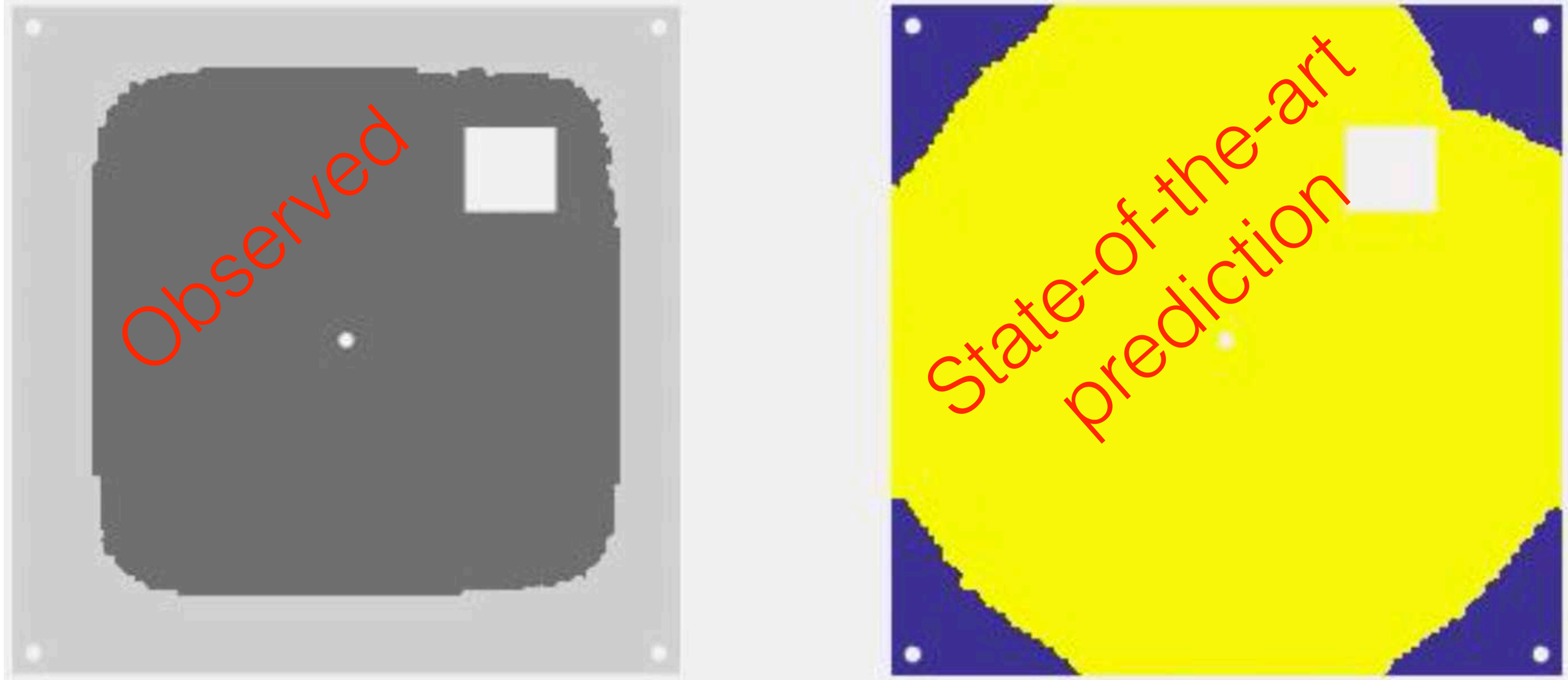
$$K = \texttt{argmin}_{K^*} |\Omega^{\texttt{num}}(K^*) - \Omega^{\texttt{exp}}|$$



$\mathbf{K}?$

Model prediction versus measures




Observed
State-of-the-art
prediction

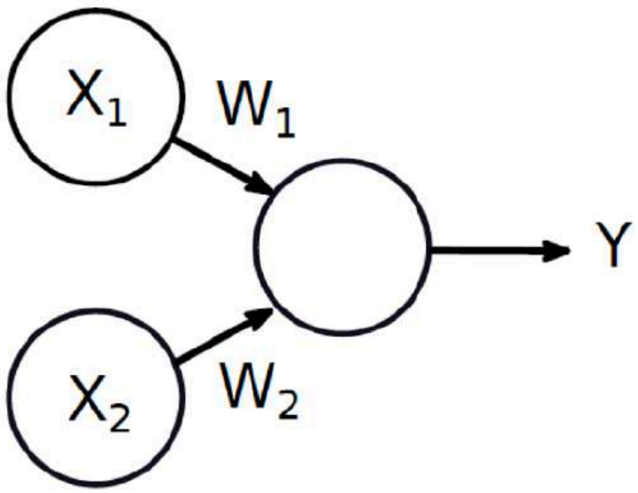
Data-driven model of the deviationn

... in the scarce data limit

Some of our proposals:

- **Multi-Local Sparse PGD**-Based NL Regression
- ***Code2Vect*** for heterogeneous / scarce data
- **Reduced Incremental Dynamic Mode Decomposition**
- **Thermodynamically Consistent ML**
- **Physically Informed Neural Networks**:
  combining tensor-flow and tensor formats

Data-Driven modeling: Neural Network



$$Y = W_1 X_1 + W_2 X_2$$

with N inputs $$Y = \sum_{i=1}^{\mathrm{N}} W_i X_i$$

$$\varepsilon(\mathbf{W}) = \sum_{k=1}^{\mathrm{P}} \left(Y^k - \mathbf{W}^T \mathbf{X}^k \right)^2$$

$$\left.\begin{array}{l} \mathbb{Y}^T = \left(Y^1 \; Y^2 \; \cdots \; Y^{\mathrm{P}} \right) \\ \mathbb{X} = \left(\mathbf{X}^1 \; \mathbf{X}^2 \; \ldots \mathbf{X}^{\mathrm{P}} \right) \end{array}\right\} \quad \varepsilon(\mathbf{W}) = \frac{1}{2} \left(\mathbb{Y}^T - \mathbf{W}^T \mathbb{X} \right)^2$$

Nonlinear: $\varepsilon(\mathbf{W}) = \frac{1}{2} \left(\mathbb{Y}^T - \sigma\left(\mathbf{W}^T \mathbb{X} \right) \right)^2$

Ensuring thermodynalic consistency

$$\dot{\boldsymbol{z}}_t = \boldsymbol{L}(\boldsymbol{z}_t)\nabla E(\boldsymbol{z}_t) + \boldsymbol{M}\nabla S(\boldsymbol{z}_t), \quad \boldsymbol{z}(0) = \boldsymbol{z}_0$$

Poisson matrix: reversibility

Friction matrix: irreversibility

with

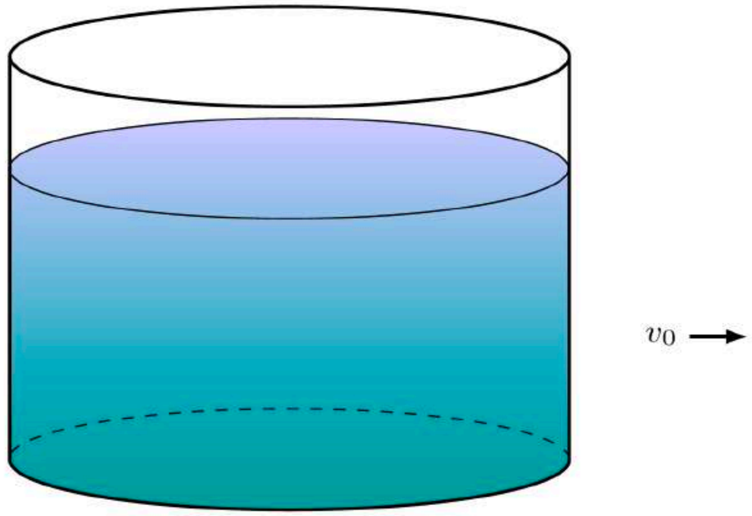
$$\boldsymbol{L}(\boldsymbol{z}) \cdot \nabla S(\boldsymbol{z}) = \boldsymbol{0},$$
$$\boldsymbol{M}(\boldsymbol{z}) \cdot \nabla E(\boldsymbol{z}) = \boldsymbol{0}.$$

$$\frac{\boldsymbol{z}_{n+1} - \boldsymbol{z}_n}{\Delta t} = \mathsf{L}(\boldsymbol{z}_{n+1}, \boldsymbol{z}_n)\mathsf{DE}(\boldsymbol{z}_{n+1}, \boldsymbol{z}_n) + \mathsf{M}(\boldsymbol{z}_{n+1}, \boldsymbol{z}_n)\mathsf{DS}(\boldsymbol{z}_{n+1}, \boldsymbol{z}_n)$$

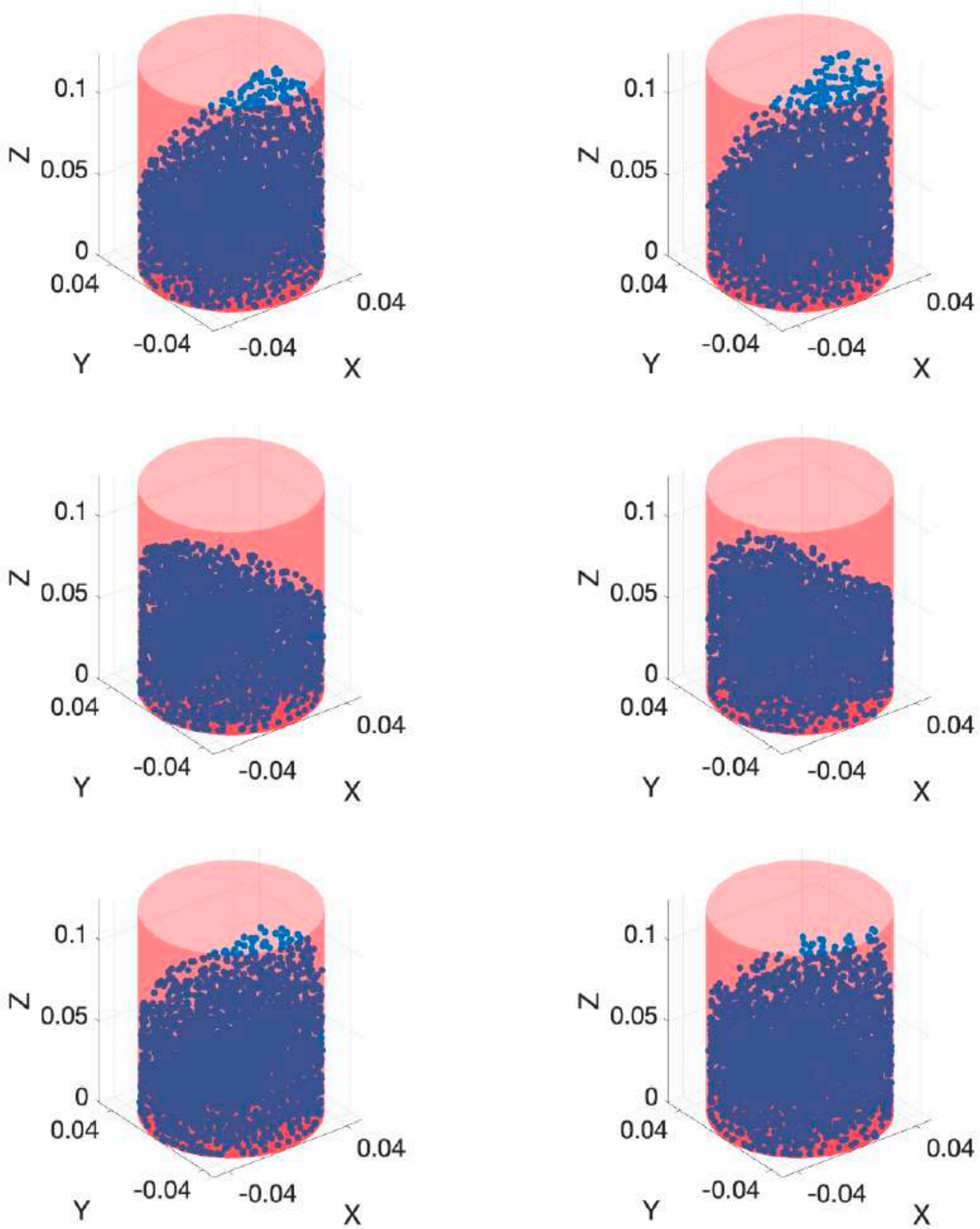
$$\boldsymbol{\mu} = \{\mathsf{L}, \mathsf{M}, \mathsf{DE}, \mathsf{DS}\} = \arg\min_{\boldsymbol{\mu}*} ||\boldsymbol{z}(\boldsymbol{\mu}) - \boldsymbol{z}^{\texttt{meas}}||$$

with

$$\mathsf{DE} = \boldsymbol{A}\boldsymbol{z}$$
$$\mathsf{DS} = \boldsymbol{B}\boldsymbol{z}$$



$$\dot{\boldsymbol{z}}_t = \boldsymbol{L}(\boldsymbol{z}_t)\nabla E(\boldsymbol{z}_t) + \boldsymbol{M}\nabla S(\boldsymbol{z}_t), \quad \boldsymbol{z}(0) = \boldsymbol{z}_0$$



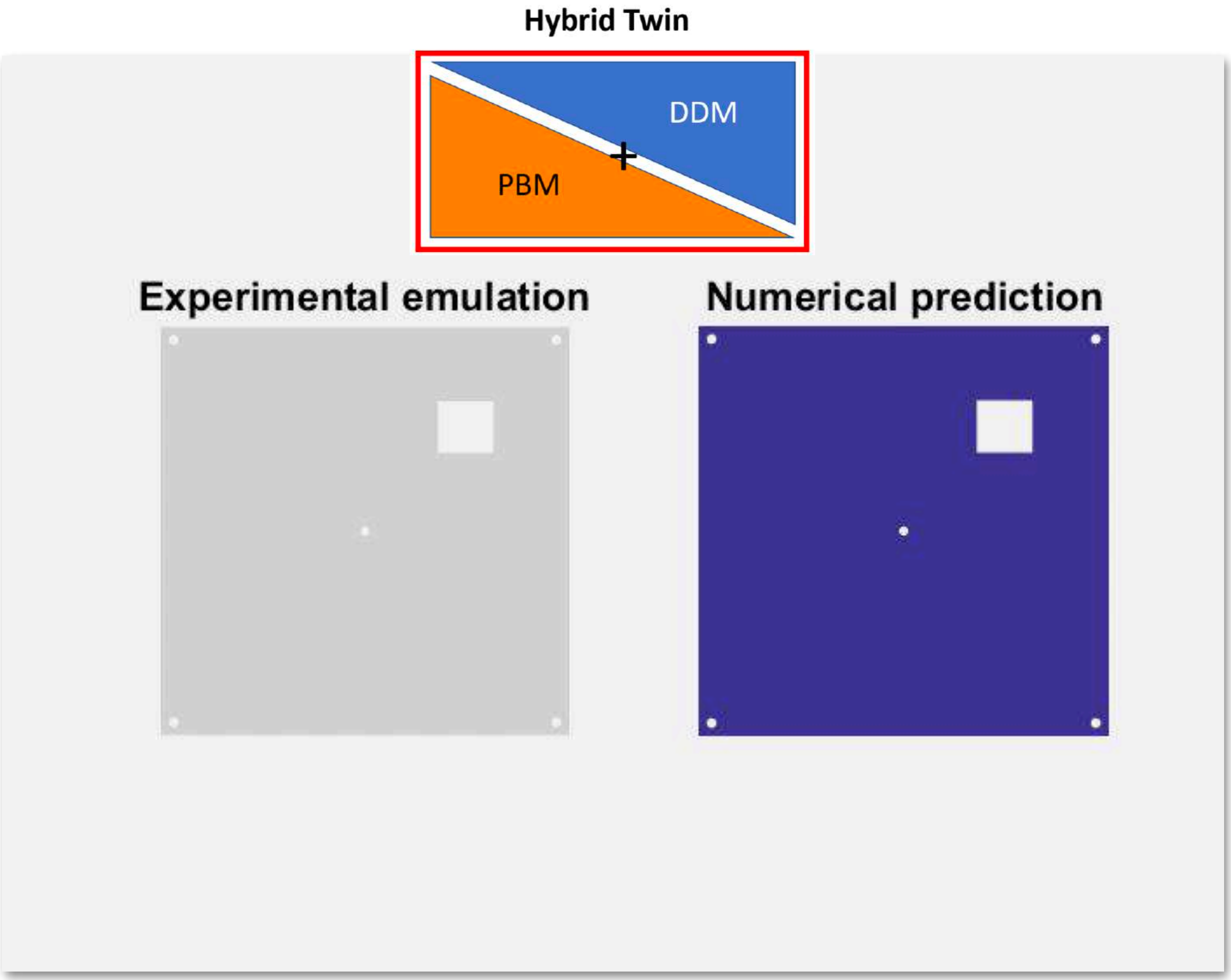
Physically sound, self-learning digital twins for sloshing fluids

B. Moya, I. Alfaro, D. González, F. Chinesta, E. Cueto

Universidad Zaragoza 1542

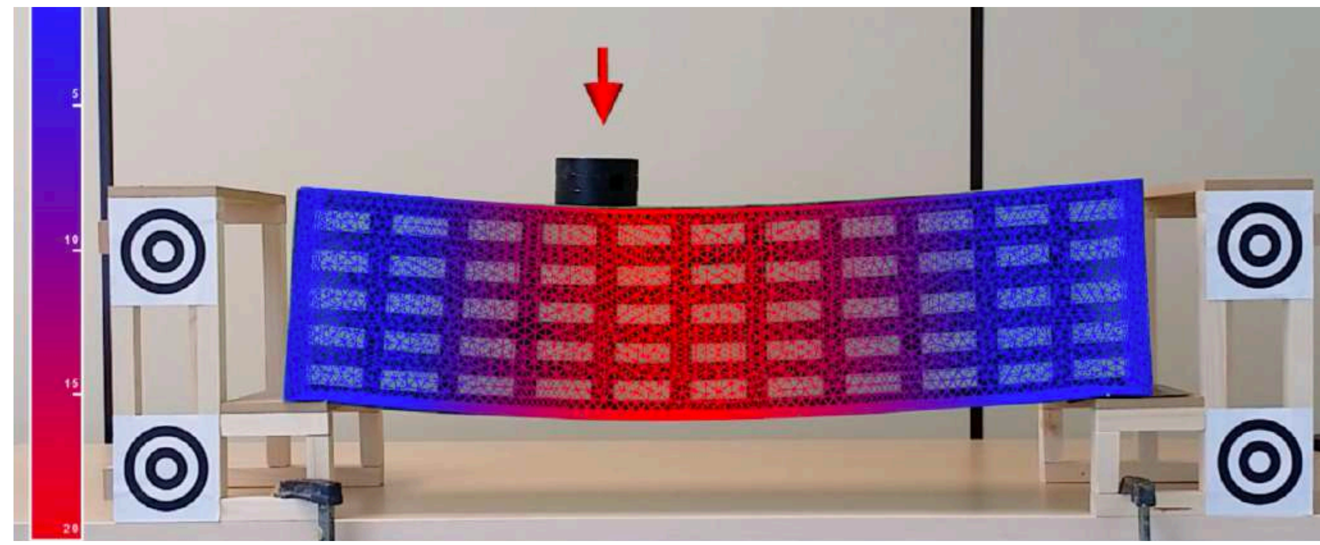
unizar.es

HT in action


Hybrid Twin
DDM
PBM
+
Experimental emulation
Numerical prediction

Digital twins that learn and correct themselves‡

Beatriz Moya[1] | Alberto Badías[1] | Icíar Alfaro[1] | Francisco Chinesta[2] | Elías Cueto[1]

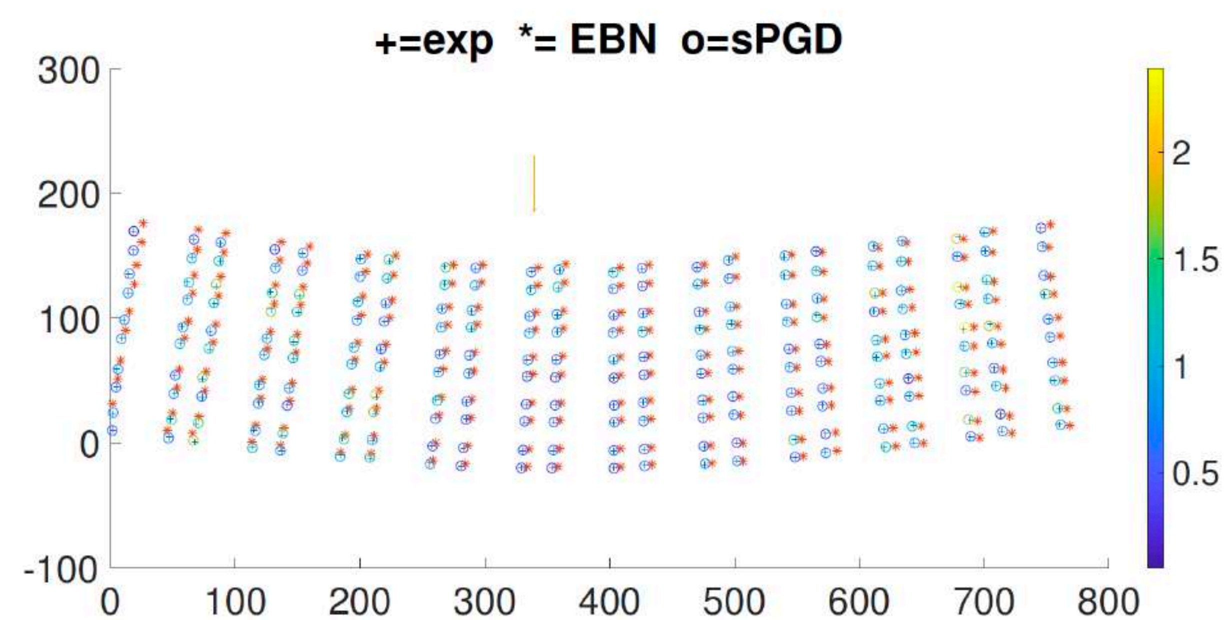


Parametric deterministic contribution PGD | Data-Driven correction | Control | Noise

$$\begin{cases} \dot{\mathbf{X}} = \mathbf{A}(\mathbf{X}, t, \boldsymbol{\mu}) + \mathbf{B}(\mathbf{X}, t) + \mathbf{C}(\mathbf{X}) + \mathbf{R} \\ \mathbf{Y} = \mathbf{D}(\mathbf{X}) + \mathbf{R}' \\ \mathbf{Z} = \mathbf{G}(\mathbf{X}) + \mathbf{R}'' \end{cases}$$

Measures involving noise

Filters: Kalman, Bayesian, …



Visco-Hyper-Elasticity as a Data-Driven correction

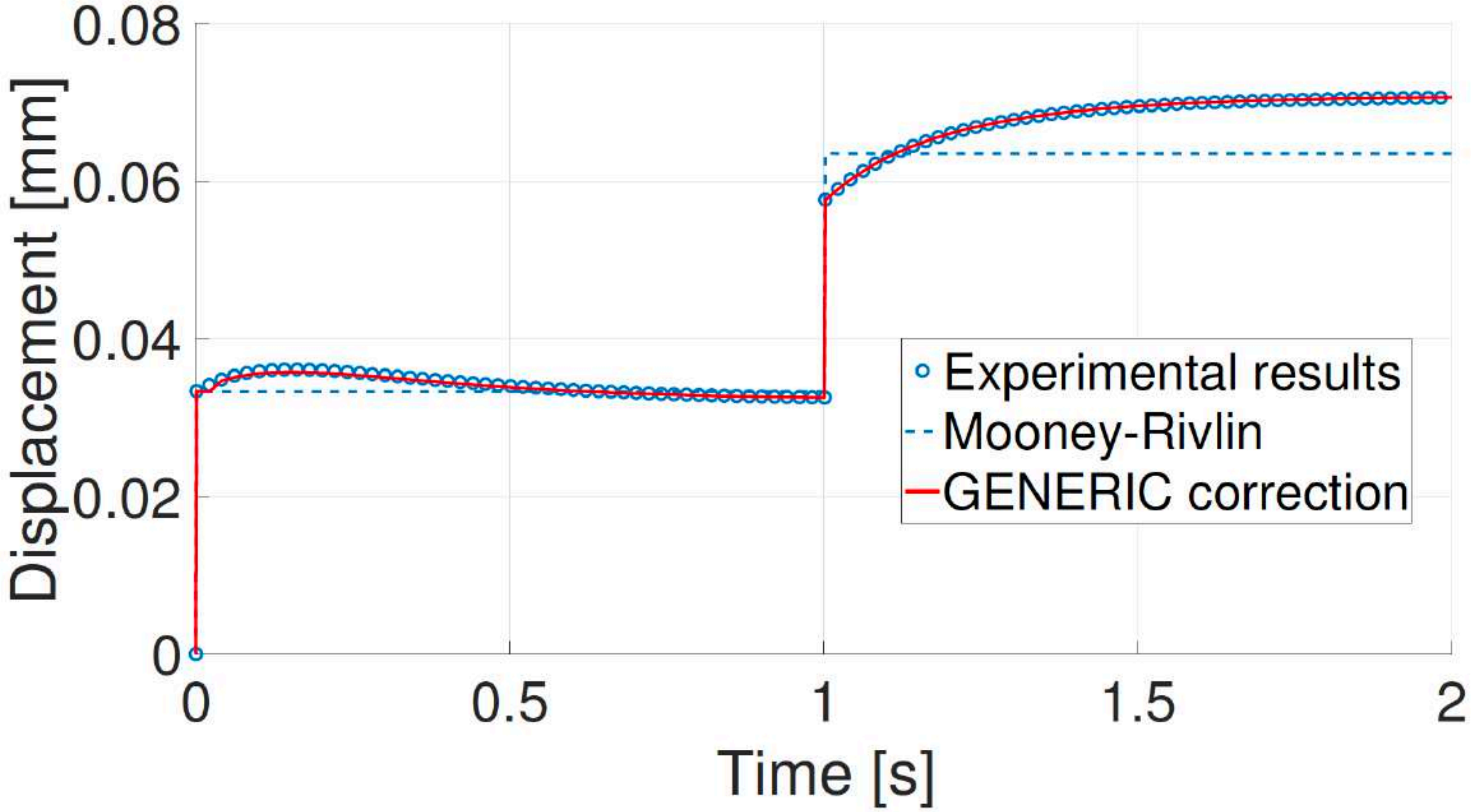
thermodynamically consistent of a purely-hyper-elasticity

$$\dot{\boldsymbol{z}}^{\text{exp}} = \boldsymbol{L}^{\text{model}}(\nabla E^{\text{model}} + \nabla E^{\text{corr}}) + (\boldsymbol{M}^{\text{model}} + \boldsymbol{M}^{\text{corr}})(\nabla S^{\text{model}} + \nabla S^{\text{corr}})$$

$$\dot{\boldsymbol{z}}^{\text{exp}} = \boldsymbol{L}^{\text{model}}(\nabla E^{\text{model}} + \nabla E^{\text{corr}}) + \boldsymbol{M}^{\text{corr}}\nabla S^{\text{corr}}$$

$$\frac{\boldsymbol{z}^{\text{exp}}_{n+1} - \boldsymbol{z}^{\text{exp}}_{n}}{\Delta t} = \mathsf{L}\ \mathsf{DE}(\boldsymbol{z}^{\text{exp}}_{n+1}) + \mathsf{M}(\boldsymbol{z}^{\text{exp}}_{n+1})\mathsf{DS}(\boldsymbol{z}^{\text{exp}}_{n+1})$$

$$\boldsymbol{\mu}^* = \{\mathsf{M}, \mathsf{DE}, \mathsf{DS}\} = \arg\min_{\boldsymbol{\mu}} ||\boldsymbol{z}(\boldsymbol{\mu}) - \boldsymbol{z}^{\texttt{meas}}||$$



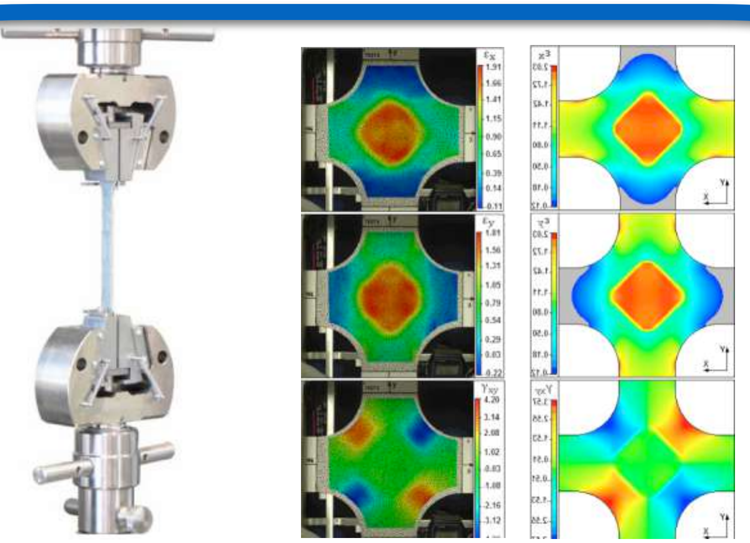
Augmented reality

Physics-based Interactive Holograms

A. Badías, D. González, I. Alfaro, F. Chinesta, E. Cueto

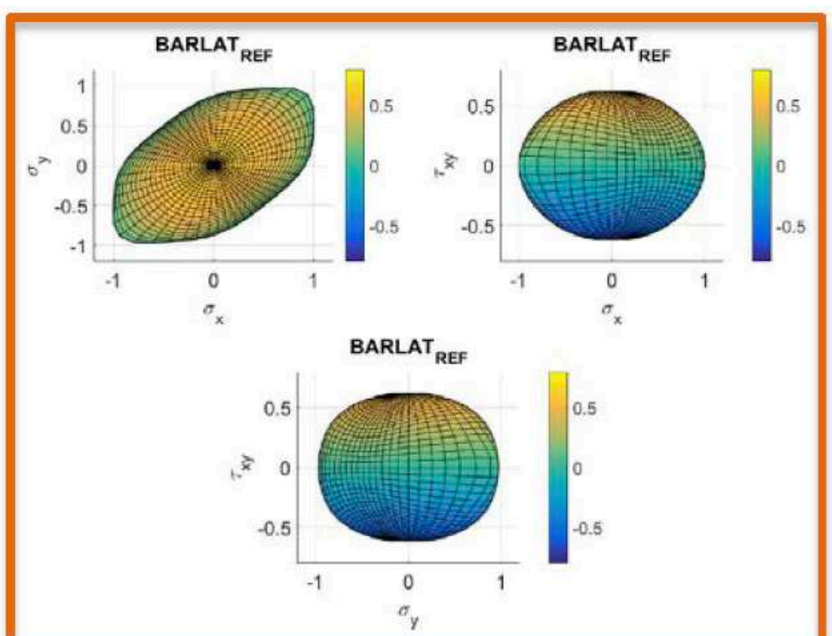
Universidad Zaragoza 1542

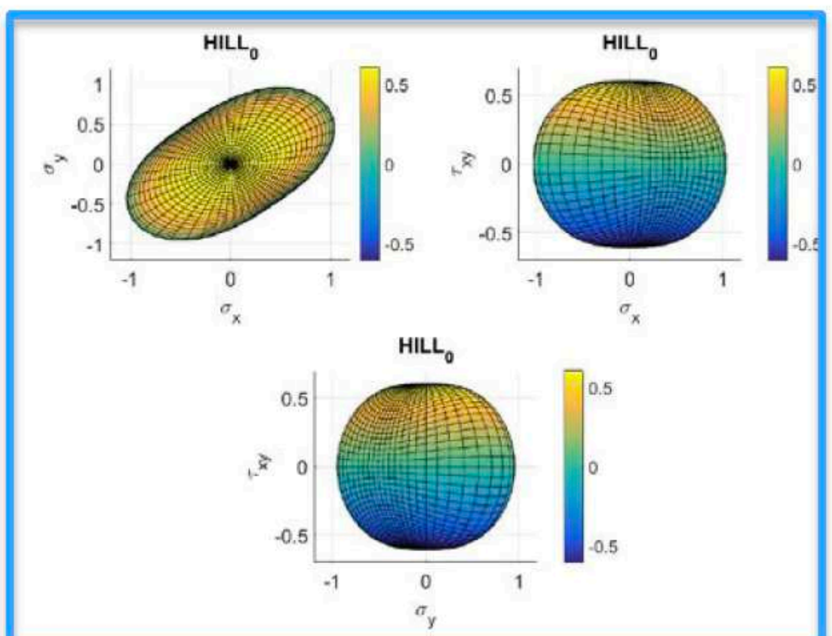
Plasticity correction

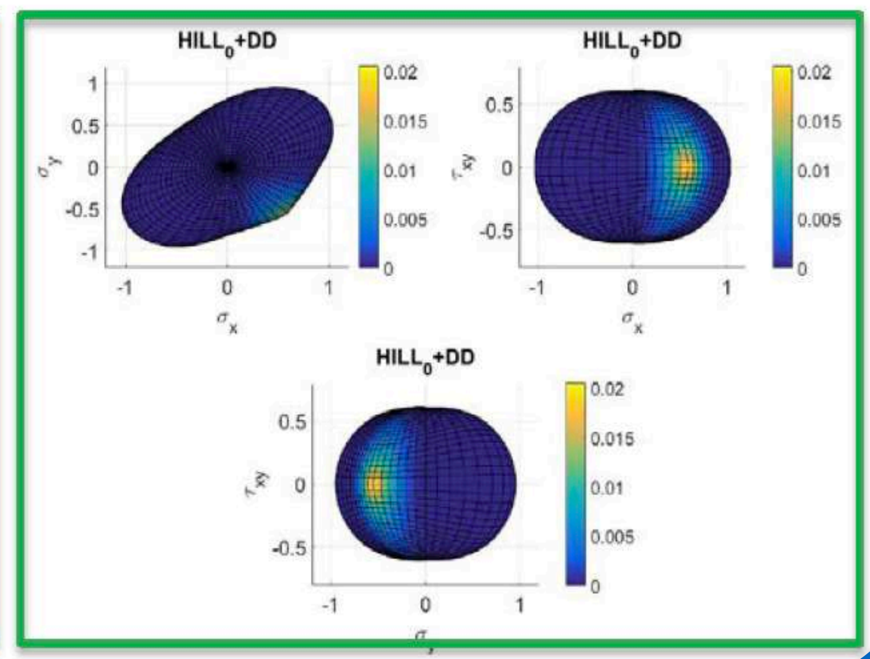


Reality = First order model + Deviation model

e.g. **Barlat Yld2004-18p** = e.g. **Quadratic Hill** + **Perturbation Model**

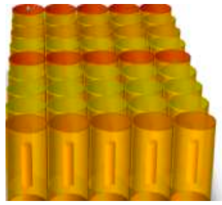


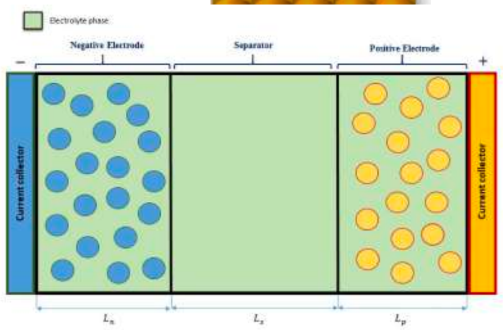




Battery Hybrid Twin for real-time planning

Micro





Newman's P2D model

$$\frac{\partial c_s}{\partial t} = \frac{D_s}{r^2}\frac{\partial}{\partial r}\left(r^2 \frac{\partial c_s}{\partial r}\right); \qquad \left.\frac{\partial c_s}{\partial r}\right|_{r=0} = 0; \quad D_s \left.\frac{\partial c_s}{\partial r}\right|_{r=R_s} = -\frac{j^{Li}}{a_s F}$$

$$\frac{\partial}{\partial x}\left(\kappa^{eff} \frac{\partial \phi_e}{\partial x}\right) + \frac{\partial}{\partial x}\left(\kappa_D^{eff} \frac{\partial}{\partial x} ln(c_e)\right) + j^{Li} = 0; \qquad \left.\frac{\partial \phi_e}{\partial x}\right|_{x=0} = \left.\frac{\partial \phi_e}{\partial x}\right|_{x=L} = 0$$

$$\frac{\partial}{\partial x}\left(\sigma^{eff} \frac{\partial \phi_s}{\partial x}\right) - j^{Li} = 0;$$

$$-\sigma^{eff} \left.\frac{\partial \phi_s}{\partial x}\right|_{x=0} = \sigma^{eff} \left.\frac{\partial \phi_s}{\partial x}\right|_{x=L} = \frac{I}{A}; \quad \left.\frac{\partial \phi_s}{\partial x}\right|_{x=0} = \left.\frac{\partial \phi_s}{\partial x}\right|_{x=L} = 0$$

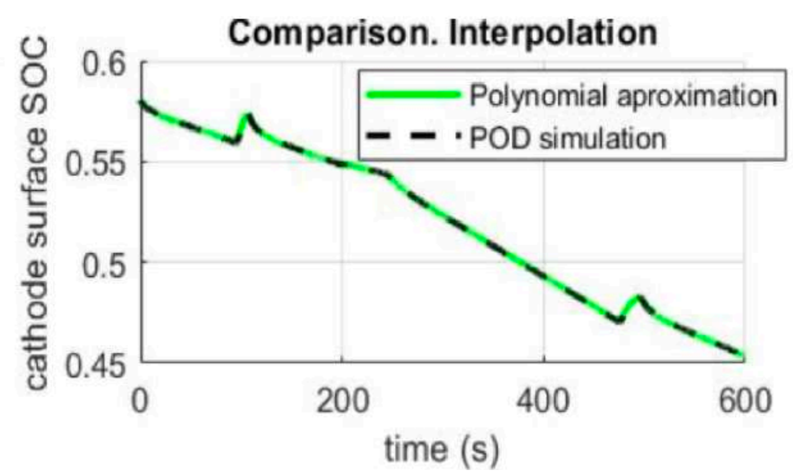
$$\frac{\partial (\varepsilon_e c_e)}{\partial t} = \frac{\partial}{\partial x}\left(D_e^{eff} \frac{\partial c_e}{\partial x}\right) + \frac{1-t_+^0}{F} j^{Li} \qquad \left.\frac{\partial c_e}{\partial x}\right|_{x=0} = \left.\frac{\partial c_e}{\partial x}\right|_{x=L} = 0$$

POD & PGD

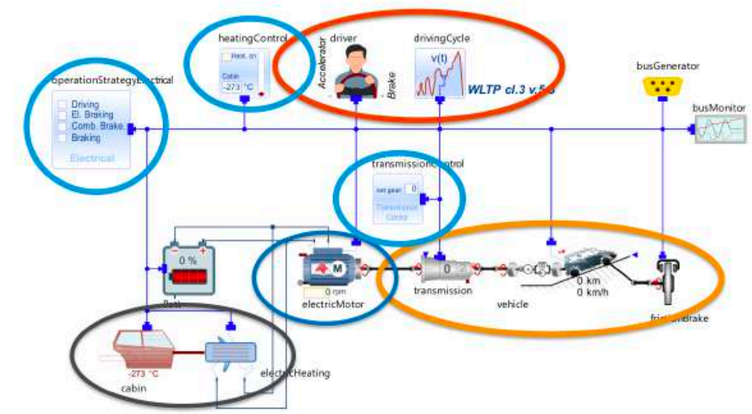
Meso

$$SOC(t) = f(SOC(t=0), Load, Env)$$
$$Voltage(t) = g(SOC(t=0), Load, Env)$$

AI: sPGD & T-MD

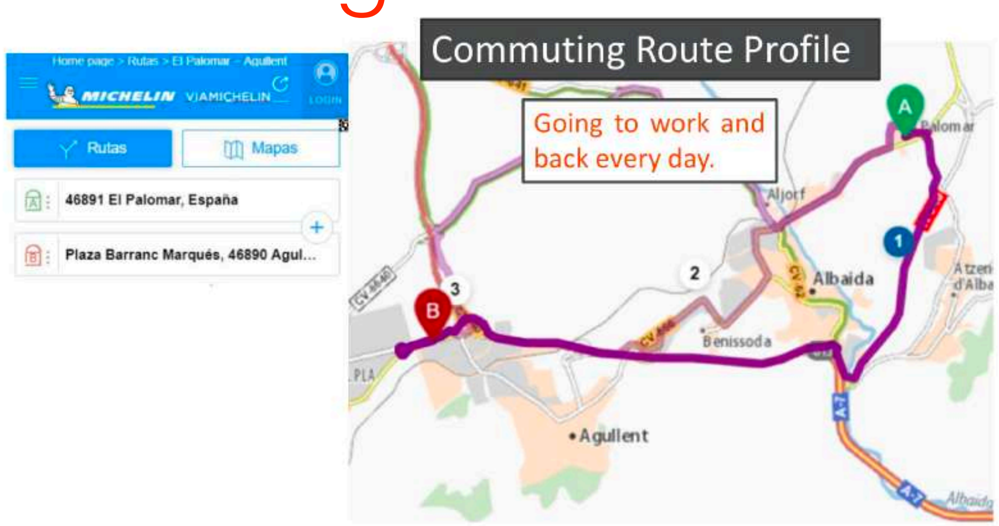


Macro

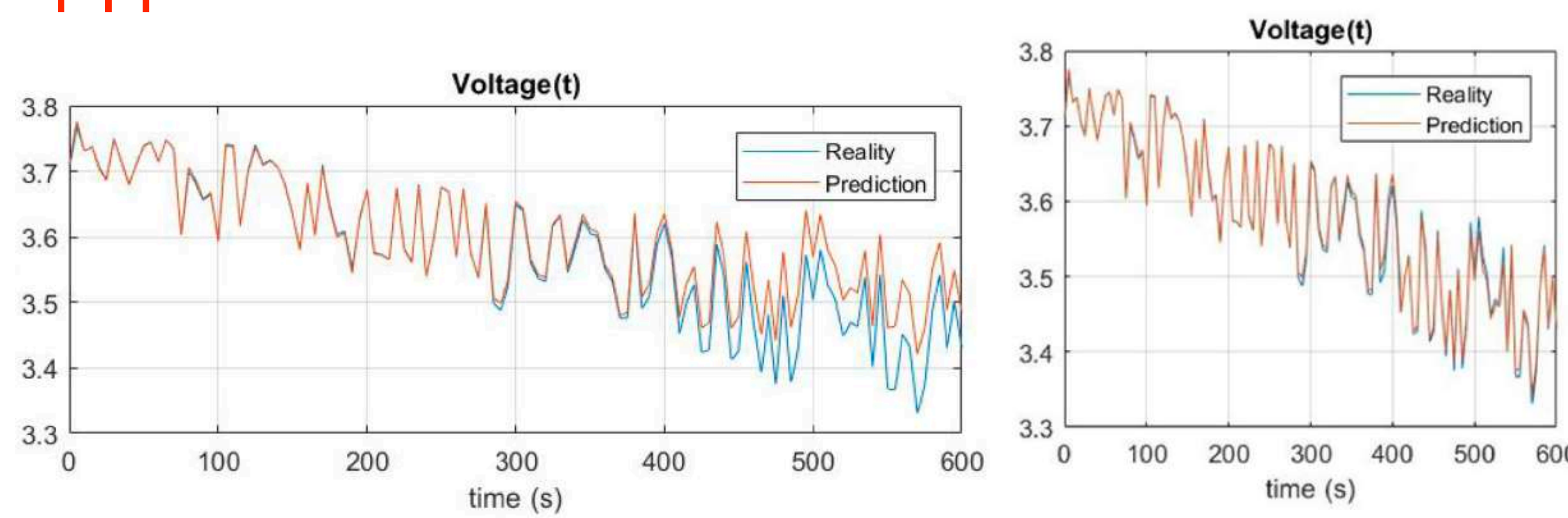


System modelling

Planning



HT



Data-Driven Correction

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