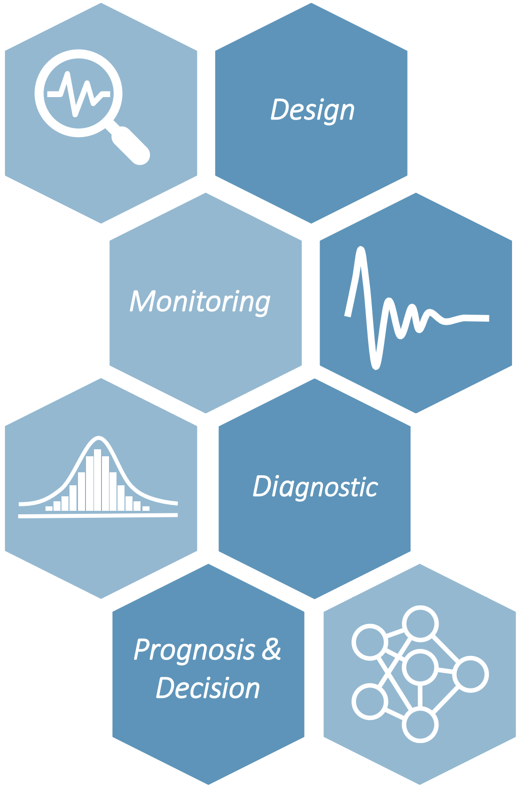
Physics Informed Digital Twins to empower engineering design and operation



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THE TWO ENGINEERINGS

Performances in designs

Few Data for Model Calibration

Nominal Physics-Based Model

Simulation

Nominal Loading

Design based on the predictions of performances

Performances in operation

Real load

$\tau \leq t$

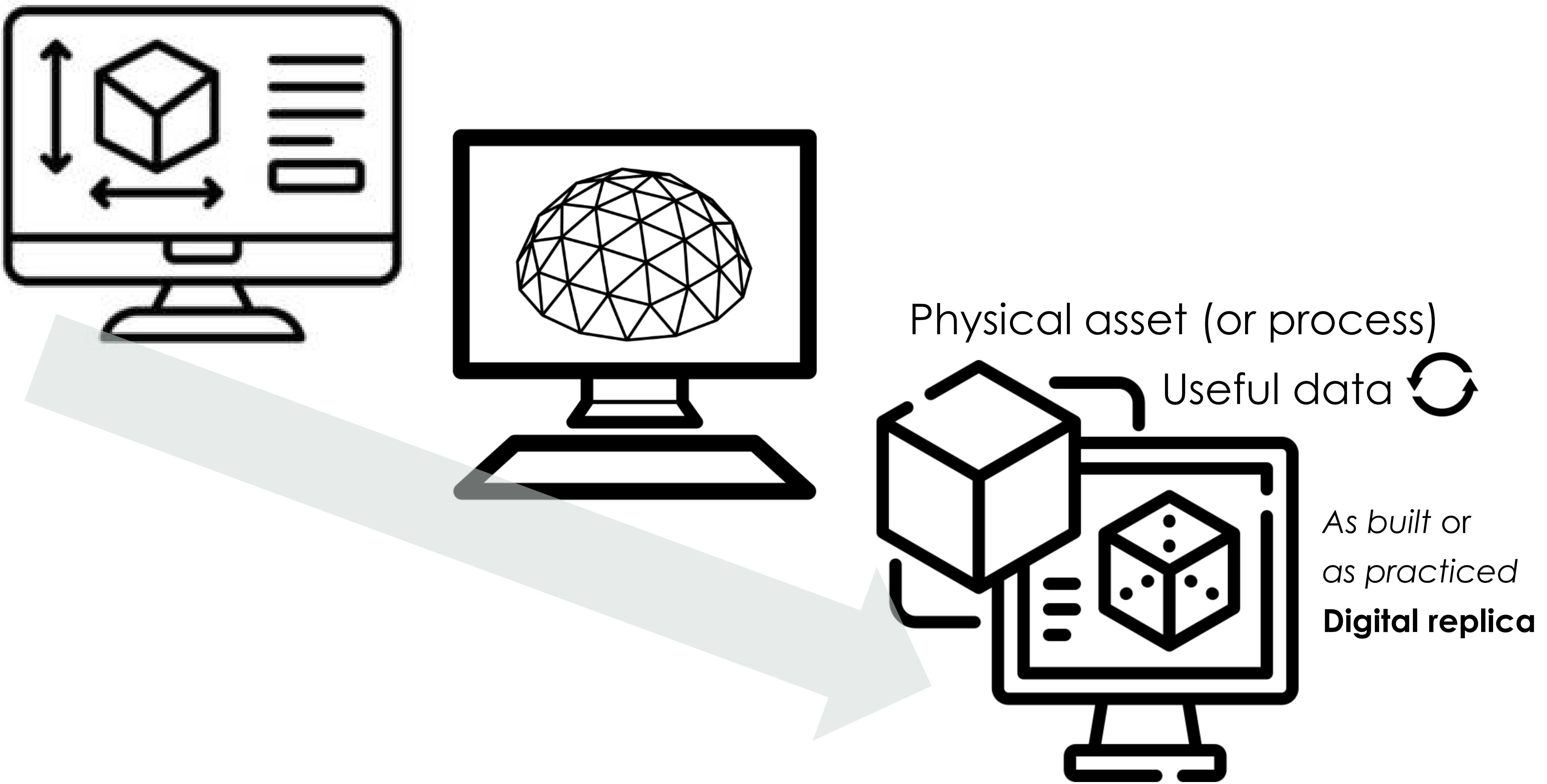
Real system in service at time t

Prediction $\tau \geq t$

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 …

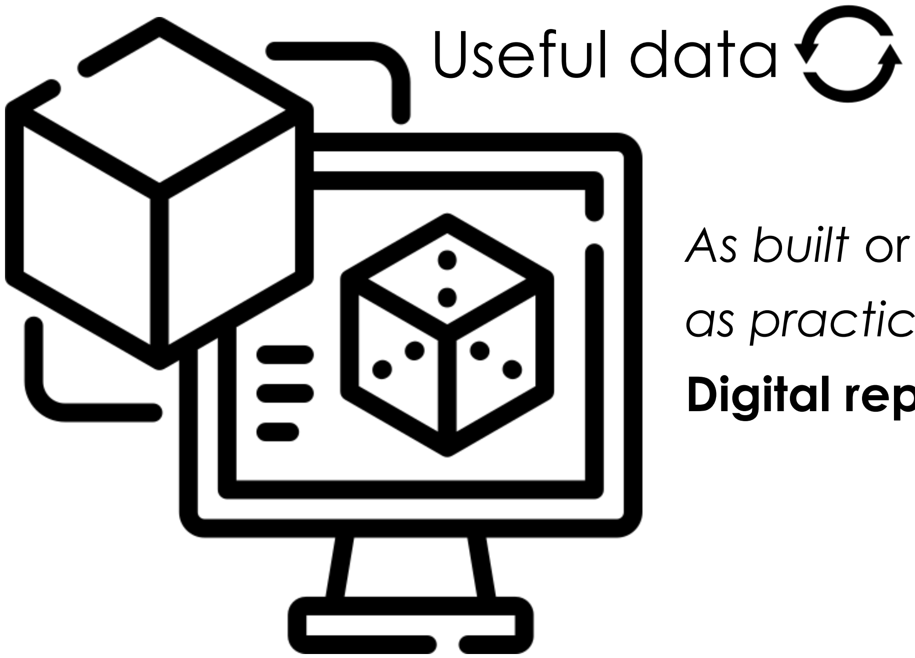
PREDICTING FAST & WELL

INTRODUCTION: three levels of digitalization as proposed by Charbel FARHAT



INTRODUCTION: Digital Twin instance – anatomy and function

Physical asset (or process)



As built or

as practiced

Digital replica

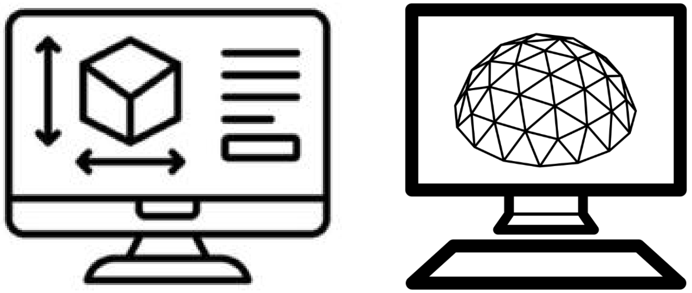
Based on:

- the best available multi-physics, multiscale & probabilistic computational models
- sensor data

To mirror & predict the functioning and performances over the life cycle of the associated physical asset.

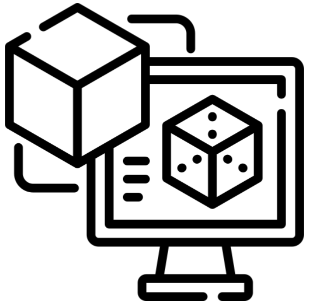
INTRODUCTION: Digital Twin Types

- **the digital twin prototype**



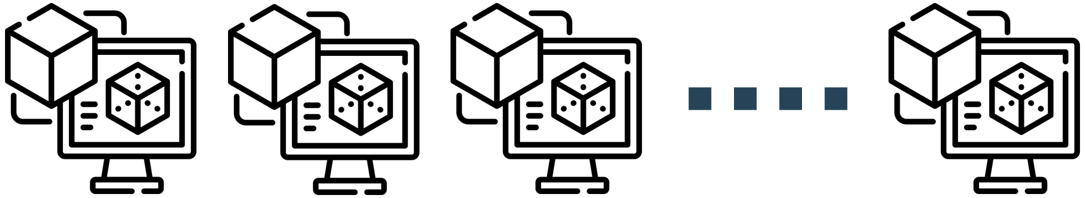
designs, analyses and processes used to realize the physical product

- **the digital twin instance**



digital twin of each individual instance of the product once it is manufactured

- **the digital twin aggregate**



allows for a larger set of data to be collected and processed for interrogation about the physical product.

THE LIMITS OF THE EXISTING PARADIGMS

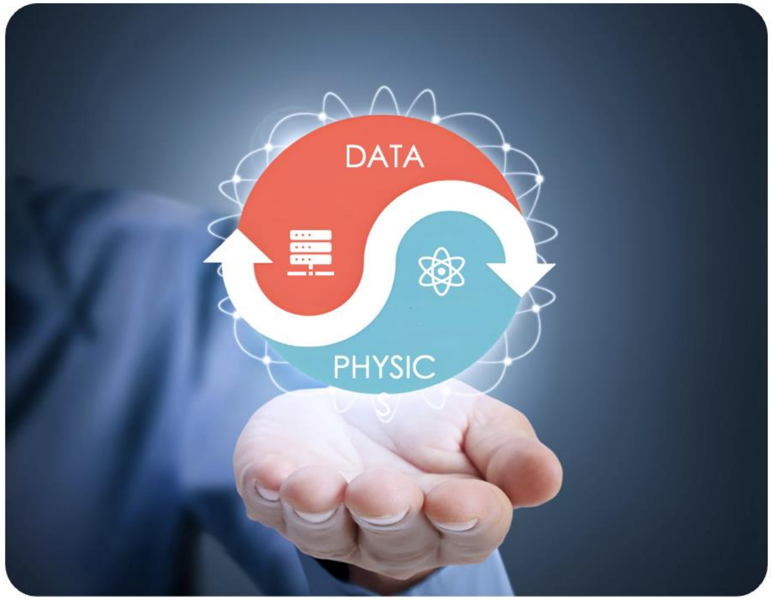
The usual simulation-based paradigm fails to perform diagnosis, prognosis and decision making when addressing complex systems of systems because of

- **Physics-based:** the lack of fidelity of state-of-the-art models, and the lack of efficiency related to their solution procedures.
- **Data-driven:** the availability of data, its quality, as well as the limitations related to the extrapolation or the ability to explain the predictions offered by the trained models.

The **hybrid paradigm** conciliates both paradigms, knowledge and data enrich mutually, reducing the amount of data, driving their collection, enabling explaining and certifying predictions and decisions, accounting for human and societal interests and constraints.

THE HYBRID PARADIGM

The **hybrid paradigm** conciliates both paradigms, knowledge and data enrich mutually, reducing the amount of data, driving their collection, enabling explaining and certifying predictions and decisions, accounting for human and societal interests and constraints.



Reality = Knowledge + Ignorance

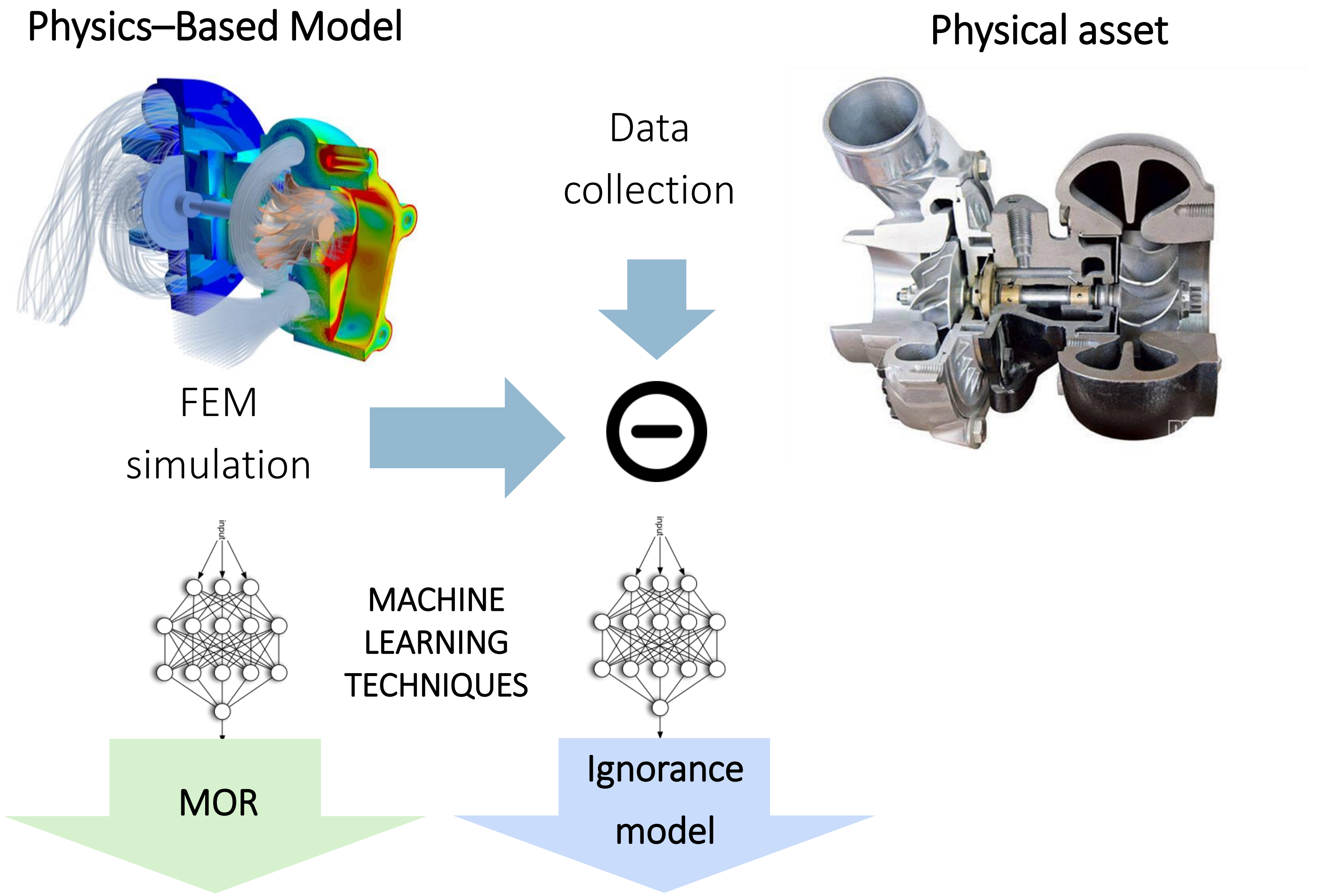
Physics-based

Data-driven

Real-time physics

Real-time frugal ML

A SUCCESFULLY APPLIED HAI TECHNOLOGY FOR PREDICTING FAST & WELL

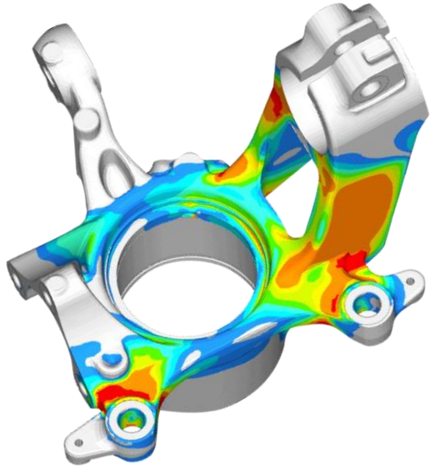


$$\frac{dx}{dt} = f^{\texttt{physics-based}}(x, \mathbf{z}) + f^{\texttt{data-driven}}(x, \mathbf{z})$$

PHYSICS BASED MODELS

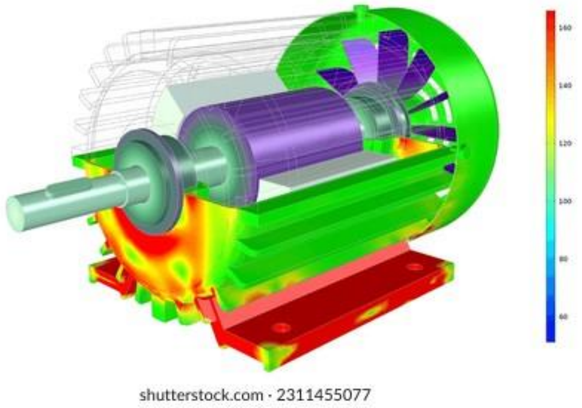
A representation of the universal governing laws of nature complemented with phenomenological behavior relationships

Linear & Nonlinear Elasticity



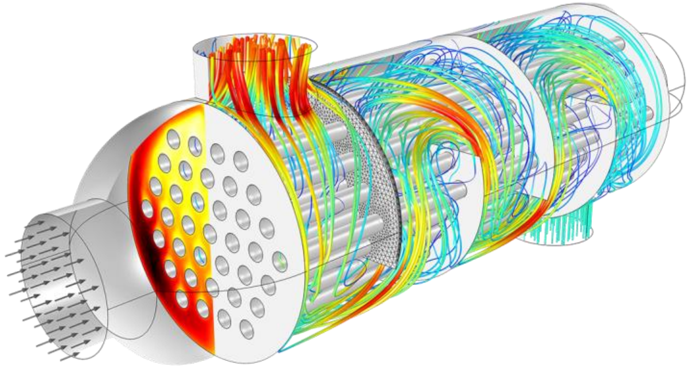
minutes, hours, …

Electromagnetism & Acoustics



hours, days, …

Fluid Dynamics



days, weeks, …

- **Expensive but accurate**
- **Cheaper by using Model Order Reduction**

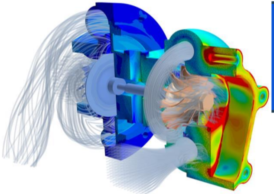
MODEL ORDER REDUCTION AND THE "ART OF SURROGATING"

Active Learning

- Goal-oriented GP
- Extended Fisher Information
  - Tensor decompositions
  - Information surrogates

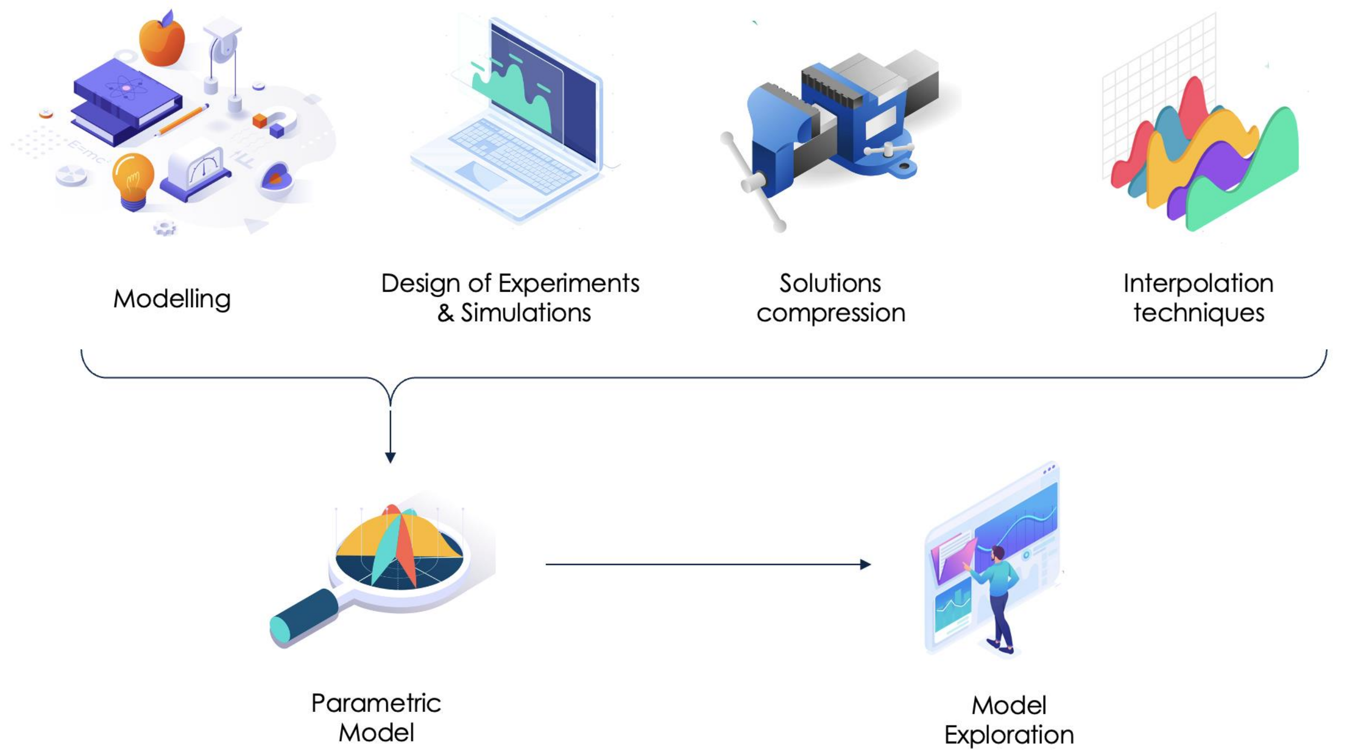
Data Reduction

- Linear (PCA)
- Nonlinear:
  - Manifold learning
  - Autoencoders



MOR / Surrogate

$$\frac{dx}{dt} = f^{\mathtt{physics-based}}(x,\mathbf{z}) + f^{\mathtt{data-driven}}(x,\mathbf{z})$$

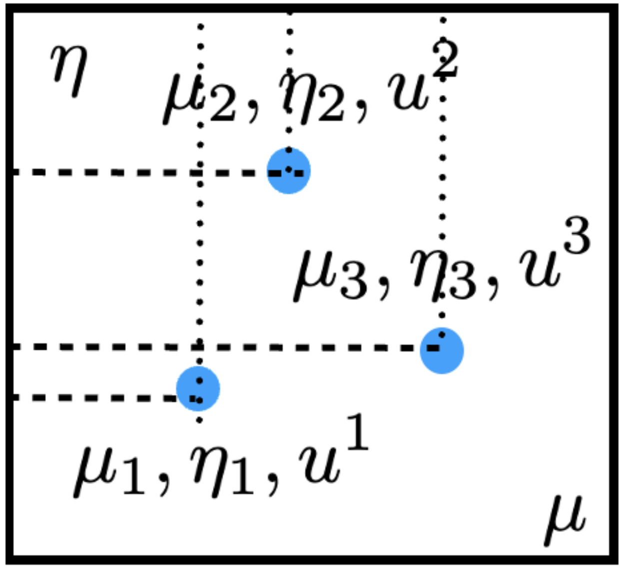


Regression (informed)

- Regularized Lineal Polynomial
  - Elastic Net, Ridge, Lasso, …
- Nonlinear:
  - NN-based
  - Optimal transport

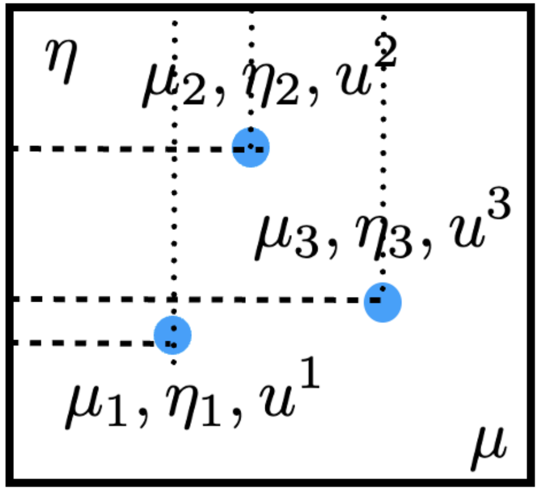
Postprocessing

- Data analytics
- Optimizers
- Uncertainty propagation
- Inversion / Data assimilation
- Control



Linear regression
Linear approximation

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



SPARSE

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

$$u(\mu, \eta) = \sum_{i=1}^{N} c_i \mathcal{F}_i(\mu, \eta)$$

$$N \gg 3$$

Regularization

$$\sum_{j=1}^{3} \|u(\mu_j, \eta_j) - u^j\|_2^2 + \lambda \sum_{i=1}^{N} |c_i|$$

VARIANTS: Separated Representation in High-Dimensional Settings

$$f(s^1, \ldots, s^d) \approx \tilde{f}^M(s^1, \ldots, s^d) = \sum_{m=1}^{M} \prod_{k=1}^{d} \psi_m^k(s^k),$$

$$\psi_m^k(s^k) = \sum_{j=1}^{D} N_{j,m}^k(s^k) a_{j,m}^k = (\boldsymbol{N}_m^k)^\top \boldsymbol{a}_m^k,$$

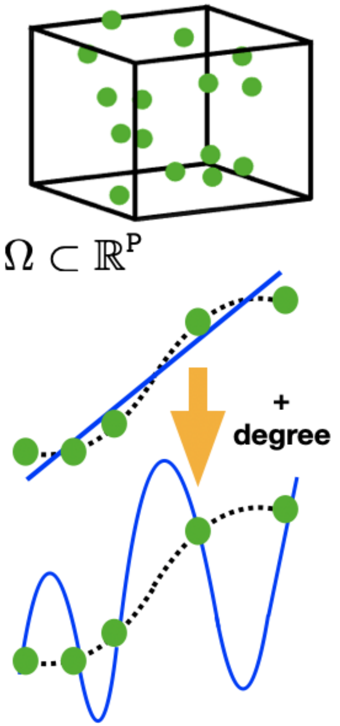
$$\tilde{f}^M = \arg\min_{f^*} \sum_{i=1}^{n_t} (f(\boldsymbol{s}_i) - f^*(\boldsymbol{s}_i))^2,$$

$$\tilde{f}^M = \sum_{m=1}^{M-1} \prod_{k=1}^{n_d} \psi_m^k(s^k) + \prod_{k=1}^{n_d} \psi_M^k(s^k).$$

VARIANTS: SUMMARY

POLYNOMIAL

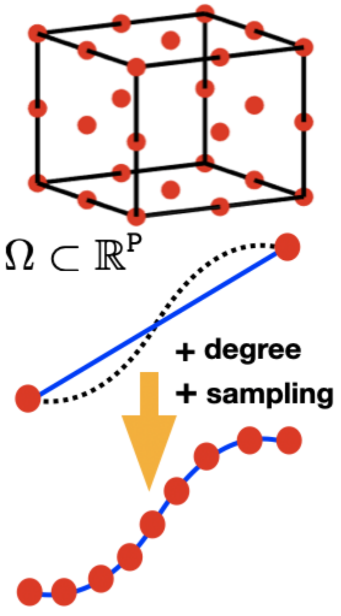
Standard regression



- Overfitting
- Can be alleviated by using orhogonal bases on structured grids or by using kriging
- Multi-parameters and low-data issues

SSL-PGD

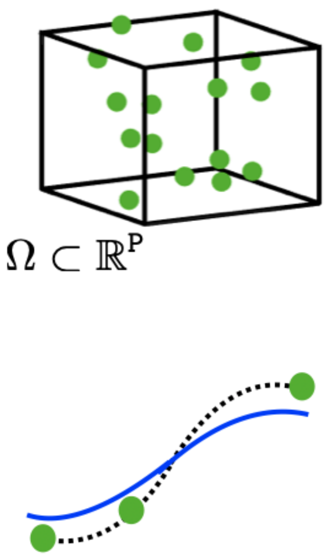
Sparse Subspace Learning based PGD



- Orthogonal hierarchical bases on structured grids
- Adaptive enrichment
- Interpolation property
- Separated form
- Amount of data in high dimensions or high degree approximations
- Level 0 approximation: 2^P #data

s-PGD

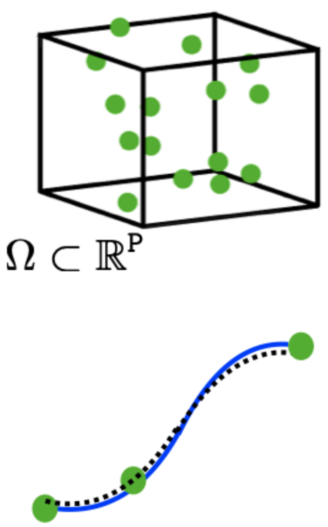
Sparse-PGD



- Sparse sampling ~ #P
- Modal Adaptivity -MAS
- Moderately nonlinear regressions
- Separated form
- Avoids overfitting -MAS
- Works @ low-data limit
- Solution smoothing

rs-PGD

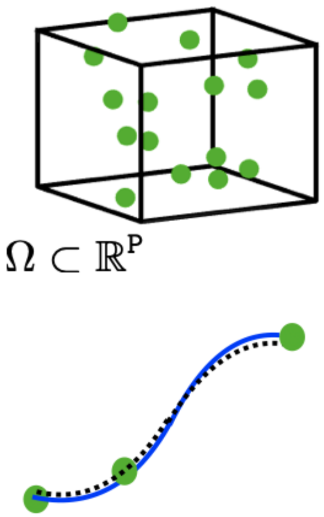
Regularized Sparse PGD



- Sparse sampling ~ #P
- Elastic-Net (combining Ridge & Lasso regularizations
- Nonlinear regression
- Separated form
- Avoids overfitting
- Works @ low-data limit
- Hyperparameters

s2-PGD

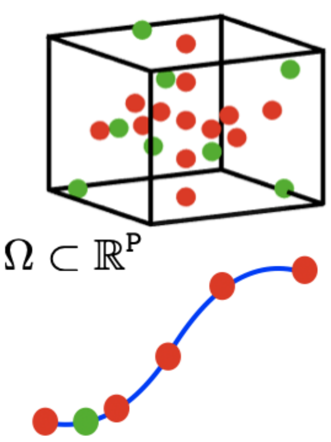
Doubly Sparse PGD



- Sparse sampling ~ #P
- Sparse dimensions search & LASSO regularization
- Modal Adaptivity -MAS in the other dimensions
- Nonlinear regression
- Separated form
- Avoids overfitting
- Works @ low-data limit

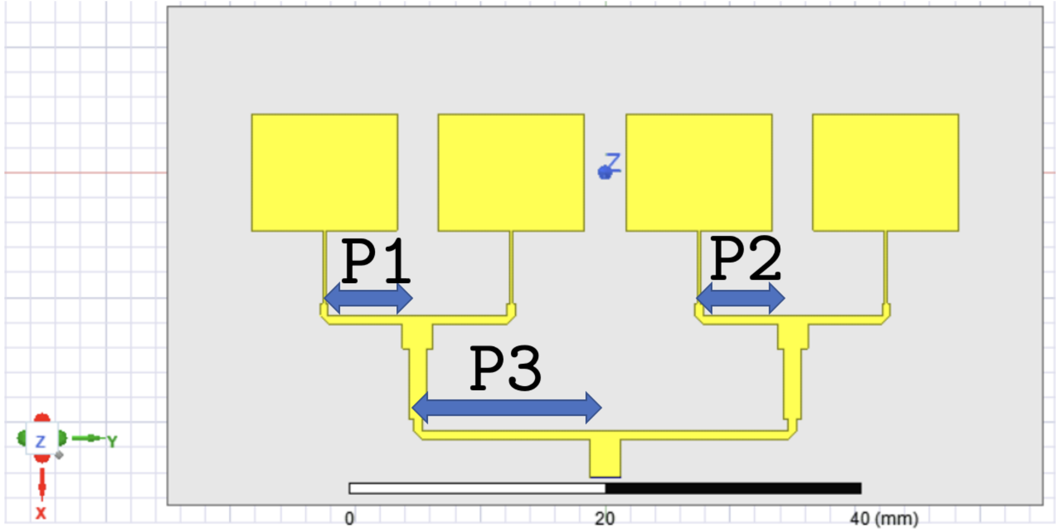
ANOVA-PGD

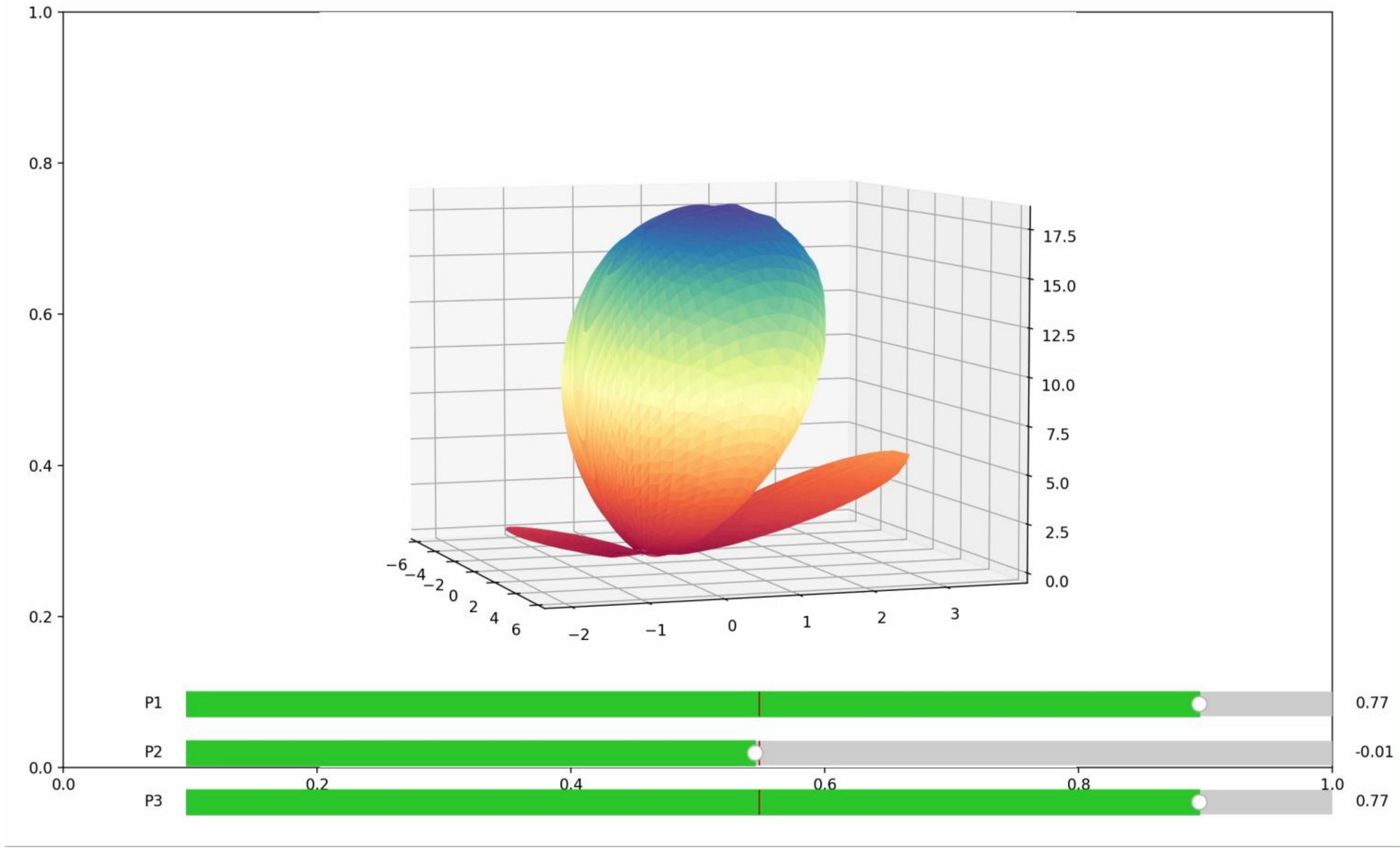
ANOVA-based rs-PGD / s2-PGD



- Anchored ANOVA orthogonal bases in each dimension / 1D rs-PGD, s2-PGD or interpolative.
- rs-PGD in correlated dimension (residual)
- Nonlinear regression
- Separated form
- Avoids overfitting
- Works @ low-data limit
- Parameters selection
- Parameteres sensibility
- Sampling: ~ #2P and ~ #P

PHYSICS IN REAL TIME





ML/AI TECHNICAL POINTS

Ignorance model

$$\frac{dx}{dt} = f^{\texttt{physics-based}}(x, \mathbf{z}) + f^{\texttt{data-driven}}(x, \mathbf{z})$$

- Regularized polynomial regressions, GP, DT, RF, SVR, …
- CNN
- GNN
- rNN, LSTM, ResNET, NeuralODE, DeepONet, Reservoir computing, Koopman…
- GAN
- Transformers
- Autoencoders
- PINN, SPNN, PANN, …

ML/AI TECHNICAL POINTS

Ignorance model

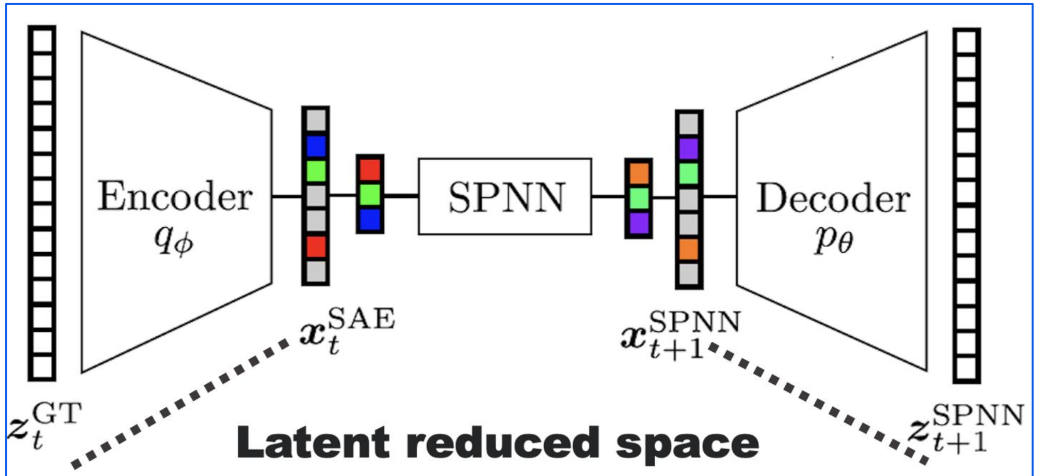
$$\frac{dx}{dt} = f^{\texttt{physics-based}}(x, \mathbf{z}) + f^{\texttt{data-driven}}(x, \mathbf{z})$$

Physically sound, self-learning digital twins for sloshing fluids

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

Universidad Zaragoza 1542

unizar.es



GENERIC

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

Poisson matrix: reversibility

Friction matrix: irreversibility

with

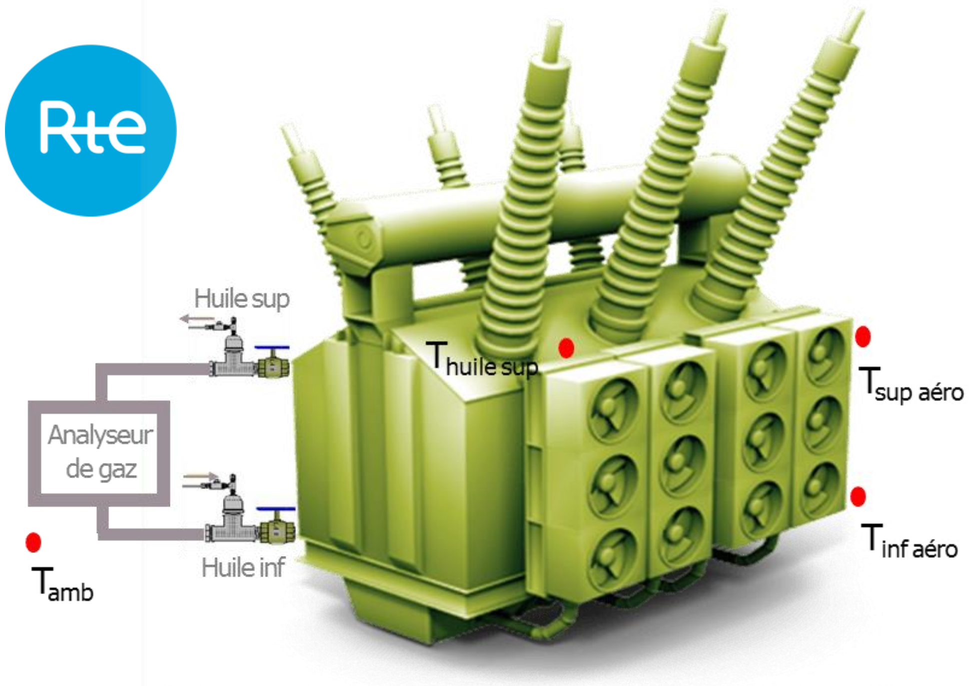
$$\boldsymbol{L}(\boldsymbol{z}) \cdot \nabla S(\boldsymbol{z}) = \boldsymbol{0}, \quad \boldsymbol{M}(\boldsymbol{z}) \cdot \nabla E(\boldsymbol{z}) = \boldsymbol{0}.$$

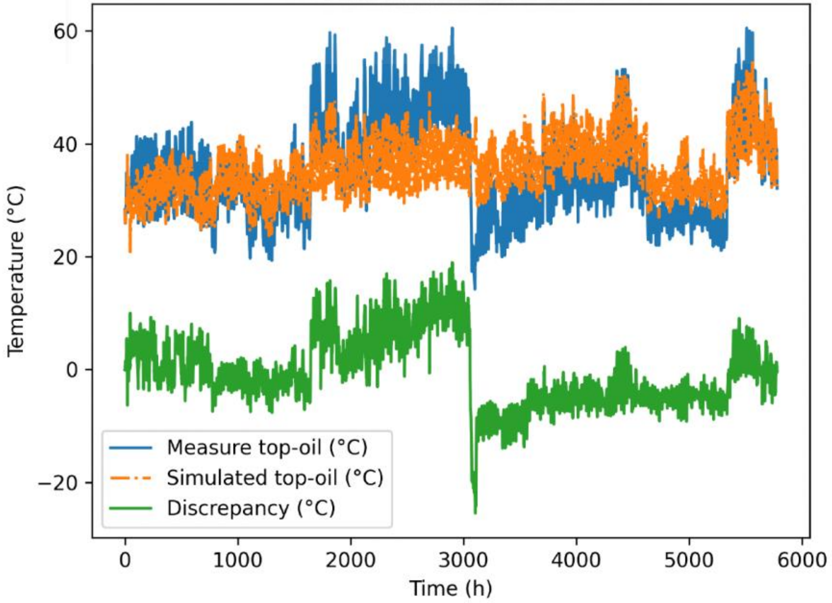
$$\frac{\boldsymbol{z}_{n+1} - \boldsymbol{z}_n}{\Delta t} = \mathsf{L}(\boldsymbol{z}_{n+1}, \boldsymbol{z}_n)\mathsf{DE}(\boldsymbol{z}_{n+1}, \boldsymbol{z}_n) + \mathsf{M}(\boldsymbol{z}_{n+1}, \boldsymbol{z}_n)\mathsf{DS}(\boldsymbol{z}_{n+1}, \boldsymbol{z}_n)$$

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

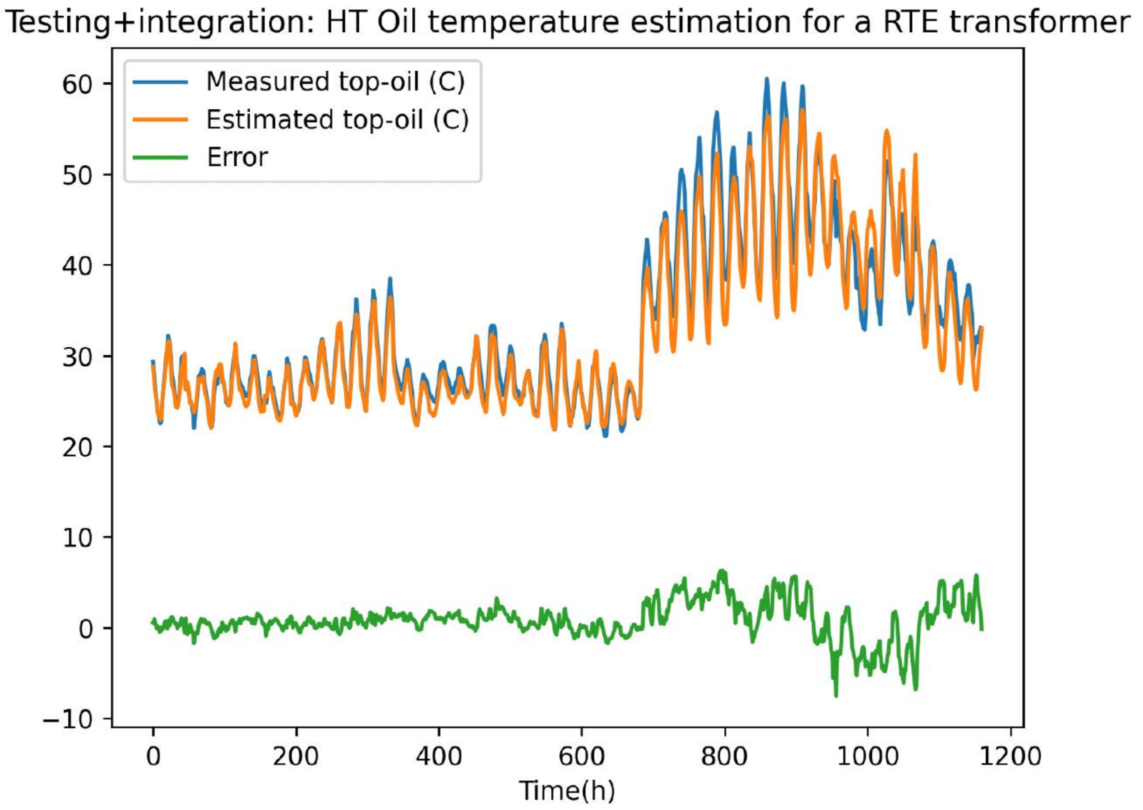
with $\mathsf{DE} = \boldsymbol{A}\boldsymbol{z}$, $\mathsf{DS} = \boldsymbol{B}\boldsymbol{z}$

TRANFORMER HYBRID TWIN INSTANCE





$$\frac{dx}{dt} = f^{\texttt{physics-based}}(x, \mathbf{z}) + f^{\texttt{data-driven}}(x, \mathbf{z})$$



RESEARCH TOPICS

I - MODEL ORDER REDUCTION: LEGO-LIKE & MULTI-TIME

II - RANK REDUCTION AUTOENCODERS / CONSTRAINTS IN THE LATENT SPACE

III - LEARNING PARSIMONIOUS PARAMETRIC (DYNAMICAL) MODELS

IV - LEARNING HIERARCHICAL MULTI-TIME MODELS

V - GENERATIVE AI for GENERATIVE DESIGN

VI - GRAPHS NN: SHM, MULTI-PHYSICS, T-GCN & EVOLVING GCN, …

VII - INDUCTIVE BIASES

VIII - QUANTUM COMPUTING

Intelligent modelling for decision making in critical urban systems

CNRS@CREATE

International research centres set up by top global institutions worldwide in Singapore:

2007: **Massachusetts Institute of Technology** Antimicrobial resistance, sustainable technologies for agricultural precision.
2010: **Swiss Federal Institute of Technology, Zurich** Future Cities, Future Resilient Systems, Future Health Technologies.
2010: **Hebrew University of Jerusalem** New materials and fabrication mainly via Additive Manufacturing processes.
2011: **Technical University of Munich** Food Tech, Med Tech, Energy Tech
2012: **Shanghai Jiao Tong University** Environmental science, public health, marine economy, carbon capture, coast protection.
2012: **University of California, Berkeley** Energy-efficient sustainable tropical buildings.
2013: **Cambridge University** Carbon reduced industries, sustainable reaction engineering, low-carbon options in the maritime sector.
2017: **University of Illinois at Urbana-Champaign** Cyberphysical systems security, AI & cybersecurity, applied cryptography.
2019: **French National Centre for Scientific Research** Hybrid AI & digital twins.
2024: **Imperial College London** Security of medical devices and wearables

City Digital Twin

technologies enabling digital twins of critical urban systems

DesCartes

THALES

AZUR DRONES

NAVAL GROUP

EDF

expleo

esi get it right

IMMERSION IMAGINATION, INTERACTION ...

SKF

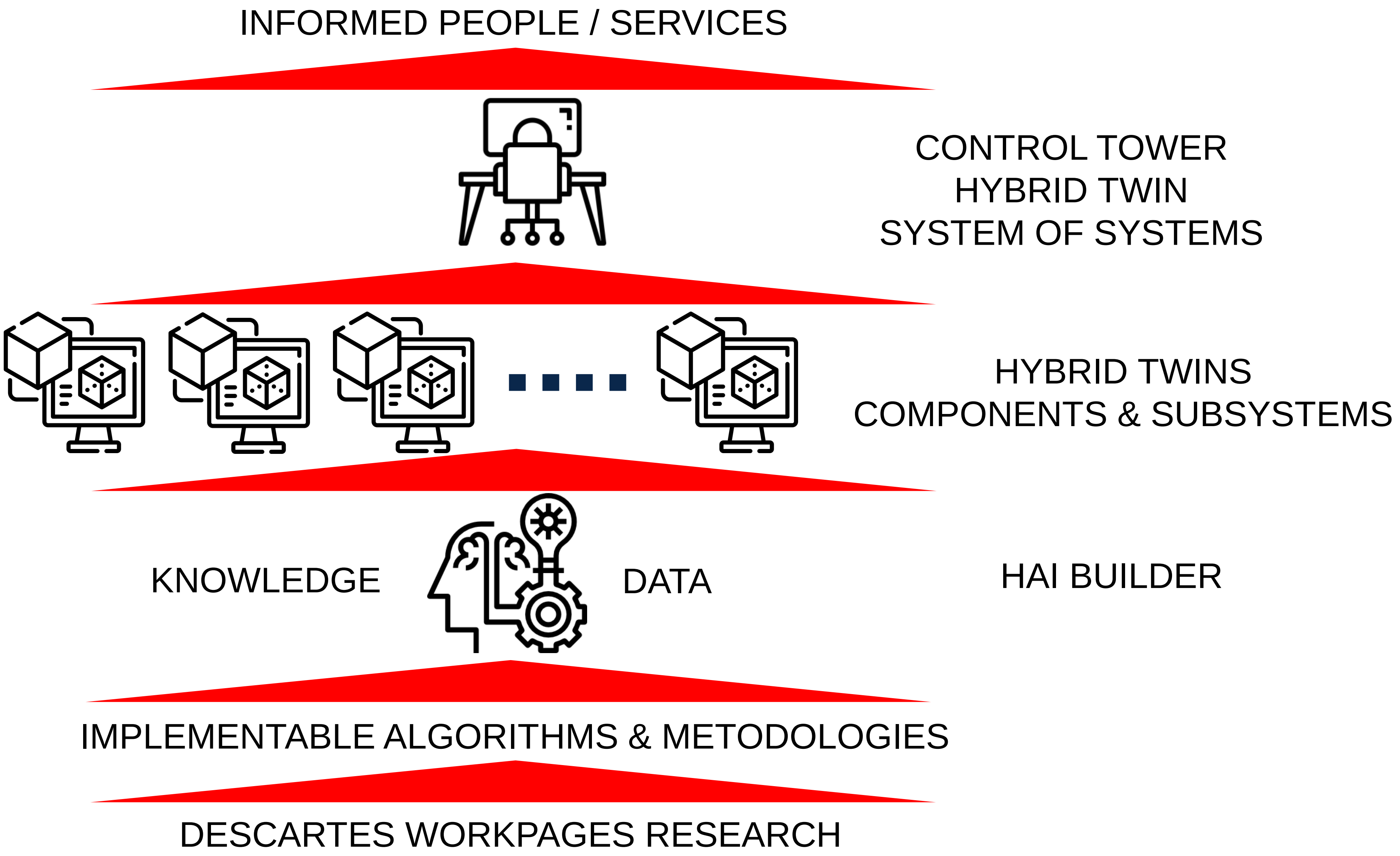
suez

cetim

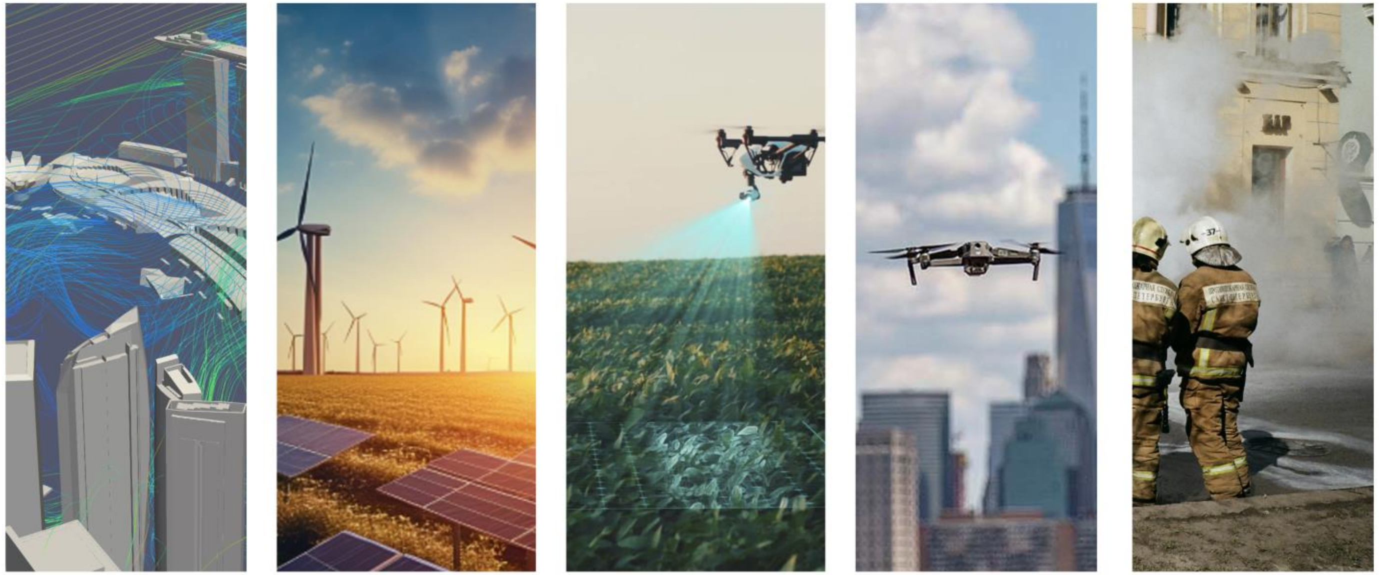
MATCOR a cetim company

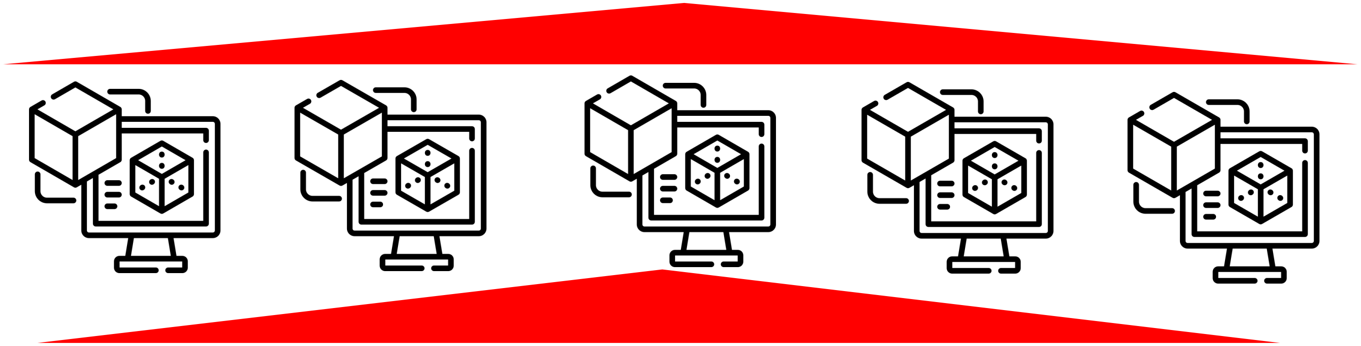
FLYING WHALES

FROM RESEARCH TO APPLICATION

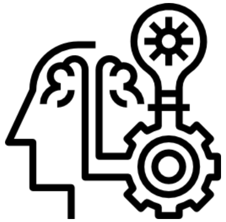


FROM RESEARCH TO APPLICATION



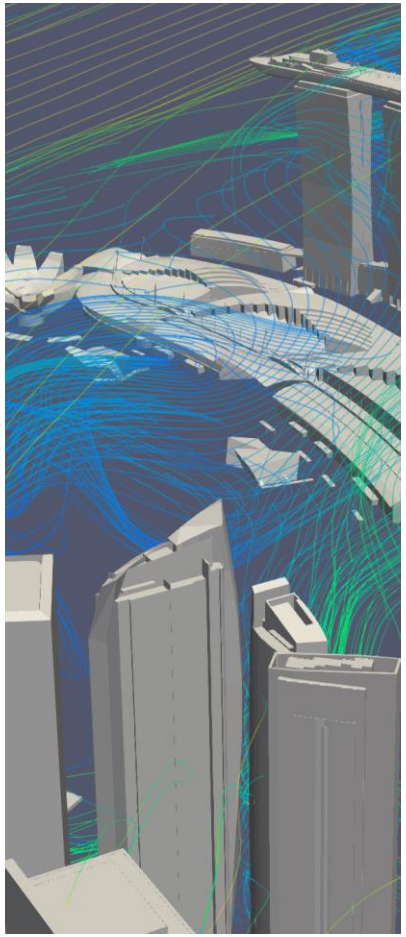


HYBRID TWINS



HAI BUILDER

ENVIRONMENTAL DIGITAL TWIN



Augmented Marina Bay Twin

Digital Energy

Remote Sensing

Drone Trajectory Planning

Emergency crisis

Interest of having a wind map at the city level

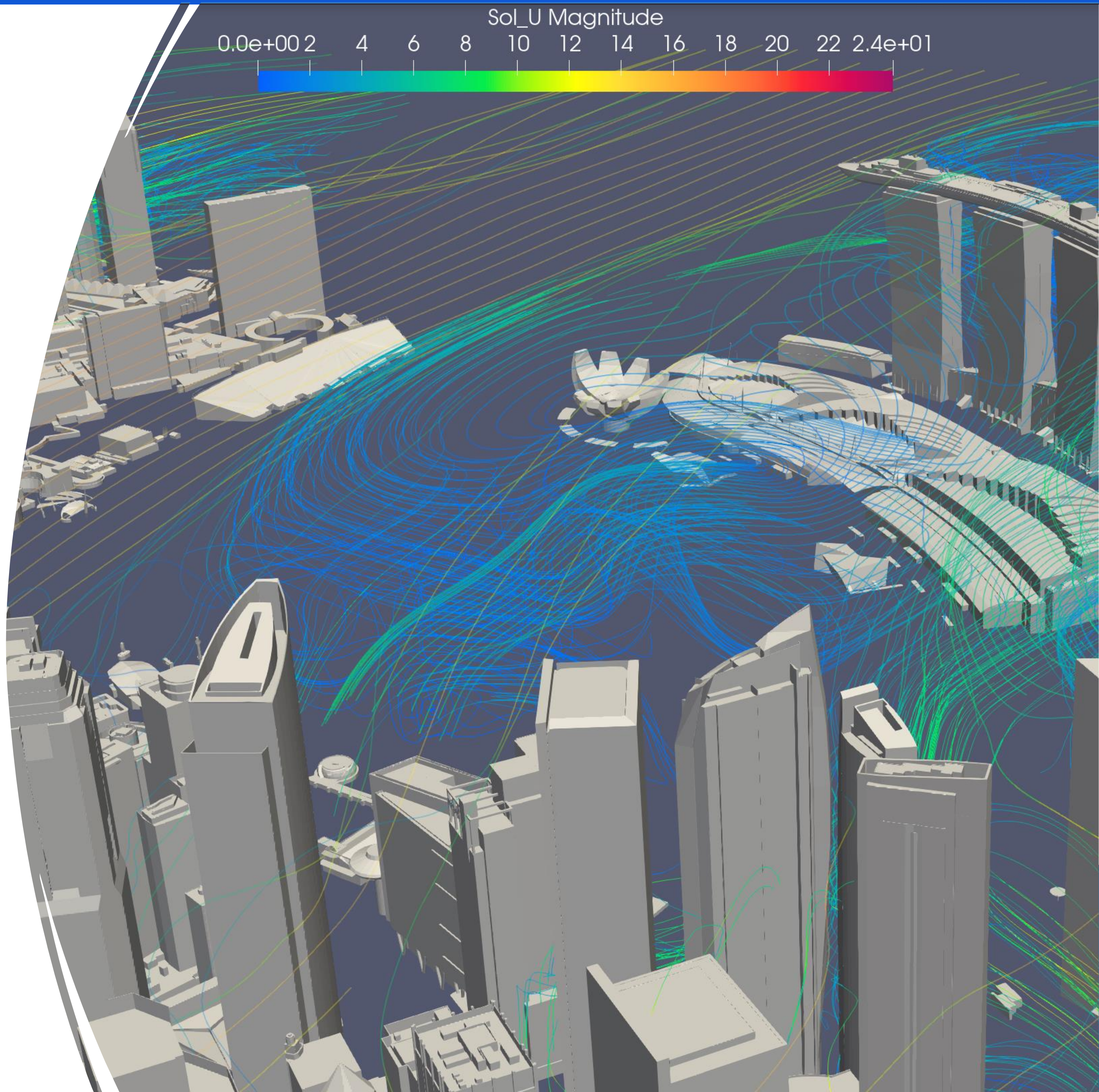
- Inferring emissions dispersion
- Inferring air quality
- Inferring temperature and thermo-convective flows
- Drone trajectory optimal planning
- … and many others …

SLA SINGAPORE LAND AUTHORITY

HTX

esi get it right

ARIA TECHNOLOGIES

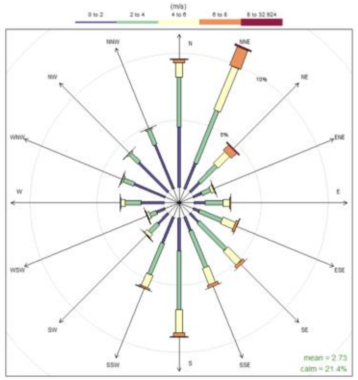


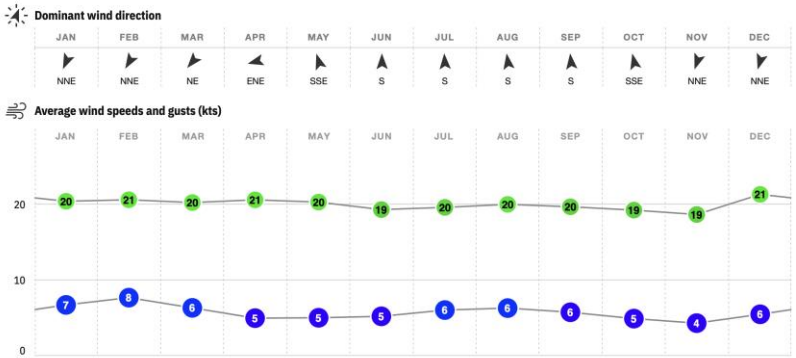
WIND MAP

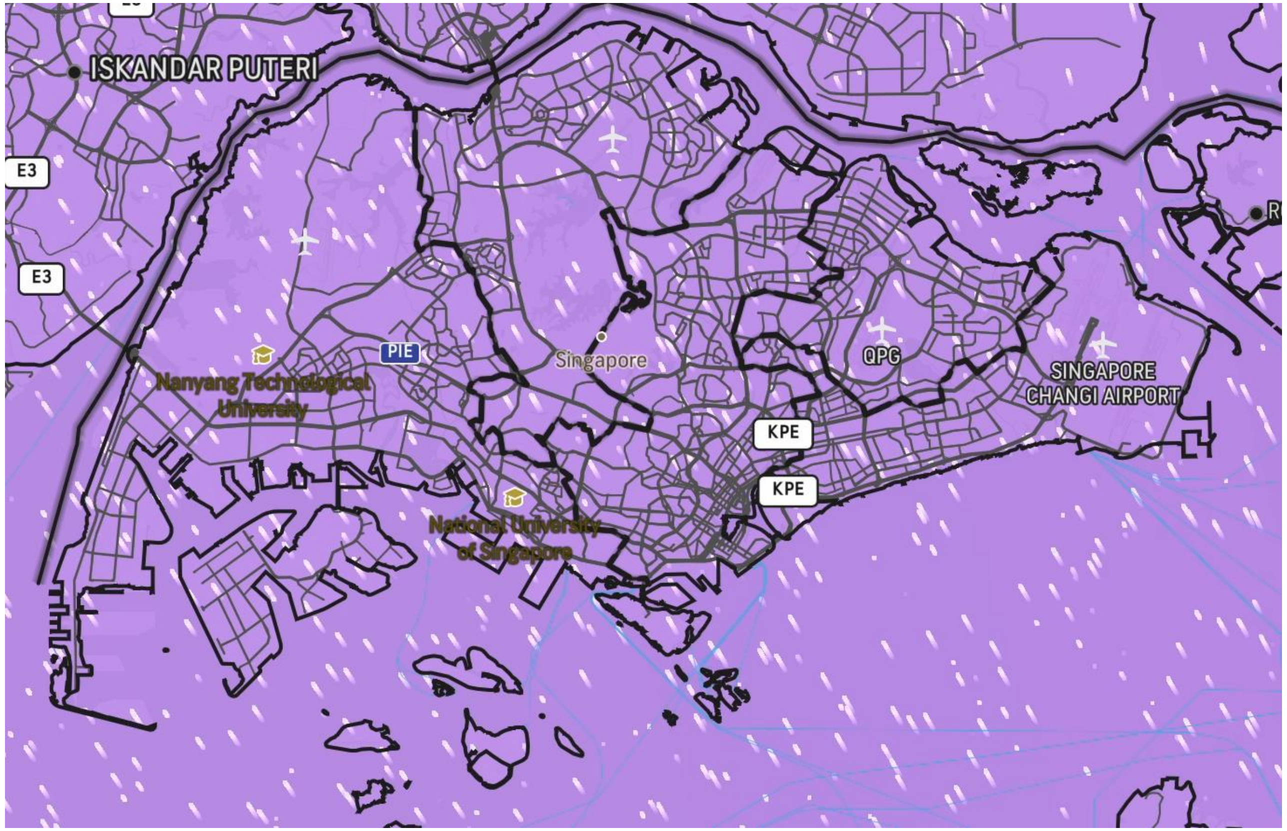
Available forecast is too coarse for providing local (street level) information on the wind velocity.

However, it provides the boundary conditions for district-level calculations

That solution is computationally too expensive

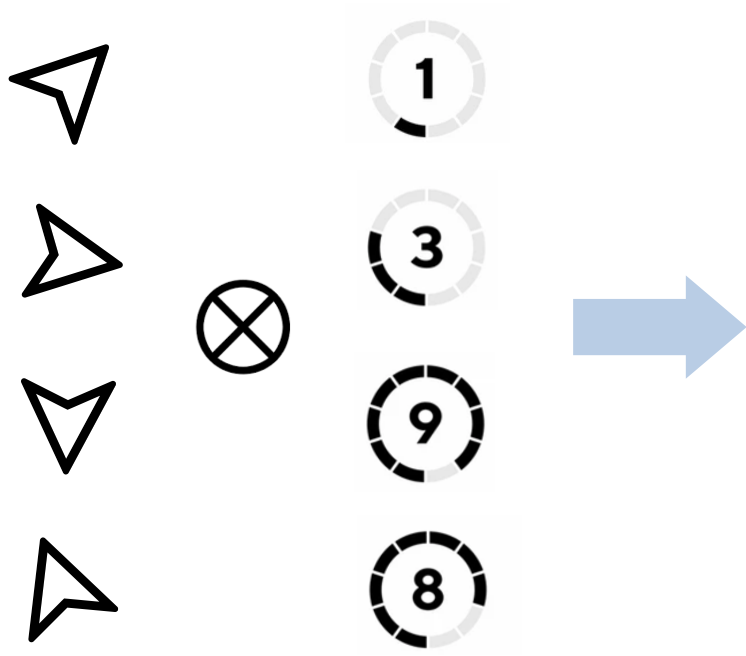




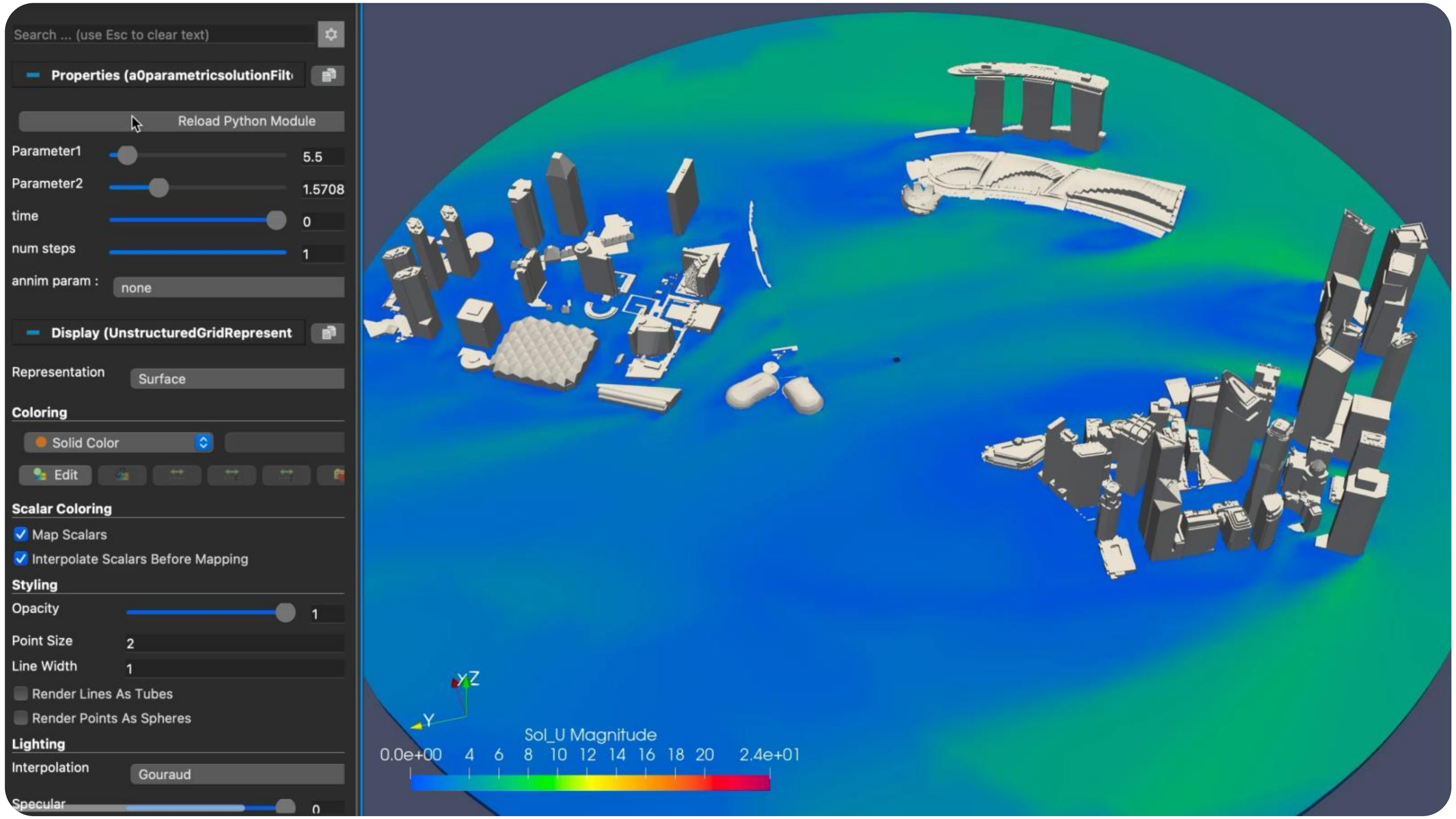


WIND MAP

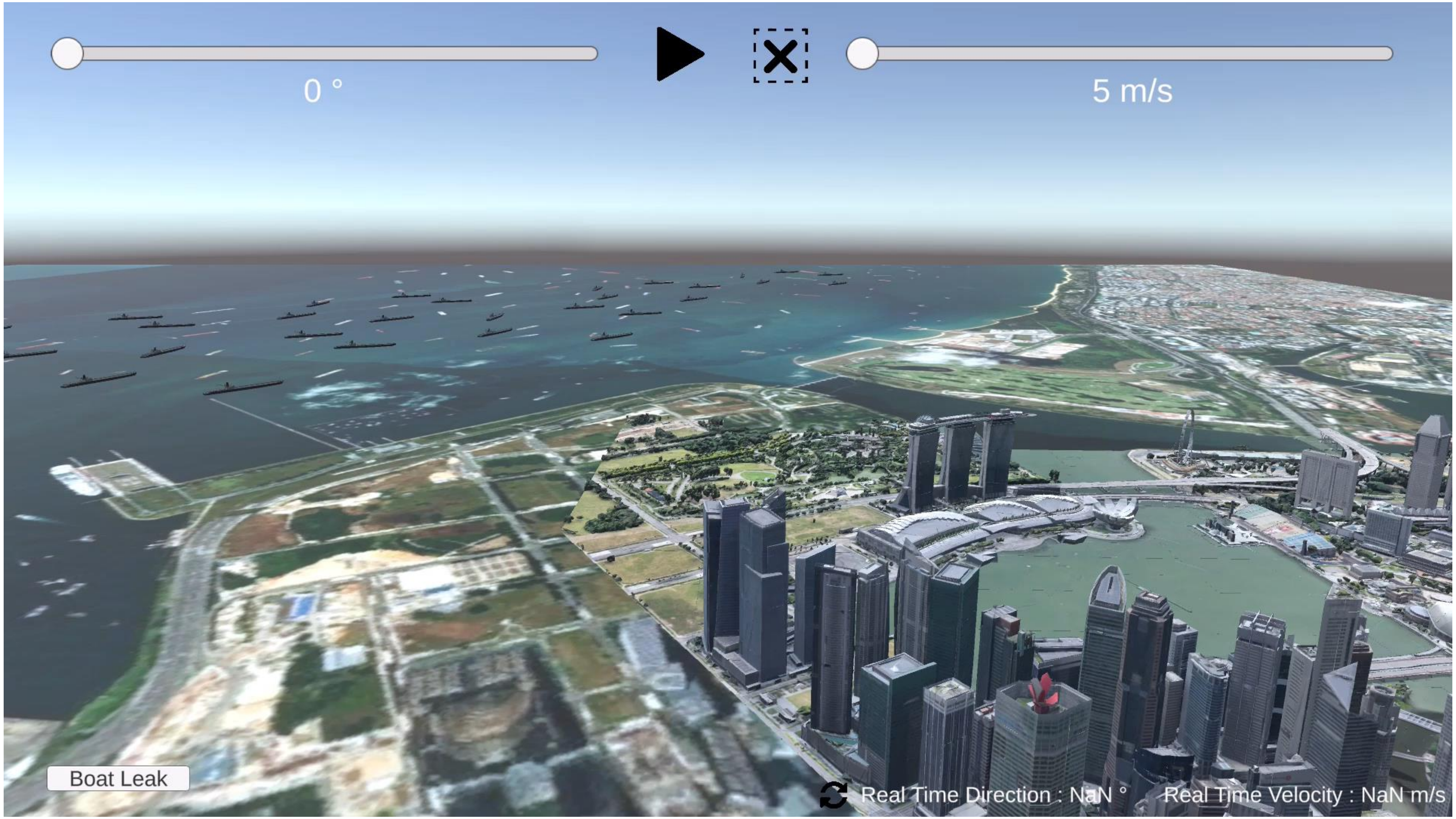
Direction   Intensity



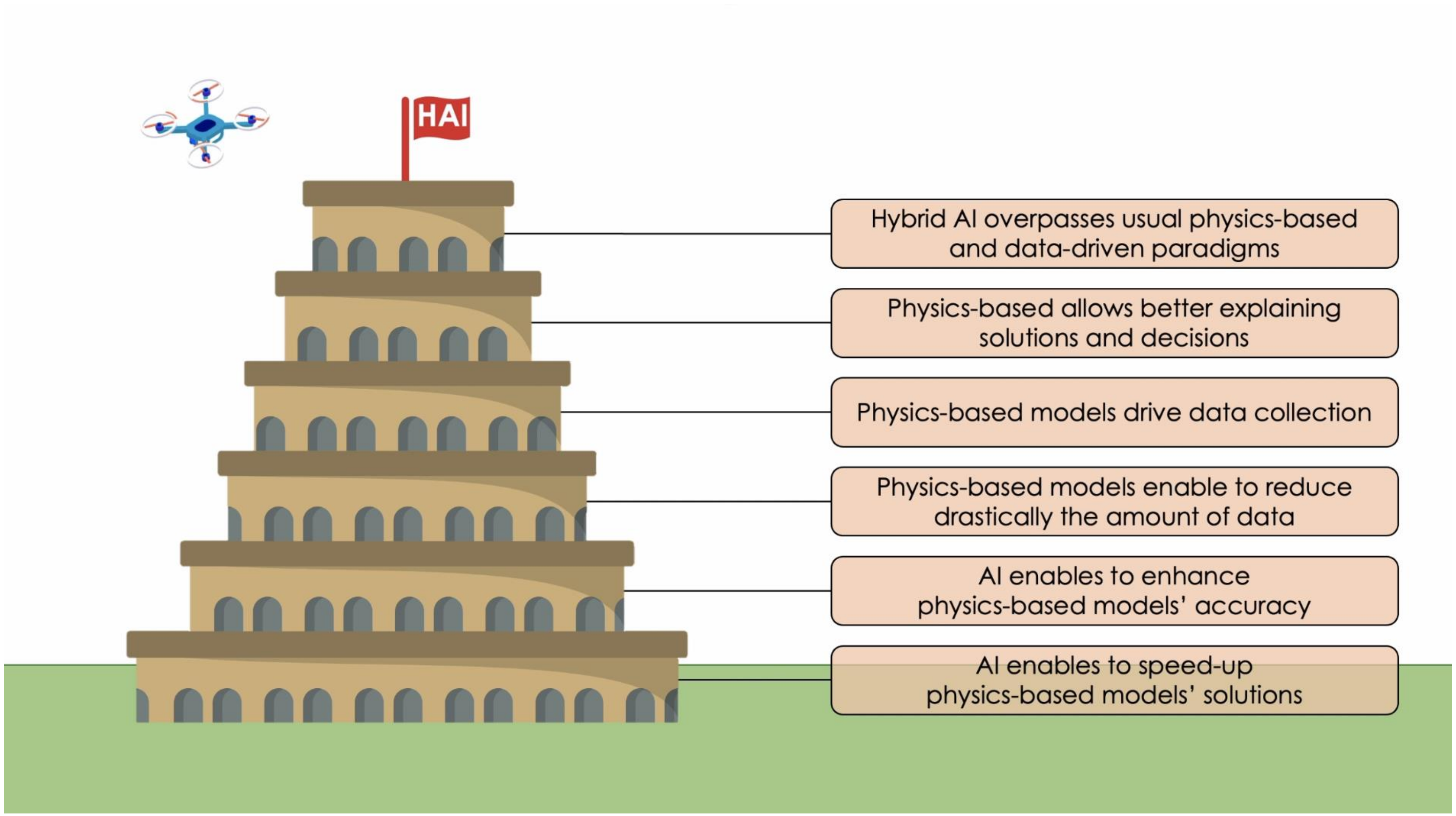
Marina Bay Wind-map



EMERGENCY CRISIS - PLUME DISPERSION



CONCLUSION


HAI
Hybrid AI overpasses usual physics-based and data-driven paradigms
Physics-based allows better explaining solutions and decisions
Physics-based models drive data collection
Physics-based models enable to reduce drastically the amount of data
AI enables to enhance physics-based models' accuracy
AI enables to speed-up physics-based models' solutions