

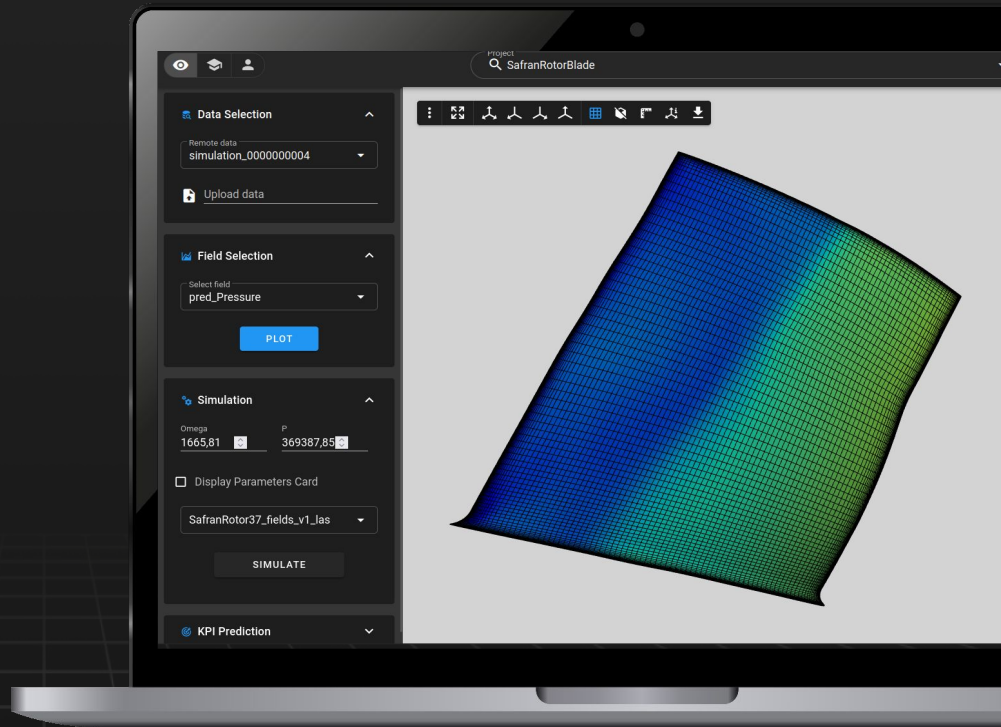
# AUGUR

## Séminaire Couplage IA et Simulation

10 Juin 2026



NAFEMS



# Programme

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01 Déjà 1 an

02 Parlons un peu de vous

03 Cas d'usage : IA pour la simulation thermique de composant électroniques

**Nicolas KERUZORE (Thales)**



Il y a un an ...

AUGUR



*Inria*

- Chercheurs de l'Inria, l'IFPEN et l'IRT SystemX
- Incubés au startup studio de Inria
- Augur a été créée il y a un an

npco.ai

**NPco**

**The optimal design  
already exists.**



The optimal design already exists

Pour chaque design, l'optimum se trouve quelque part dans un espace trop vaste pour être exploré de façon traditionnelle

Nous développons des modèles permettant à chacun de vos ingénieurs de le trouver instantanément, sans compromis

## Performance radicale

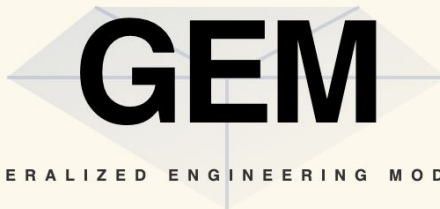
L'ingénierie à la vitesse de l'imagination

## Alchimie des données

Transformer efficacement vos données de simulations et opérationnelles en Intelligence

## Efficacité extrême

quelle que soit la physique, la géométrie et ce avec peu de données



## Ingénierie unifiée

Accessible à tous vos ingénieurs des designers aux experts

## Souveraineté absolue

Votre IP, vos data, vos serveurs





The optimal design already exists

npco.ai

## The NP Company lève 6M€ en Pre-Seed

*avec Partech et la famille Peugeot*



NPco - Confidential





# Questionnaire



# Thales x Augur

Foundation diffusion model for  
Semiconductors simulation

N. KERUZORÉ  
NAFEMS- TERATEC 2026

[www.thalesgroup.com](http://www.thalesgroup.com)



# The problem

## > Thales Technical context – Why do we need Thermal management ?

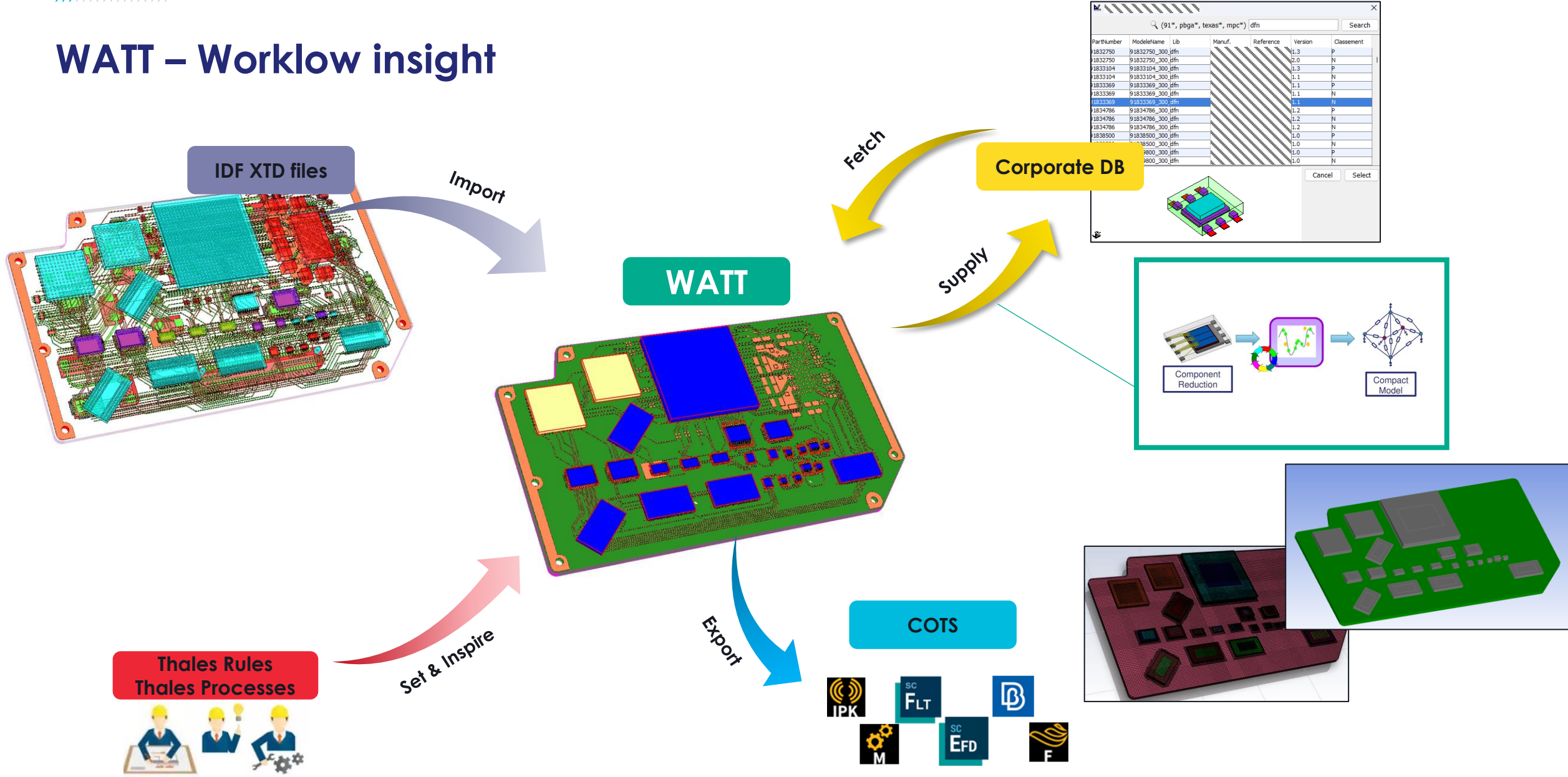
- Predicting electronic components' thermal behavior is critical for reliability.
- decreasing the temperature by 1°C on an electronic board is equivalent to reducing the failure rate by 4%.

## > Some fun facts :

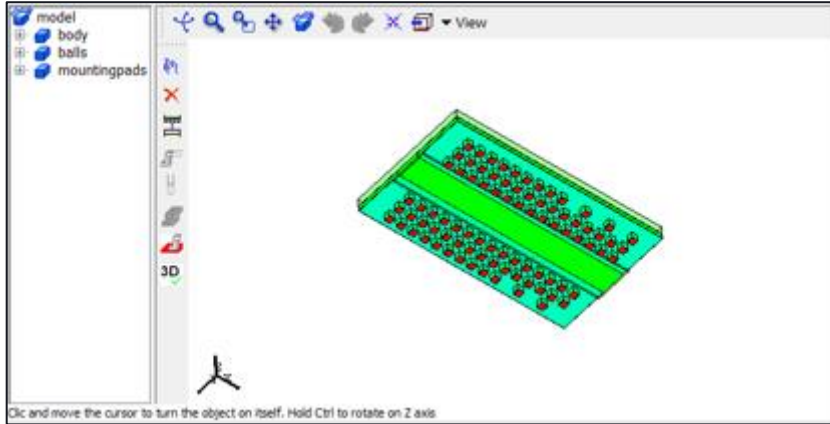
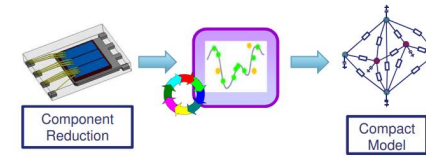
- On an equivalent scale, a component dissipates more energy than a rocket [ $10^9$  Vs  $10^7$  W/m<sup>3</sup>].
- The scale of our simulation extends from meters to micrometers (and soon 50 nanometers) [ $10^8$ ].
- Without specific tooling, the simulation setup and calculation time would exceed hundreds of hours, even with HPC servers.



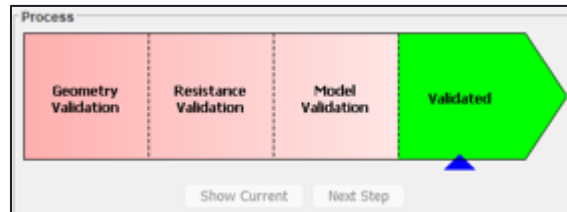
# WATT – Worklow insight



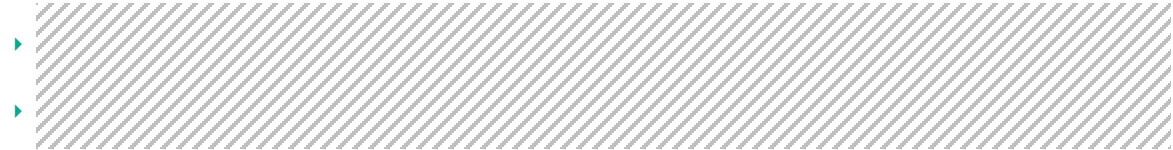
# WATT – 3D model to surrogate reduction feature



Geometry Data		
Basic    Advanced    Materials		
Package length	<input type="text" value="14.0"/>	mm
Package width	<input type="text" value="8.0"/>	mm
Package thickness	<input type="text" value="1.3"/>	mm
Balls nb	<input type="text" value="135"/>	
Missing Balls nb	<input type="text" value="6"/>	
Pitch	<input type="text" value="0.8"/>	mm



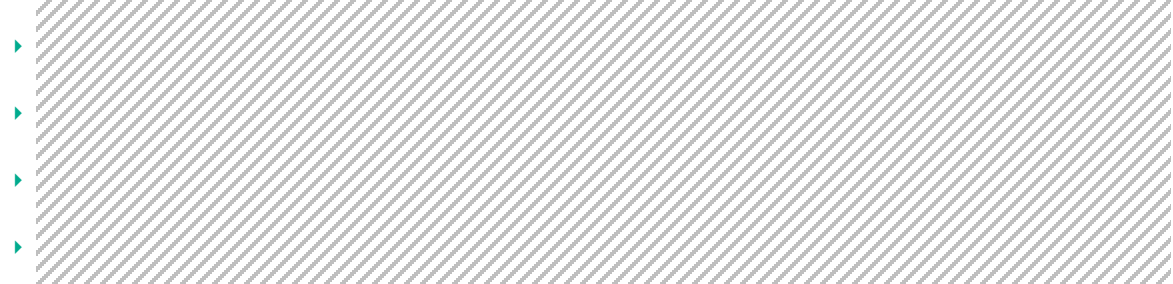
## > 3D Modeler – Component Genetator



## > Standardized Reduced Order Models



## > Powerful Thales tailored Algorithms

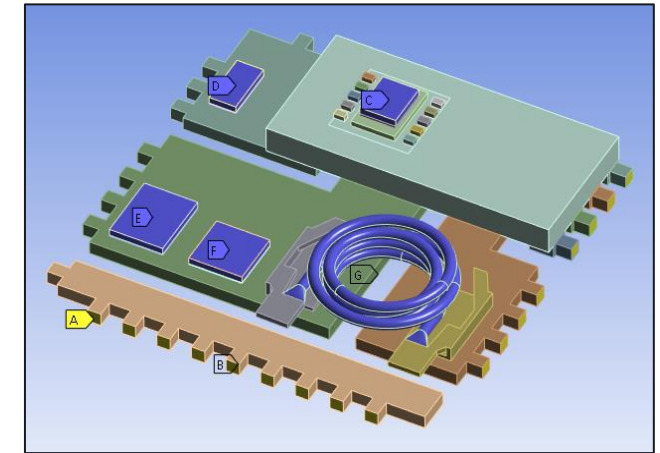
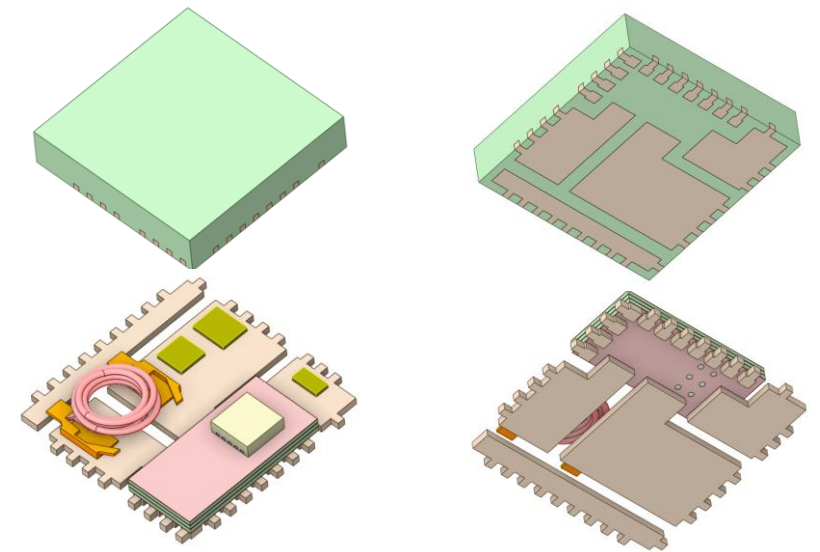


# Thermal Surrogates Factory

# WATT – What next ?

## > Limits of actual process

- ▶ Modeler hit a hard limit :
  - ‘Complex’ geometries are not supported.
  - Every shape besides cubic and cylinder shapes are considered ‘Complex’.
- ▶ Computations takes a lot of time :
  - ‘Complex’ packages are not supported.
  - Every semiconductor with more than 1 heat source is considered ‘Complex’.
  - $(50 \text{ steady} + 9 \text{ transient computation}) \times (\# \text{sources} + 1)$ .
  - 1 to 10 iterations per package...



## For this SiP

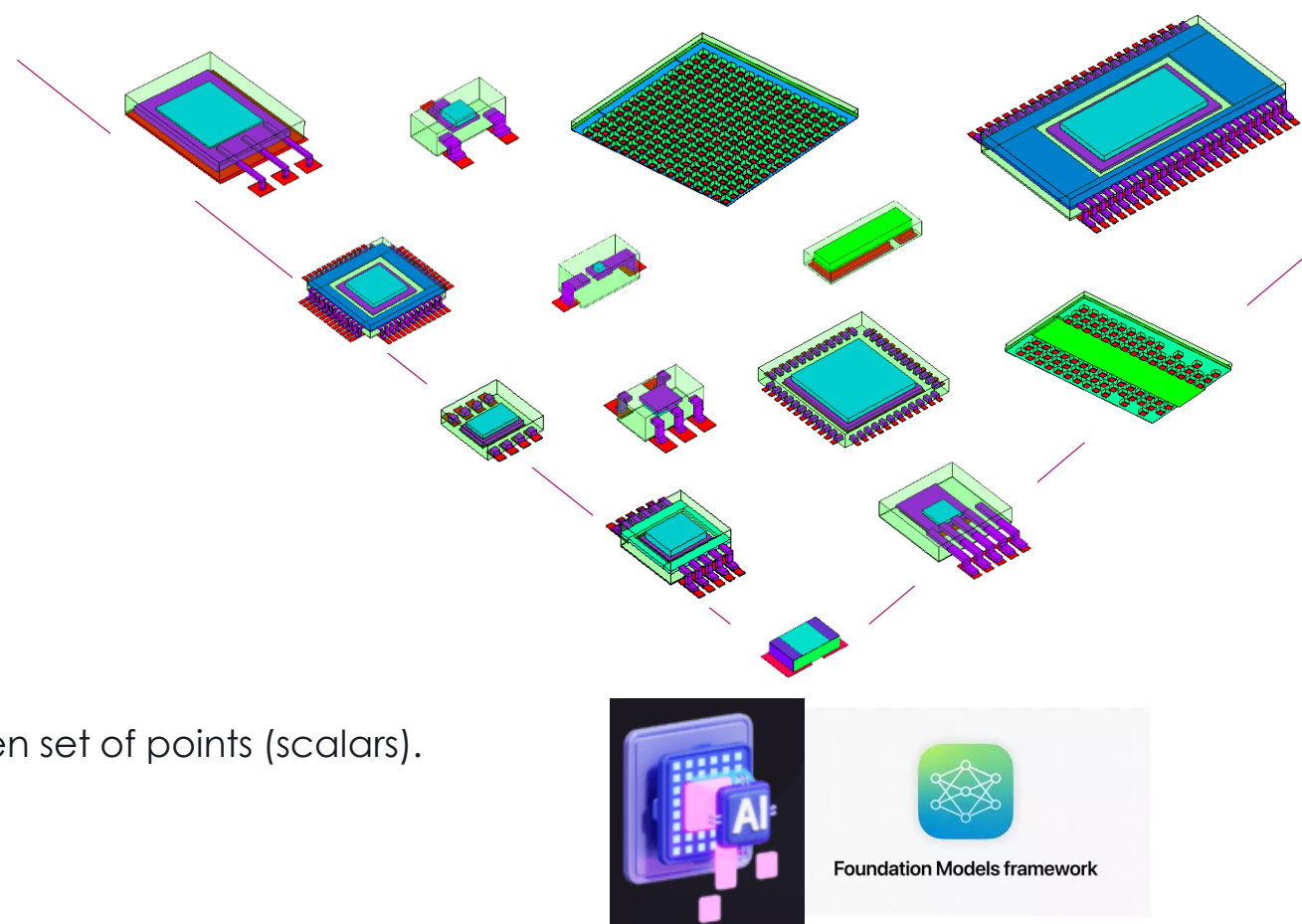
$(54 \text{ steady} + 9 \text{ transient}) \times 6$  computations are needed :

- 324 steady computations.
- 54 transient computations.

# The Idea...

## > How about a model that could :

- ▶ V1 (MVP) - Handle quickly any geometry :
  - Not limited by shapes and material properties.
  - Not limited by meshes number (or at least up to 10M).
- ▶ V1 (MVP) - Compute temperature :
  - For a given and fixed DOE (JEDEC - DELPHI).
  - Return transient temperature of any points (field) or given set of points (scalars).
  - With thermal diffusion physics only.
- ▶ V12++ - Be plugged into a simulation software :
  - Declines itself as many times as there are components on a PCB based on each extracted mesh.
  - Exchange informations back and forth with the solver.



## This solve

The issue of reducing increasingly complex geometries

The issue of how quickly (DELPHI) models are created

The issue of having to manage a model by geometry

# The first step...

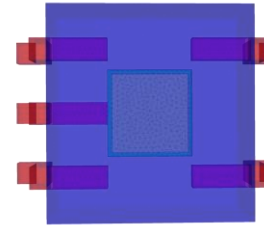
## > Geometry Generalization & Reduced Simulation Budget

- ▶ AUGUR's surrogate models can be pre-trained on a base of existing components and then fine-tuned on new geometries with only a handful of additional simulations. This amortizes the simulation cost across the entire component catalog: each new package leverages all the thermal knowledge accumulated from previous ones, rather than starting at zero.
- ▶ Over time, this transforms the economics of thermal modeling:
  - Today :  $(50 \text{ steady} + 9 \text{ transient}) * \text{nb\_heat\_source} + 1$ . Linear scaling with no reuse.
  - With AUGUR : initial pre-training corpus + fine-tuning batches per new component.
- ▶ The current step focuses on validating the methodology.

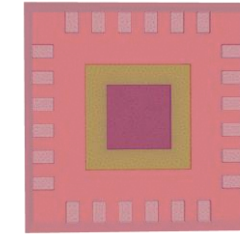
# Dataset

## > Geometries

- 32 transient thermal simulations, distributed across 2 fixed geometries with 16 simulations / geometry.



Geometry A with Leads



Geometry B without Leads

## > Inputs scalars

- P** : Dissipated power in the junction[W].
- Hbot** : Heat transfer coefficient on bottom surface [W/m<sup>2</sup>.K].
- Htop** : Heat transfer coefficient on top surface [W/m<sup>2</sup>.K].
- Hsides** : Heat transfer coefficient on lateral surfaces [W/m<sup>2</sup>.K].
- Hleads** : Heat transfer coefficient on leads (0 for geometry B) [W/m<sup>2</sup>.K].

## > Outputs

- Junction Temp : mean temperature at the junction.
- Top / Bot / Leads Temp : mean temperature at the top / bottom / leads.

```
=====
DESIGN OF EXPERIMENTS - inputs and 'Exceed 150 °C' flag
=====
```

sim	geom	set	P [W]	Hbot	Hleads	Hsides	Htop	Exceed
sim01	A	init	1	1000	10	50	100	NO
sim02	A	init	1	100	1000	10	50	NO
sim03	A	init	1	50	100	1000	10	NO
sim04	A	init	1	10	50	100	1000	NO
sim05	A	init	1	100	100	100	100	NO
sim06	A	init	2.4	205.2	683.6	982.1	5	NO
sim07	A	init	1.8	646.4	184	242.6	562.7	NO
sim08	A	init	0.7	455.9	542.6	92.67	812	NO
sim09	A	init	3.1	995.6	857.8	707.1	296	NO
sim10	A	init	1.3	72.45	221.9	497.9	645.5	NO
sim11	A	new	1	632.9	789.3	503.5	266.6	NO
sim12	A	new	1	56.11	898.8	316.3	491.5	NO
sim13	A	new	1	357.2	71.52	180.1	183.6	NO
sim14	A	new	1	10	800	10	10	NO
sim15	A	new	1	10	600	100	100	NO
sim16	A	new	1	5	600	10	600	NO
sim17	B	init	1	1000	-	50	100	NO
sim18	B	init	1	100	-	10	50	YES
sim19	B	init	1	50	-	1000	10	YES
sim20	B	init	1	10	-	100	1000	YES
sim21	B	init	1	100	-	100	100	YES
sim22	B	init	2.625	184	-	646.4	356.9	YES
sim23	B	init	2.218	36	-	267.3	517.7	YES
sim24	B	init	1.727	596.1	-	831.5	634.8	YES
sim25	B	init	0.3658	790.7	-	398	77.45	NO
sim26	B	init	1.844	804.1	-	21	944.6	YES
sim27	B	new	1	854	-	457	17	NO
sim28	B	new	1	239	-	28	933	NO
sim29	B	new	1	36	-	921	604	NO
sim30	B	new	1	500	-	100	500	NO
sim31	B	new	1	1000	-	10	10	NO
sim32	B	new	1	1000	-	10	500	NO

```
=====
32 samples - 20 initial / 12 new | Exceed YES: 8 NO: 24
=====
```

# Strategy

## > Metrics

- ▶ Given the very low number of samples (32 total), we evaluate using a “LOO” (Leave One Out) strategy.
- ▶ LOO = Given N samples, train on N-1 and evaluate on the target sample.
- ▶ The metric used is a relative RMSE given in %. For the LOO we take the mean over the predictions.

$$RMSE_{rel}^{(i)} = 100 \times \frac{\sqrt{\frac{1}{T} \sum_{t=1}^T (\hat{y}_{i,t} - y_{i,t})^2}}{y_{max} - y_{min}}$$

## > Benefits extrapolation

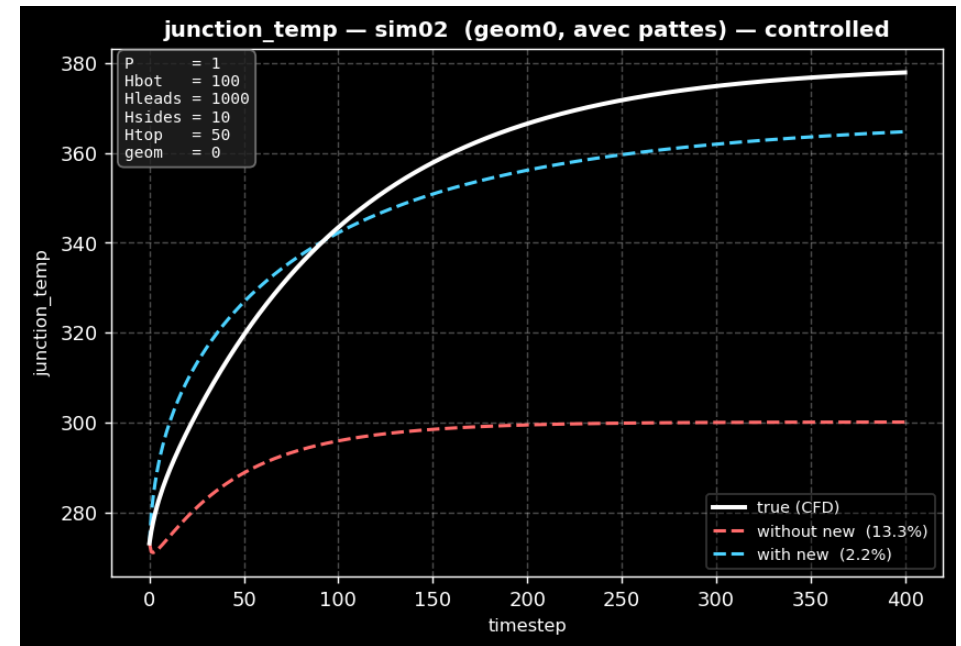
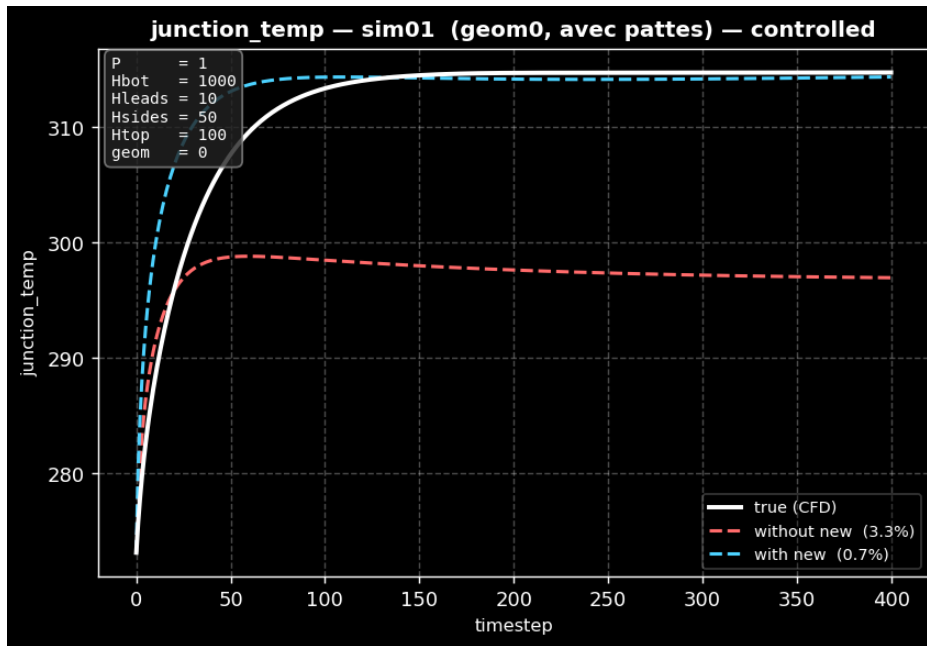
- ▶ In addition to last week result, we will investigate the benefit of adding the 12 new data.
  - **IT1 = we train on 20 LDB and predict on 12 VDB.**
  - **IT2 = we train on 19 LDB and predict on 1 LDB.**
  - **IT3 = we train on 31 LDB + VDB and predict on 1 LDB + VDB.**

# Results

## > Metrics

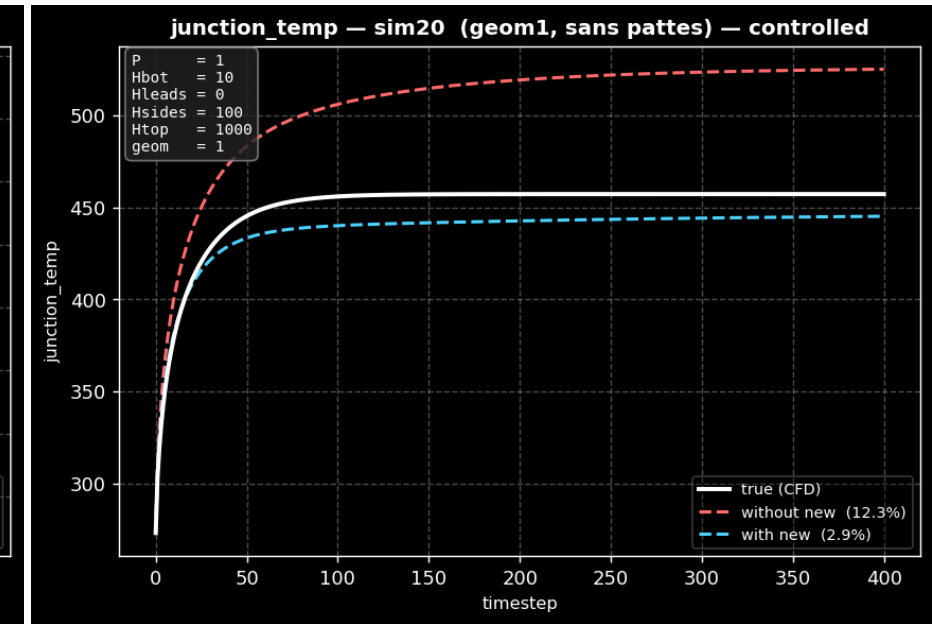
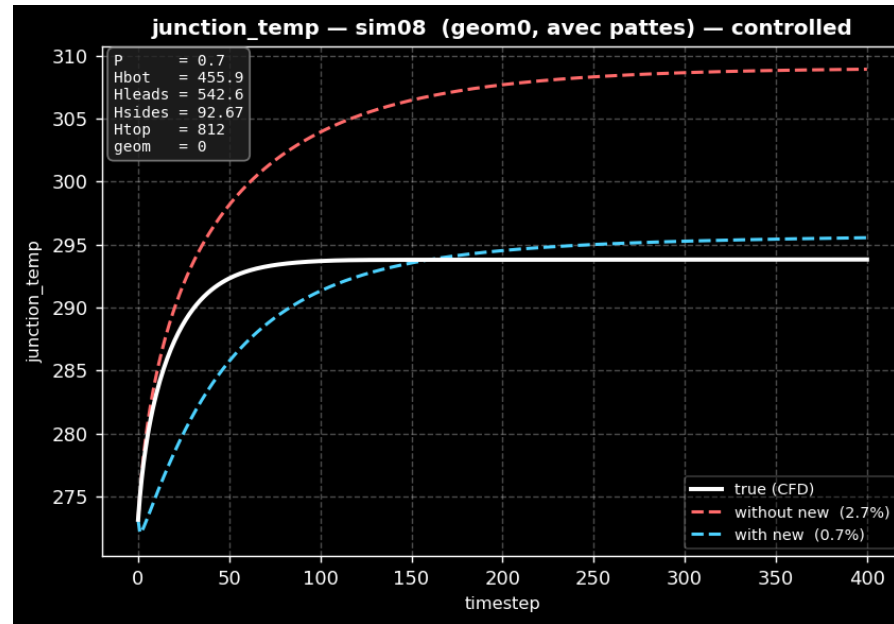
Output	RMSE% IT1	RMSE% IT2	RMSE% IT3
Junction Temp	14.61	8.74	7.57
Top Temp	10.96	10.58	7.40
Bot Temp	15.30	9.31	7.37
Leads Temp	13.67	17.07	10.64

## > Probes

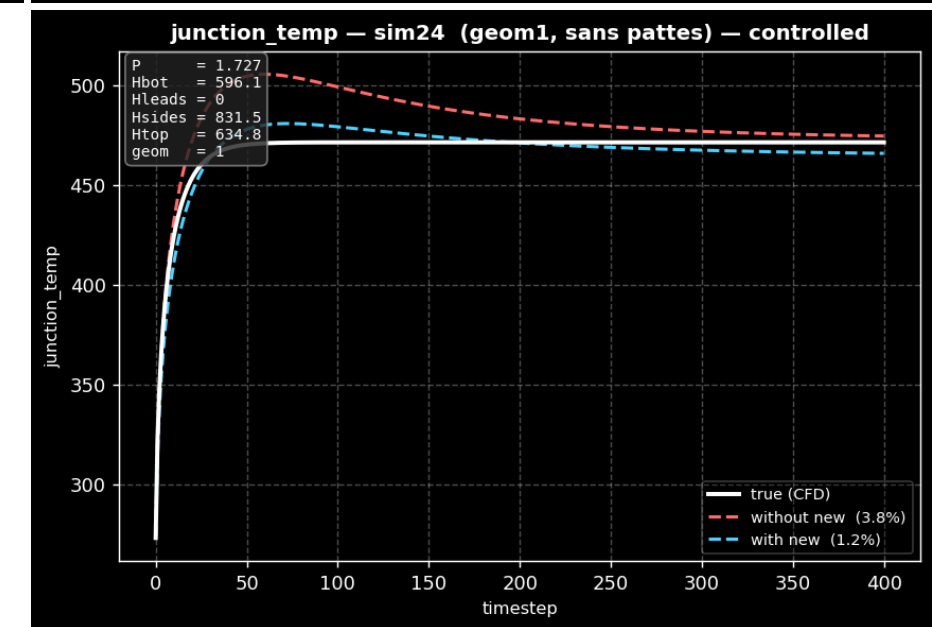


# Results

## > Probes

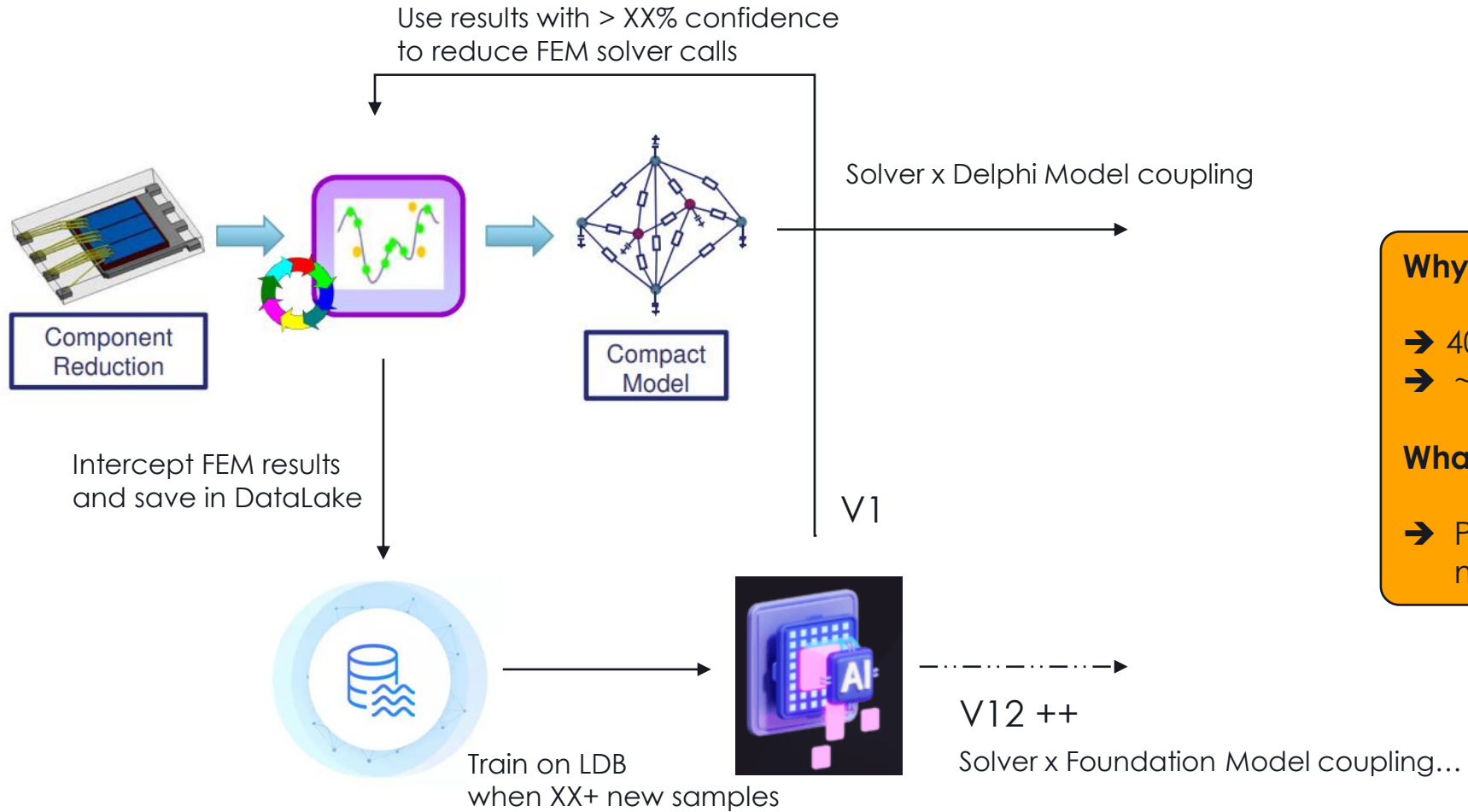


- ▶ + Transient dynamics and behavior are qualitatively good !
- ▶ + A few samples more in LDB improved a lot the prediction !
- ▶ - Adding physics informed feature to the Transformer architecture could help to improve RMSE and prevent physical aberrations.
- ▶ - The values obtained are not quantitatively good.



# And then ...

## > Captialize on reduction data to build step by step a foundation model

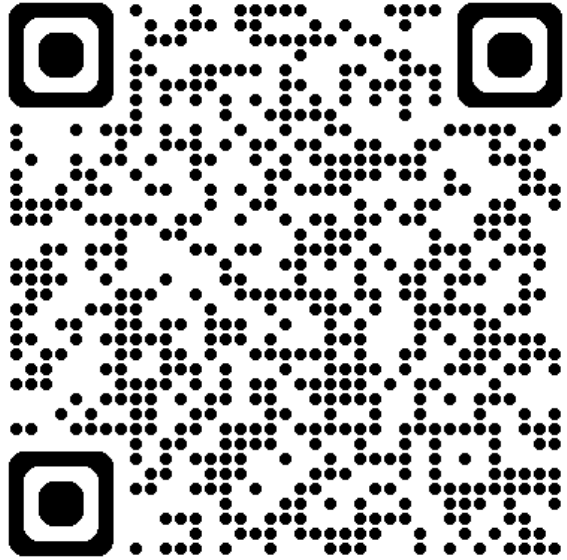


### Why could this work @ Thales ?

- 400+ DELPHI models / year
- ~20 to 100.000 FEM samples / year

### What could be difficult ?

- Proprietary solver with non standard meshing features & results.



EQ  
community

Thank you

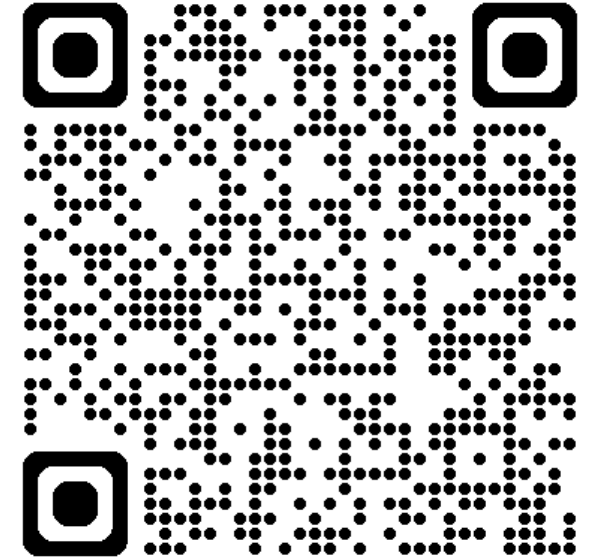
Contact

Nicolas KERUZORÉ

Thermal Specialist – WATT Senior Coach

 06.49.10.69.09

 [nicolas.keruzore@thalesgroup.com](mailto:nicolas.keruzore@thalesgroup.com)



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