Metamodeling physical systems for industrial asset management

How to combine physical models and data for decision-making?

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Agenda

MEWS: WHO WE ARE

RTE: THE FRENCH TRANSMISSION SYSTEM OPERATOR

PROJECT ACHIEVEMENT & LESSONS LEARNT

WRAP-UP & PERSPECTIVES

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Mews
Who we are

Mews Partners is an independent management consulting firm

About us

60 million euros in revenue (2023)

280 Employees

40 Partners

7 Offices

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Our Expertise

4 Business offers

INNOVATION

R&D PERFORMANCE

MANUFACTURING PERFORMANCE

SUPPLY CHAIN & PROCUREMENT

6 Cross-functional offers

- Product Lifecycle Management
- Data & modelling
- Environmental performance
- Agile transformation
- People booster
- IT Performance

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We cover 14 industrial sectors

- AERONAUTICS
- ARCHITECTURE, ENGINEERING & CONSTRUCTION
- AUTOMOTIVE & MOBILITY
- DEFENCE
- ELECTRONICS & HIGH TECH
- ENERGY & UTILITIES
- TRANSPORT & LOGISTICS
- FOOD & BEVERAGE
- HEALTHCARE
- LUXURY GOODS & ACCESSORIES
- MACHINERY & INDUSTRIAL EQUIPMENT
- PROCESS INDUSTRIES
- RETAIL & CONSUMER GOODS
- SPACE

A long story with airbus since 2005

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Connecting Business knowledge with our data science & AI expertise to enhance asset management

Data, AI and complex modelling

Predictive analytics & **data science** combined with physical models

Hybrid modelling (data + simulation) of complex systems

Multifactor optimization (operational planning)

80% of our staff have a PhD in maths, physics or computer science, and we have a strong proximity with **top research centers** for the integration of specific expertise

AI & physical modelling — école normale supérieure paris—saclay

Digital Twins — École nationale des Ponts et Chaussées

25 R&D engineers in Mews Labs & network with universities

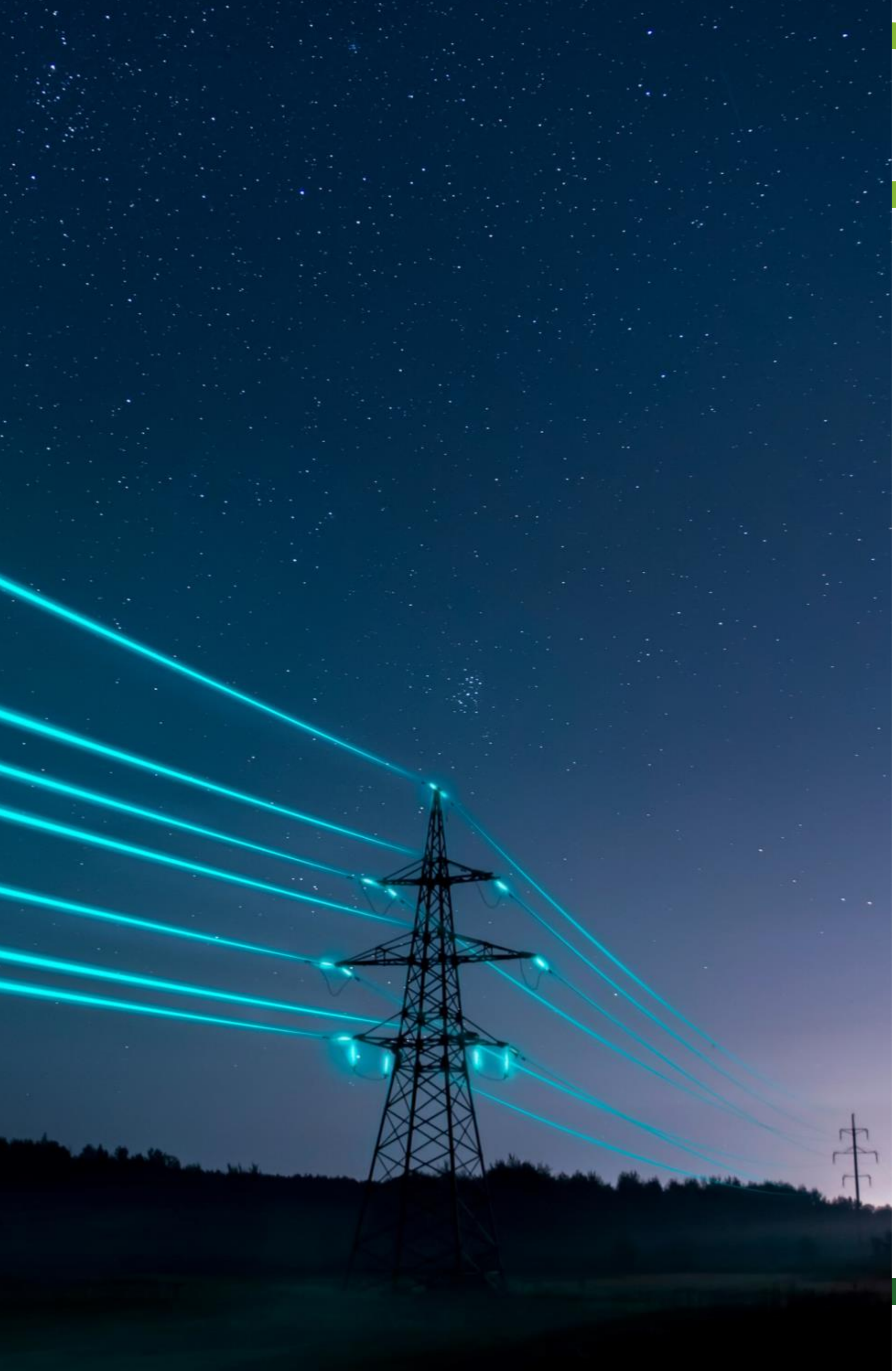
Asset Management Expertise

Custom-made methodology to formulate the **decision problem** and identify the **feared events**

Understand **business context,** assess data readiness and processes

Scale-up reliability models, Machine Learning and hybrid modelling to characterize **events' likelihood** and help **decision-making process**

Search for **optimal decision** and **acceptable risk**



Rte

The French Transmission System Operator

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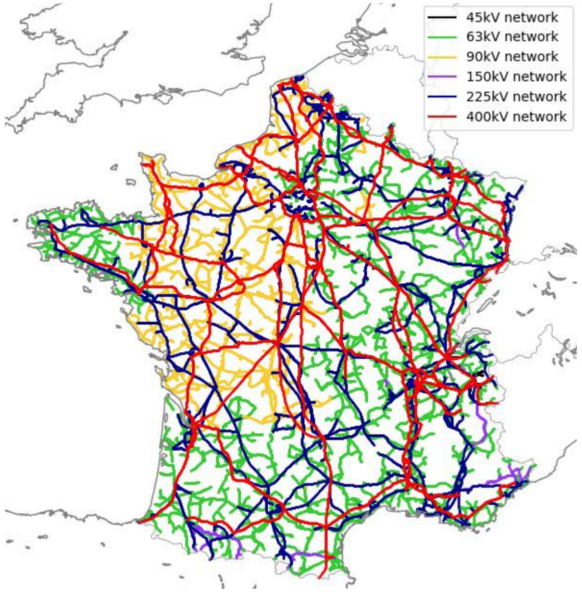
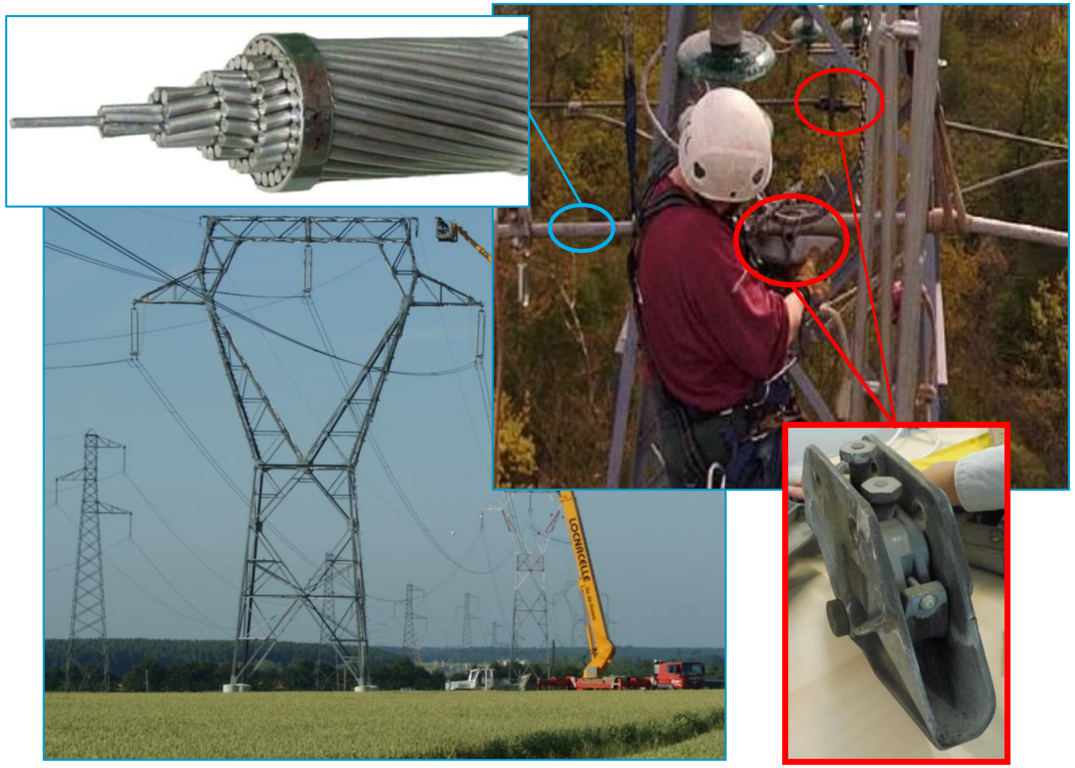
Industrial context

RTE (Réseau de Transport d'Electricité) is the largest in Europe and only Transmission System Operator (TSO) in France, with two main roles:

- Power delivery to industrial consumers and electricity distributors
- Management and development of high and extra high voltage network: 100,000 km of lines





- Among its physical assets, the overhead lines are critical for RTE
  - Line failure would result in critical consequences for large regions and infrastructures
  - Most of the lines, installed in 70s, are near their end of life and need to be replaced

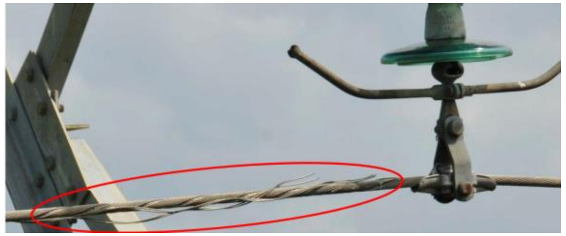
- RTE faces a complex problem by nature
  - High heterogeneity of lines & network components.
  - Complex physical phenomena induced by electric current and environmental influences (wind, snow, sun, …).

A similar problem in other domains?

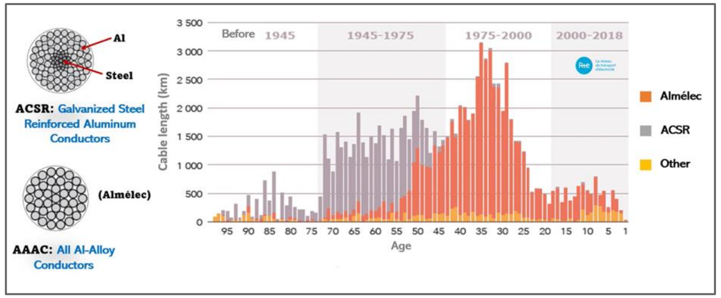
RTE motivations for our **collaborative work**

Needs

- How can we predict the **risk of future faults** appearing on the network, in order to guide maintenance budgets in the region?



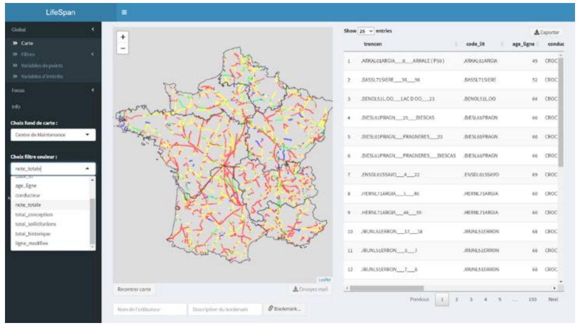
- How can we **smooth out the peaks in investment** needed to renew assets, while continuing to provide a risk-free service?



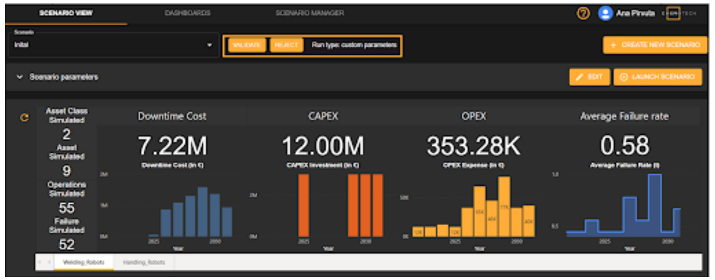
Source : https://assets.rte-france.com - SDDR 202019

Solutions

- **Risky assets classification**: Targeting **at-risk individuals** using past experience (defects, maintenance, etc.)

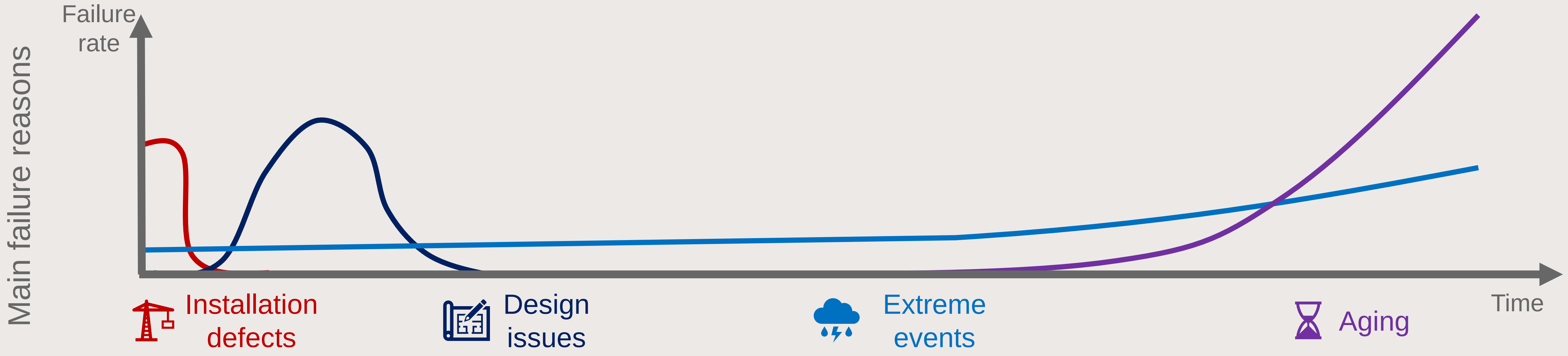


- **Residual life assessment**: Creation of **aging laws** integrated into a constrained optimization tool to size and quantify asset renewal plans with the best cost-performance-risk ratio



Source : https://cosmotech.com/fr/

What are the challenges for managing an asset over time?



Main actions for asset managers

Installation defects

- Process improvement & training

Design issues

- Protective device installation
- New designing rules

Extreme events

- Prioritization of maintenance operations
- Predictive maintenance
- Study of network resilience

Aging

- Non-Destructive Tests
- Prioritization of renewals
- Remaining life predictions
- New component design

Project achievements and lessons learnt

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Our story with Rte

Diagnostic support

- Automated capitalization process
- Signal processing for internal interpretation

Monitoring database

- Data model design
- Rules to synchronize and gather data

Physical modelling

- Thermomechanics
- Fatigue
- Vibrations
- Fluid structure interaction

Forecasting

- Machine learning based on observed defaults
- Risk Informed Decision Making process
- Extrapolation of physical behavior in the resilience framework

The big picture of our actions with Rte

Diagnostic support

- Automated capitalization process
- Signal processing for internal interpretation

Consolidation

- LiDAR points clouds segmentation
- CAO models fitting

Monitoring database

- Data model design
- Rules to synchronize and gather data

Quality checking

- Consistency, accuracy, reliability requirements
- Anomaly detection

Data As A Service

- CI / CD pipeline
- DevOps & versioning

Physical modelling

- Thermomechanics
- Fatigue
- Vibrations
- Fluid structure interaction

Dashboarding

- Interactive operational reporting
- Decision-making improvement

Forecasting

- Machine learning based on observed defaults
- Risk Informed Decision Making process
- Extrapolation of physical behavior in the resilience framework

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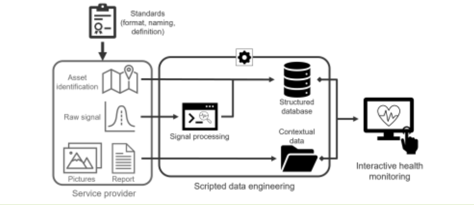
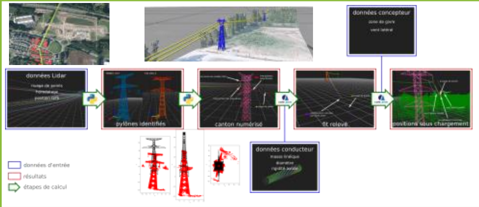
The big picture of our actions with Rte

See our Webinar on 09/11/23
replay – slides

Diagnostic support

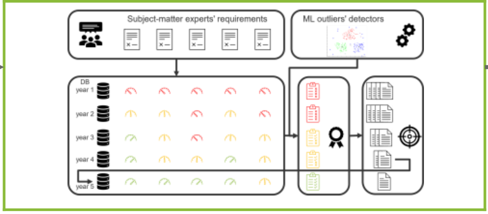


Consolidation

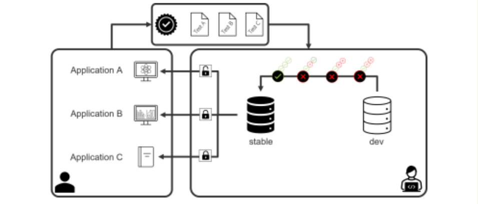


Monitoring database

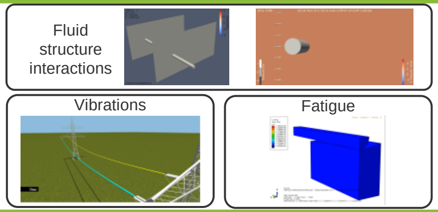
Quality checking



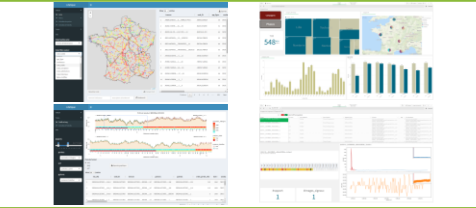
Data As A Service



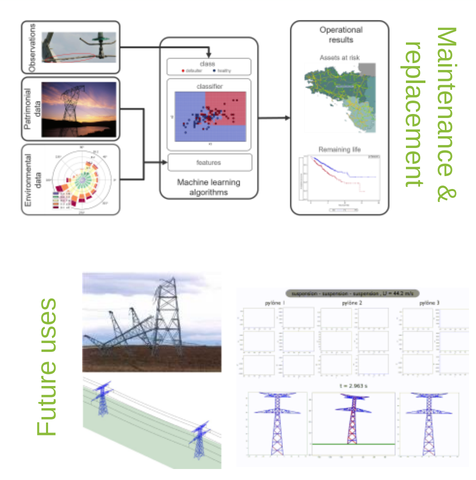
Physical modelling



Dashboarding



Forecasting



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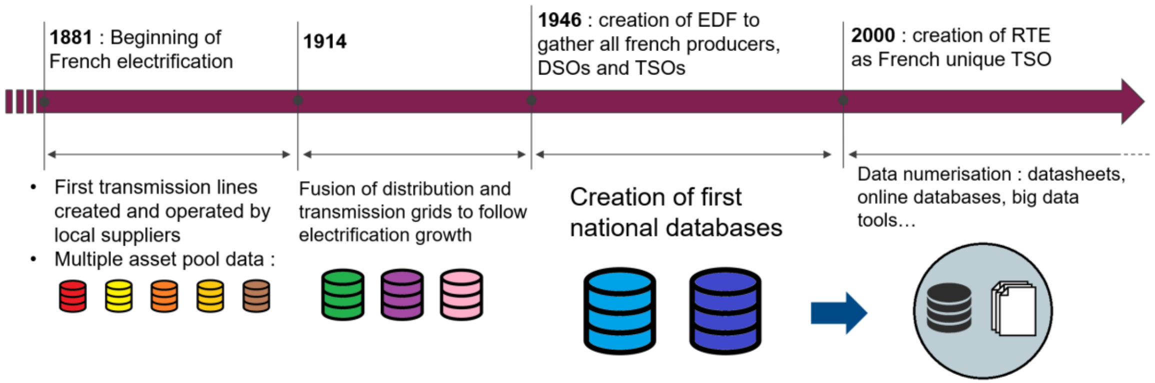
Focus on data-driven asset management

- **Need of consistent data quality efforts** to improve data overtime, leveraging physical models
- **Involving subject matters experts in the definition of *(initial)* data quality rules** to challenge data and results
- **Automate outlier detection by combining business rules with likelihood testing principles** through multivariate assessment and modelling

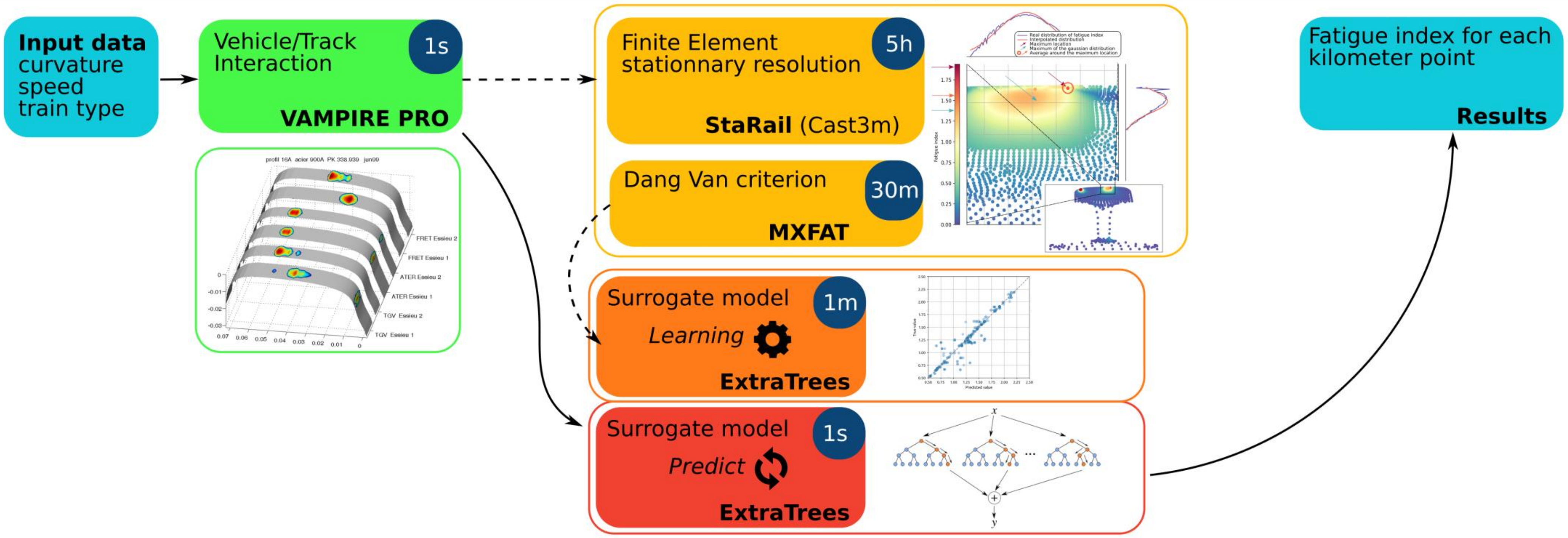


A few figures on the data handled

- **Assets: 400,000 kms of power cables** (300,000 spans & 270,000 pylons)
- Electrical transit: **every 5 minutes on 7,000 overhead lines** since 2012
- Monitoring: each line is covered **at least once a year** by ground or helicopter crews
- Observations: **over 200,000 field returns** on defects (mostly minor) since 2003

Automatic data quality enhancement using physical models is key for modelling performance

Focus on AI-boosted physical simulation



Physical models are used to classify assets risks on a large network, and to quantify ageing speed over time.

Surrogate models are a good compromise for this context, which can admit an accuracy around 95%.

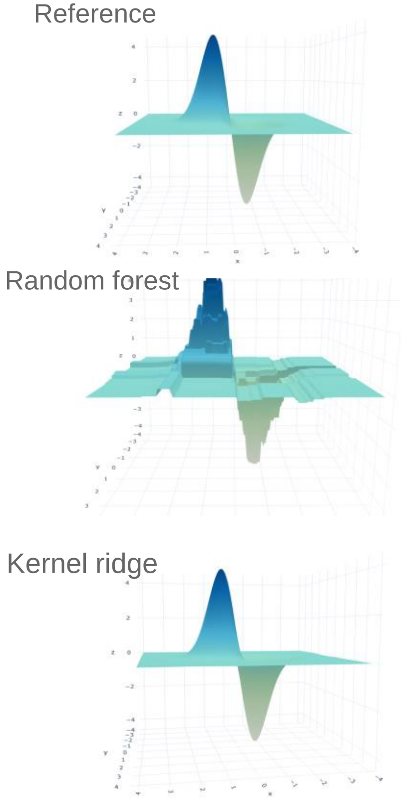
Each context requires a different accuracy target.

Focus on AI-boosted physical simulation

- The choice of the surrogate model depends on the complexity of the expected previsions and the computation time.

- The type of model used can be (non-exhaustive list):
  - Decision trees and Random Forests are easy to parametrize and interpret. However, their predictions are constant by part and do not reflect the continuous aspect of the variable.
  - When using Regression and Kriging methods, the predictions are continuous functions of the variables. This aspect is more consistent with physics, where the underlying process are often driven by differential equations.
  - Neural Network and Physics-informed Neural Network (PINNs) allow to make more complex previsions, like solutions of differential equations. These models are however more complex to build and parametrize, and therefore not relevant for the prediction of single values as fatigue index. *(more information in the next presentation)*

- These models can also be used to study the sensitivity to parameters. The importance of parameters, or the Gini index are usually computed in order to better understand the model. The sensitivity can give a justification about which parameters can be fixed, and the difficulty to estimates their values from data.

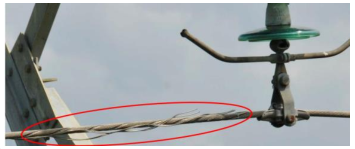


Ipol: Active learning for surrogate models

Forecasting

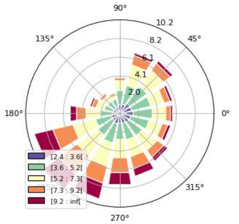
Focus on risky assets classification

Observations

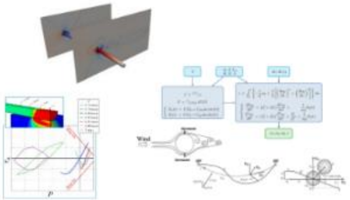


Assets data

Environmental data



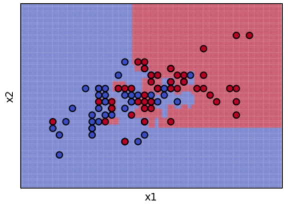
Simulations of key physical phenomena



class

- defects
- healthy

classifier



Features

Machine learning algorithms

DECISION-TOOLS USED DAILY BY RTE OPERATIONAL TEAMS

Targeting at-risk individuals
vs
past experience (defects, maintenance, etc.)

We rely on **explainable machine learning algorithms** to ensure reliability of models.

Gen AI models are nonetheless interesting avenues, but their contribution has not been quantified and compared with the risk of loss of control over extrapolations carried by physical models.

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Focus on risky assets classification

- Classifiers, as decision trees, predict the **probability *p*** that an assets belongs to the 'risky' group.
- In order to obtain a meaningful prevision, a threshold ***s*** has to be determined :

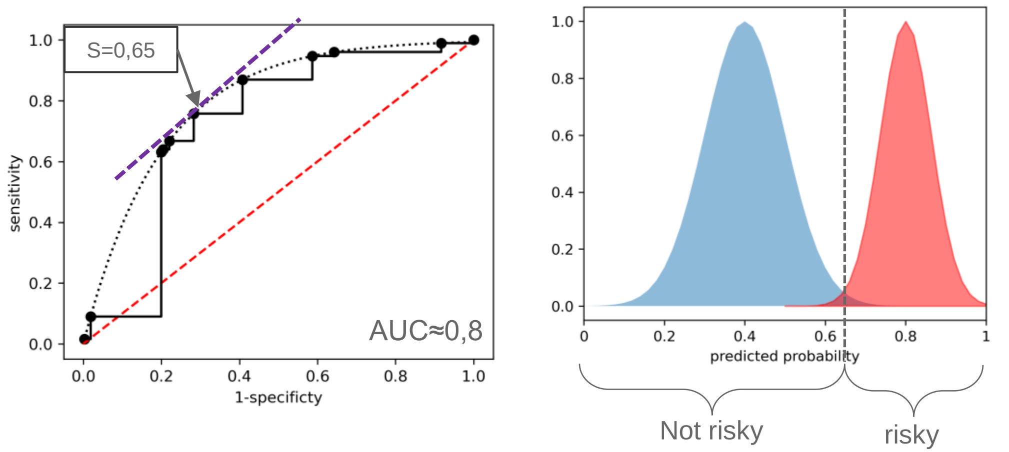
$$risk\ of\ asset(p) = \begin{cases} healthy, & p < s \\ risky, & p \geq s \end{cases}$$

- This threshold ***s*** is determines using ROC curve:
  - Each point correspond to the sensitivity and the 1- specificity for a given threshold

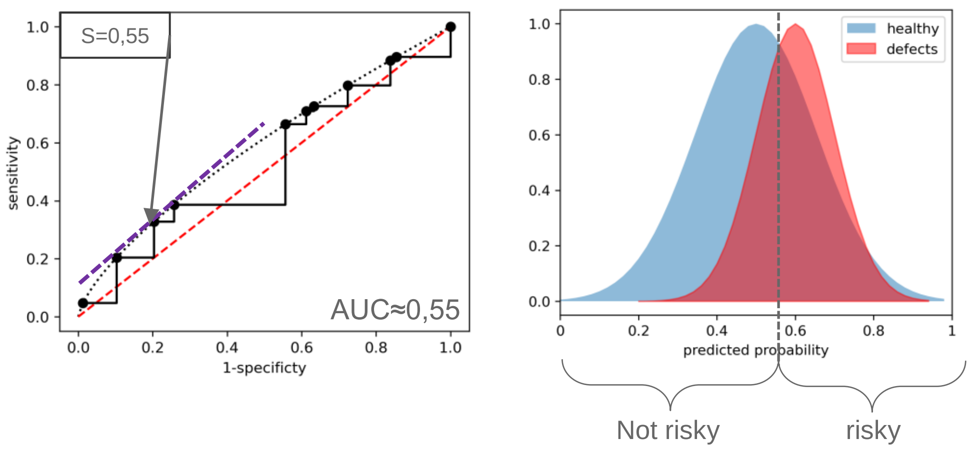
$$\begin{cases} sensitivity = \dfrac{True\ Positive}{True\ Positive + False\ Negative} \\ 1 - specificity = \dfrac{False\ positive}{True\ Negative + False\ Positive} \end{cases}$$

- The Area Under the Curve (AUC) indicates the accuracy of the model and point where tangent equals 1 give the threshold ***s.***
- These models can be used to select which assets should be monitored or replace in priority. However, they are not reliable to give quantitative results about the risk of failure of a given asset.

An example of accurate model



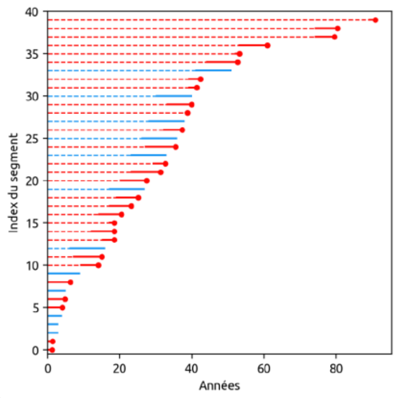
An example of realisticly accurate model



Focus on residual life assessment

Forecasting

Fault history for each asset

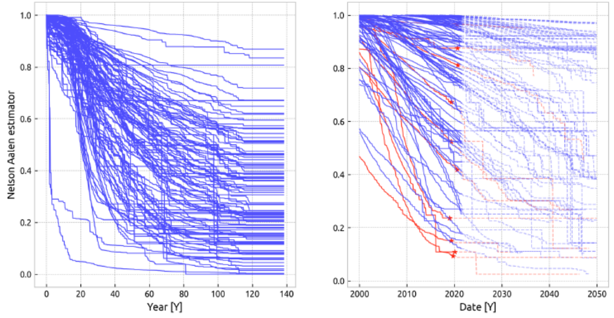


Assets data

Environmental data

Simulations of key physical phenomena

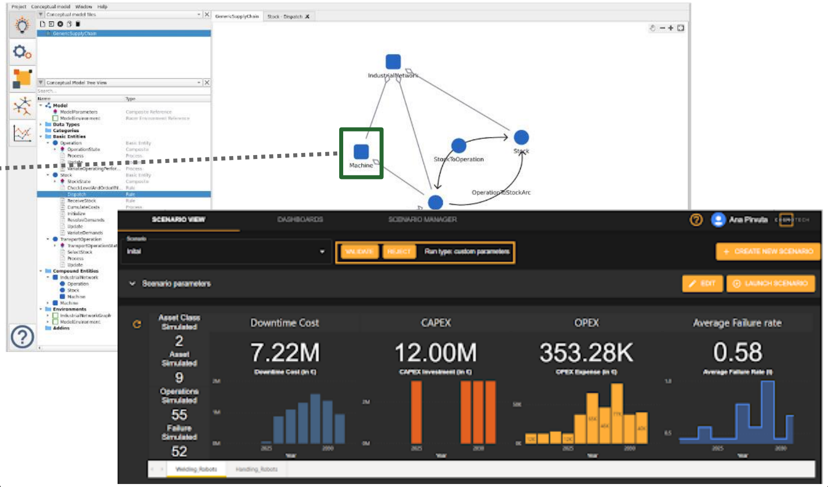
Survival curves obtained for each asset using the dedicated random forests



API

OUTPUTS ARE CRITICAL FOR LONG-TERM MAINTENANCE POLICY AND NEGOTIATION WITH NATIONAL AGENCIES

Input of an optimization tool to size and quantify asset renewal plans with the best cost-performance-risk ratio



Source : *https://cosmotech.com/fr/*

Quantifying the lifespan of an asset is far more difficult than classifying assets in terms of ageing risk. However, this is essential for predicting maintenance needs.

However, **through recent machine learning approaches**, we can search for groups of assets aging at the same rate, without any initial business a priori, based on the data.

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Focus on residual life assessment

- Based on the history, the first step is the computation of the estimated the survival function ***S(t)***. The most-used estimators are:
  - The non-parametric Kaplan-Meyer estimator : $\hat{S}(t) = \prod_{i:t_i<t}\left(1 - \frac{number\ of\ failed\ assets\ at\ time\ i}{number\ of\ assets\ at\ time\ i}\right)$
  - Parametric function, using maximum likelihood ($L(\mu, p) = \prod_i \frac{dS(t_i,\mu,p)}{dt}$) as :
    - Exponential $S(t) = e^{-\mu t}$
    - Weibull $S(t) = e^{-\mu t^p}$
    - Gompertz $S(t) = e^{-\mu(e^{pt})}$
- This estimation can also be adapted to take into account censoring, i.e. asset for which the failure age is not observed due to a limited observation window. The likelihood becomes $L(\mu, p) = \prod_i \frac{dS(t_i,\mu,p)}{dt}^{\delta_i} . (S(t_i, \mu, p))^{1-\delta_i}$.
- The residuals life of an assets can also be computed as $\frac{1}{S(today)}\int_{today}^{\infty} S(t)dt$.
- This function can then be estimated for each group of assets.
- Hazard functions $\left(\lambda(t) = \frac{1}{S(t)}\frac{dS(t)}{dt}\right)$ can then be used to parametrized Poisson Process, allowing to perform stochastic simulations to test management scenarios, or build digital twins.

Wrap-up & perspectives

Outcomes of our projects with RTE

Prediction on complete network

A **data-driven approach** is applied across the entire lines network for **long term anticipation and planification**, in which predictions of the future behavior of network assets are based on **past observations**, but also on **physical ageing models**

Decision making enabler

The models developed can be used to **improve strategic decision-making** and leverage **technical and economic modelling** for maintenance, renovation/renewal and replacement policies.

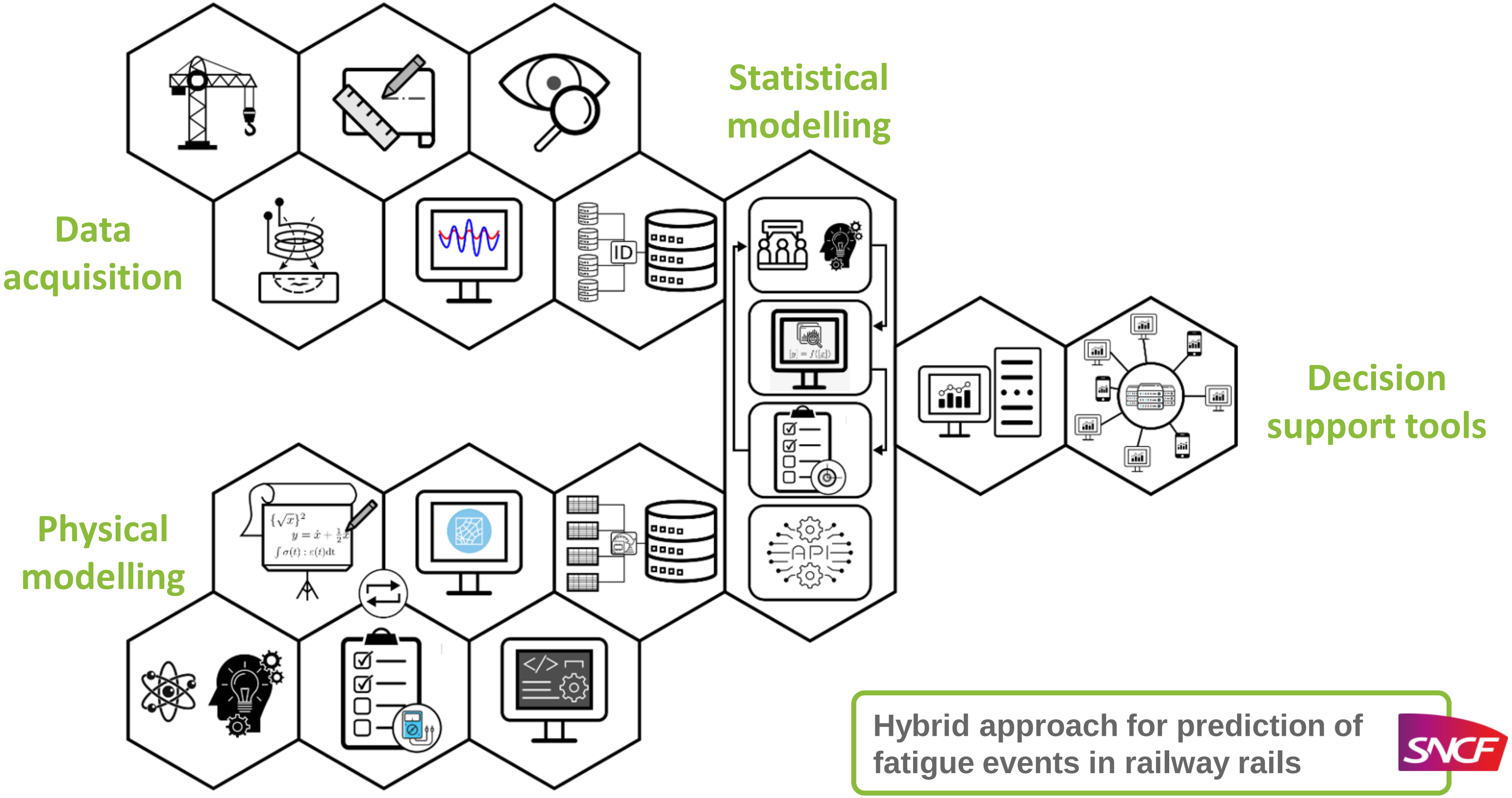
Quality of data

Depending on the description of the assets and their experience, the project-team has developed expertise in the deployment of an **understandable database** and automated **quality control management**.

Reusable techno bricks

The codes produced, mostly published in open-source, can be re-used at **various stages of asset management:** design and refurbishment projects, daily maintenance support, health status of an existing network.

The hybrid modelling: Principles reminder



Hybrid approach for prediction of fatigue events in railway rails

Constraint programming tool for underground rail maintenance

Our approach…

… is based on a so-called **hybrid model** that combines **physical modelling** and **statistical learning** method from several data sources such as:

- Industrial specific (historical design, observations, measurements)
- External (geographical information systems, weather data).
- From calculation chains in the form of Physical indicators.

Our expertise…

… includes the **steps** required for hybrid modelling.

- Acquisition, cleaning, consolidation and formatting of the data.
- Implementation of machine learning and physical models and their interactions.
- Ad hoc development of decision-making tools.

Thank you for your attention