Making Reliability Engineering Smart:

When Principles of Failure Meet with Industrial Big Data

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Short Curriculum Vitae

Personal path

07/2011 Ph.D. in Reliability and Systems Engineering, **Beihang University**, Beijing, China.

12/2017 Assistant Professor, **CentraleSupélec,** Paris, France.

B.Eng. in Quality and Reliability Engineering, **Beihang University**, Beijing, China.

01/2016 Postdoc, **CentraleSupélec,** Paris, France.

07/2022 Assistant Professor (HDR), **CentraleSupélec,** Paris, France.

Chaire on Risk and Resilience of Complex System

Season 1: 2010-2016

- Director: Prof. Enrico Zio

Season 2: 2016 – 2019

- Director: Prof. Enrico Zio

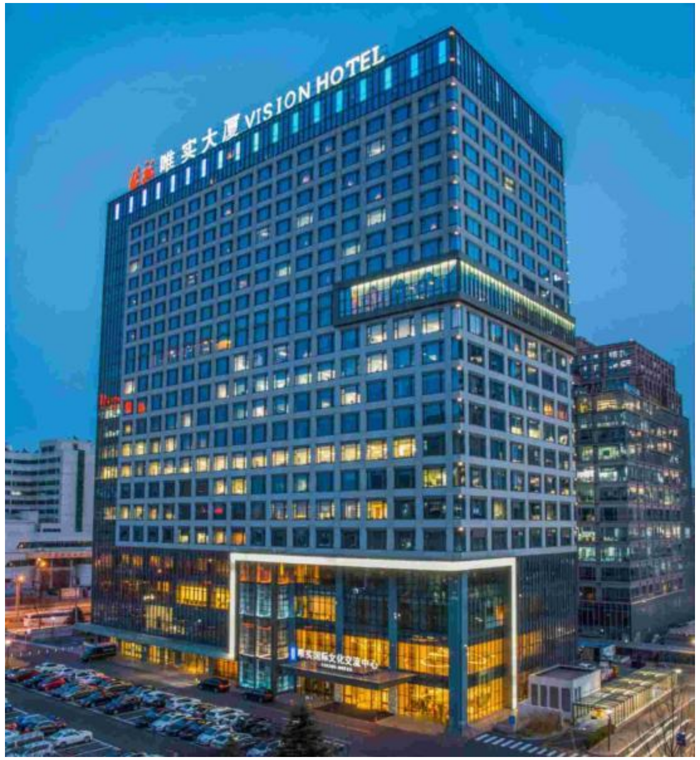
Season 3: 2019 - 2024

- Director: Prof. Anne Barros

Introduction

A vision from Vision Hotel

- "What if we have only one data point? (Making good reliability assessment under this circumstance) It is a vision." – Prof. Way KUO
- A challenge: if we do not have enough historical failure data, how can we still evaluate the reliability with sufficient degree of confidence?



Source: http://en.beijingvision.cn/

Overview of research activities

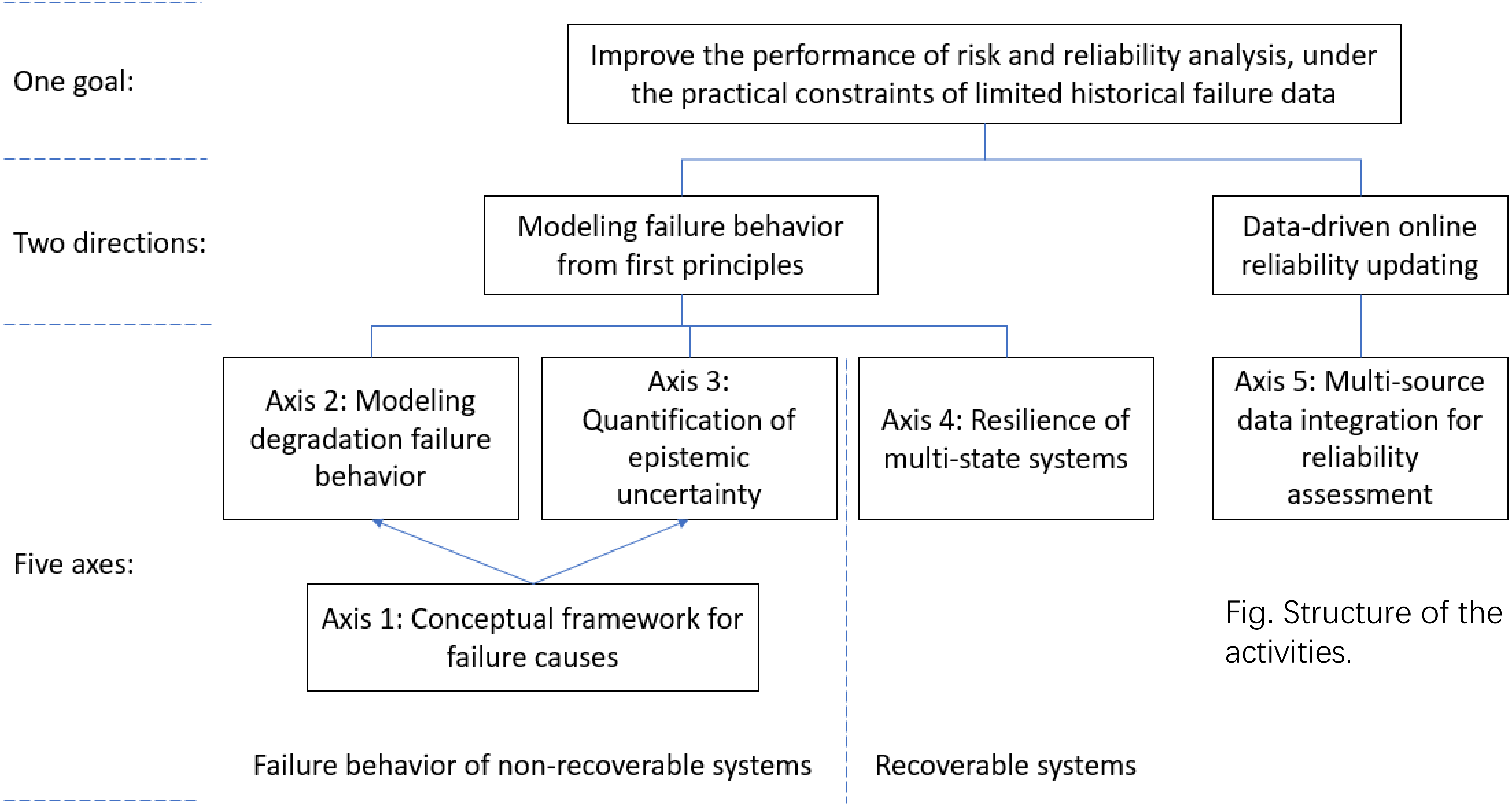


Fig. Structure of the research activities.

Zoom in to axis 1: Conceptual framework for failure causes

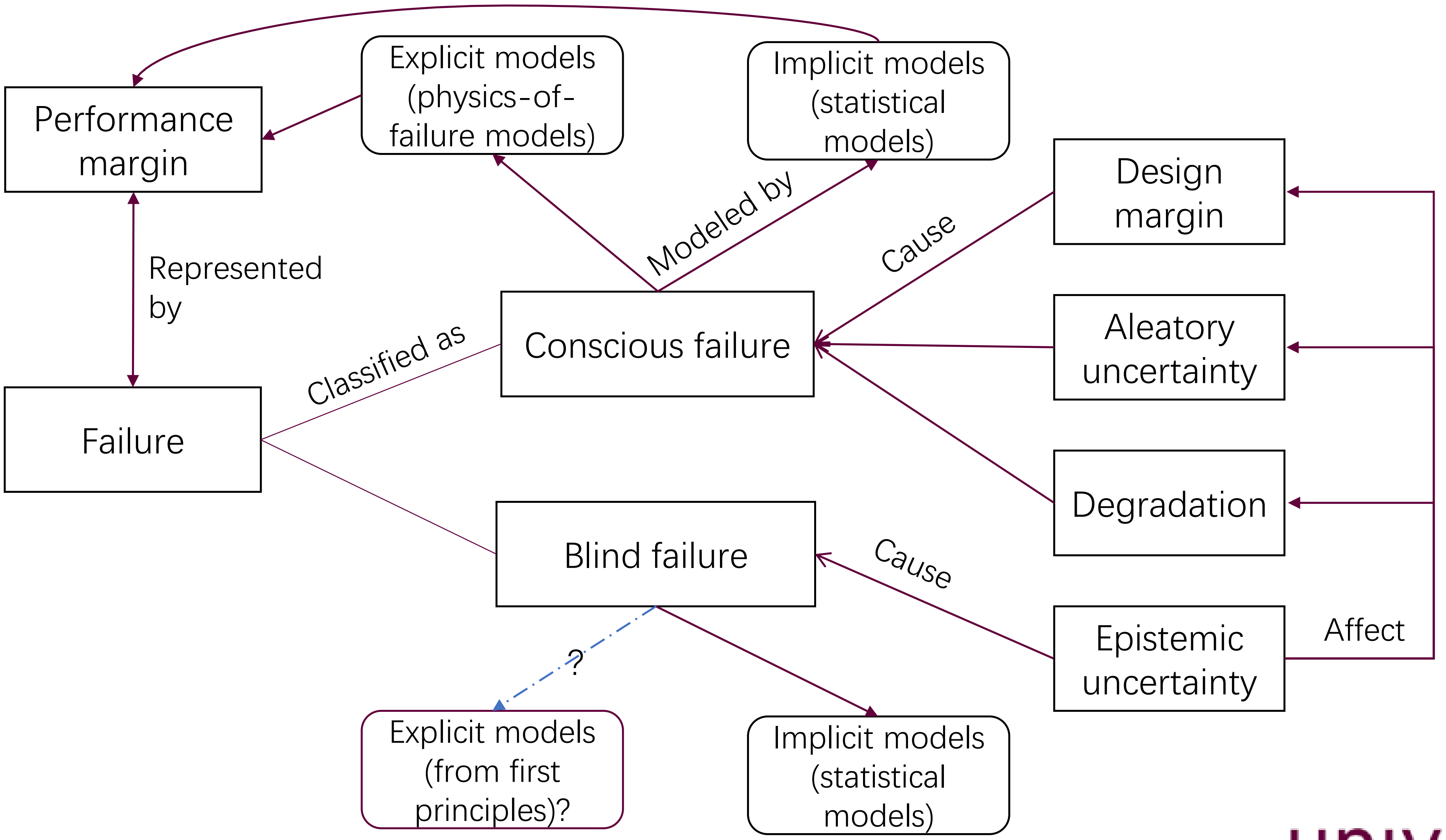


Fig. A conceptual framework for failure causes

Zoom in to axis 1: Integrated index for risk and reliability

- Belief risk index $Risk_B$:
  - Belief degree of the decision maker that a given consequence occurs, considering the prediction of the PRA model and the EU in the PRA model.
    - Design margin, degradation, aleatory uncertainty are modeled by $Risk_P^*$.
    - Epistemic uncertainty is modeled by σ_E.
  - Impact of knowledge and epistemic uncertainty.
    - $Risk_B = 0.5$: Total ignorance: due to EU, we cannot use the PRA model to make decisions.
    - Perfect knowledge: $\alpha_e \to 0$: $Risk_B \to Risk_P^*$
  - Graphical explanation: measures the distance from origin to the boundary of the failure region in the extended uncertainty space.

$$Risk_B = \Phi\left(\frac{-\mu_S}{\sqrt{\sigma_S^2+\sigma_e^2}}\right) = \Phi\left(\frac{-1}{\sqrt{\frac{1}{\left(\Phi^{-1}(Risk_P^*)\right)^2}+\alpha_e^2}}\right)$$

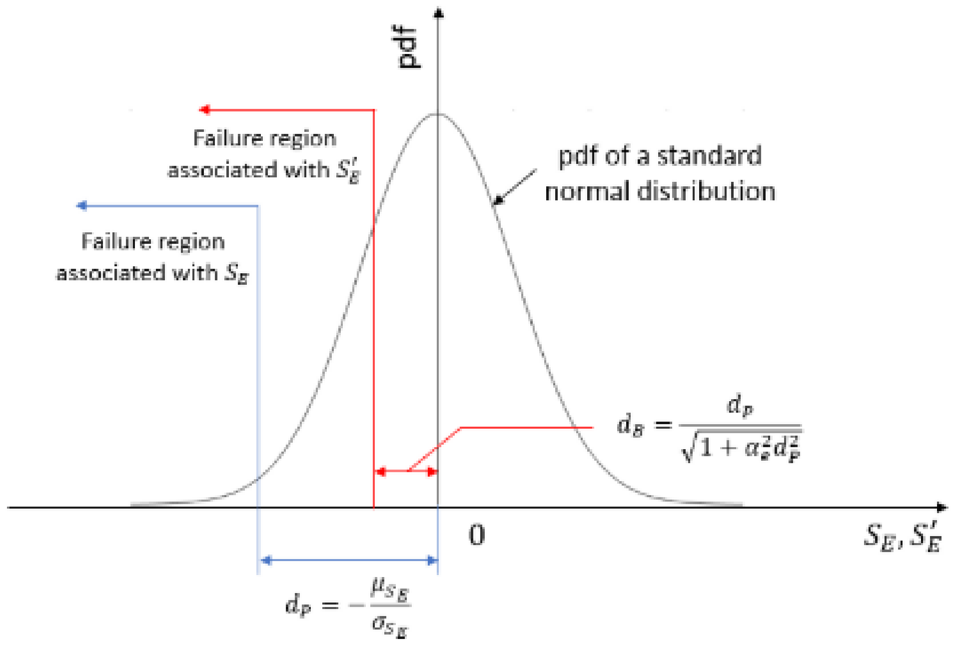


Fig. Interpretation of belief risk index in terms of distance to the failure region.

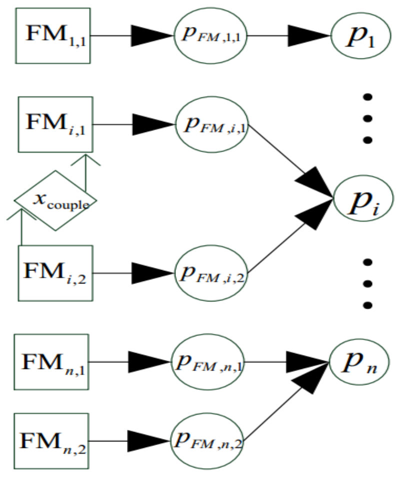
For more details see: Zeng Z, Bani-Mustafa T (SS), Flage R, Zio E. An integrated risk index accounting for epistemic uncertainty in Probability Risk Assessment (PRA). Journal of Risk and Reliability 2021.

Example: When first-principles meets data

Dependent failure process: modeling and analysis:

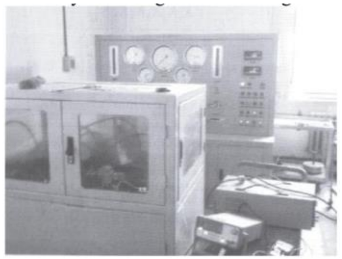
➢ Selected work - component-level dependency modeling:

- A top-down method to identify dependency relations among failure mechanisms.
- A bottom-up “compositional” method for dependency modeling.
- A case study and experimental validations on a aviation valve.

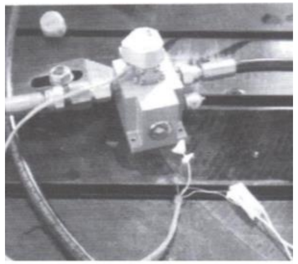


$$x(t) = \frac{k_2 - \exp\left\{-k_1^{'} t + \ln k_2\right\}}{k_1^{'}}.$$

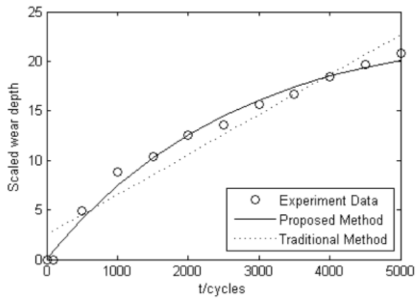
Compositional modeling



Test set-up



Test sample



Test results

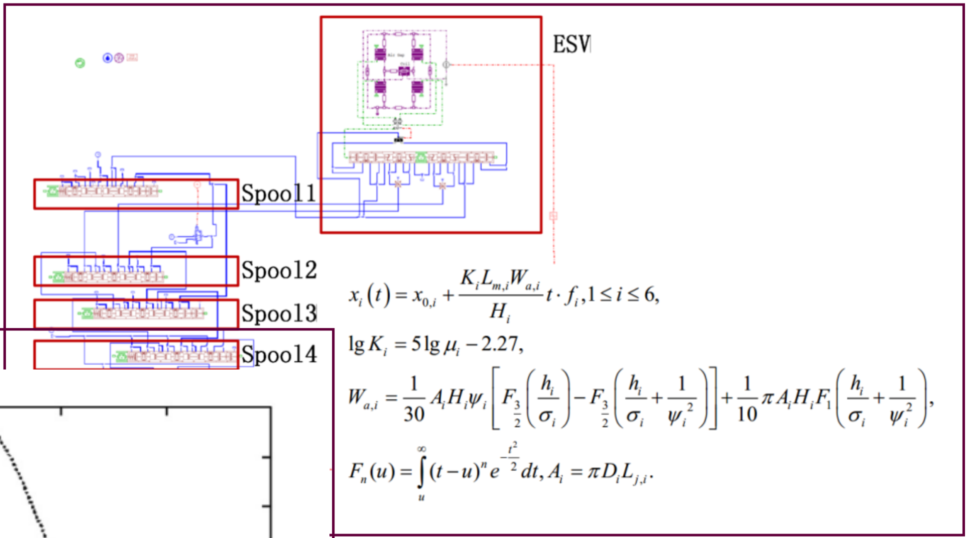
Model validation

For details see: Z. Zeng, Y. Chen, E. Zio and R. Kang., 2017. A compositional method to model dependent failure behavior based on PoF models. *Chinese Journal of Aeronautics*, *30*(5), pp.1729-1739.

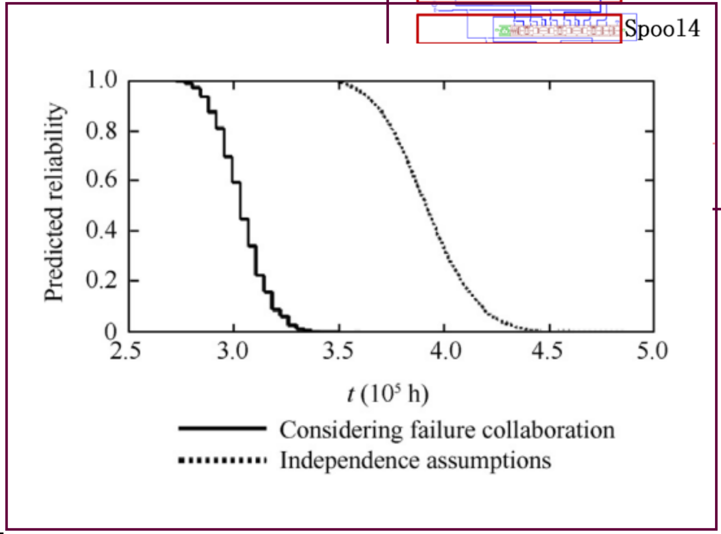
Example: When first-principles meets data

Dependent failure process: modeling and analysis:

- ➢ Selected work - system-level dependency modeling:
  - ◻ An integrated model to consider system-level dependencies.
  - ◻ A bisection-based reliability analysis method.
  - ◻ An application on a hydraulic servo actuator.



Application on a HSA



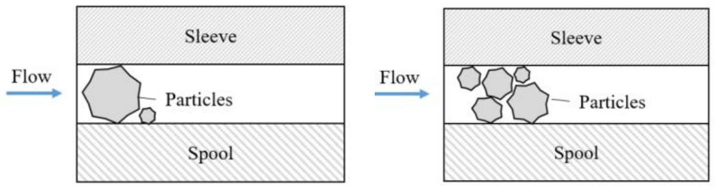
Reliability analysis

For details see: Zeng, Z., Kang, R. and Chen, Y., 2016. Using PoF models to predict system reliability considering failure collaboration. *Chinese Journal of Aeronautics*, *29*(5), pp.1294-1301.

Example: When first-principles meets data

Dependent failure process: modeling and analysis:

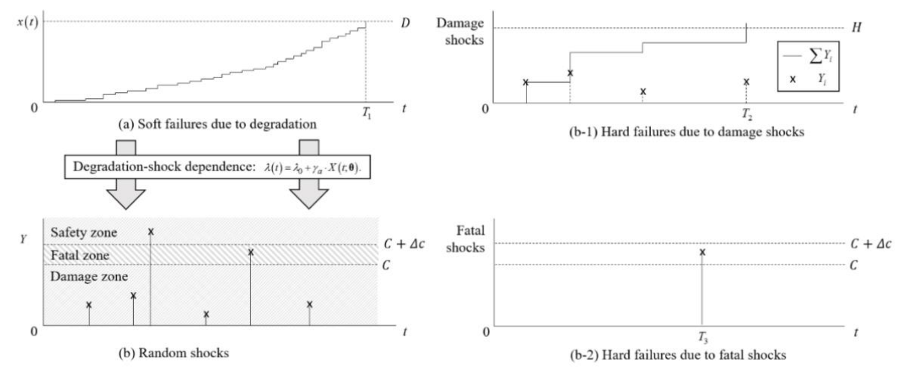
- ➢ Selected work - degradation-shock dependency modeling:
  - ☐ A new reliability model is developed for degradation-shock dependence.
  - ☐ Zone effect of random shocks magnitudes is considered.
  - ☐ The model is applied on a sliding spool.



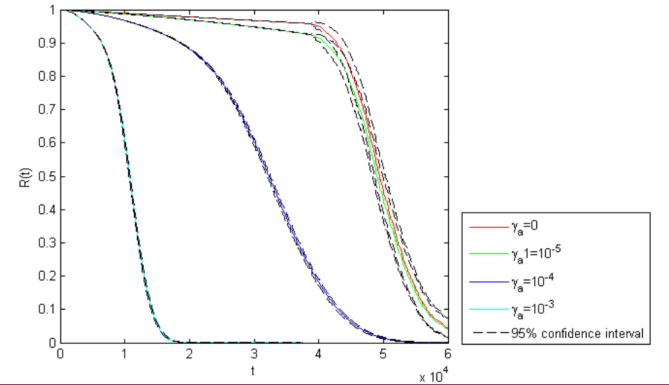
(a) Immediate stagnation

(b) Cumulative stagnation

An example of degradation-shock dependence & zone effect



$$R(t)=\sum_{i=0}^{\infty}\int_{\boldsymbol{\theta}} P(E_1|A,B)\cdot P(E_2|A,B)\cdot P(E_3|A,B)\cdot P(A|B)\cdot f_{\boldsymbol{\theta}}(\mathbf{x})\,\mathrm{d}\mathbf{x},$$



Results of the application

For details you can refer to: Fan, M., Zeng, Z., Zio, E. and Kang, R., 2017. Modeling dependent competing failure processes with degradation-shock dependence. *Reliability Engineering & System Safety*, *165*, pp.422-430.

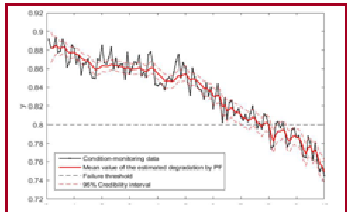
Example: When first-principles meets data

Dynamic reliability updating

- Comparison to existing methods:
  - ➢ Comparisons are made to methods using only statistical data and only condition-monitoring data.
  - ➢ The developed method integrates information from the two sources.
  - ➢ Parameter K determines our trusts on the information sources.

Year	1	2	3	4	5	6	7	8	9	10
C_1	1	0	0	1	0	1	2	3	1	2
C_2	1	1	0	0	1	0	1	2	2	2
C_3	0	0	1	1	1	0	2	5	2	2
C_4	1	1	1	3	1	1	2	1	1	1
C_5	0	1	0	1	0	2	2	1	1	1
C_6	1	1	1	1	0	2	2	1	1	1
C_7	1	1	1	0	0	2	1	1	1	1
C_8	0	1	1	0	0	1	1	1	1	1
C_9	1	1	1	0	2	2	0	0	1	1
C_{10}	0	1	1	0	0	1	1	1	1	0
C_{11}	1	1	1	1	0	0	0	0	1	1

Statistical failure data from a population of similar systems



Condition-monitoring data from the system of interests

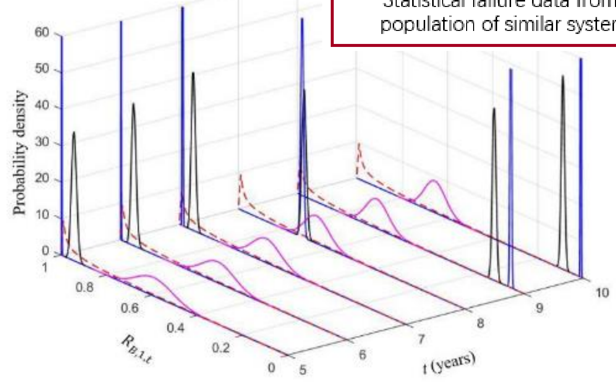


Fig. Comparison of the posterior densities estimated using different data

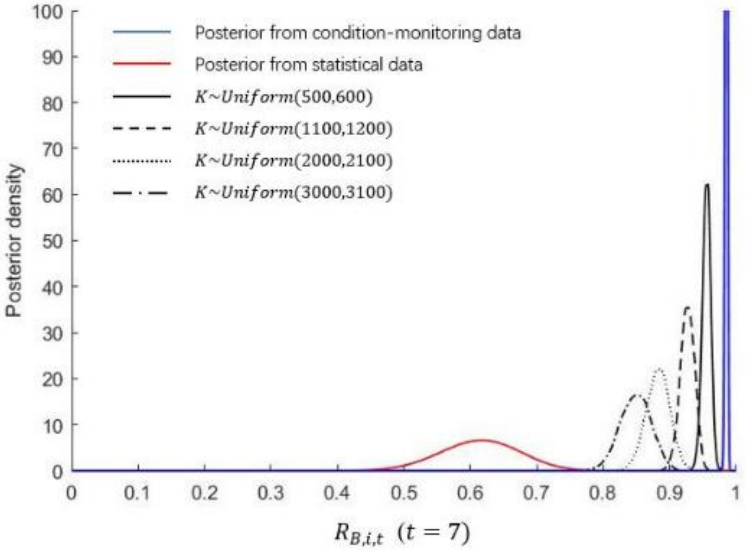
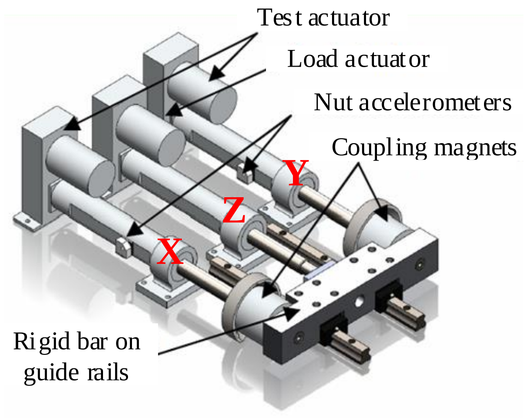


Fig. Posterior distributions under different values of K

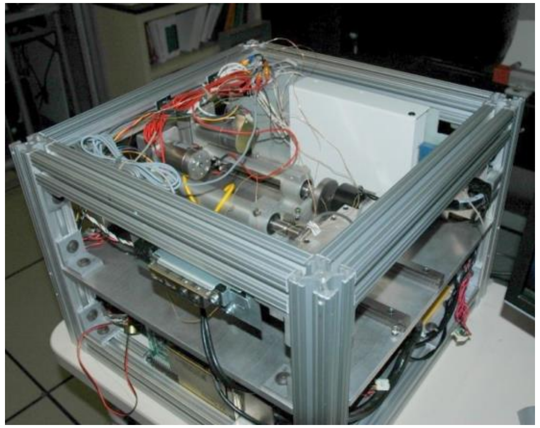
See Zeng, Z. and Zio, E., 2018. Dynamic risk assessment based on statistical failure data and condition-monitoring degradation data. *IEEE Transactions on Reliability*, *67*(2), pp.609-622.

Example: When first-principles meets data

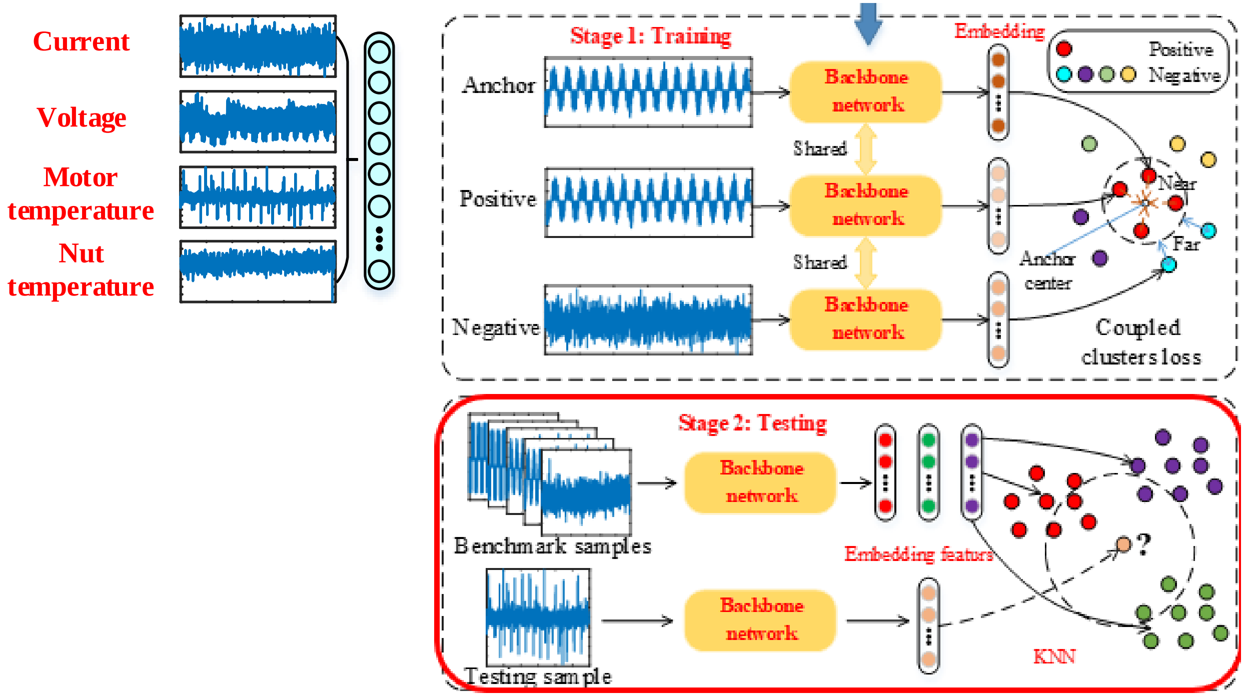
Big data driven fault diagnosis through deep and transfer learning



(a)



(b)



Wang, J., Zeng, Z., Zhang, H., Barros, A. and Miao, Q., 2022. An Improved Triplet Network for Electromechanical Actuator Fault Diagnosis Based on Similarity Strategy. *IEEE Transactions on Instrumentation and Measurement*, *71*, pp.1-10.

When principles of failure meet with industrial big data?

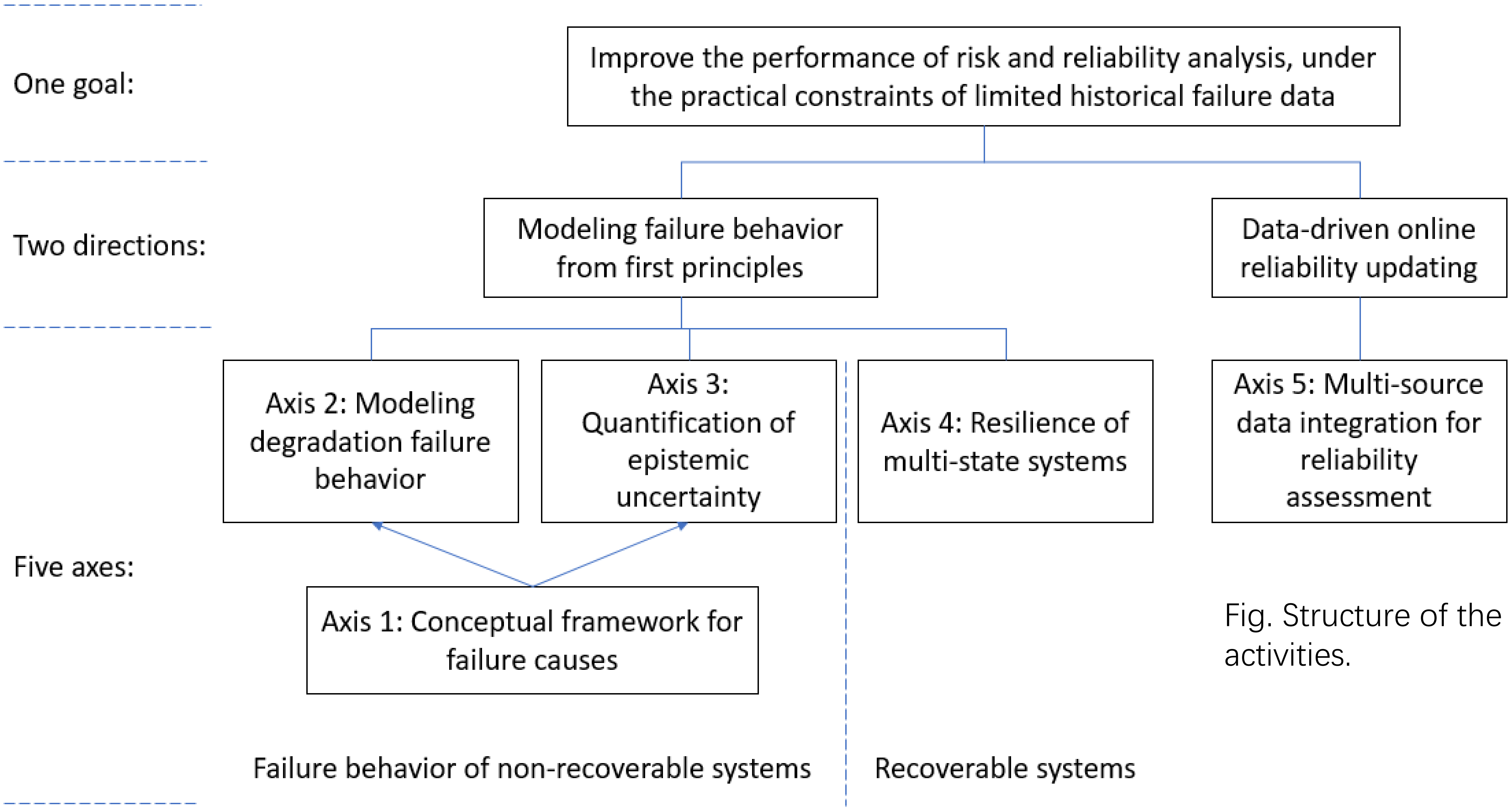
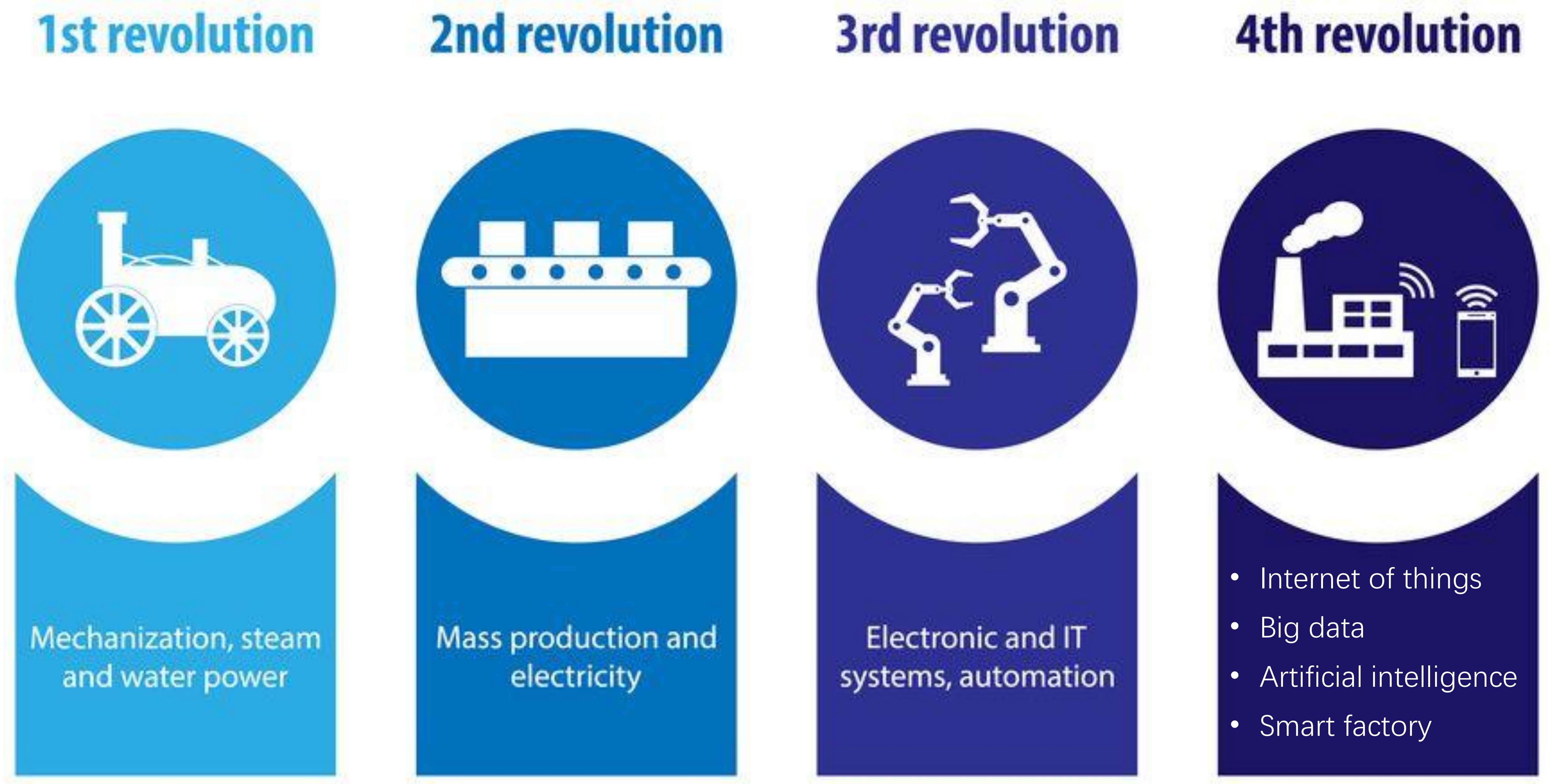


Fig. Structure of the research activities.

Looks good? Then?

Smart reliability engineering: Facing the challenges and opportunities of industry 4.0

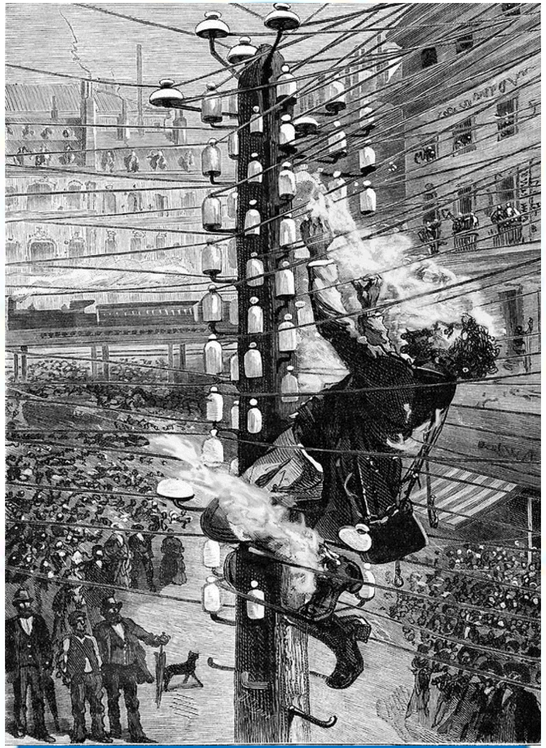
It was the best of times,
it was the worst of times.


1st revolution
2nd revolution
3rd revolution
4th revolution
Mechanization, steam and water power
Mass production and electricity
Electronic and IT systems, automation
• Internet of things
• Big data
• Artificial intelligence
• Smart factory

1st revolution

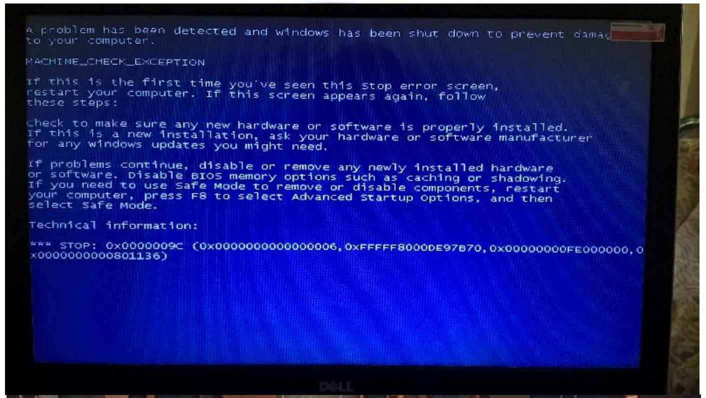
Mechanization, steam and water power

2nd revolution



Mass production and electricity

3rd revolution



Electronic and IT systems, automation

4th revolution

- Internet of things
- Big data
- Artificial intelligence
- Smart factory

Cyber-physical system

Physical system
- Sensor
- Actuator

Communication

Cyber system
- Computation
- Decision-making

- Cyber-physical systems are corner stones for industry 4.0.
- How to model?

Reliability of industry 4.0:

- Large scale, distributed system.
- Everything connected.
- Highly interdependent.
- Large amount of new technologies.
- Emergence of failures for complex systems.

Industry 4.0 for reliability

- More data and knowledge are available.
- How to use them to in reliability?

Reliability of Industry 4.0

Modeling of risk and resilience of interconnected infrastructures – 4 PhD projects funded by the chaire RRSC

Modeling interdependent transport and electrical networks

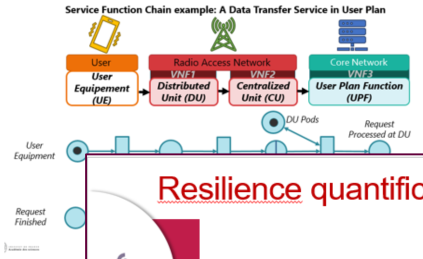
- Andrea Bellè - Prévention contre les attaques extérieures pour les infrastructures critiques - 1er novembre 2019
- Anne Barros et Zhiguo Zeng

- Bellè, Andrea, Zhiguo Zeng, Marc Sango, and Anne Barros. "Towards a Realistic Topological and Functional Modeling for Vulnerability Analysis of Interdependent Railway and Power Networks." In *31st European Safety and Reliability Conference*, pp. 2063-2070. Research Publishing Services, 2021.
- Bellè, Andrea, Zhiguo Zeng, Carole Duval, Marc Sango, and Anne Barros. "Modeling and vulnerability analysis of interdependent railway and power networks: Application to British test systems." *Reliability Engineering & System Safety* (2021): 108091.
- Bellè, Andrea, Adam F. Abdin, Yi-Ping Fang, Zhiguo Zeng, and Anne Barros. "A mathematical framework for the optimal coupling of interdependent critical infrastructures." *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, under review.
- Bellè, Andrea, Adam F. Abdin; Yi-Ping Fang; Zhiguo Zeng; Anne Barros. " A data-driven distributionally robust approach for the opt *European Journal of Opera*

SCIENCE & ENSEIGNEMENT

Modeling of 5G network

- Rui Li - Modélisation d'un réseau 5G (ou B5G) pour estimer sa capacité à répondre aux exigences de résilience des verticales – 2 novembre 2020
- Bertrand Decocq (Orange), Brigitte Cardinael (Orange), Anne Barros (CS, Directrice de thèse), Yiping Fang (CS, Co-encadrant), Zhiguo Zeng (CS, Co-encadrant).
- Rui Li, Bertrand Decocq, Anne Barros, Yiping Fang, Zhiguo Zeng. Complexity in 5G Network Applications and use cases. *31st European Safety and Reliability Conference*, Sep 2021, Angers, France. pp.3054-3061, (10.3850/978-981-18-2016-8_211-cd).



Cooperative scheduling of maintenance for interdependent critical infrastructure

- Khaled Sayad - Coopération entre Systèmes Interdépendants basée sur l'Echange d'Information de Disponibilité – 20 octobre 2020
- Benoit Lemoine (Orange), Maria Luisa Guerra Feliz De Vargas (Orange), Anne Barros (CS, Directrice de thèse), Yiping Fang (CS, Co-encadrant), Zhiguo Zeng (CS, Co-encadrant).
- Khaled Sayad, Benoit Lemoine, Anne Barros, Yi-Ping Fang and Zhiguo Zeng : "Dynamic Orchestration of Communication Resources Deployment for Resilient Coordination in Critical Infrastructures Network", Proceedings of the 31st European Safety and Reliability Conference (ESREL 2021), Angers, France

SCIENCE & ENSEIGNEMENT

Resilience quantification for interdependent electrical networks

- Youba Nait Belaid - Quantification de la résilience des réseaux électriques intelligents – 2 avril 2020
- Patrick Coudray, José Sanchez et Anthony Legendre (EDF), Anne Barros (CS, Directrice de thèse), Yiping Fang (CS, Co-encadrant), Zhiguo Zeng (CS, Co-encadrant)
- Mobilité à l'institut EIFER (Allemagne) laboratoire de recherche EDF associé au KIT de Karlsruhe, en collaboration avec Enrique Kremers, chercheur expert dans cet institut
- Youba Nait Belaid, Patrick Coudray, José Sanchez-Torres, Yiping Fang, Zhiguo Zeng, Anne Barros, Resilience quantification of Smart Distribution Networks – A bird's eye view perspective. Energies, MDPI, 2021, 14 (10), pp.2888. (10.3390/en14102888)

SCIENCE & ENSEIGNEMENT

Industry 4.0 for reliability

Digital failure twin for online reliability assessment and predictive maintenance of future manufacturing systems

- Project funded by ANR JCJC 2022 (1 PhD + 1 Postdoc).

Challenges to the reliability of future industrial systems:

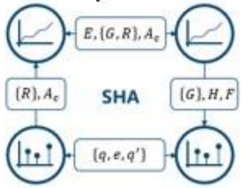
- Few failure data available. ⇨ New reliability model needed.
- Existing digital twin-based models only consider a single failure process. ⇨ Need to consider multiple dependent failure processes.

In this project, we intend to develop:

- Digital Failure Twin (DFT).
- Online reliability assessment methods based on DFT.
- Predictive maintenance models based on DFT.

Digital twin

Multiple dependent failure processes

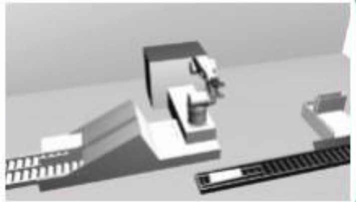


In order to:

- Improve the reliability.
- Reduce the operation costs of future manufacturing systems.

Use cases:

- An intelligent production line
- Supported by GE Healthcare and orange.



Industry 4.0 for reliability

Data-driven reliability modeling and opportunistic maintenance planning under deep uncertainty and dependencies

- Joint work with GE Health care
  - Real data -> Messy and deep uncertainty
  - Potential dependency among the components but needs to be explored from data
  - Objectives:
    - Develop data-driven approach for reliability modeling considering possible dependencies.
    - Develop data-driven covariate models for reliability prediction.
    - Develop data-driven opportunistic maintenance model considering the possible dependency among the components.

Pilot study (I): Reliability modeling of a smart railway grid from cyber-physical system perspective

Work with Romain Ray, as part of the master project (09/2020 – 04/2021)

Context : Why we need railway smart grid ?

- The transport sector is responsible for nearly **23% of energy-based CO_2 emissions worldwide**. All transport modes have increased their GHG emissions **except railways.**
- **Road transport** has the largest carbon footprint from transportation-related sources (**72%**) whereas **railway has the lowest footprint (4%)**.
- Due to their **low-carbon performance, railway transportation is a key element to reduce GHG gas emitted through transportation** and meet the threshold set by the Paris agreement.
- However, the railway industry is heavily **reliant on electricity** and a lot of wasted energy could be used as renewable energy or the braking energy from the train.
- This issue can be solved by developing **Railway Smart Grid** which are composed of different interconnected elements.

The implementation of RSG is driven by 4 key drivers :

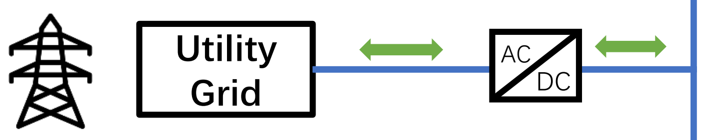
- **Decreased reliance on fossil fuels** (energy recuperation, more efficient drive chain…)
- **Lower the costs** (Meets the emissions targets, fewer delays and penalties…)
- **Attracting customer** (Fewer delays, better services in peak…)
- **Futureproofing** (Reduced supply uncertainty with diverse mix, Scalable management…)

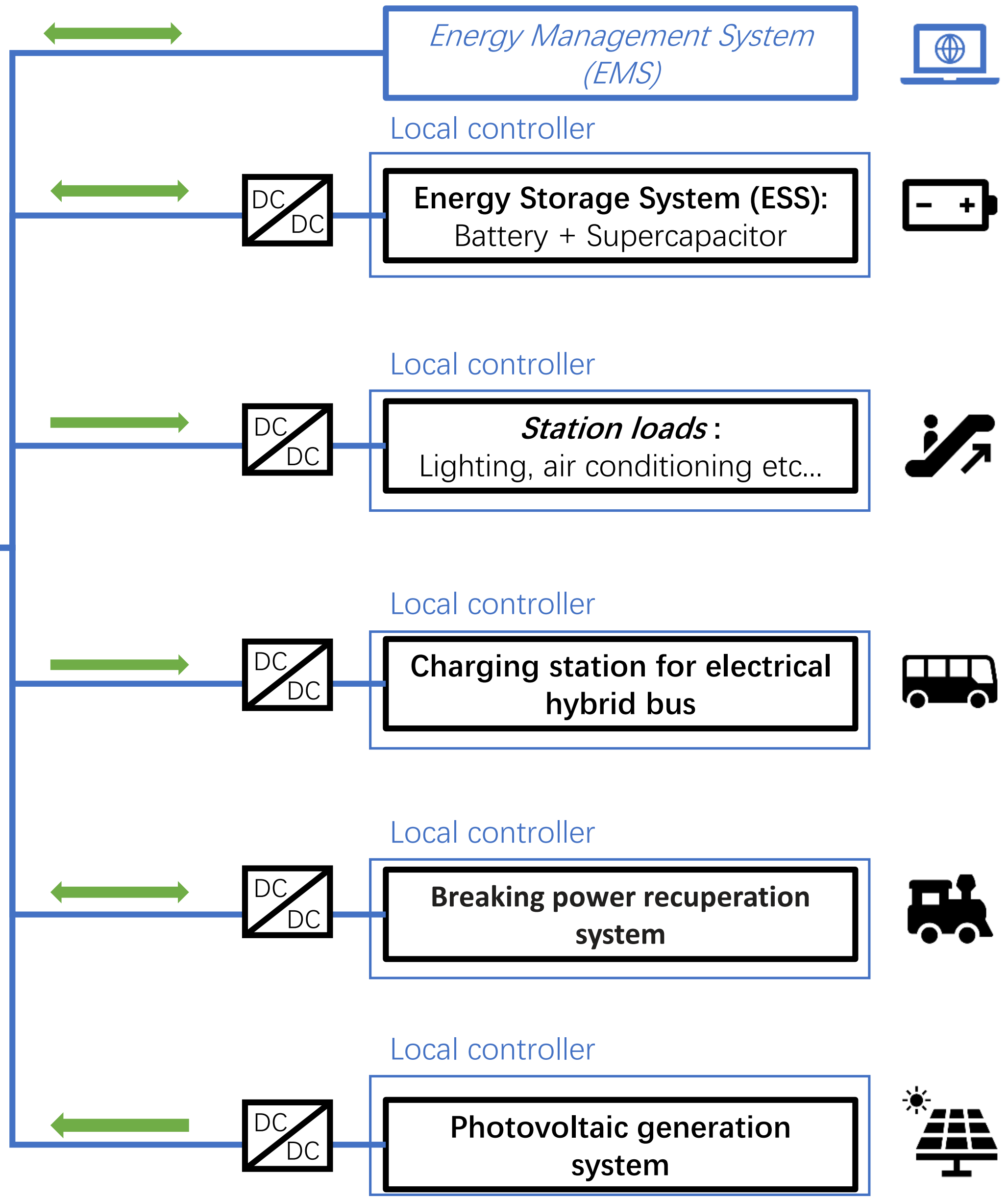
Source: International Union of Railways (UIC). « Energy Consumption and CO2 Emissions of world railway sector », 2012.
Steele et al,« Railway Smart Grids: Drivers, Benefits and Challenges », 2019

An example of a smart railway station

Functions of this system:

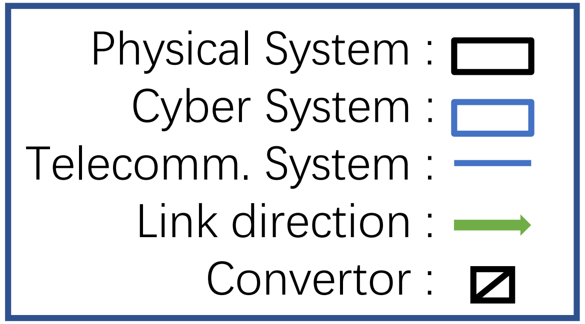
- Recuperate the breaking energy from the train.
- Photovoltaic generation.
- Manage the energy flow:
  - When to buy/sell from the utility grid.





Implementation of the system:

- A distributed control system.
- Telecommunication is important to ensure the functionality of the control system.



Key Performances Indicator :

Performance Indicator	Typical value
SOC value	50%
Busbar voltage	880V, 920V
DC/DC converter on railway voltage	820V, > 750V and < 900V
Inverter voltage	860 < V < 940
P f (Power factor)	1

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Motivation of the case study

Research questions : As we move from “traditional” system to CPS, **Is there some benefits in term of reliability ?**

What are the challenges we face when developing CPS ?

To answer those questions, we want to model a railway station with power consumption from :

- **Loads in the station** (50kw):
    - Lighting.
    - Air conditioning.
    - Elevators etc…
- Charging station of an electrical hybrid bus (200KW, 4 mins every hour).
- And **potential energy source**:
    - Utility grid.
    - Solar energy.
    - Breaking power from the train (The theoretical share of recoverable energy in railway system depends on the train’s speed profiles and the timetable and range from 15% for the main lines to 45% for the suburban lines.).

Objective: Develop a **smart energy management system** to reduce operating costs (**CPS model**)

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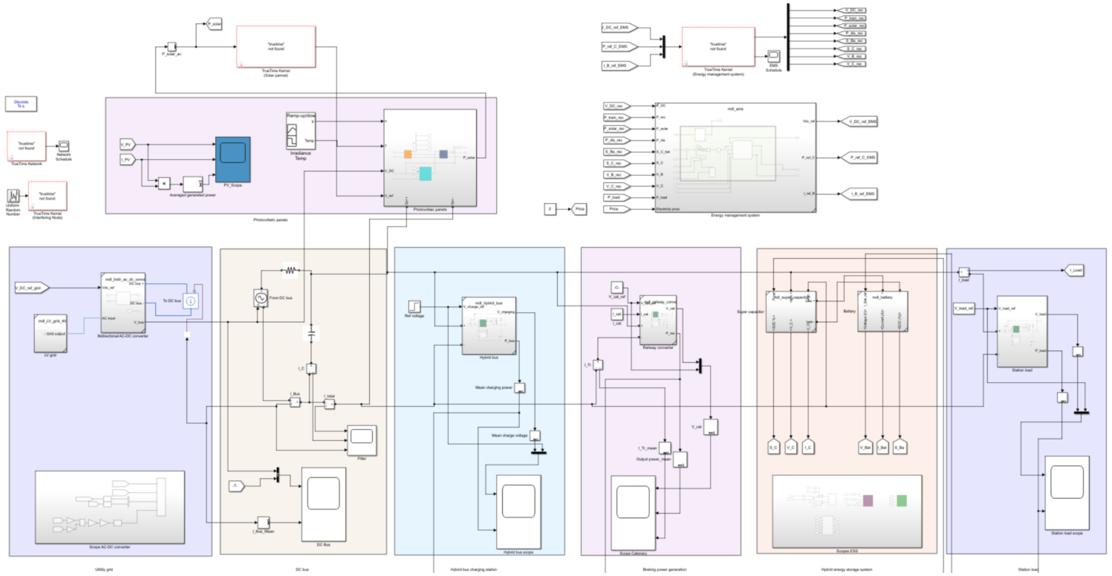
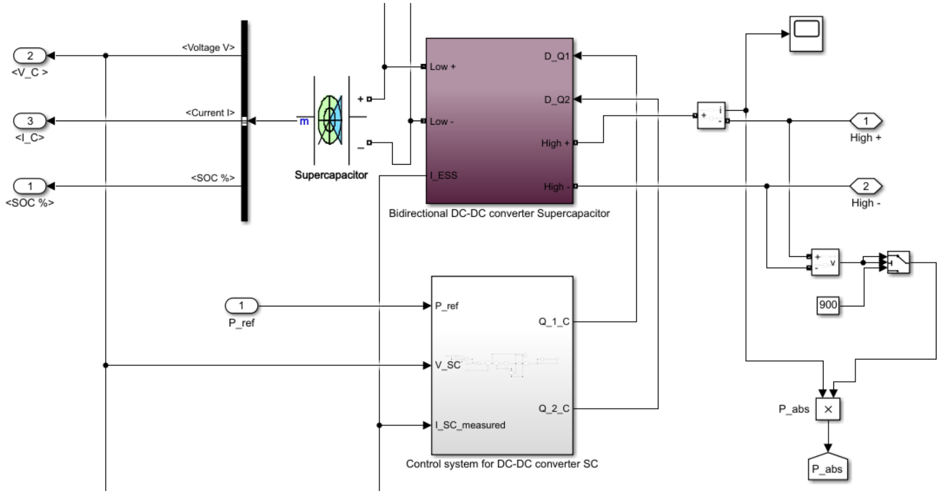
Modeling - Physical system

- **Utility grid**: Energy source delivering electricity to the whole system.
- **Breaking power recuperation system**: Modelled as a random peaks power source injected into the grid to simulate the trains braking.
- **Photovoltaic generation system:** Generating power injected into the grid depending on the sun.
- **Station load**: The station's components that consumes electric power and modelled as a resistive load (e.g electrical signs, lighting fixtures, escalators, elevators…).
- **Charging station for electrical hybrid bus:** modelled as a critical load consuming high powers in short period.
- **Energy Storage System (ESS):**
  - *Supercapacitor*: Modelled using a generic component. Primary storage element due to high power storage particularly useful for storing RBE.
  - *Batteries:* Modelled using a generic component. Secondary storage equipment and continuous source of low power.
- **DC Busbar**: The busbar connecting the inverter to the internal grid
- **DC/DC converter**: Buck-boost circuit to change voltage to operating voltage of each load. It connects the railway system, ESS and hybrid buses to the DC busbar.
- **Bi-directional inverter**: Modelled using a generic component. Converts AC grid power to the DC bus voltage. It is used to regulate the DC busbar voltage.



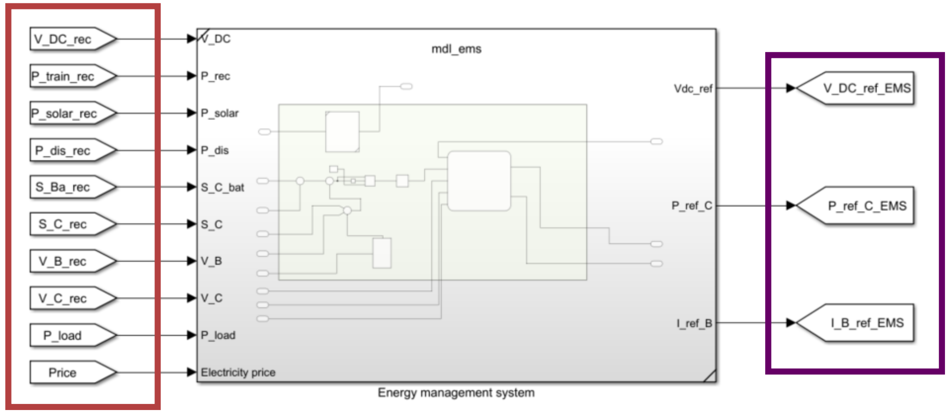
Physical model implemented on Simulink.



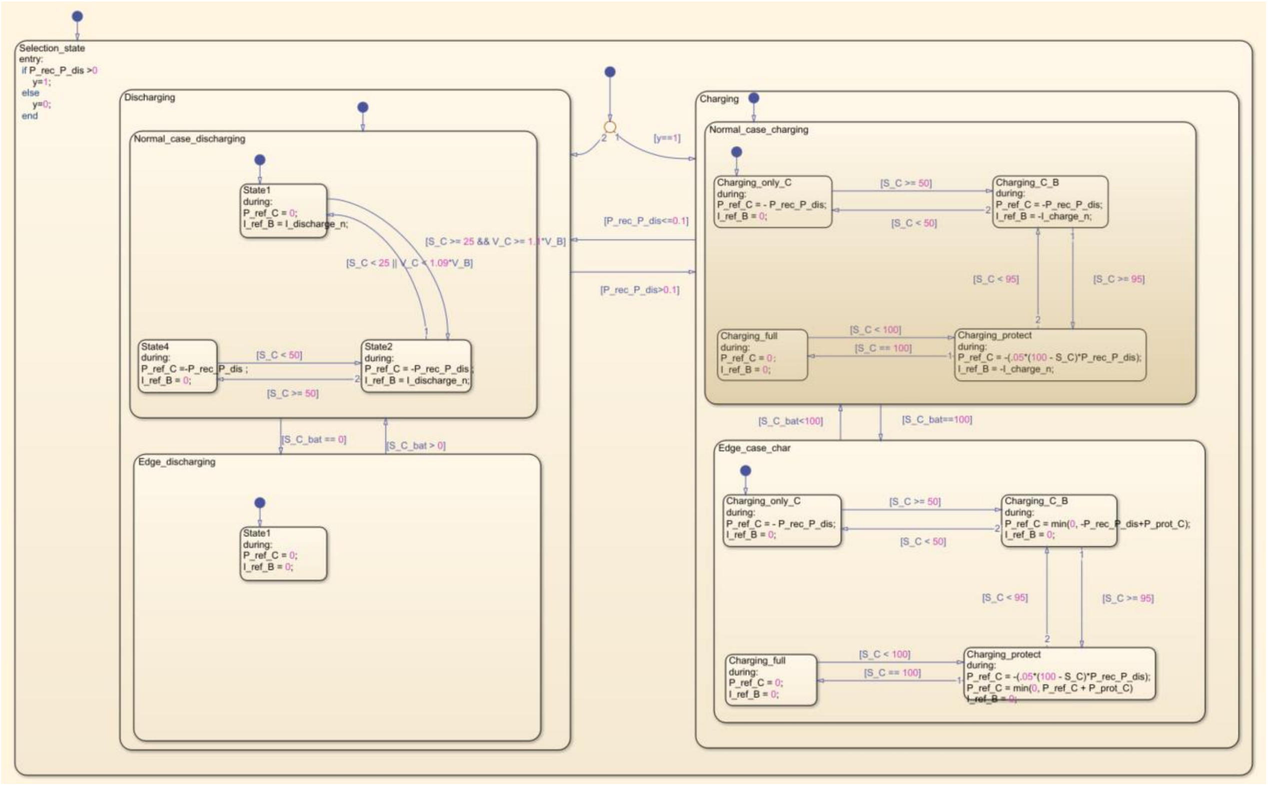
Supercapacitor implemented on Simulink.

Modeling - Cyber system

- The Cyber part manages the **micro-grid by directing power flows**.
- It takes **10 variables from sensors as inputs**, **makes a decision** and **output 3 variables to actuators.**
- It serves **three main functions**:
  - **Calculate reference value** for the DC bus voltage.
  - **Determine the output power** of the Energy Storage System depending on:
    - Demand in the DC bus.
    - Health of the super capacitor and battery.
  - **Determine if we need to sell power** to grid based on the real-time electricity price.



Inputs and outputs of the Energy Management System (EMS)



Control logic for the output power determination implemented on Stateflow.

Modeling - Communication

We consider the medium access control (MAC) layer:

- MAC is the layer that controls the hardware responsible for interaction with the wired, optical or wireless transmission medium.
- Data link layer of the OSI model.
- Two questions:
  - Who gets the access?
  - How to handle conflicts?
- Communication protocols.
- TrueTime: An open-source toolbox for modelling communication network in Simulink.

https://www.control.lth.se/research/tools-and-software/truetime/

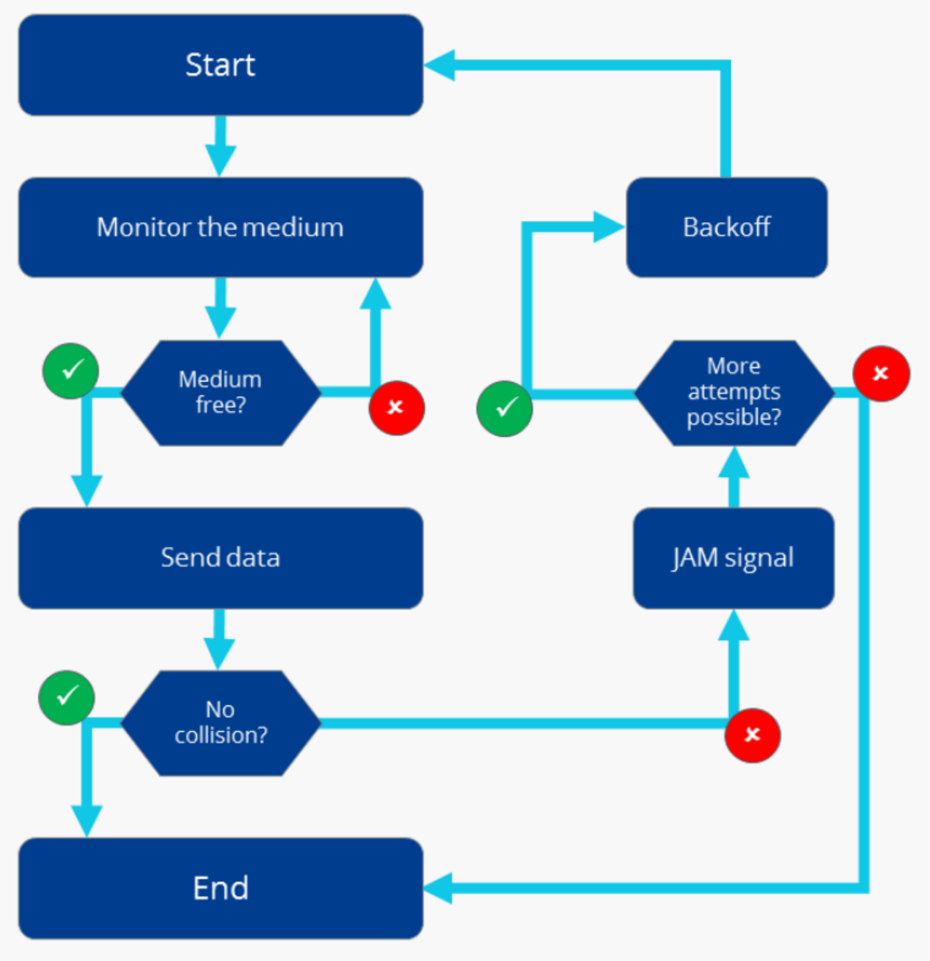
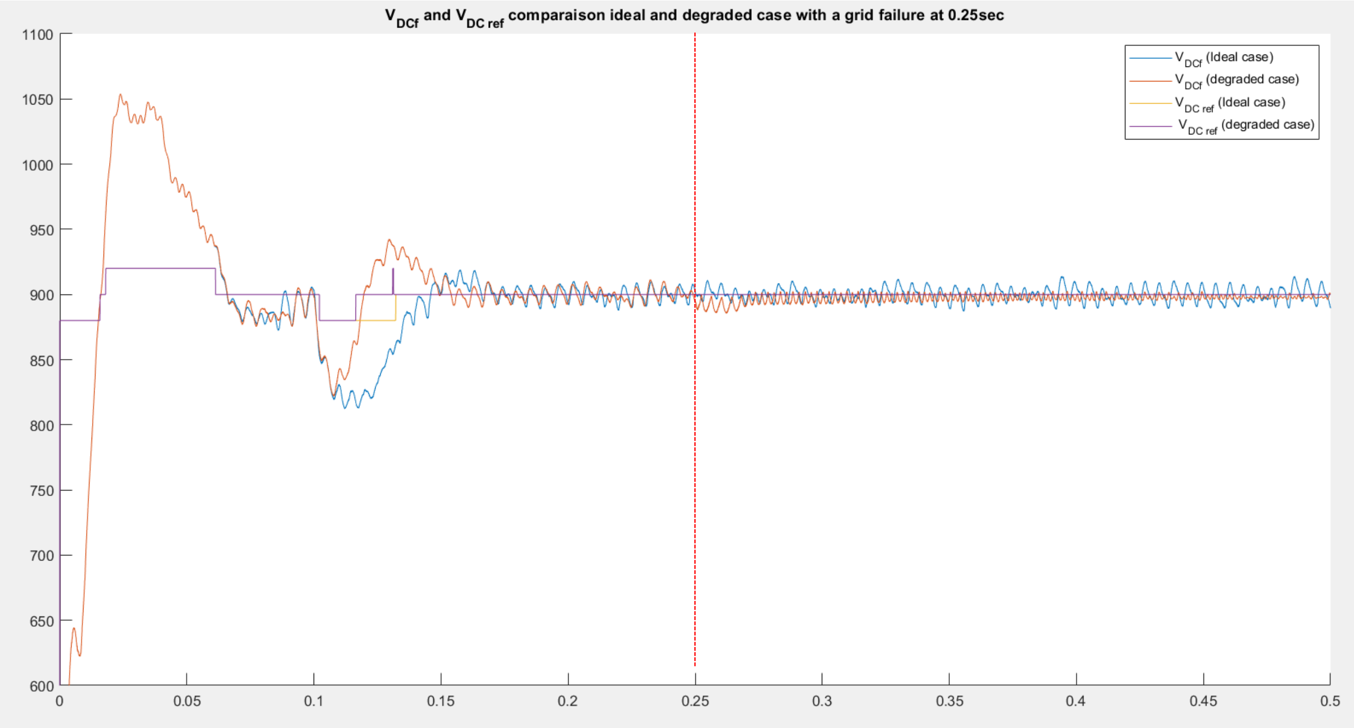


Fig. An example of CSMA/CD protocol.

Simulation of failure scenarios: Loss of utility grid

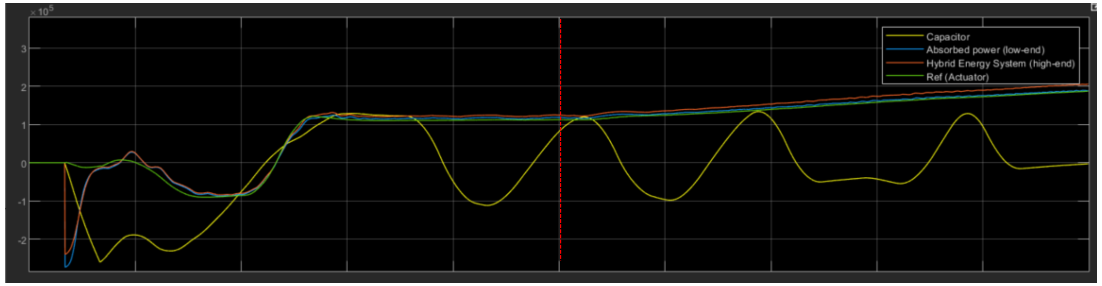
Comparaison between two simulations:
- **Ideal case** : CPS model **without** failure(s)
- **Degraded case** : CPS model **with** failure(s)

Comparaison of two KPI the reference voltage ($V_{DC\ ref}$)and the actual voltage of the DC bus (V_{DC}) in both cases.

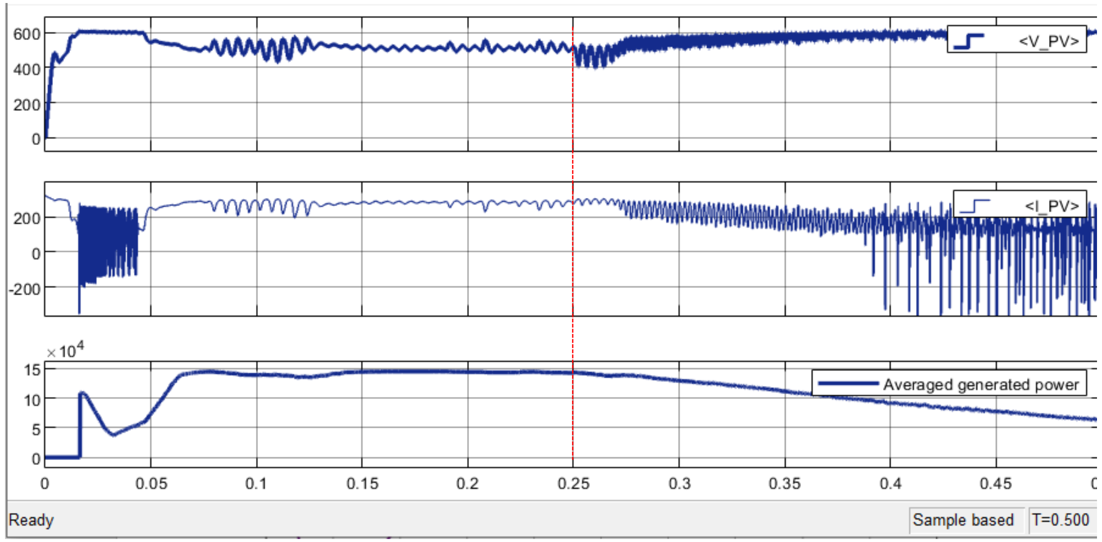


More resilient compared to the "traditional" approach.

Some outputs values of the degraded case :



Output of the EMS

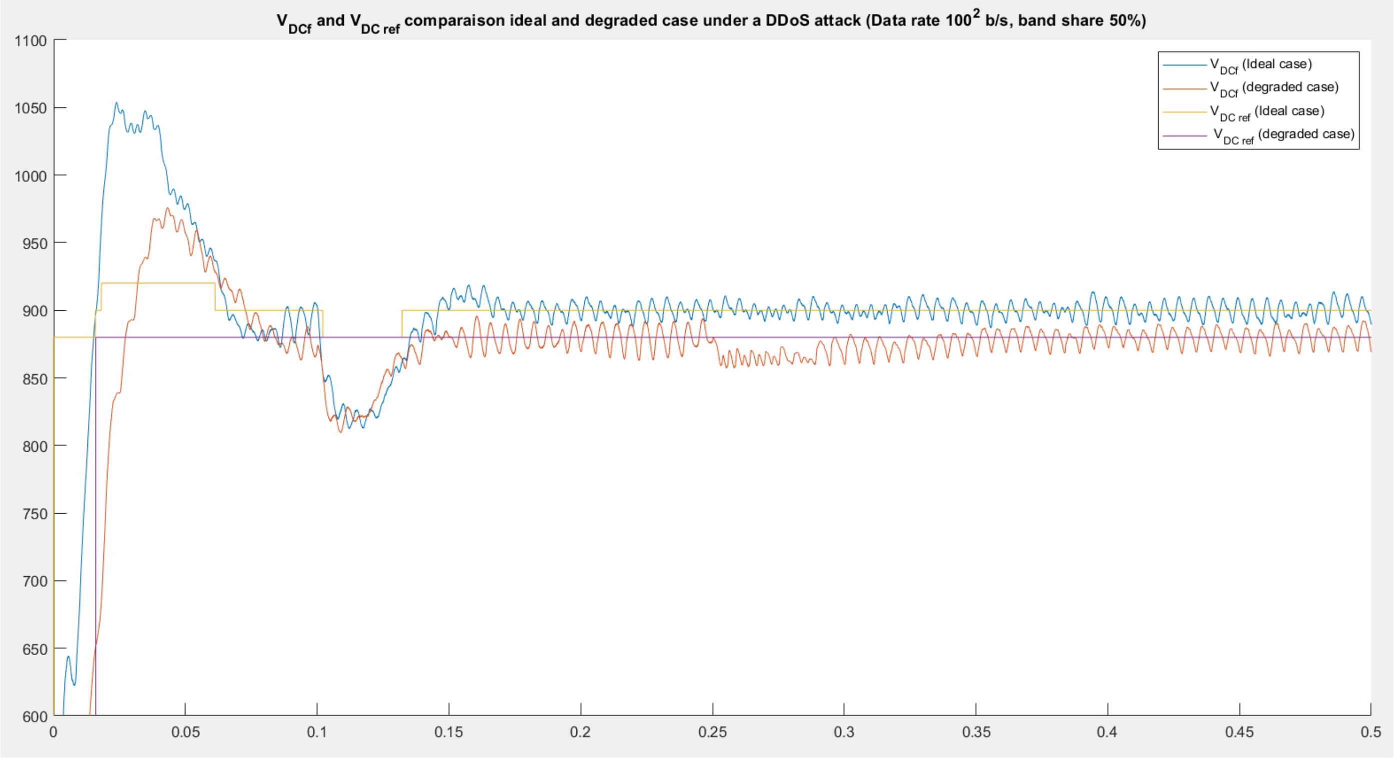


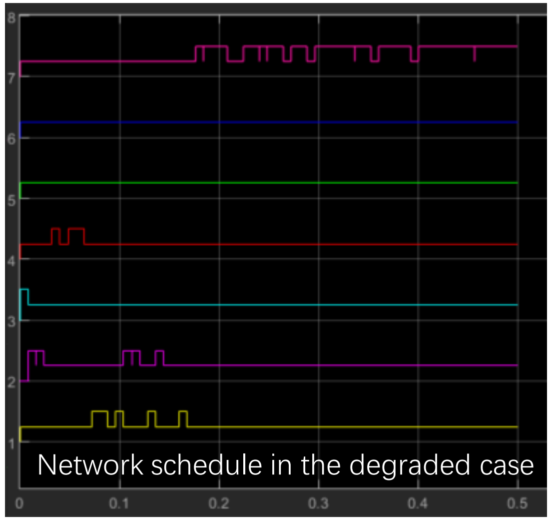
Power generated by the solar panel

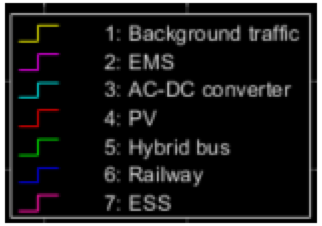
universite PARIS-SACLAY

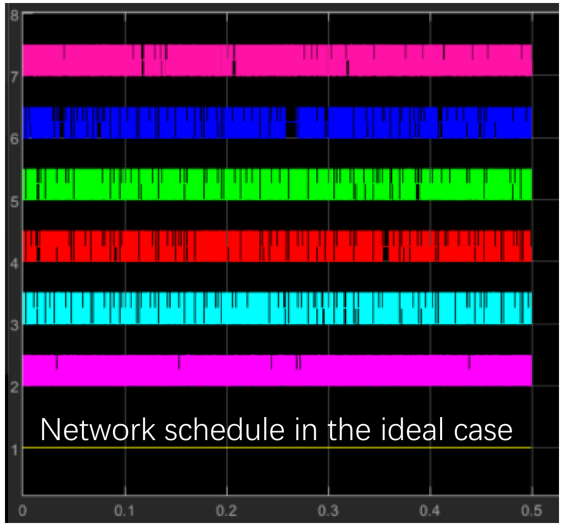
Simulation of failure scenarios: Communication performance degradation

- Since we interconnect elements, we have the **ability to gather more and more data.**
- Leads to a **new failure mechanism** introduced by CPS.

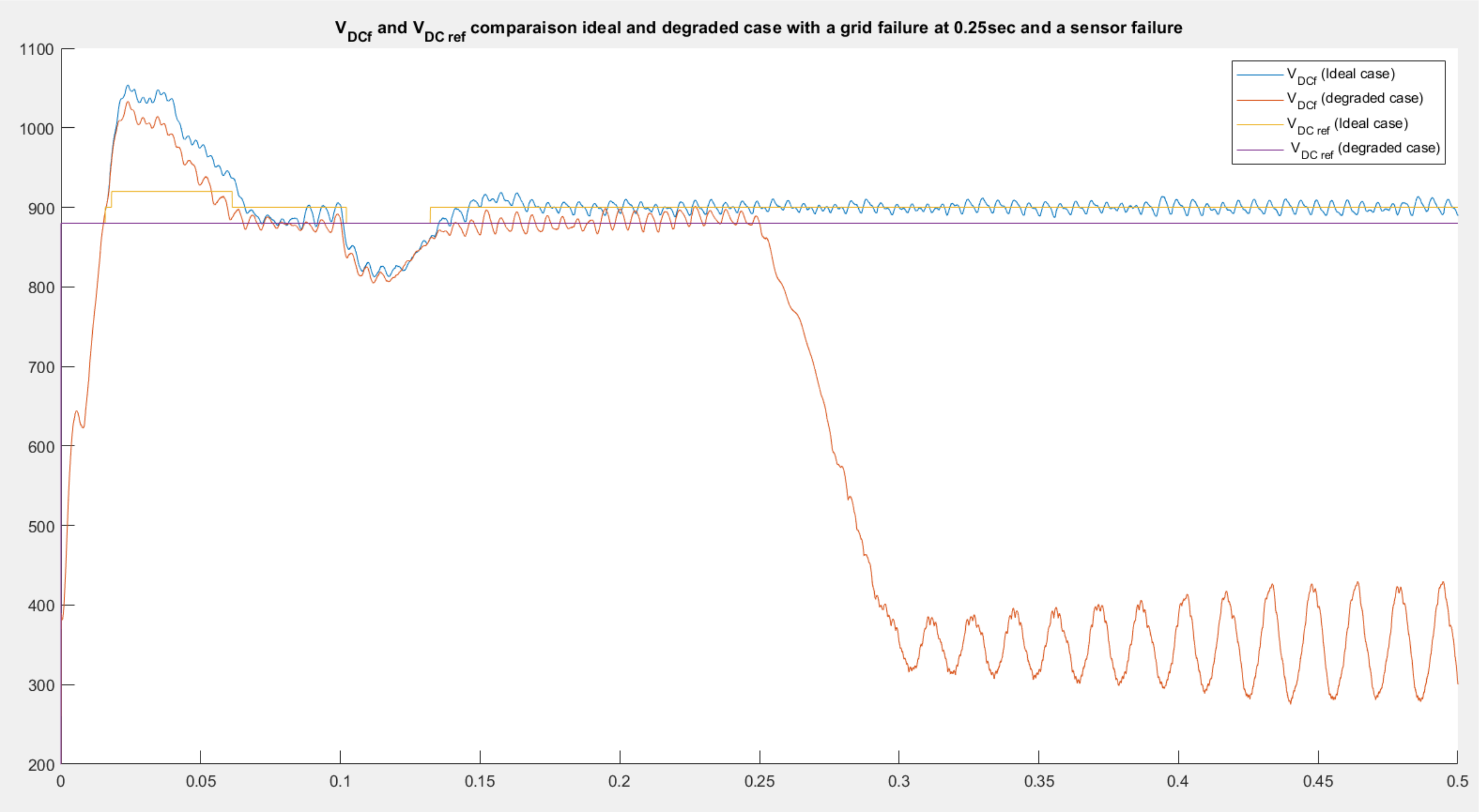



Network schedule in the degraded case




Network schedule in the ideal case

Simulation of failure scenarios: Sensor failure + grid failure



What does "being smart" mean to reliability and resilience?

Challenges:

- Complexity of the system.
- New failure modes:
  - Communication delays.
  - Interplay of sensor failures and cyber system.
  - Etc.

Opportunities

- More data and information.
- Possibility to reconfiguration the system.

The way ahead

In the future:

- Extend the modeling to a “smart railway grid”: Many stations connected as a network.
- If we move from a traditional communication network to 5G?
- Model checking for CPS based on artificial intelligence techniques.
    - How to generate the testing scenarios?
    - How to identify failures in a more efficient way?

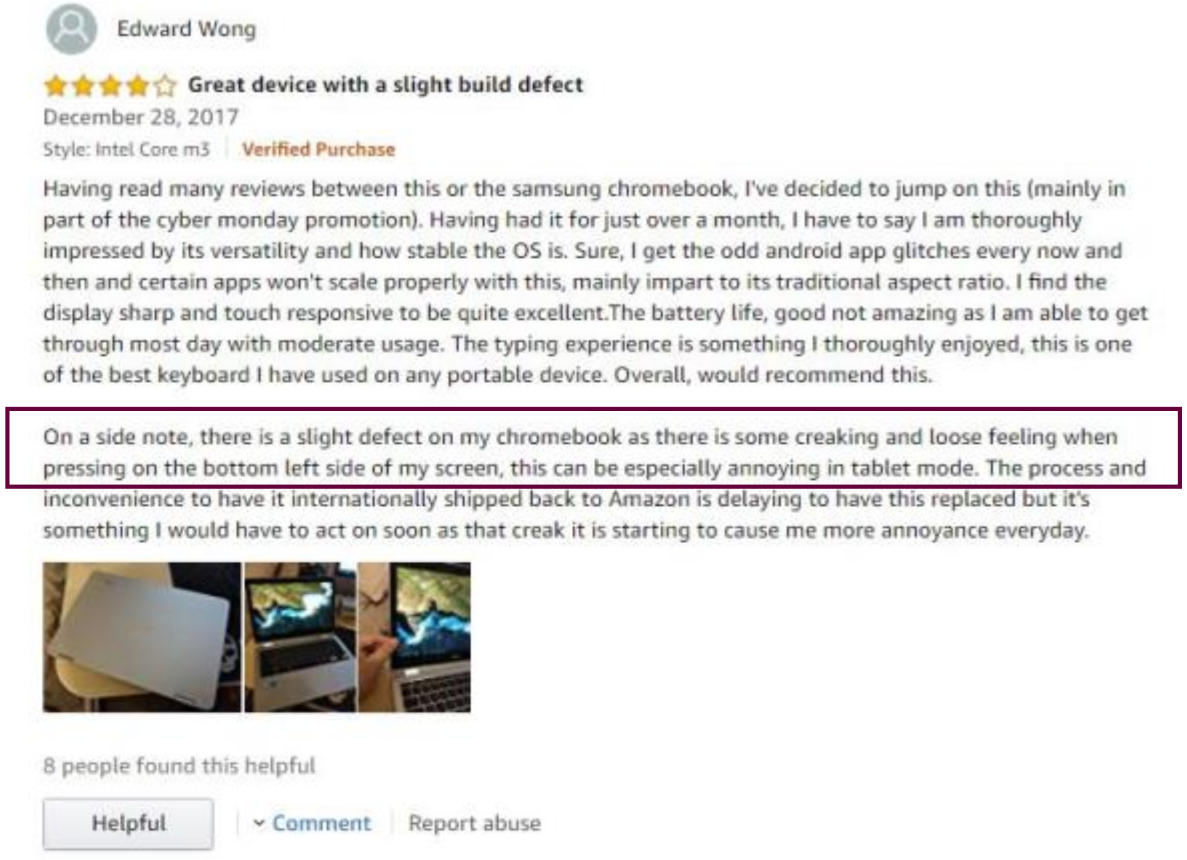
Pilot study (II): Reliability assessment and knowledge extraction from linguistic data

Work with Jean Meunier-Pion, student from Parcours Recherche (09/2020 – 06/2023)

Context: Why considering linguistic data

Because they are there!

- Customer review.
- Accident reports.
- Media reports.
- Maintenance reports from technicians.


Edward Wong
Great device with a slight build defect
December 28, 2017
Style: Intel Core m3 | Verified Purchase

Having read many reviews between this or the samsung chromebook, I've decided to jump on this (mainly in part of the cyber monday promotion). Having had it for just over a month, I have to say I am thoroughly impressed by its versatility and how stable the OS is. Sure, I get the odd android app glitches every now and then and certain apps won't scale properly with this, mainly impart to its traditional aspect ratio. I find the display sharp and touch responsive to be quite excellent.The battery life, good not amazing as I am able to get through most day with moderate usage. The typing experience is something I thoroughly enjoyed, this is one of the best keyboard I have used on any portable device. Overall, would recommend this.

On a side note, there is a slight defect on my chromebook as there is some creaking and loose feeling when pressing on the bottom left side of my screen, this can be especially annoying in tablet mode. The process and inconvenience to have it internationally shipped back to Amazon is delaying to have this replaced but it's something I would have to act on soon as that creak it is starting to cause me more annoyance everyday.

8 people found this helpful

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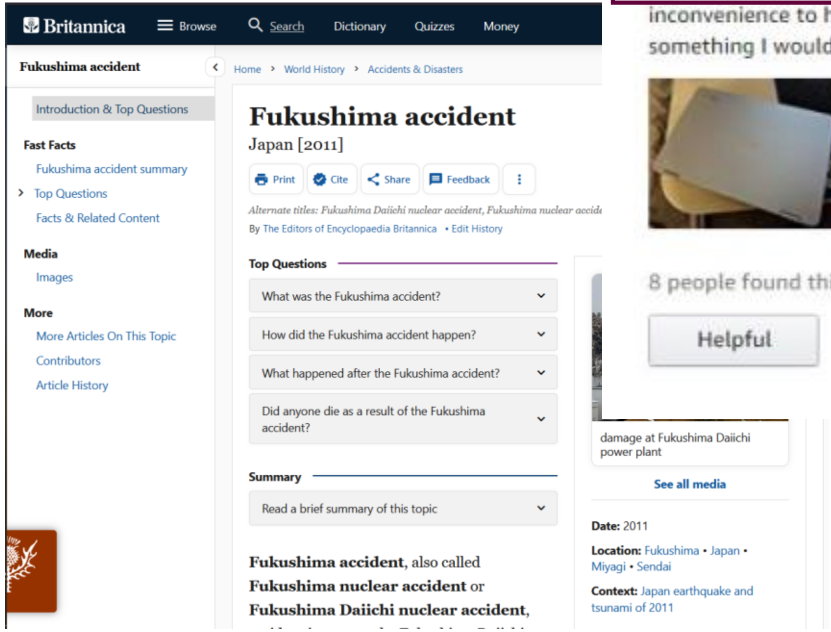
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Fukushima accident

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Fukushima accident

Japan [2011]

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Alternate titles: Fukushima Daiichi nuclear accident, Fukushima nuclear accide

By The Editors of Encyclopaedia Britannica • Edit History

Top Questions
- What was the Fukushima accident?
- How did the Fukushima accident happen?
- What happened after the Fukushima accident?
- Did anyone die as a result of the Fukushima accident?

Summary
Read a brief summary of this topic

damage at Fukushima Daiichi power plant
See all media

Date: 2011
Location: Fukushima • Japan • Miyagi • Sendai
Context: Japan earthquake and tsunami of 2011

Fukushima accident, also called **Fukushima nuclear accident** or **Fukushima Daiichi nuclear accident**,

Metrics and assessment framework

Assessment framework:

Data collection

- Collect the comment and rating from customer's review data
- Web scraper is used.

Information extraction

- Select training samples.
- Manually labels the training samples.
- Train a classification model.
- Use the classification model to determine if a review contains failures.

A Classification based assessment method is needed!

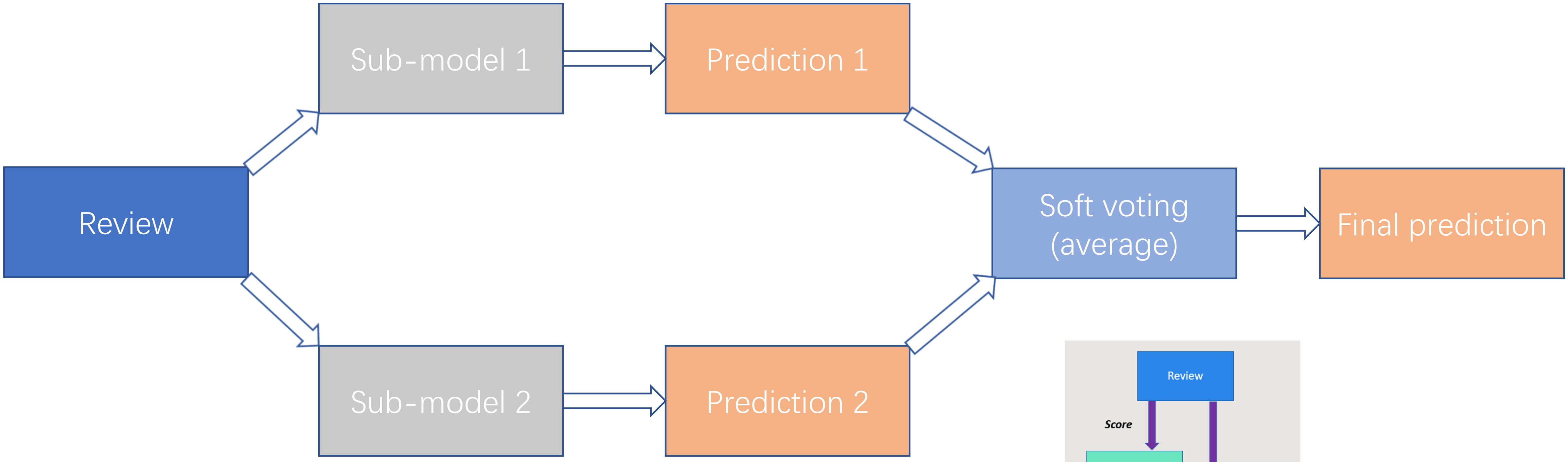
Numerical evaluation

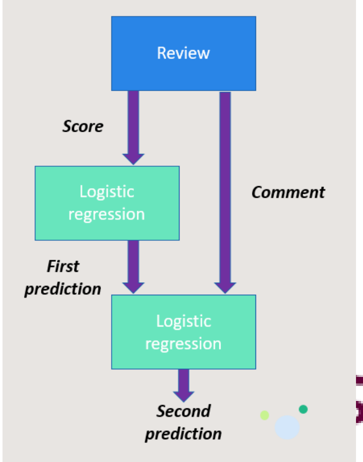
- Calculate the probability of failure.

Our effort (I): An ensemble of logistic regression

Model – General structure:

A logistic regression model using only the rating of the customer.





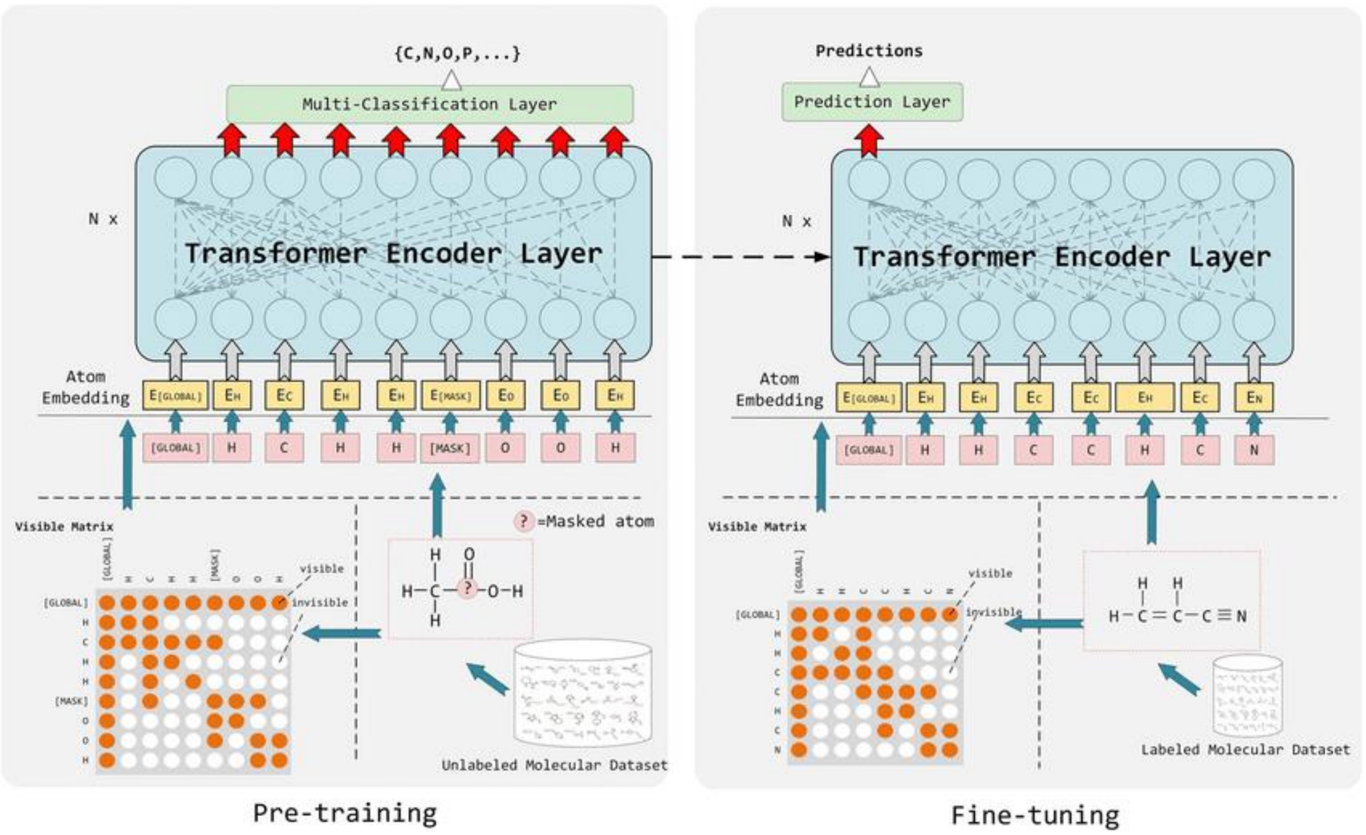
Our effort (I): An ensemble of logistic regression

Performance evaluation

Metric	Ensemble model	Sub-model 1	Sub-model 2	Human evaluation
Accuracy	0.8660	0.8279	0.8491	0.9143
Balanced Accuracy	0.8544	0.8429	0.8315	0.9077
Precision	0.7991	0.6960	0.7856	0.8718
Recall	0.8171	0.8918	0.7742	0.8855

Our effort (II): Pre-trained transformer with sliding window

Model structure



Accuracy machine : 0.8779123951537745

Precision machine : 0.8322033898305085

Recall machine : 0.8343245539507221

Balanced Accuracy machine : 0.8686803964660565

F1 machine : 0.8332626219770894

Accuracy human : 0.9145697421559491

Precision human : 0.8777219430485762

Recall human : 0.8903993203058623

Balanced Accuracy human : 0.9094503947268783

F1 human : 0.8840151834668916

The way ahead

In the future:

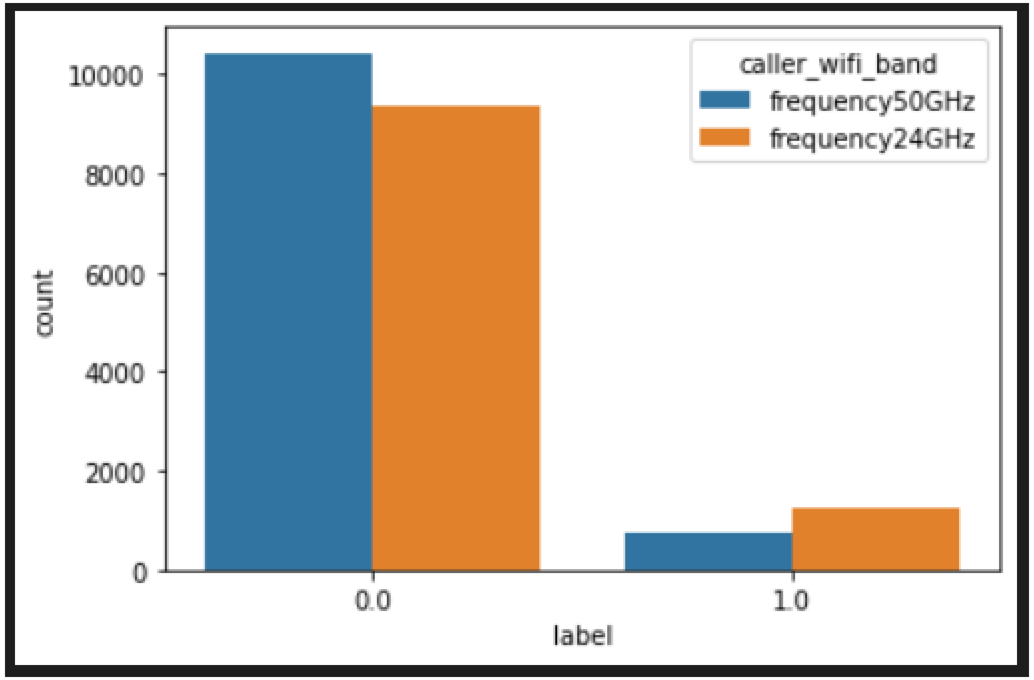
- Structured knowledge extraction.
  - When does a failure happens?
  - On which part?
  - Cause and effect?
  - Etc.
- Apply on risk and reliability data like accident reports and maintenance report.

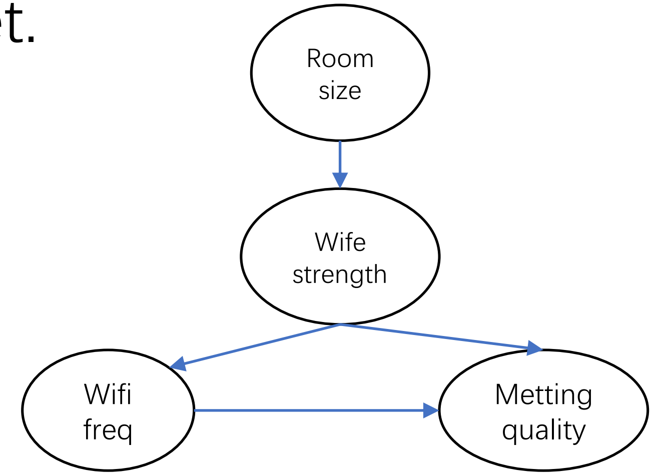
Pilot study (III): Encoding knowledge with machine learning

Why not just data-driven models?

A motivating example from SLB:

- A large dataset of Teams meeting quality.
- Decision problem: Should we recommend to use 24GHz instead of 50GHz?
- Seem yes. But…
  - 50GHz is faster but with a lower range.
  - 24GHz is slower but with a wider range.
  - Implying confounding effect in the dataset.

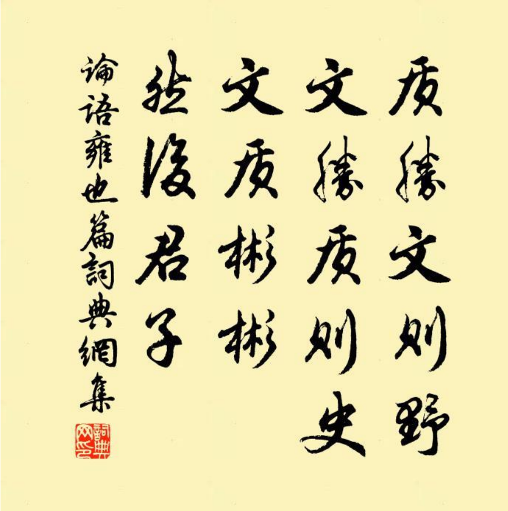




How to solve the problem?

Using knowledge to strengthen the capability of data-driven model

- Causal knowledge:
  - Renato Rosa De Oliveira
    - 1st Year Engineering student on Parcour Recherche (2022 – 2025)
    - Do not step in the same river twice - Learning from past failures through causal inference
    - Focus: Apply causal inference to improve the fault detection and diagnosis
  - Adam Younsi
    - 1st Year Engineering student on Parcour Recherche (2022 – 2025)
    - Let reports speak - Mining causal relations in critical infrastructure failures from accident reports
    - Focus: Discovery causal relationships related to critical infrastructure failures
- Physical knowledge:
  - ADITYA SANJU
    - 3rd student in Bachelaor's program, *COEP* Technological University, India
    - Apply physics-informed deep learning to improve the performance of fault diagnosis and prognosis.



Confucius: “When a man’s good nature and his accomplishments are well balanced, he thus becomes a man of virtue.“

Thank you for your attention!

Your questions/comments are sincerely welcomed!

zhiguo.zeng@centralesupelec.fr