

SMART FLEET MAINTENANCE SUMMIT 360

PROGNOSTIC EXPERT SYSTEM FOR RAILWAY FLEET MAINTENANCE

Fabien TURGIS¹, Pierre AUDIER², Rémy MARION², Valentin NEMOZ²

1 : IKOS, Paris, France

2 : SNCF, Rolling Stock Engineering, Tours, France

HEADLINES

01.

INTRODUCTION

02.

FROM RAW DATA TO INDICATOR DESIGN

03.

PROGNOSTIC EXPERT SYSTEM BASED ON FLEET STATISTICS

04.

CONCLUSION AND PERSPECTIVES





01. INTRODUCTION

INTRODUCTION

COMMUNICATING TRAINS : A NEW OPPORTUNITY TO OPTIMIZE MAINTENANCE

The emergence of **new generations of connected trains** has fundamentally transformed the rolling stock landscape.

Indeed, the introduction of on-board/wayside diagnostics systems presents a significant opportunity for reducing maintenance costs, while also having a strong positive impact on reliability, availability and quality of service.

Following this way, a new approach based on remote diagnosis and Condition Based Maintenance (CBM) has been incorporated into the SNCF maintenance process.

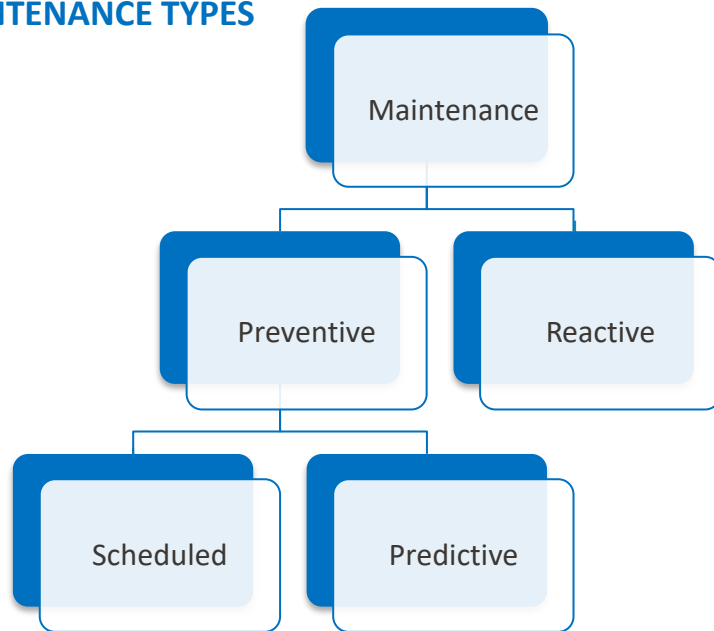


- + More than 300 natively connected NAT (Alstom)
- + More than 100 natively connected REGIO2N (Alstom)
- + More than 200 IoT connected trains
- + Logical and analogical data
- + Enhanced contextual information

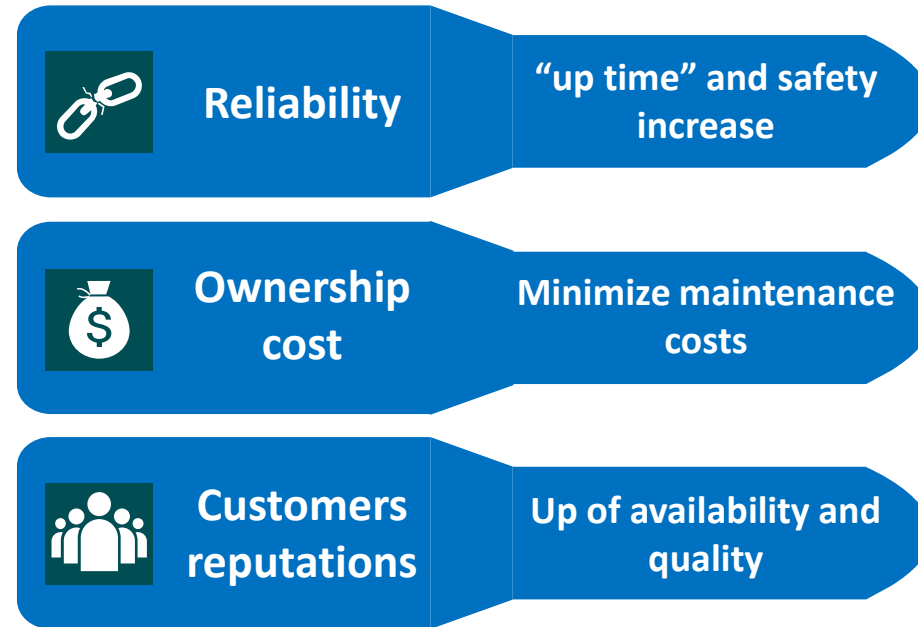
INTRODUCTION

COMMUNICATING TRAINS :
A NEW OPPORTUNITY TO OPTIMIZE MAINTENANCE

DISTINCT MAINTENANCE TYPES



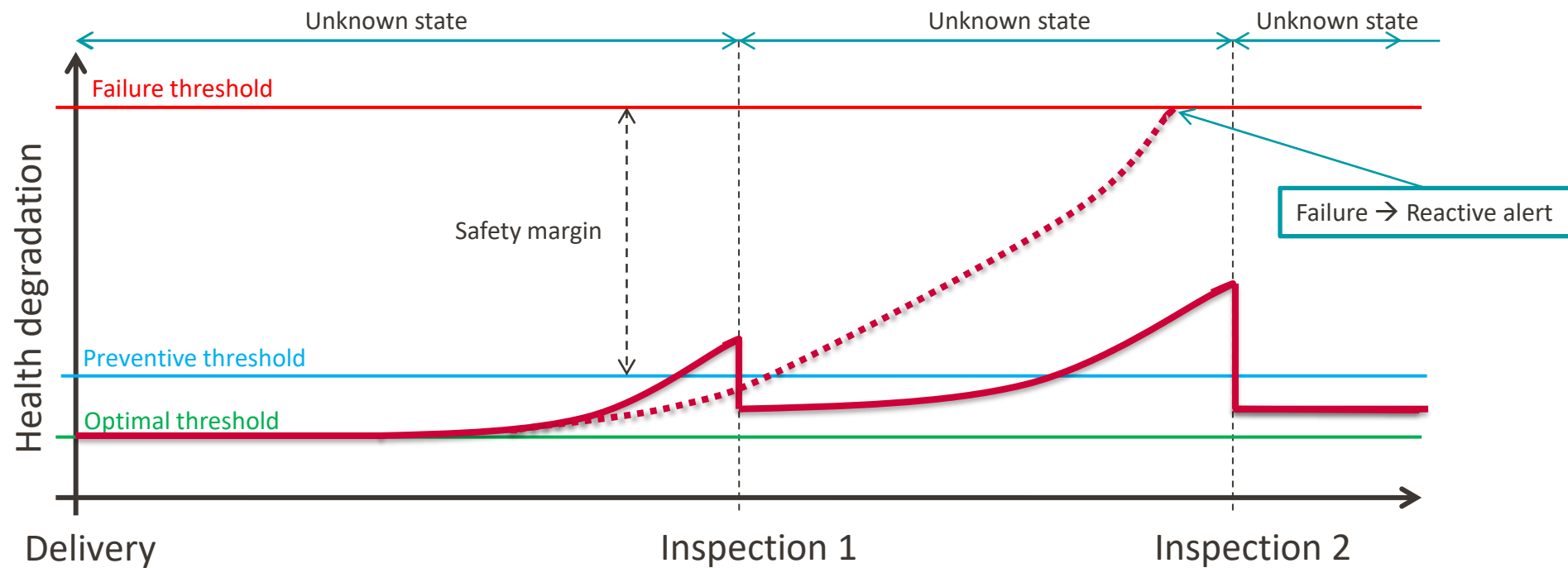
CHALLENGES



To optimize dependencies between systematic, corrective and condition-based maintenance,
SNCF has set a maintenance solution based on real-time data analysis

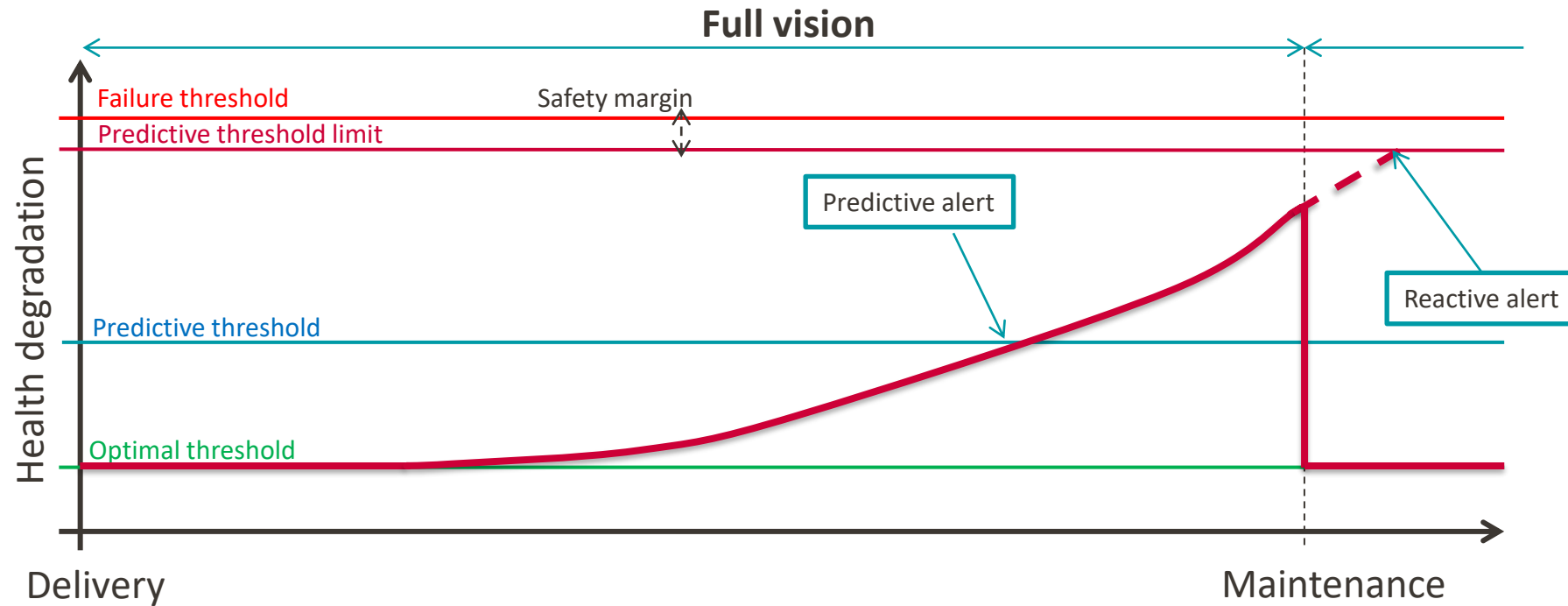
INTRODUCTION

OPTIMIZING MAINTENANCE



INTRODUCTION

OPTIMIZING MAINTENANCE



INTRODUCTION

REMOTE DIAGNOSIS AND PREDICTIVE MAINTENANCE USE CASES

Air production

Performance



Battery

Performance

Pantograph

Static effort and rising/falling time

HVAC

Performance

Passenger access

Performance

Traction

performance

Brake

performance

Toilet

tank levels





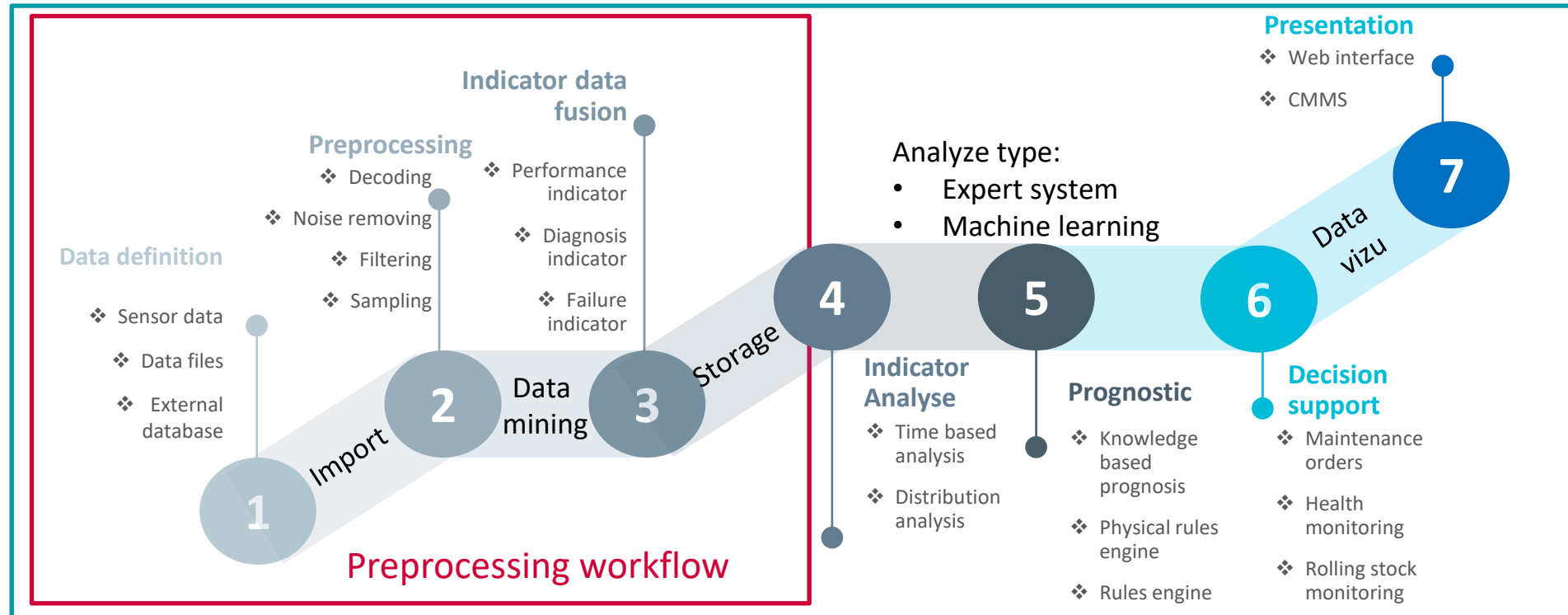
02. FROM RAW DATA TO INDICATOR DESIGN

FROM RAW DATA TO INDICATOR DESIGN

DATA WORKFLOW

SNCF prognostic expert systems

(Verdun et al. - WCRR 2019)

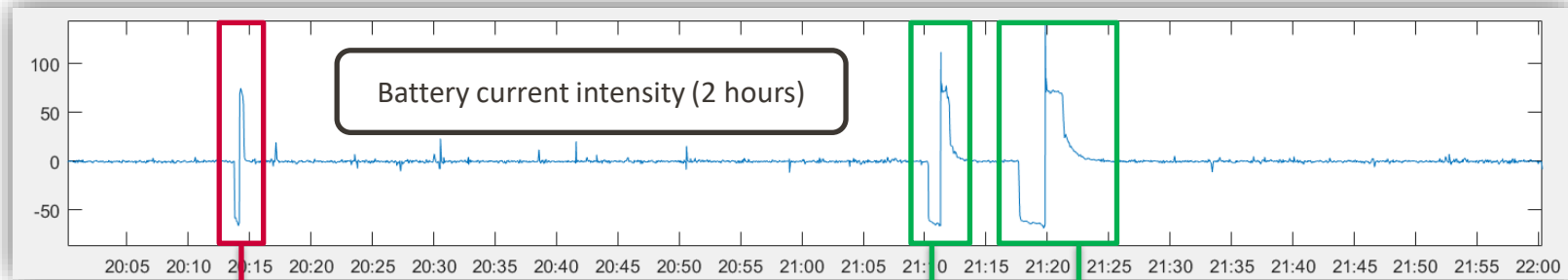


FROM RAW DATA TO INDICATOR DESIGN

DATA PROCESSING : FILTERING AND MARKER CREATION

CBM Server

2



Cycle 1

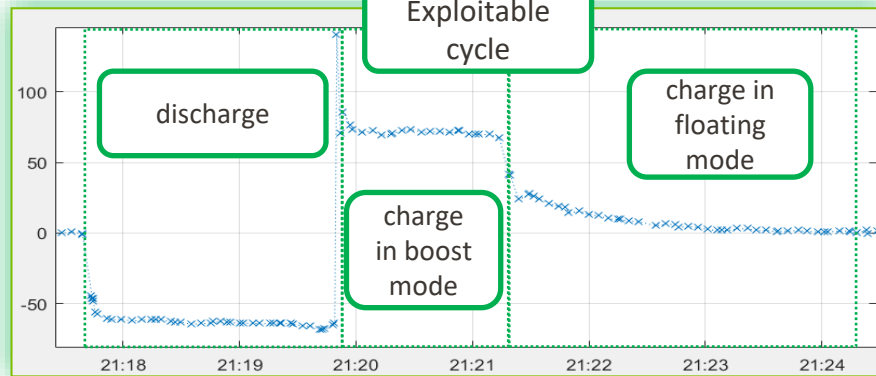
Too short



Cycle 2

Cycle 3

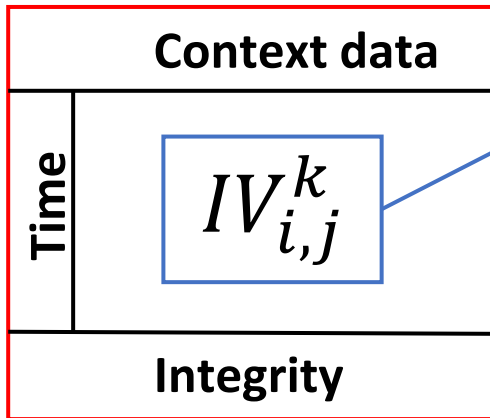
Exploitable cycle



FROM RAW DATA TO INDICATOR DESIGN

DATA PROCESSING : HEALTH INDICATOR AGGREGATION INTO INDICATOR VECTORS

3

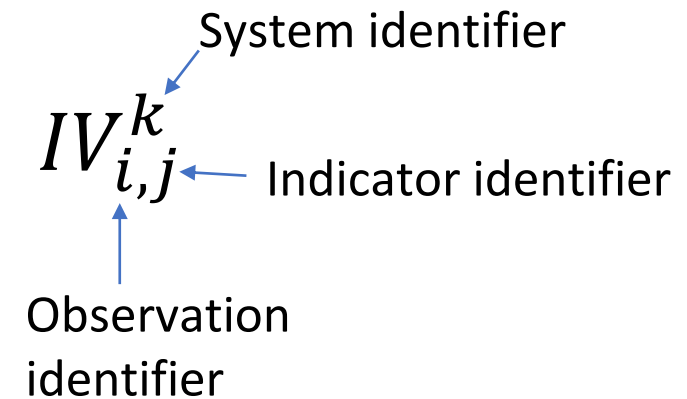


$$IV = function(data(t))$$

Example of function:

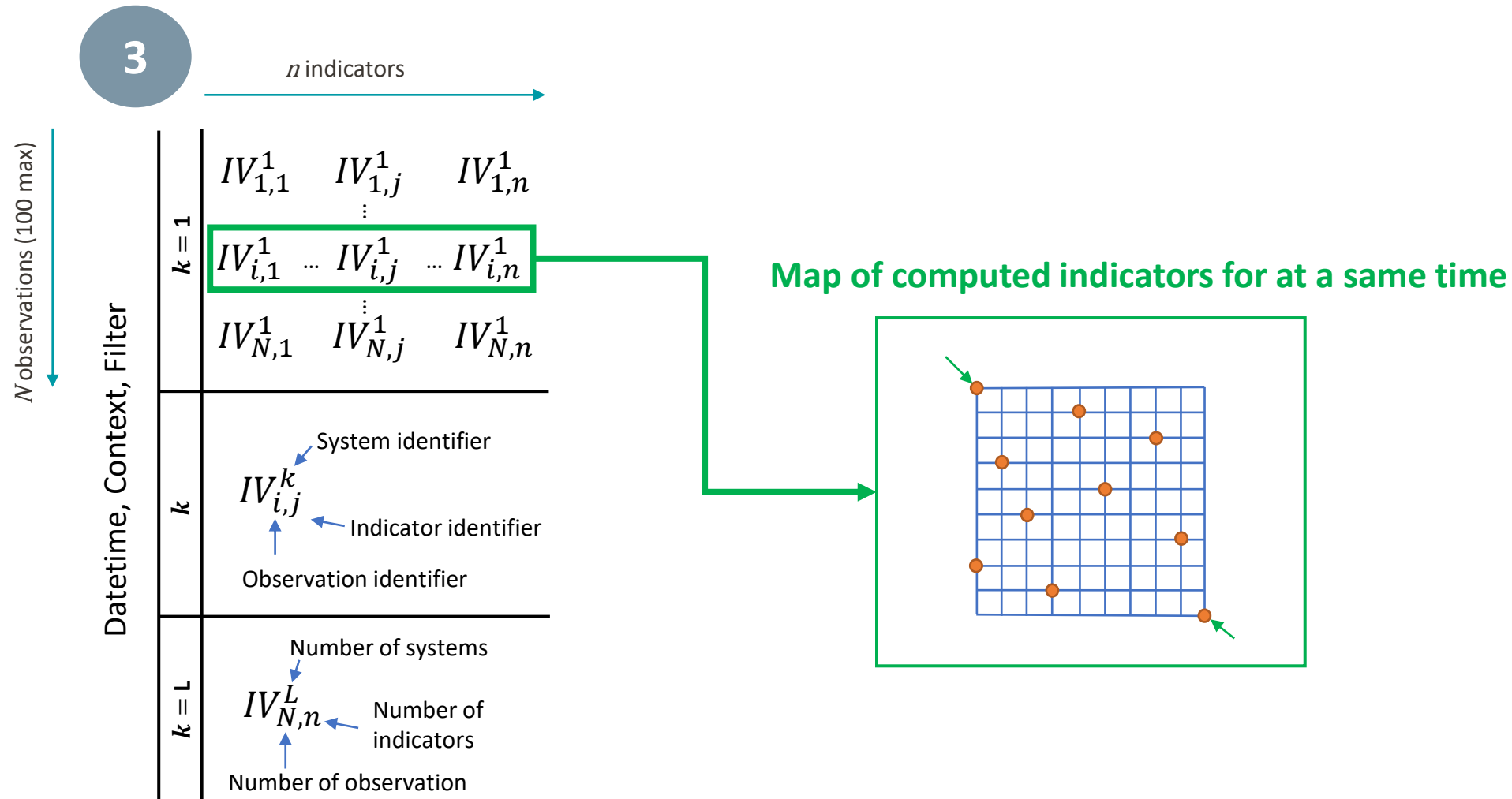
- minimum,
- maximum,
- time of reference,
- area,
- slope,
- inflexion point...

IV baseline system on train fleet:



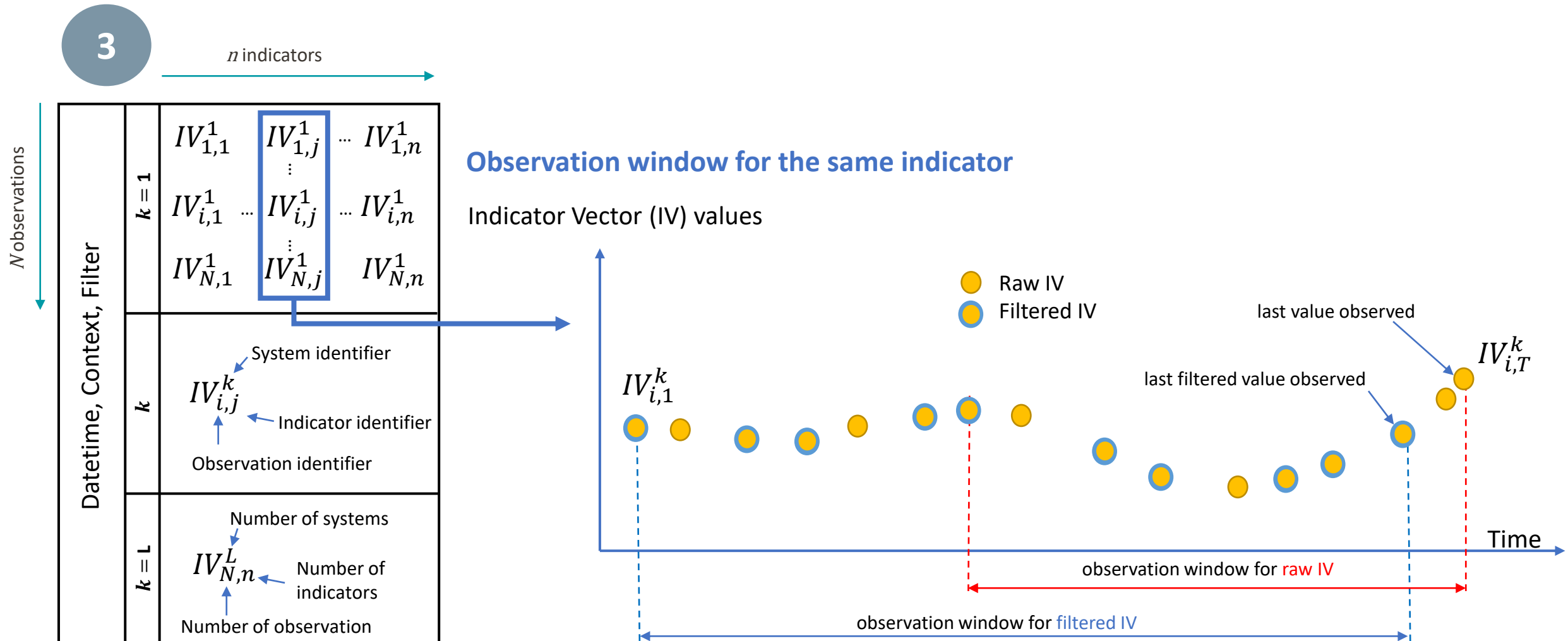
FROM RAW DATA TO INDICATOR DESIGN

DATA PROCESSING : STRUCTURATION AND STORAGE OF INDICATOR VECTORS (IV)



FROM RAW DATA TO INDICATOR DESIGN

DATA PROCESSING : STRUCTURATION AND STORAGE OF INDICATOR VECTORS (IV)

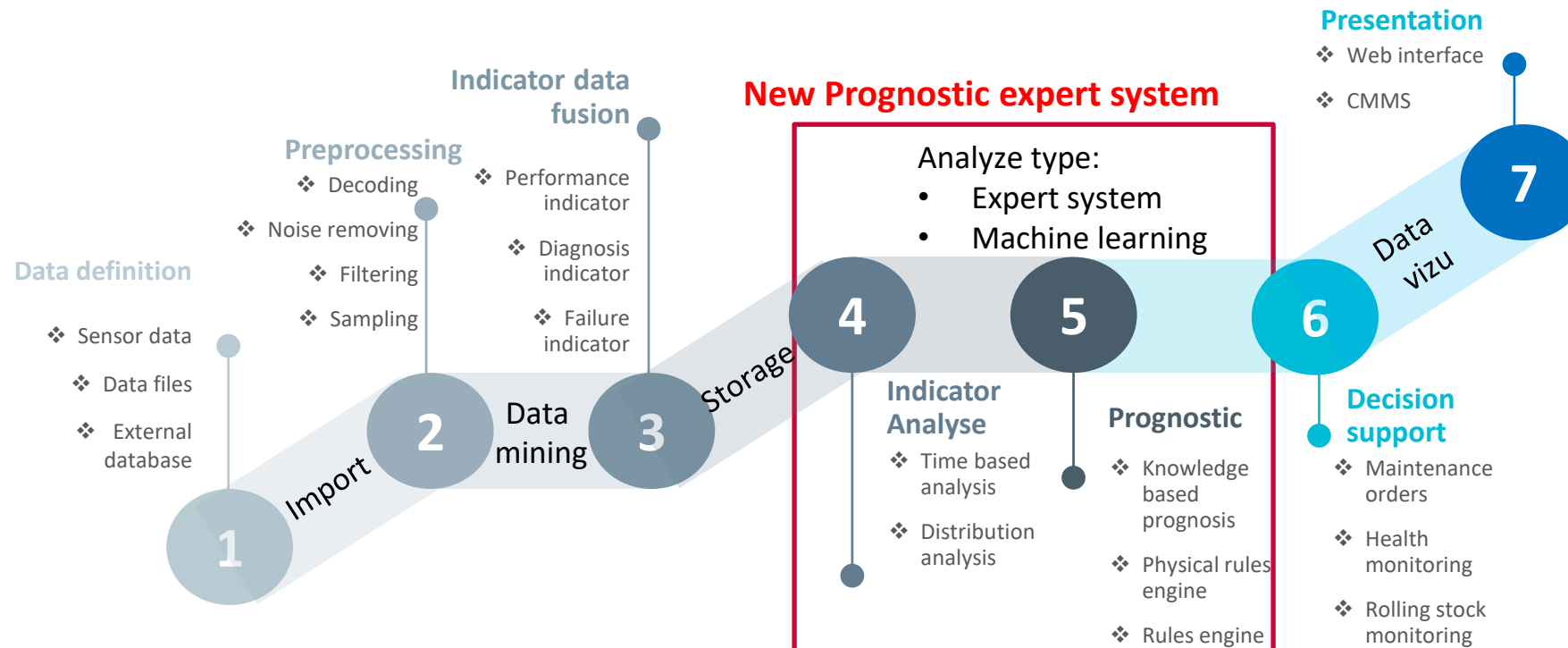




03. PROGNOSTIC EXPERT SYSTEM BASED ON FLEET STATISTICS

FUTUR SIGNALING SYSTEM

NEW PROGNOSTIC EXPERT SYSTEM BASED ON FLEET STATISTICS



03.

PROGNOSTIC EXPERT SYSTEM BASED ON FLEET STATISTICS

HYPOTHESES

HYPOTHESES

DATAFRAME HYPOTHESIS

Accuracy: each dataframe is plenty accurate to describe the functionality of a system in a way that a physical action on the system has a direct influence on the dataframe.

Amount of data: many dataframes have been collected in this study and their number will increase in time.

(ALSTOM R2N IDF : ~1000 doors, ~500 batteries, ~800 HVAC...)

Independency: each system being completely independent from one to another

=> The numerous dataframes allows a relevant computation of fleet statistics

HYPOTHESES

DISTRIBUTION HYPOTHESIS

Health status: the health of a system differs from one train to another depending on several parameters such as manufacturing quality, delivery date, operating conditions, aging or maintenance operations quality.

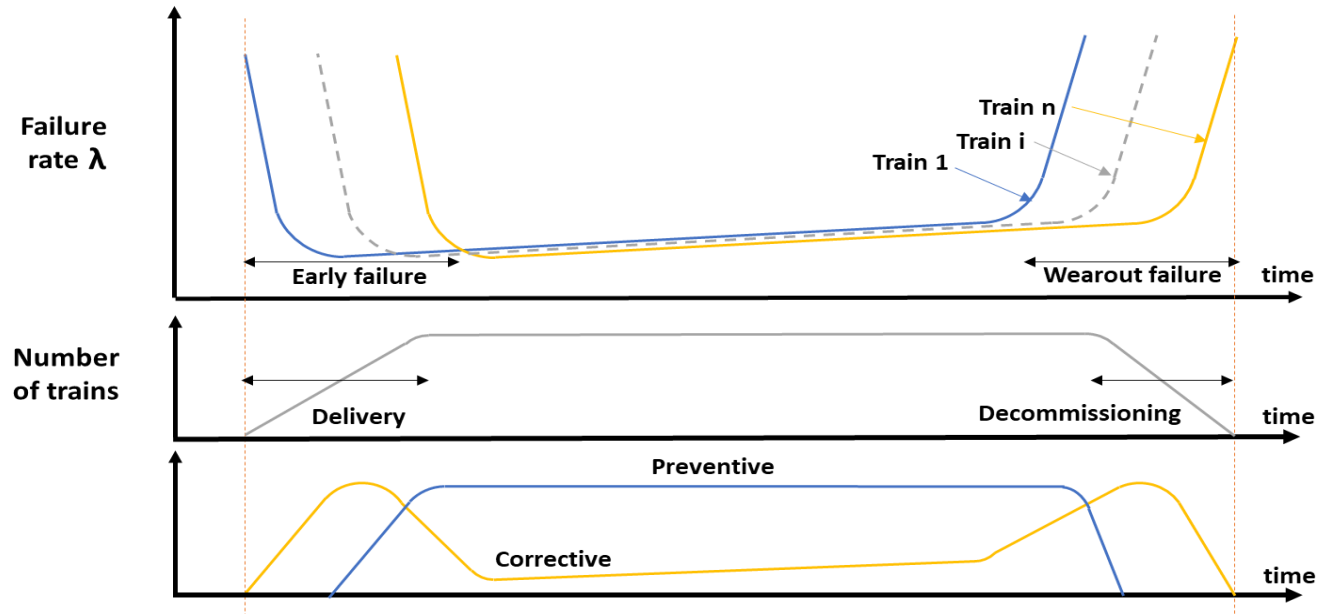
Maintenance quality: systematic maintenance is effective enough and reliability is suitable.

=> Most systems are healthy and only some of them must be repaired.

=> Distribution of health states through the whole train fleet is suitable for statistical computations

HYPOTHESES

AGEING, MAINTENANCE NEED AND OPERATIONAL EFFECTS



Time effect: ageing effect, maintenance operations, modifications or upgrades have an impact on the health state

Maintenance need: the need for reactive maintenance is higher during the delivery and the end-of-life period

=> bathtub curve of the failure rate

=> **The distribution shape will also change in time and thus the signaling system must follow the maintenance need**

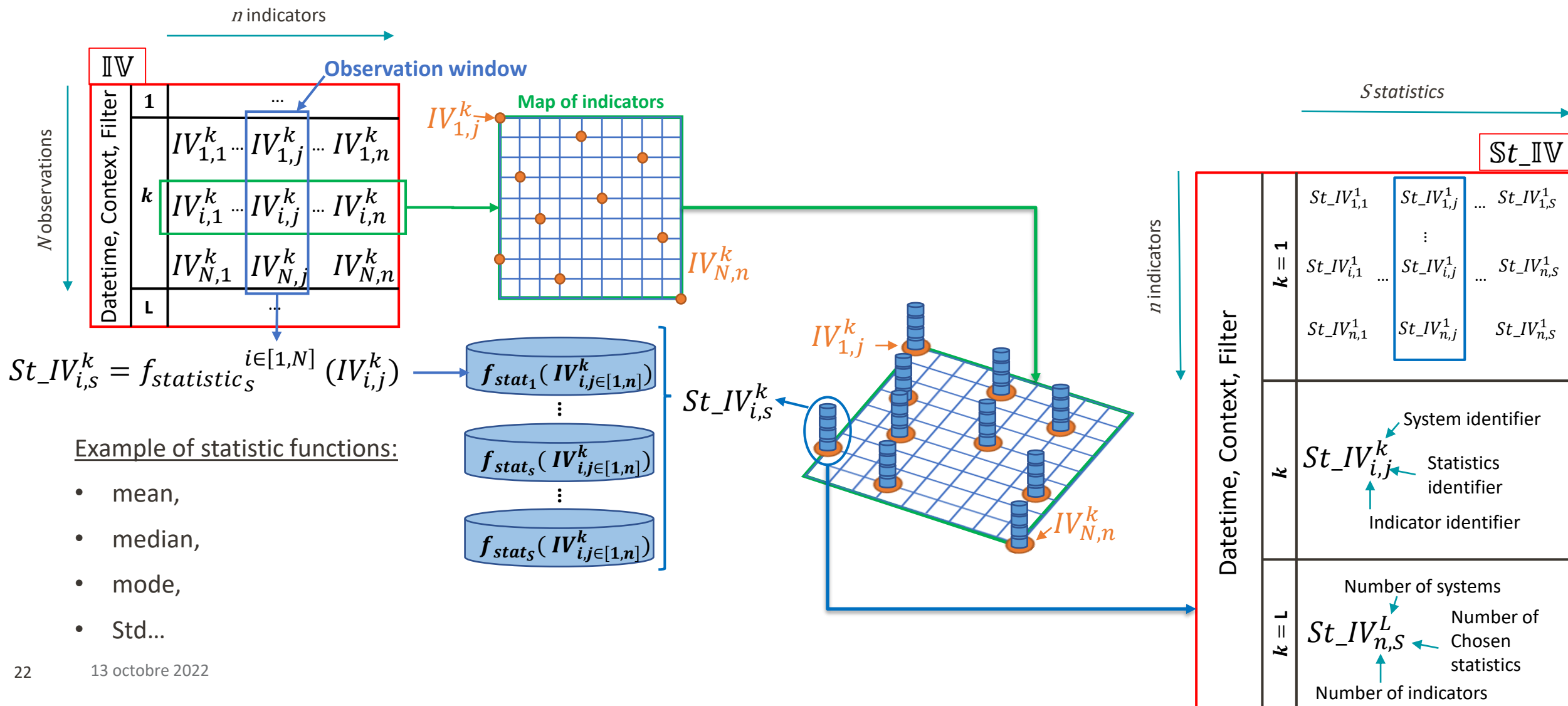
03.

PROGNOSTIC EXPERT SYSTEM BASED ON FLEET STATISTICS

DATA POST-PROCESSING

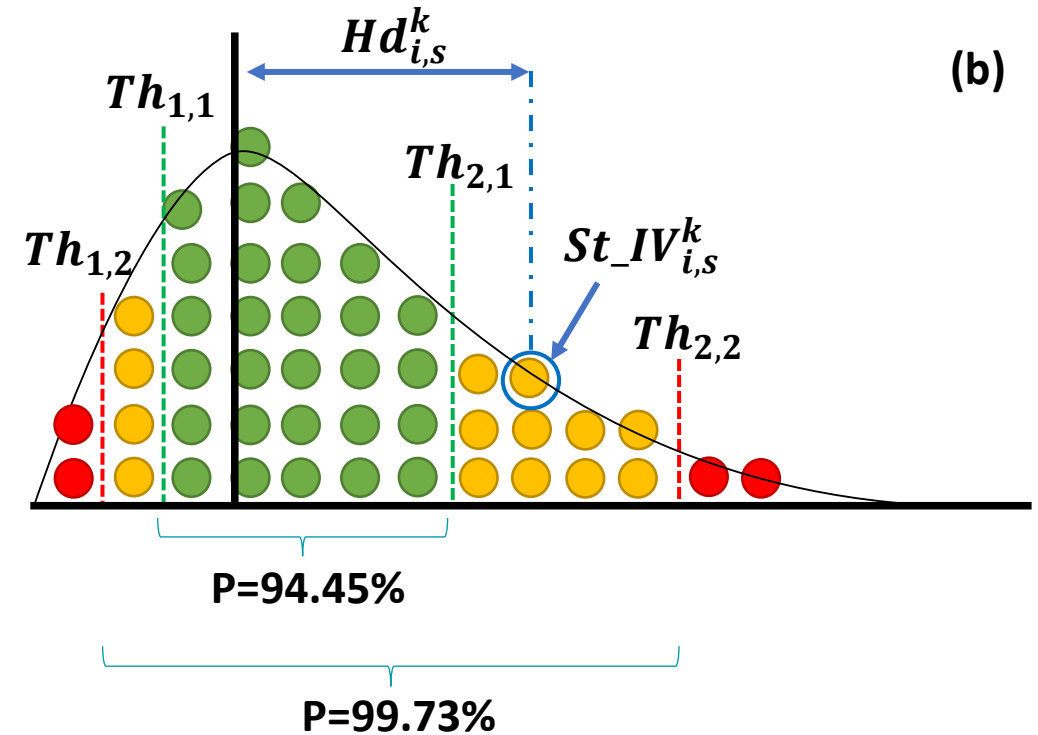
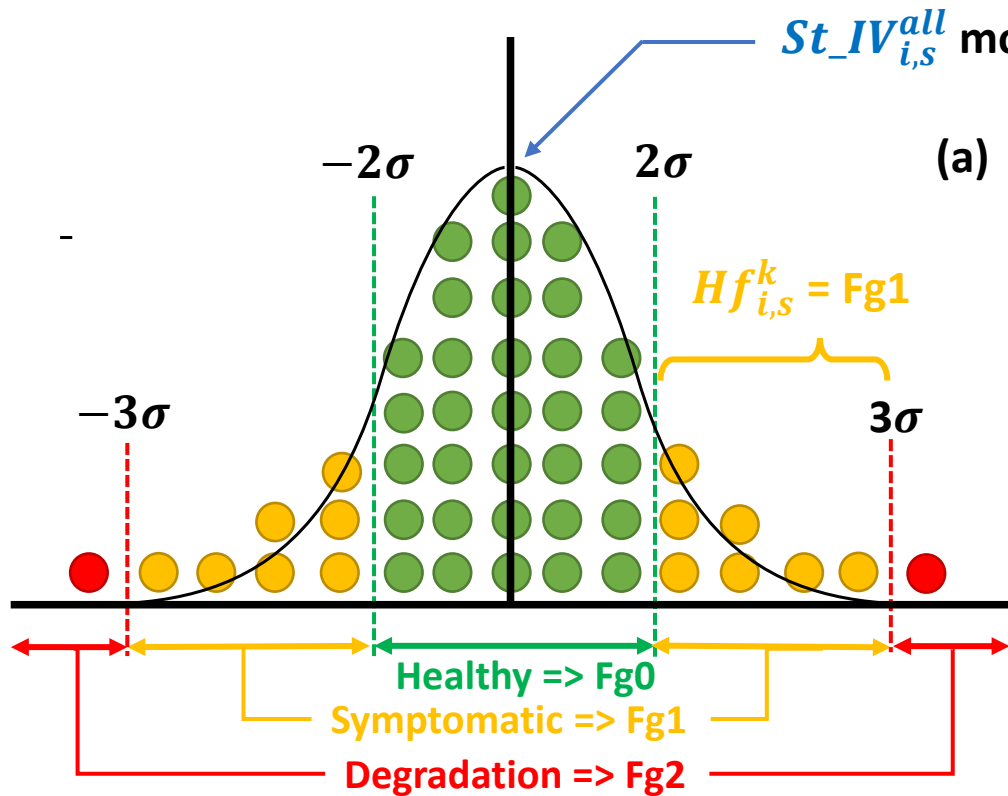
DATA POST-PROCESSING

From Indicator Vector (IV) to Statistical Indicator Vector(St_IV)



DATA POST-PROCESSING

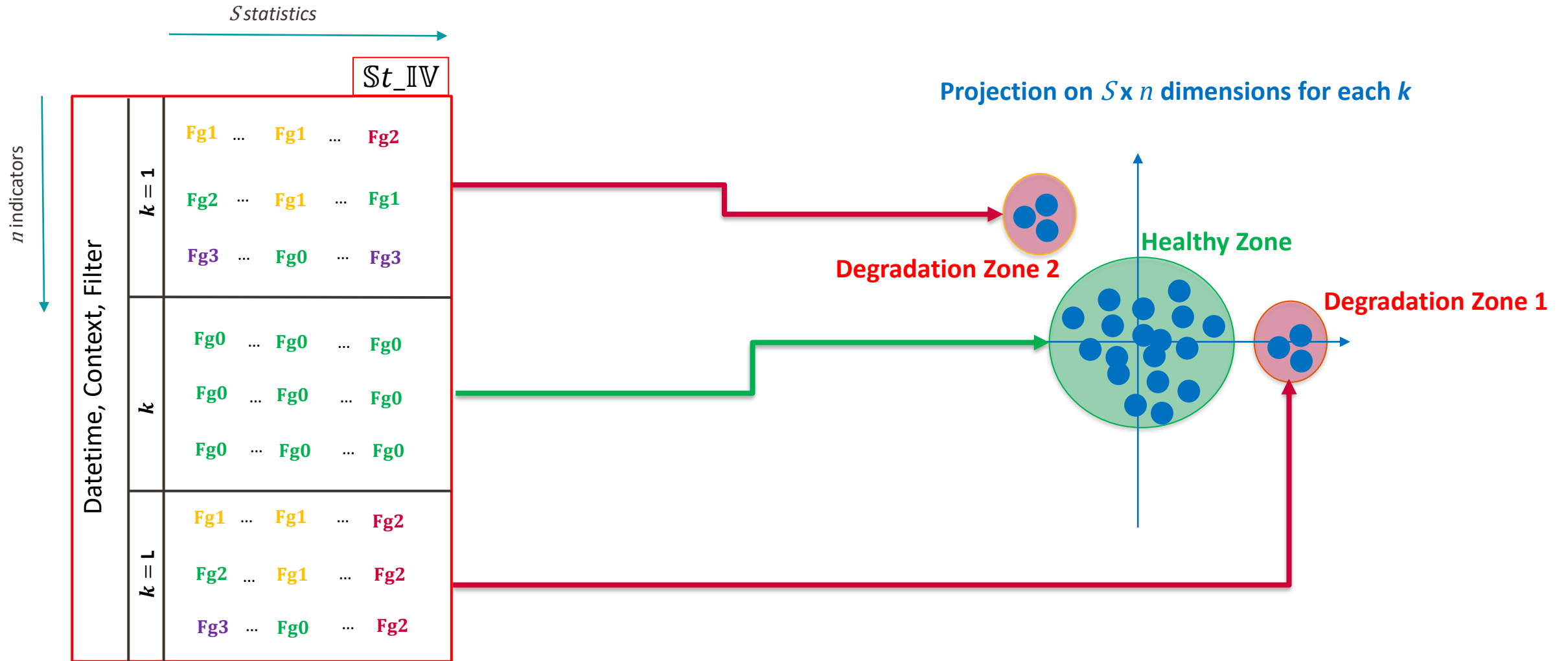
Distribution for each indicator for the complete fleet



=> Others complex distributions (« unknow ») will be treated with a Kernel density estimation

DATA POST-PROCESSING

Classification, clustering and failure signature

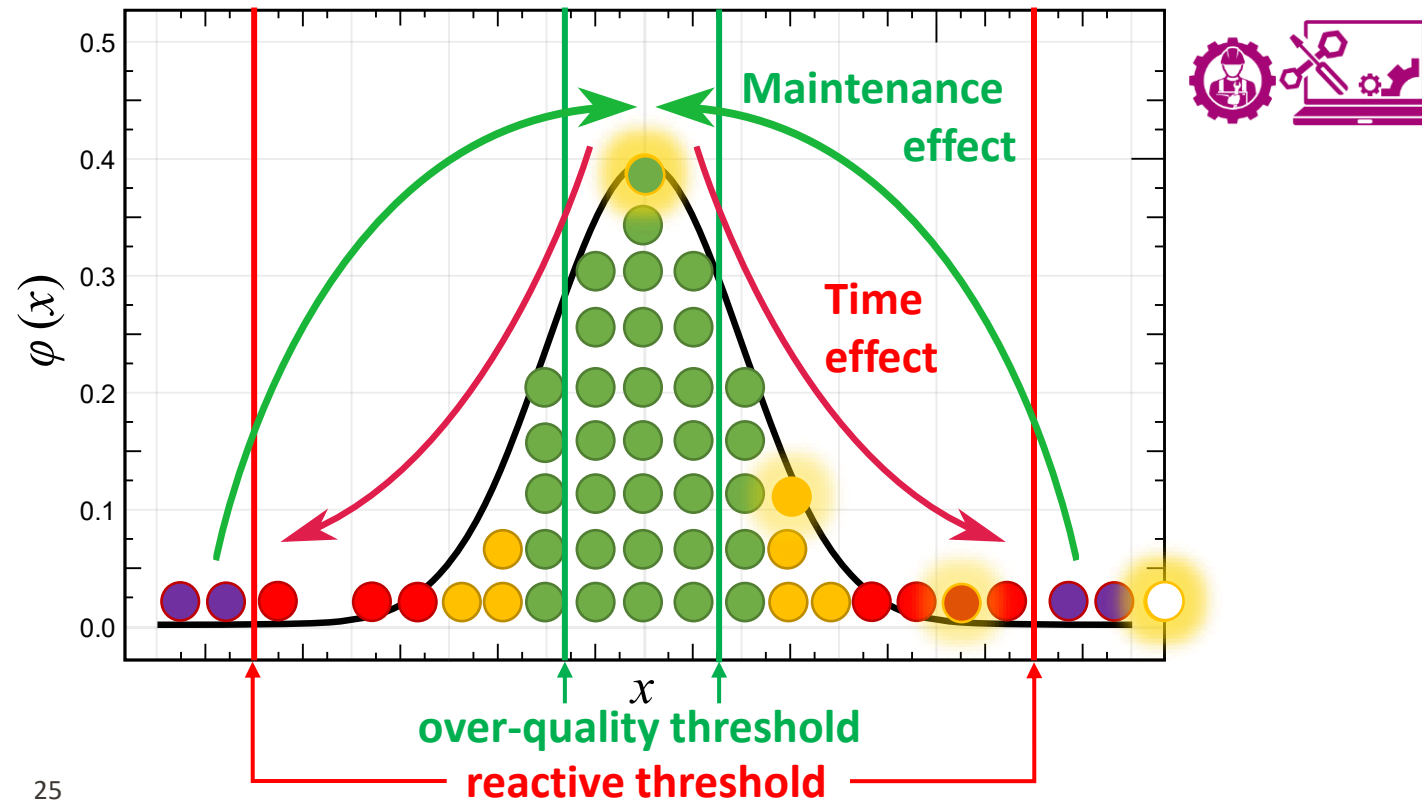


DATA POST-PROCESSING

Maintenance distribution overview

=> What happened if we let the system unregulated over lifetime ?

=> Why boundaries are needed and useful ? And how we give senses to those boundary ?

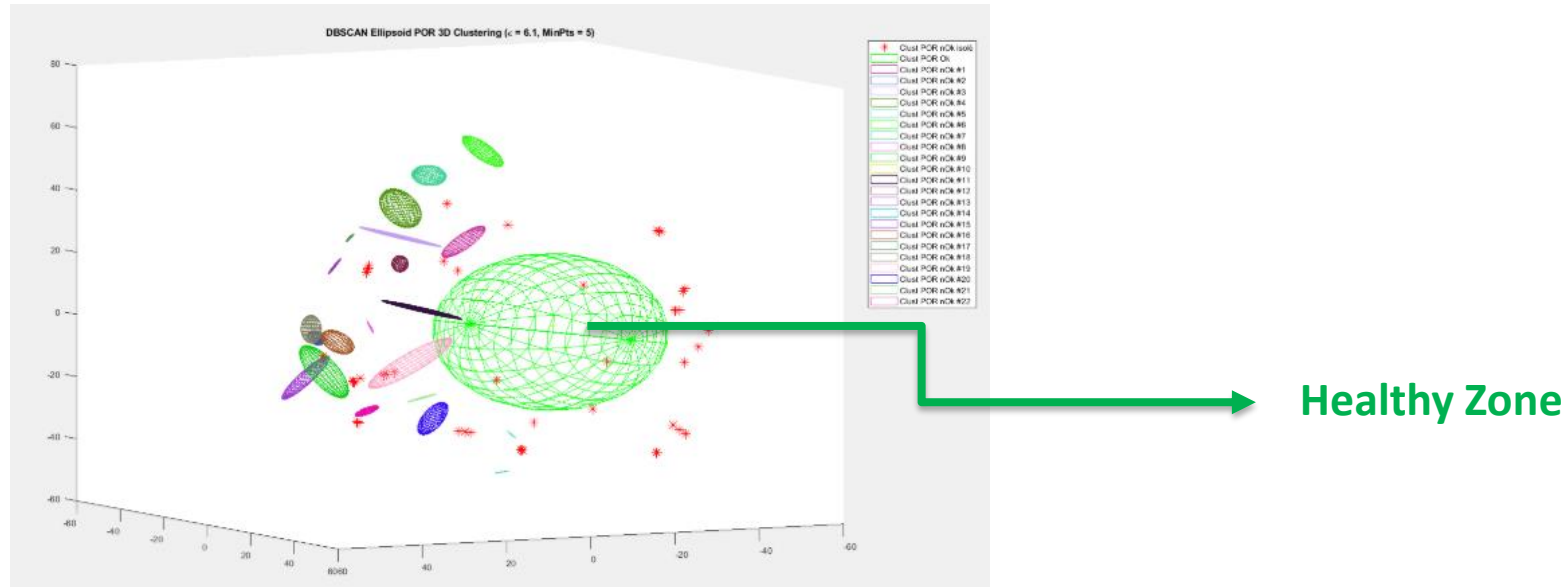




04. CONCLUSION AND PERSPECTIVES

CONCLUSION

Promising results have already been observed:



Next study will be dedicated to:

- Analyze future results obtained by this prognostic system over a year of exploitation
- Verify starting hypotheses and how results may impact the development of the expert system
- Implement the human in-the-loop system in the whole fleet maintenance statistics system
- Implement auto-generator indicators to increase the potential number of features identification (problem of curse of dimensionality).

PRELIMINARY RESULTS

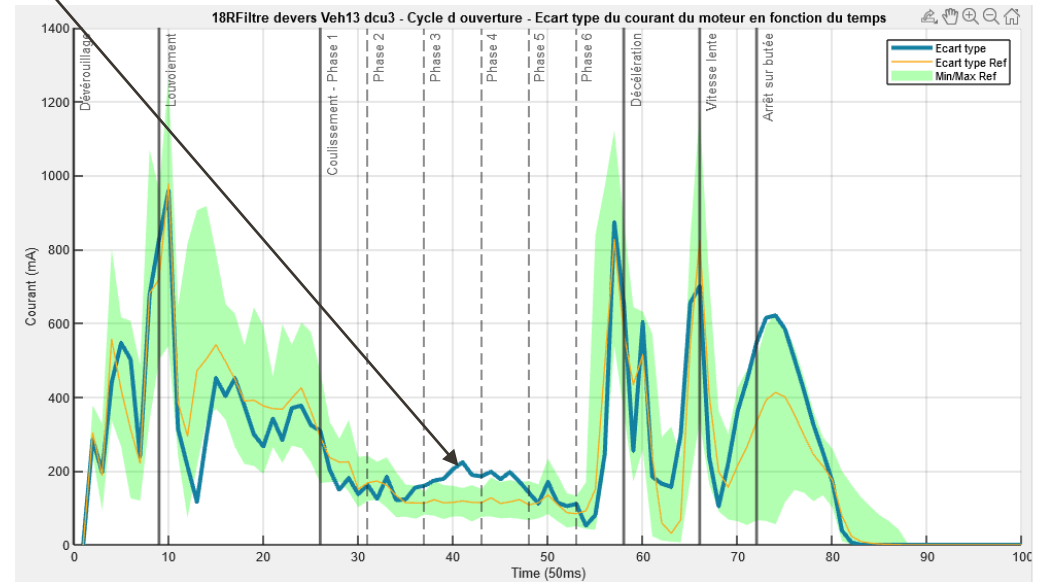
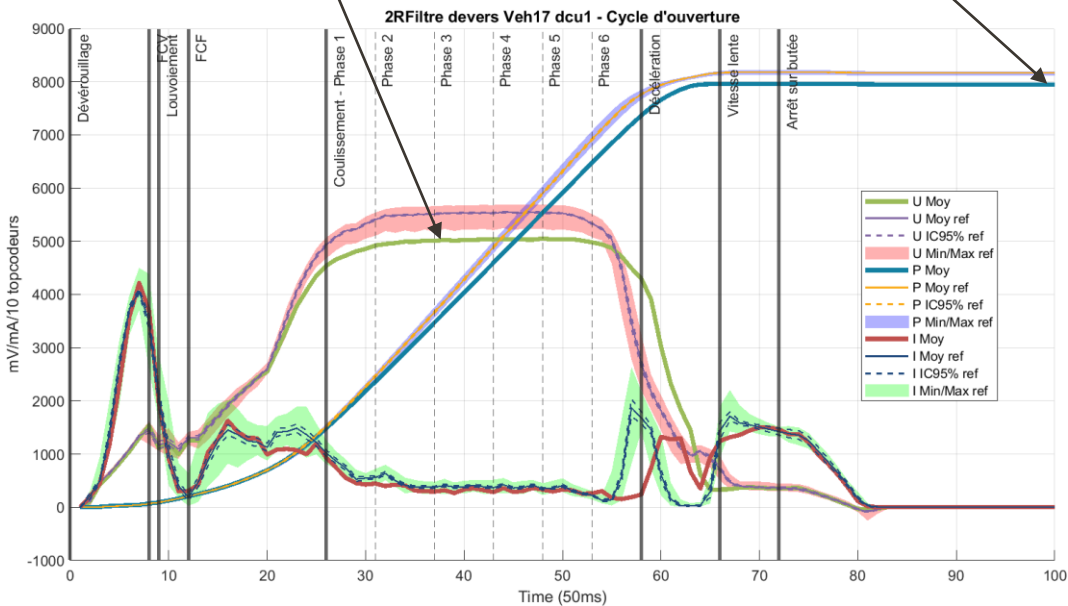
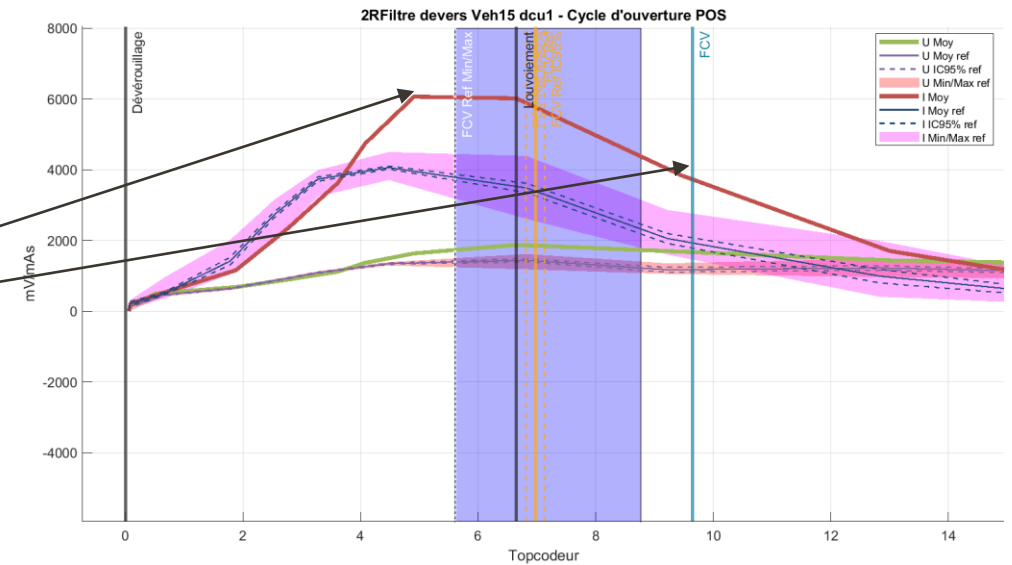
Example of identified clusters

Cluster 4 : Unidentified failure

Cluster 1 : Access door with end-stop problem

Cluster 3 : Access door with motorization problem

Cluster 2 : Tough sliding movement



PRELIMINARY RESULTS

Predictive maintenance IHM

Operation R2N_VL200K_AV sur rame 3R 5700005

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 Début visite : [Non programmée](#)
 Fin visite : [Non programmée](#)

Taches validées par CBM

Tâches	VE1NV11 5700005		VI2NV12 5714005	VI1NV13 5721005				VI2NV14 5754005	VI1NV15 5762005				VI2NV16 5774005	VI1NV17 5783005				VE2NV20 5707005		
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Date (jours)	-	-		0	0	0	0		0	0	0	0		0	0	0	0	0	-	-
	2	1		3	4	5	6		7	8	9	10		11	12	13	14	15	16	
POR_FCF				2022-08-23 ✓	2022-08-23 ✓	2022-08-23 ✗	2022-08-23 ✓		2022-08-23 ✗	2022-08-23 ✓	2022-08-23 ✓	2022-08-23 ✓		2022-08-23 ✗	2022-08-23 ✗	2022-08-23 ✗	2022-08-23 ✗			
POR_Effort_ouverture				2022-08-23 ✓	2022-08-23 ✓	2022-08-22 ✓	2022-08-22 ✓		2022-08-23 ✓	2022-08-22 ✓	2022-08-22 ✓	2022-08-22 ✓		2022-08-22 ✓	2022-08-12 ✓	2022-08-23 ✓	2022-08-23 ✓			
POR_Butée_Ouverture				2022-08-23 ✗	2022-08-23 ✗	2022-08-23 ✗	2022-08-22 ✗		2022-08-23 ✓	2022-08-22 ✗	2022-08-22 ✗	2022-08-22 ✓		2022-08-23 ✗	2022-08-19 ✓	2022-08-23 ✗	2022-08-23 ✗			

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✓	Validée
✗	Non validée
✓	Donnée (validée) non fiable / Dernier état connu
✗	Donnée (non validée) non fiable / Dernier état connu
date	Date du dernier cycle de fichiers reçu

ANY QUESTIONS ?



CONTACTS

Pierre Audier
Data Scientist
pierre.audier@sncf.fr

Rémy Marion
Data Scientist
r.marion@sncf.fr

Fabien Turgis
Research Engineer
fturgis@ikosconsulting.com

Valentin Némoz
Data Scientist
valentin.nemoz@sncf.fr



Ingénierie du Matériel

