CentraleSupélec | université PARIS-SACLAY

Fiabilité, Réparabilité et Eco-conception de l'Electronique de Puissance (FREECO)

université PARIS-SACLAY

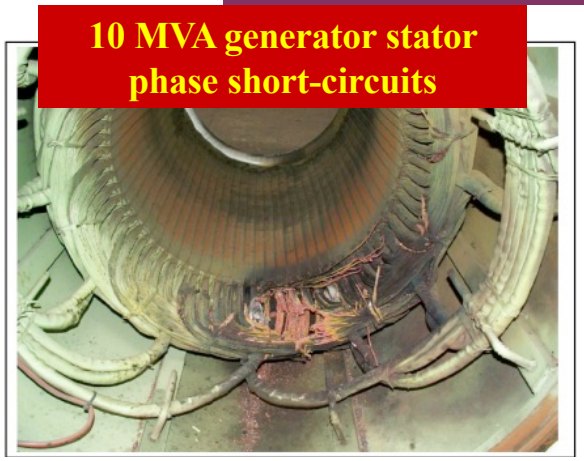
GeePS Génie électrique et électronique de Paris

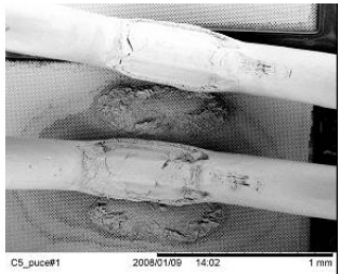
L2S Laboratoire Signaux & Systèmes

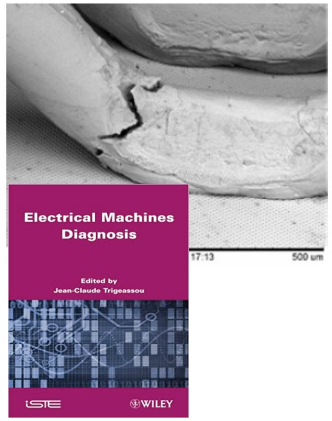
Fault Detection and Diagnosis Methodology & Applications

D. DIALLO

Université Paris-Saclay, CentraleSupélec, CNRS, Gif Sur Yvette, 91192, France



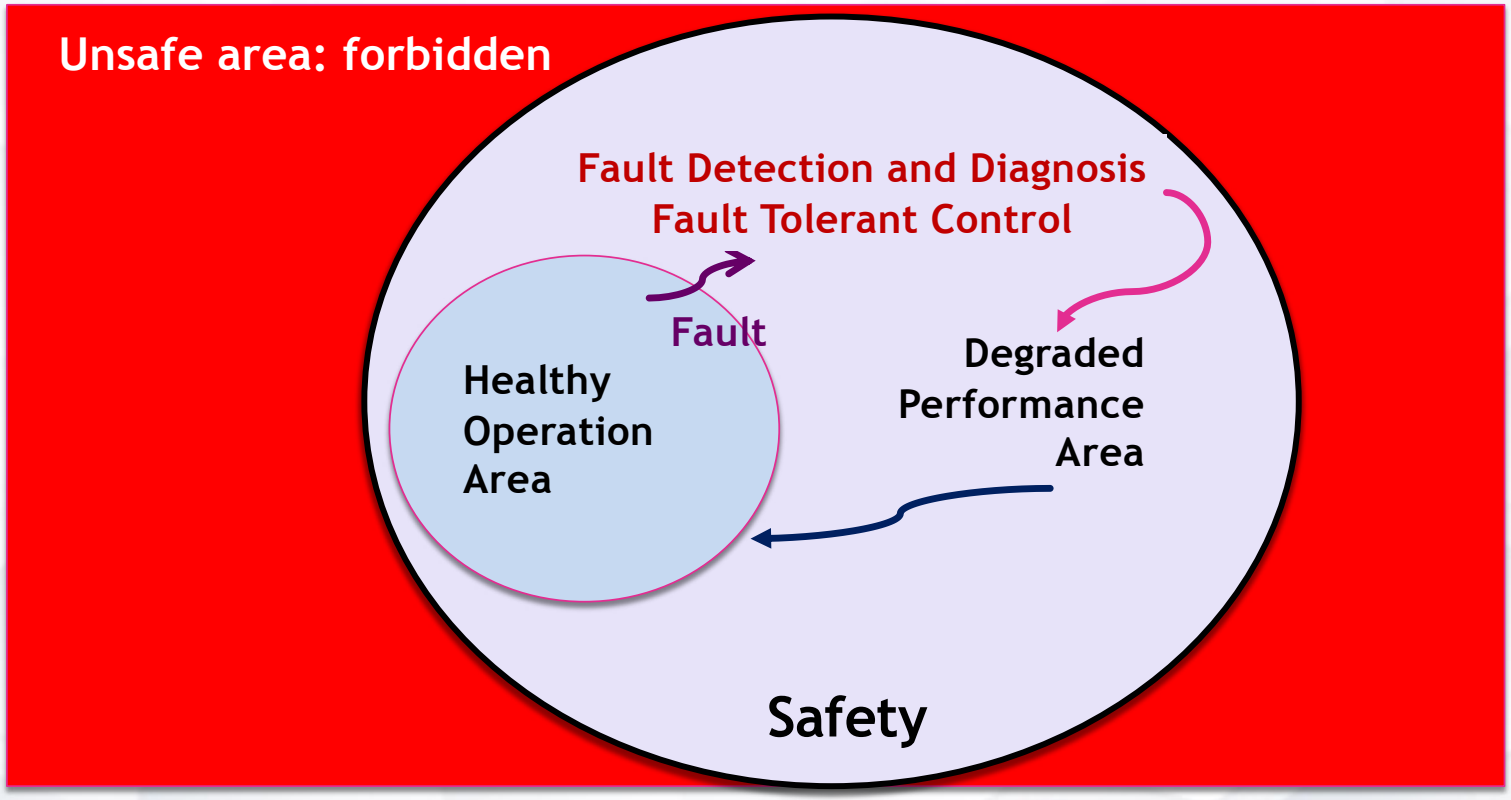




B. Brooks, The bakerseld re{a lesson in ground-fault protection," SolarPro Magazine, pp. 62-70, 2011.

1. Introduction to Fault Detection and Diagnosis

Safety and Fault Tolerance



1. Introduction to Fault Detection and Diagnosis

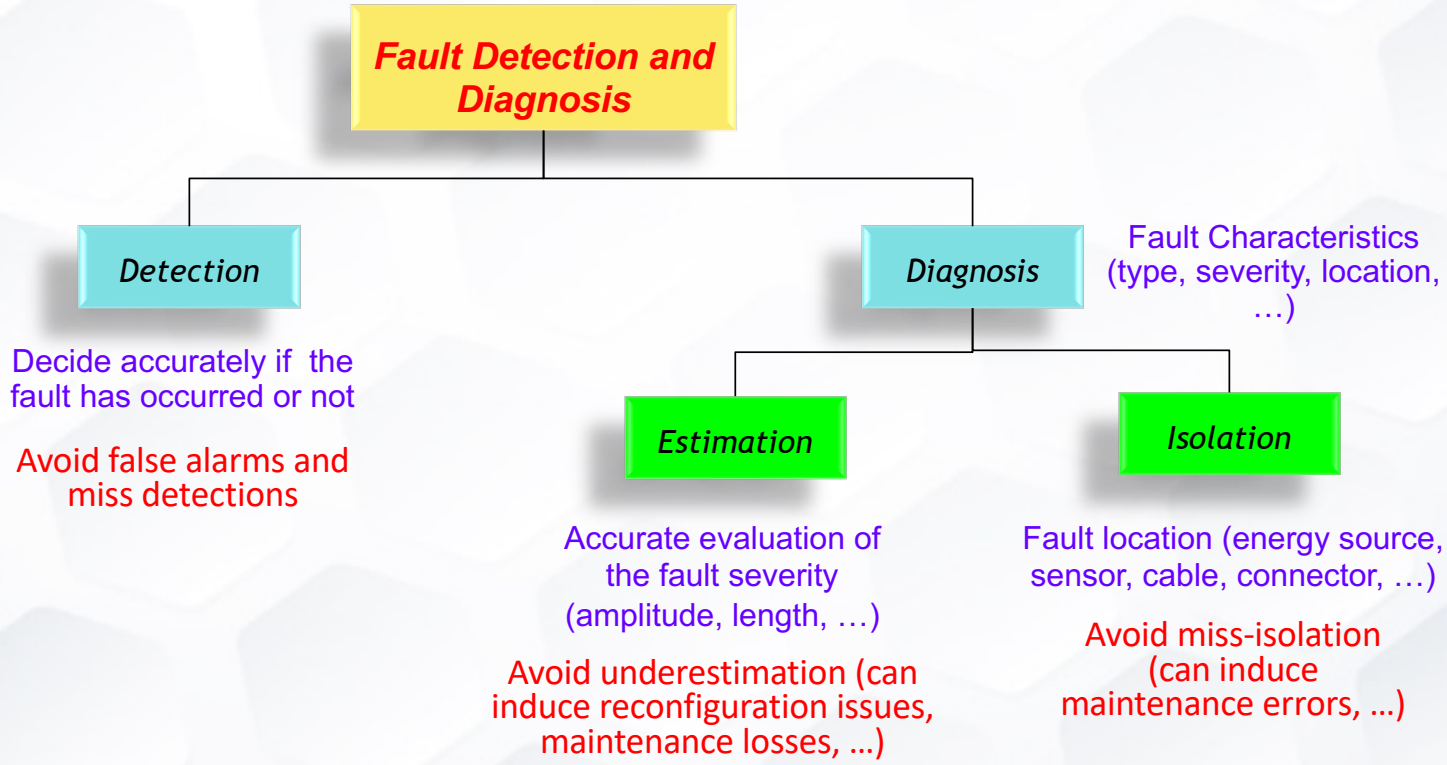
Fault types

A parameter or a variable is out of its 'healthy' operating range

Fault

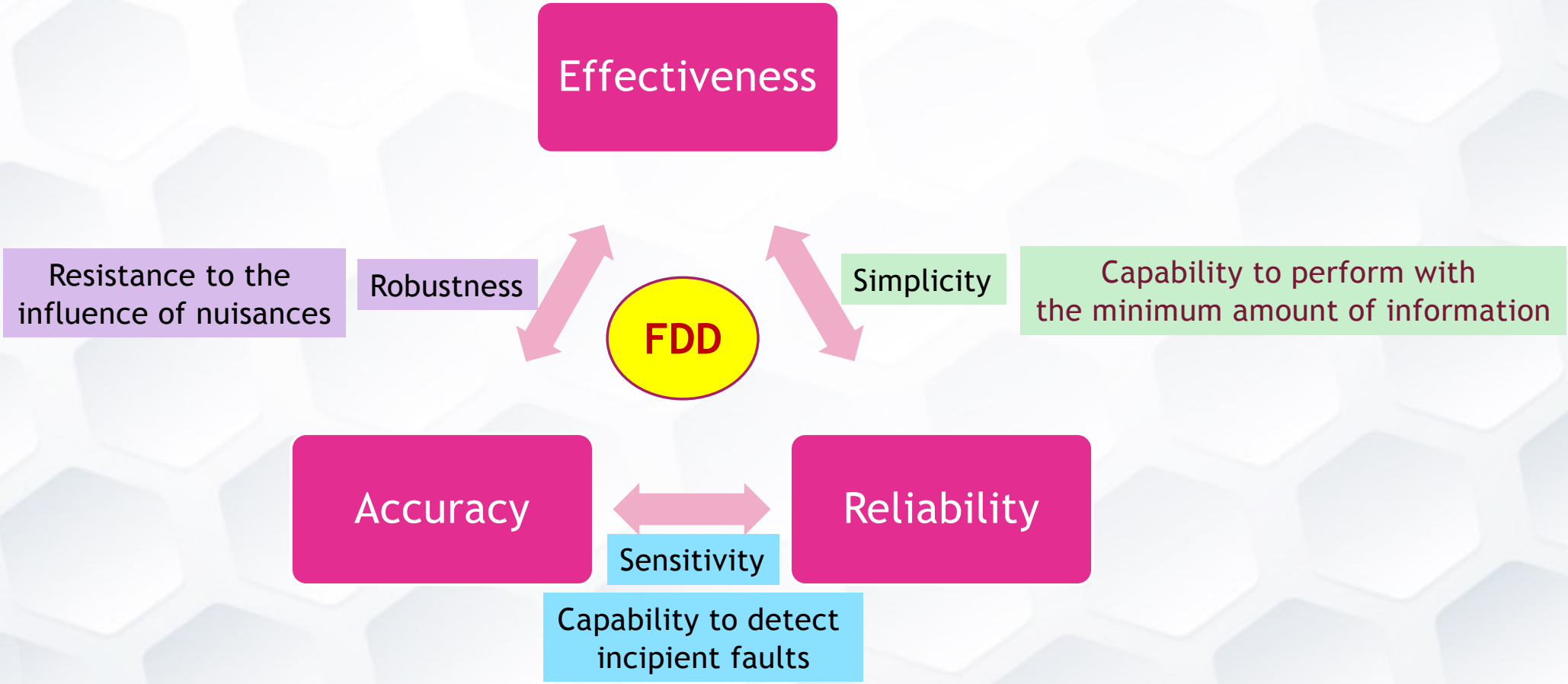
- *Persistent Strong effect*
- *Random Strong effect*
- *Persistent Low effect*

1. Introduction to Fault Detection and Diagnosis



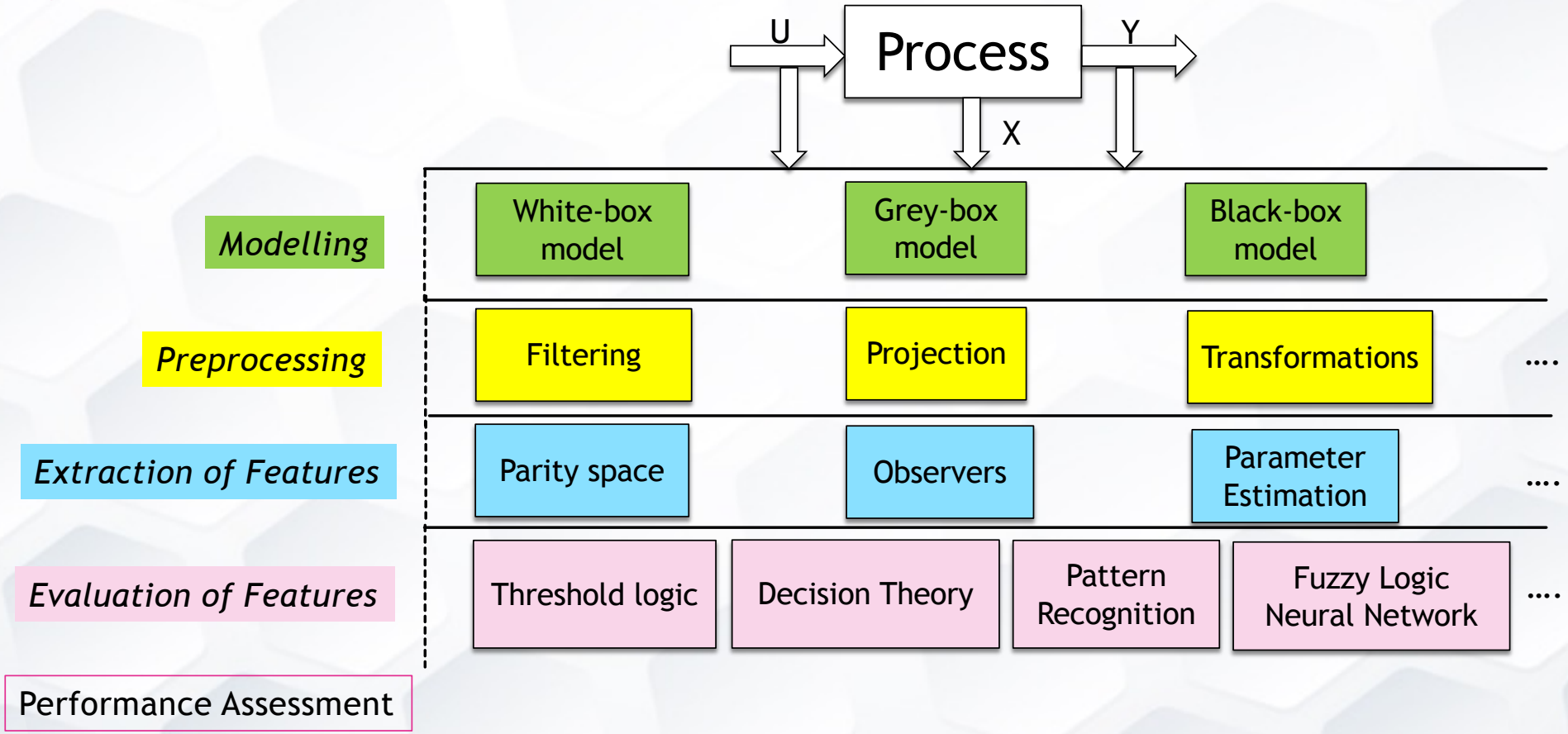
1. Introduction to Fault Detection and Diagnosis

Fault Detection and Diagnosis Methods: A compromise



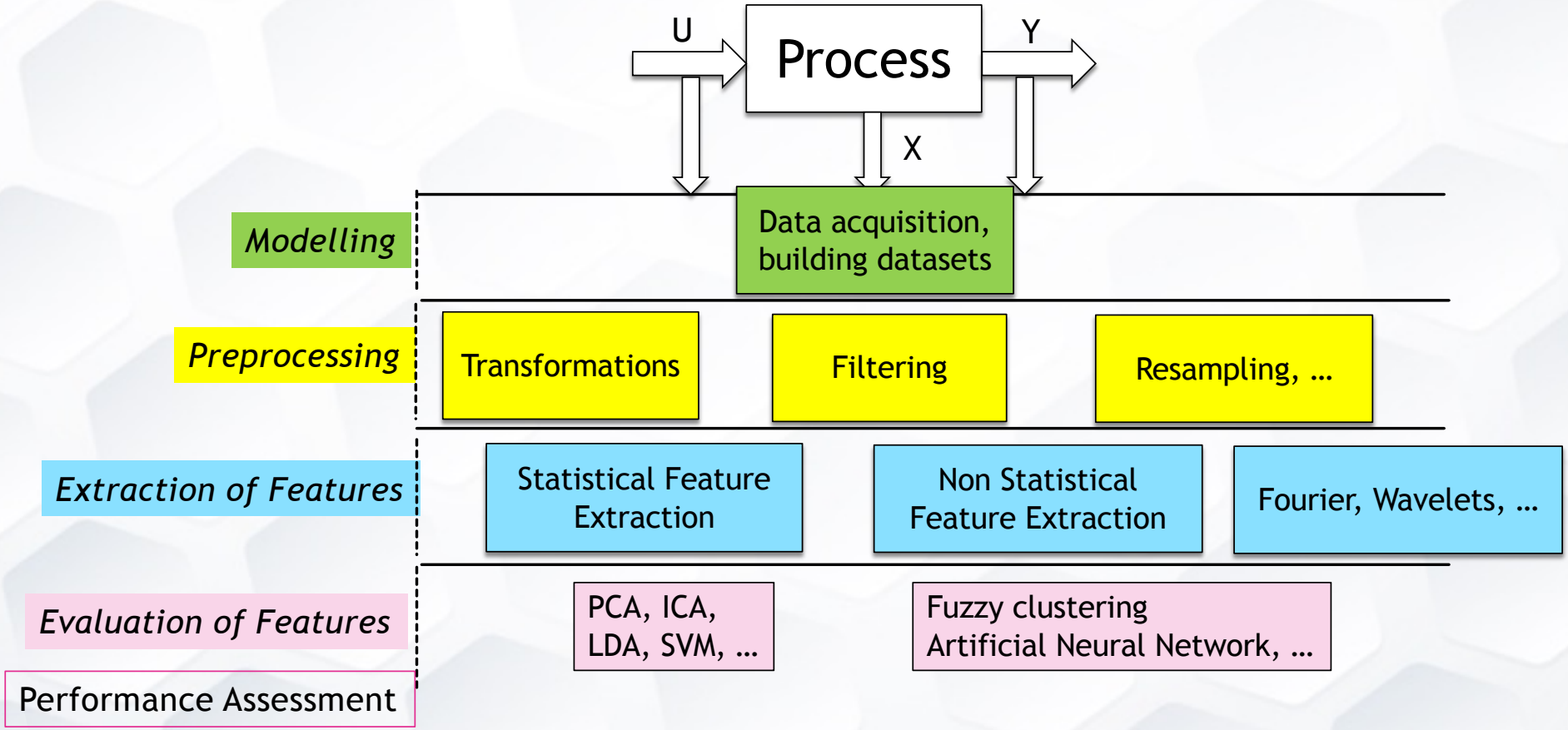
1. Introduction to Fault Detection and Diagnosis

Physics-based approach: General Scheme



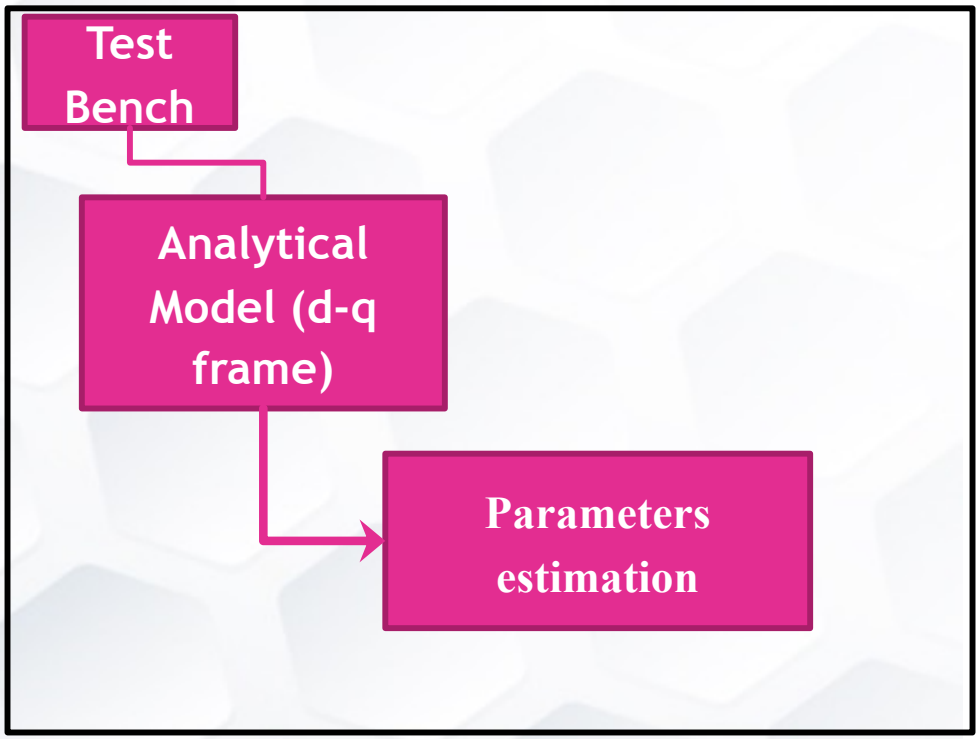
1. Introduction to Fault Detection and Diagnosis

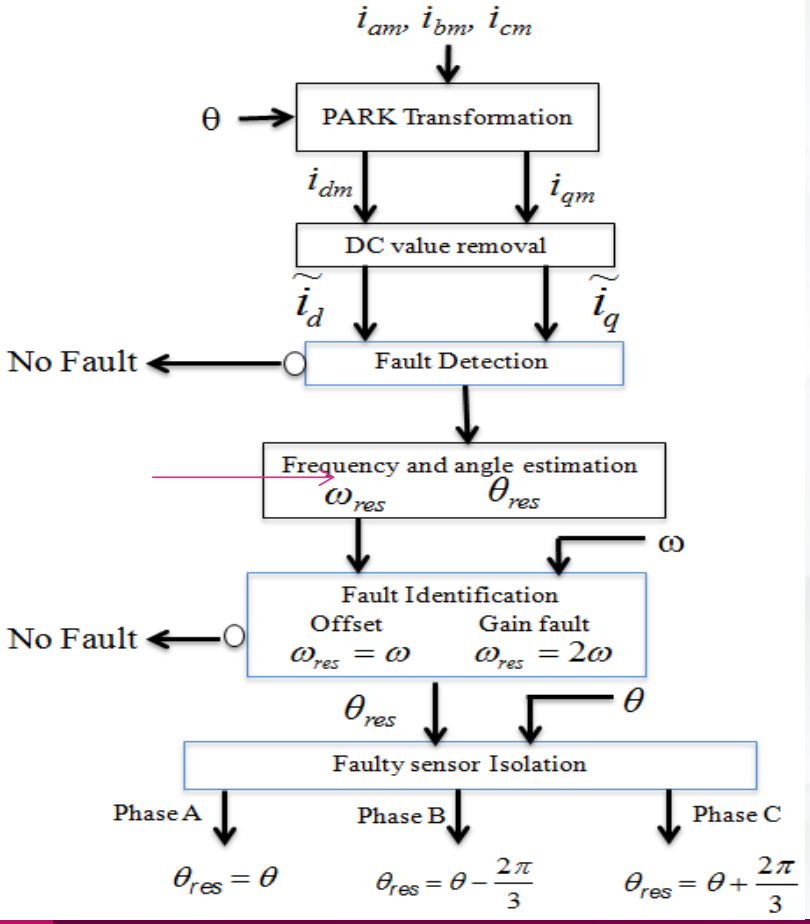
Data-driven approach: General Scheme



2. Applications

Phase Current Sensors Fault Diagnosis: Physics-based, Estimation in the Park reference frame



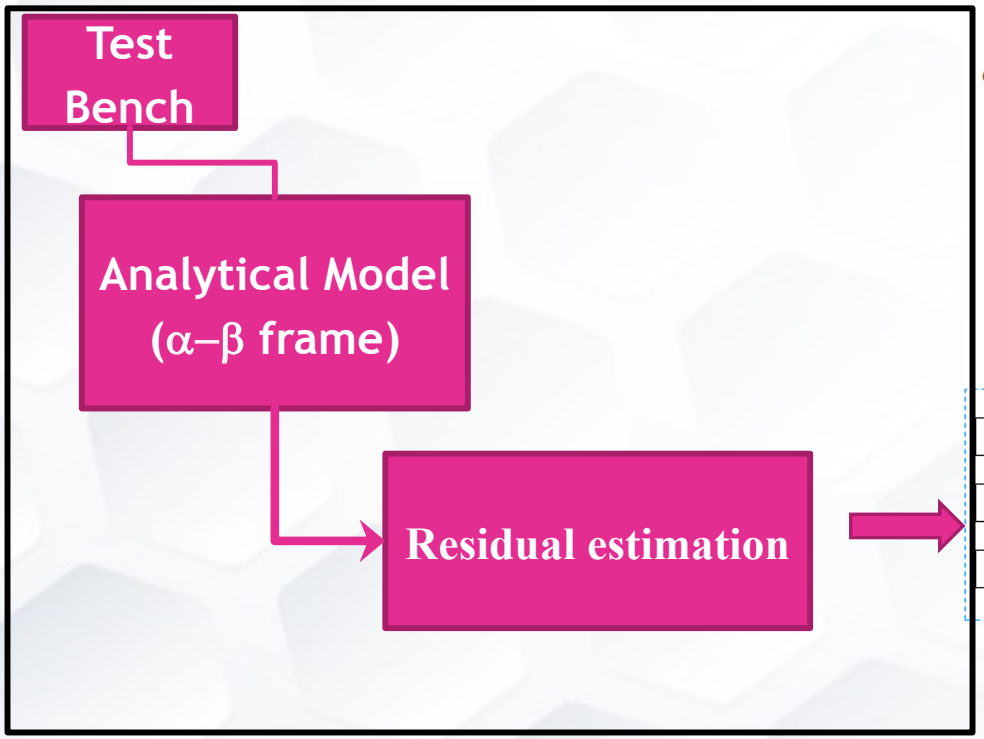


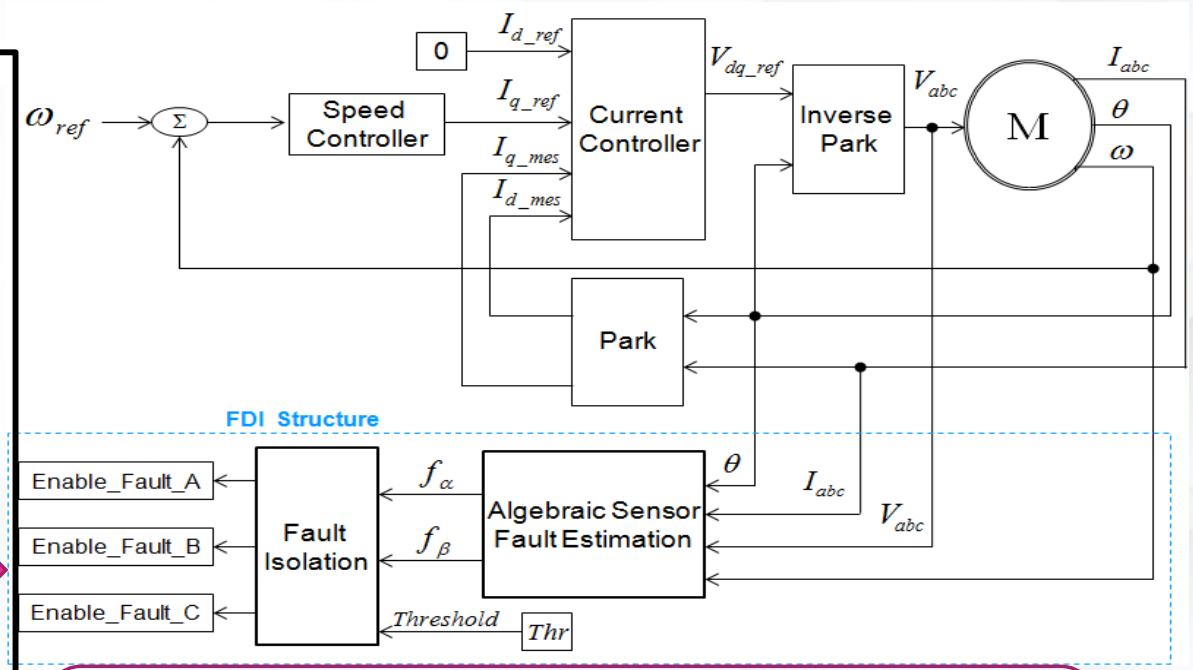
$$\theta_{res} = \arctan(-\frac{\tilde{i}_d}{\tilde{i}_q}),$$

$$\omega_{res} = \frac{d}{dt}\theta_{res}$$

2. Applications

Phase Current Sensors Fault Diagnosis: Physics-based, Estimation in the Concordia reference frame





$|f_\alpha| > thr$ and $|f_\beta| < thr$ => phase A sensor is faulty

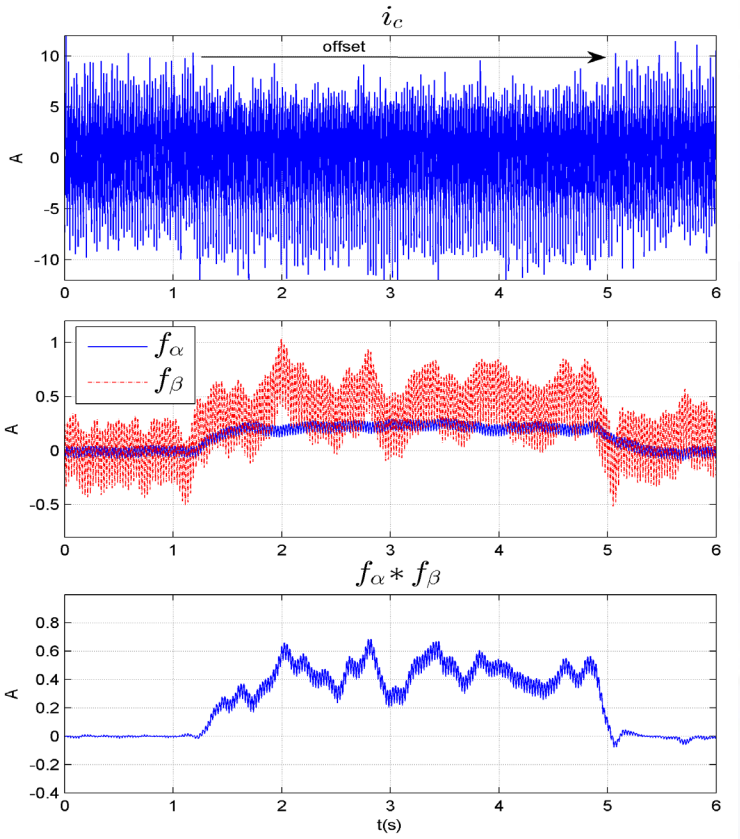
$f_\alpha > thr$ and $f_\beta > thr$ and $f_\beta * f_\alpha < 0$ => phase B sensor is faulty

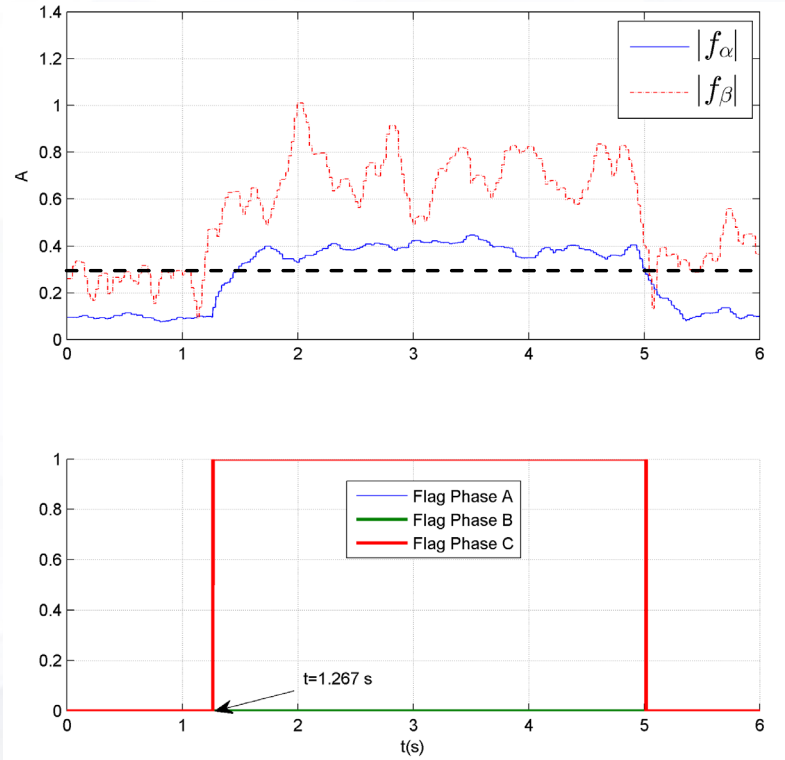
$f_\alpha > thr$ and $f_\beta > thr$ and $f_\beta * f_\alpha > 0$ => phase C sensor is faulty

2. Applications

Phase Current Sensors Fault Diagnosis

Experimental results (offset in phase *C* of 16% on the peak value)





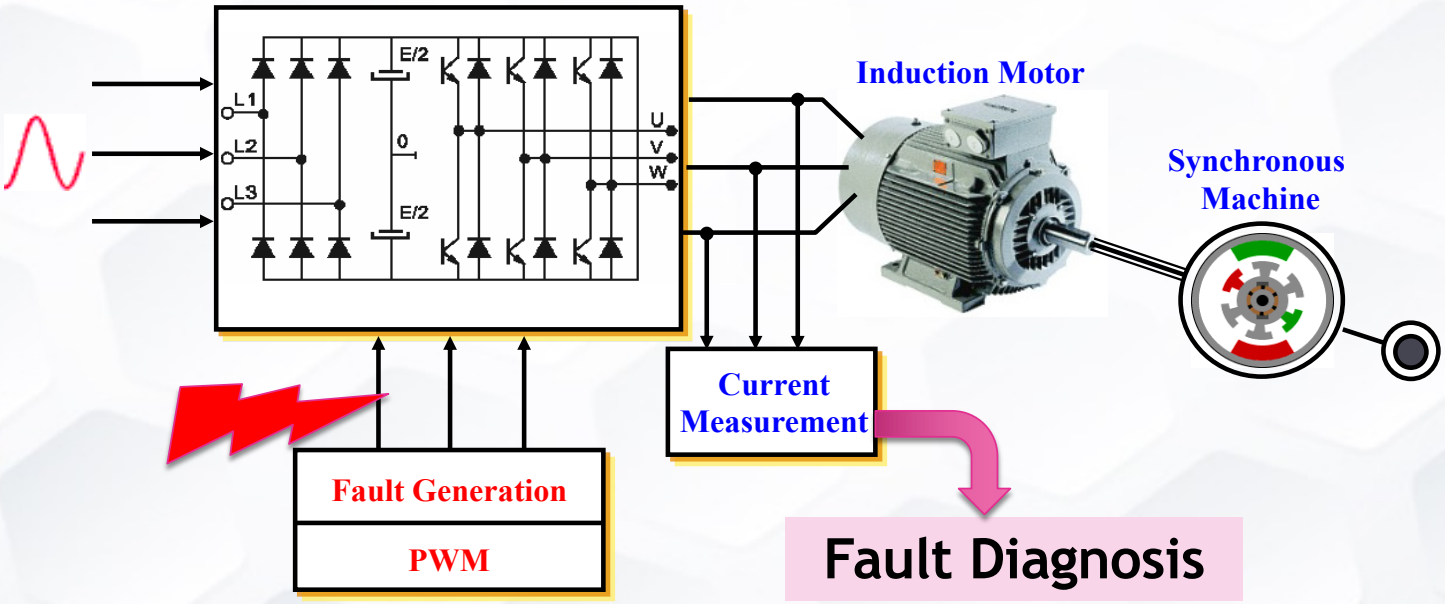
$|r_\alpha| = 0.42$ $\quad |\widehat{r_\alpha}| = 0.4$

$|r_\beta| = 0.707$ $\quad |\widehat{r_\beta}| = 0.72$

2. Applications

Power converter misfiring fault diagnosis

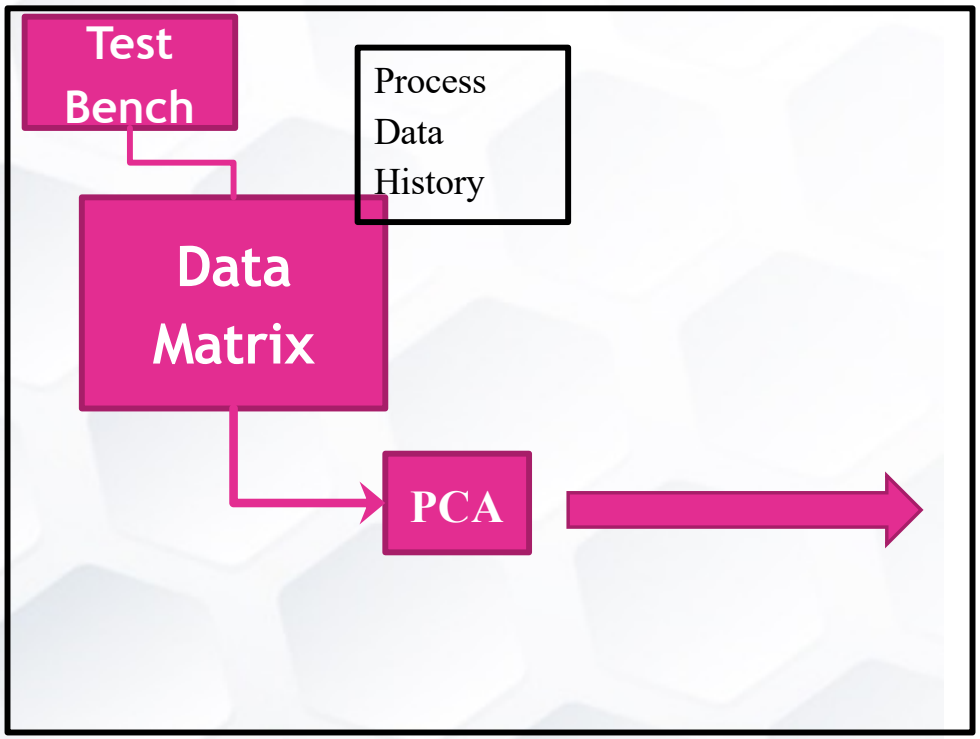
- 0.3 kW Induction Motor 0.3kW, 230/400V, 1.47/0.85 A, 1380 rpm

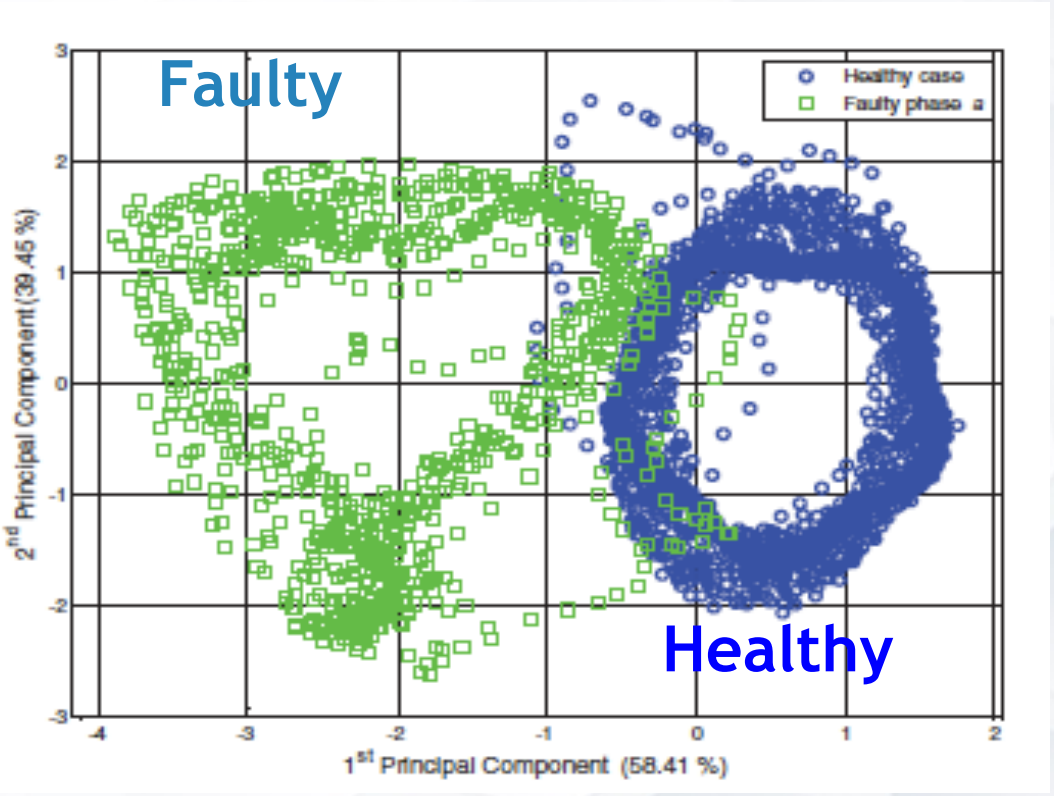


- Sampling and switching period 1ms

2. Applications

Power converter misfiring fault diagnosis: Data-based classification

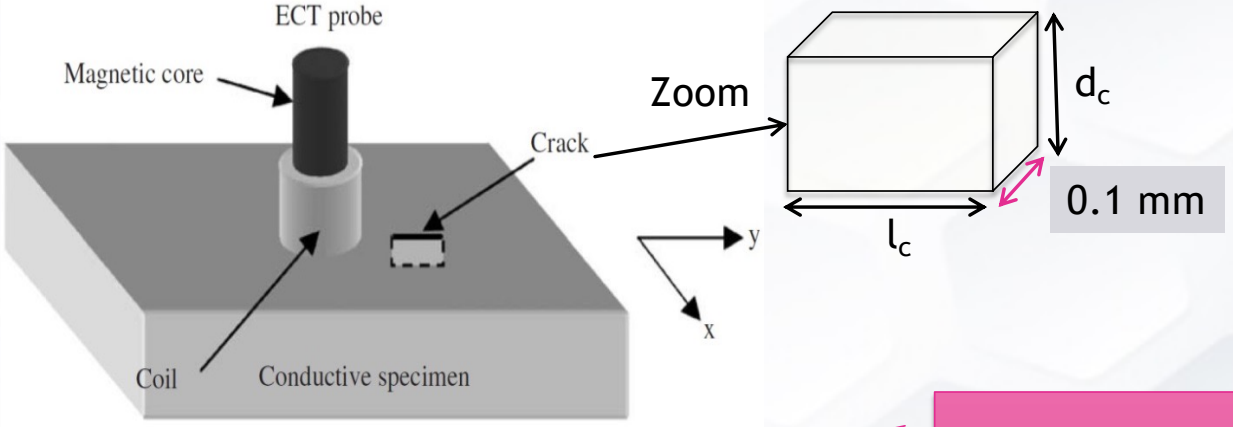




Classification in PCA framework

2. Applications

Application to Non-Destructive Evaluation with Eddy Current



Electric discharge machining thin cracks into a nickel-base plate

Crack dimensions :

Small Cracks

Area (mm^2)	0.01	0.02	0.04	0.06	0.08	0.12	0.16	0.24
l_c , d_c (mm)	0.1, 0.1	0.1 , 0.2 0.2 , 0.1	0.1 , 0.4 0.4 , 0.1 0.2 , 0.2	0.6 , 0.1	0.2 , 0.4 0.4 , 0.2	0.6 , 0.2	0.4 , 0.4	0.6 , 0.4

2. Applications

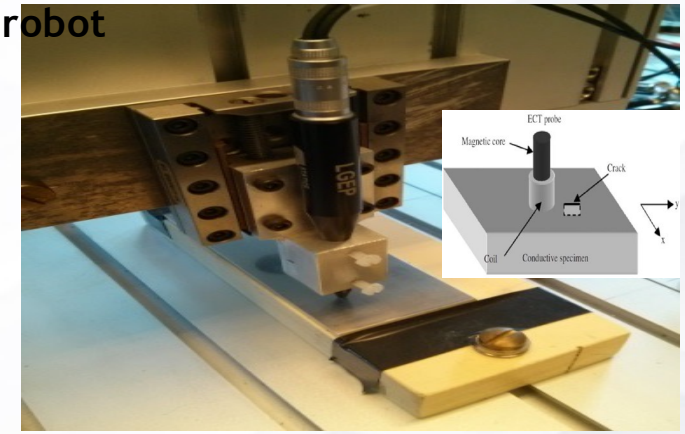
Application to Non-Destructive Evaluation with Eddy Current

Experimental test bed [1]

Agilent 4294A Precision Impedance Analyser

f_{exc} ={0.1, 1, 1.5, 3, 4, 5, 6} MHz

A three-axis computer-controlled robot



(Δx, Δy)= (0.1;0.1) mm

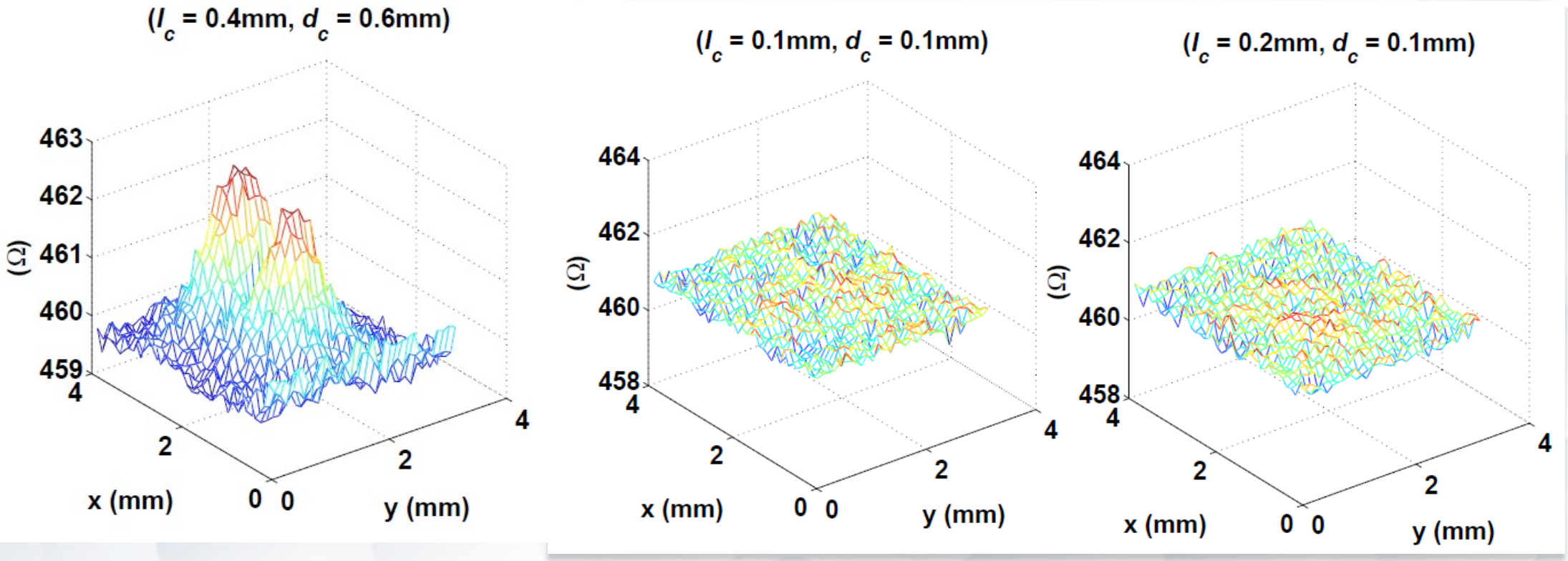
$$Z_d = R_d + j2\pi f_{exc} L_d$$

The Imaginary part is the most affected and will be under study

[1] Y. L. Bihan, J. Pavo, and C. Marchand, "Characterization of small cracks in eddy current testing", *The European Physical Journal Applied Physics*, vol. 43, no. 2, pp. 231–237, 2008.

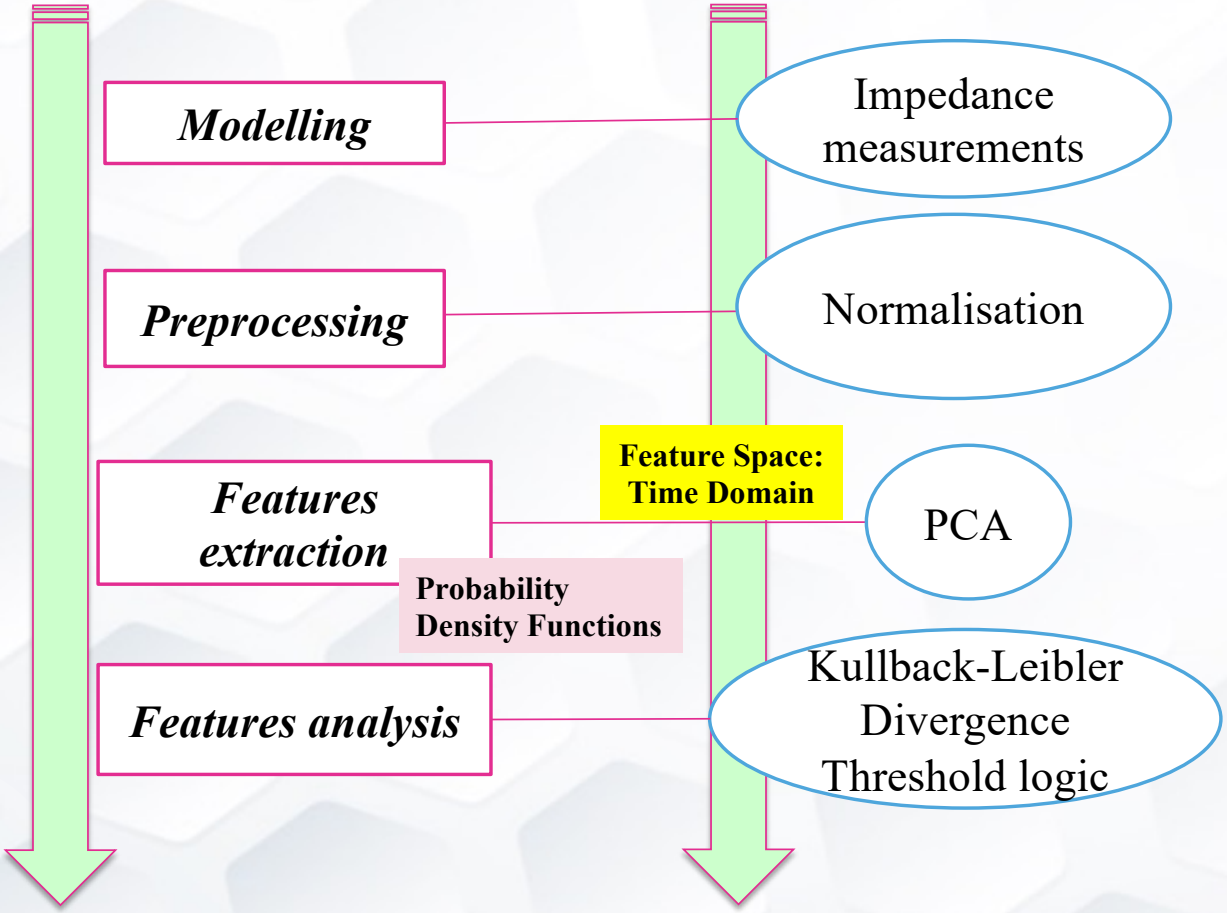
2. Applications

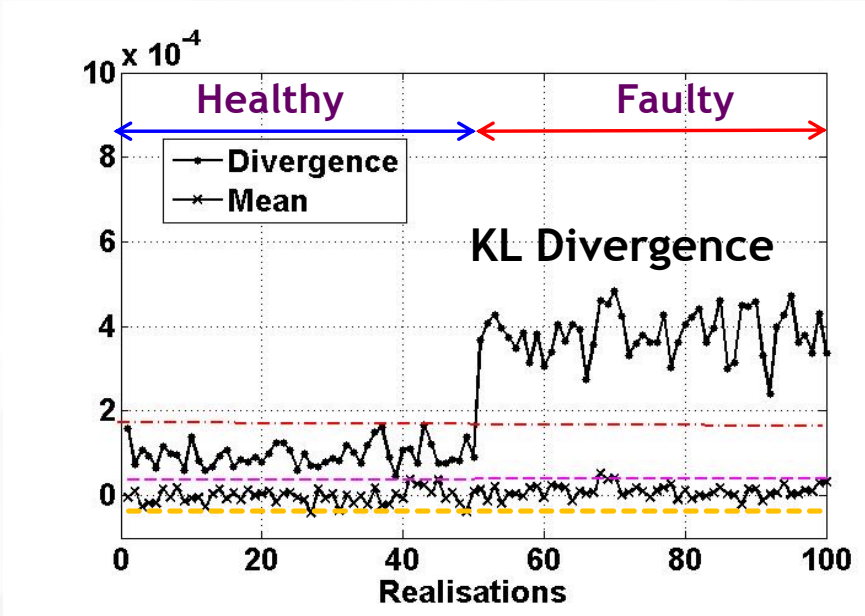
Application to Non-Destructive Evaluation with Eddy Current



2. Applications

Application to Non-Destructive Evaluation with Eddy Current: Data-driven approach



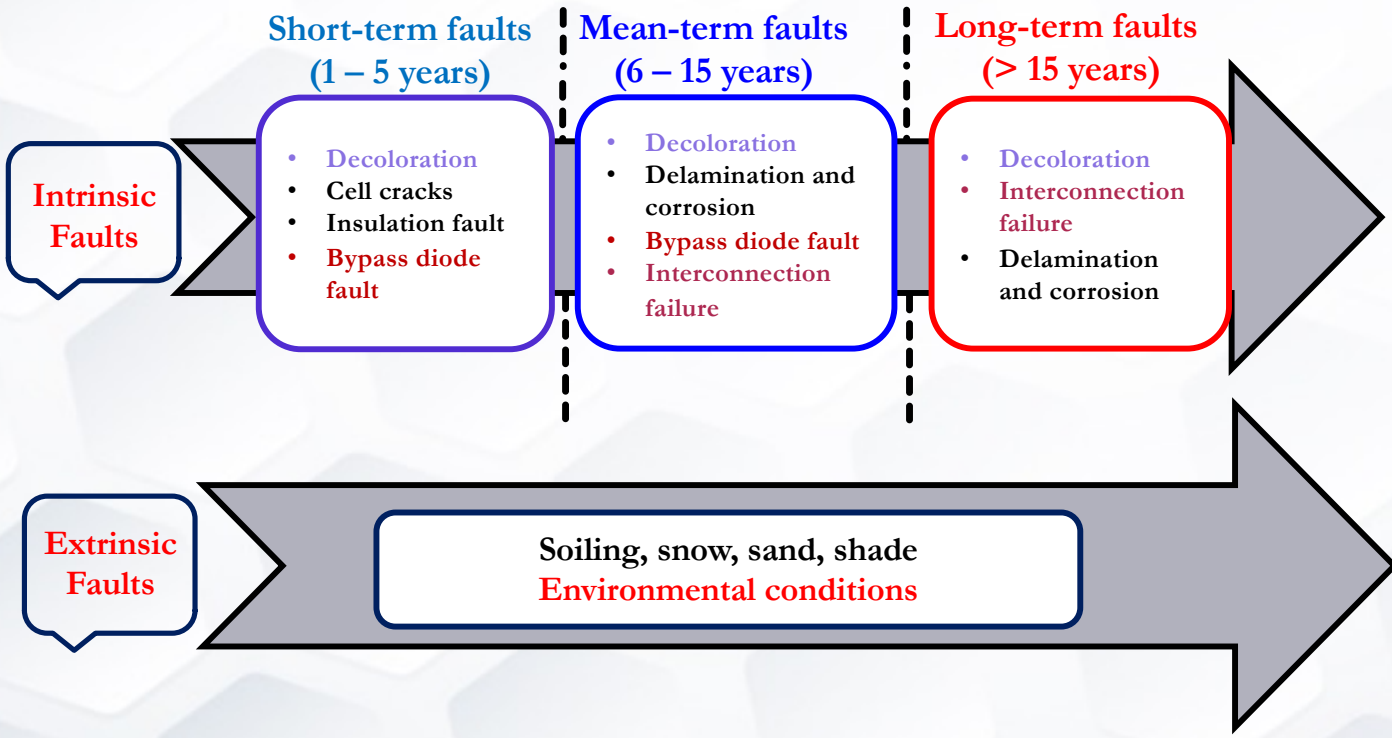


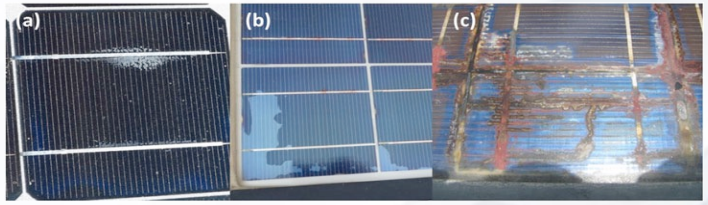
Sensitivity = 5.31 P_{MD} = 0

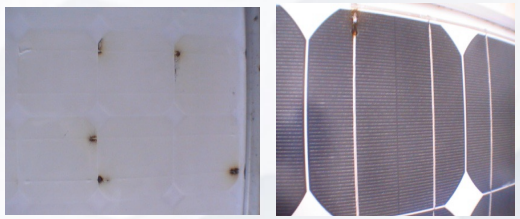
2. Applications

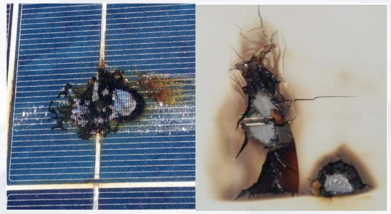
Application to PV module fault diagnosis

Timelines of the main defects of PV cells and modules







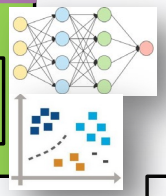


2. Applications

Application to PV module fault diagnosis

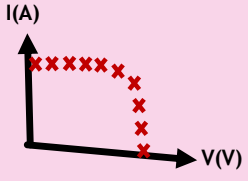
Physics-based approaches

- Environmental data
- PV module, array, plant
- Analytical model
- Measured features
- Estimated features

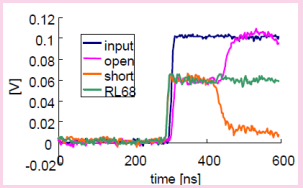


Data-driven

Electrical measurements

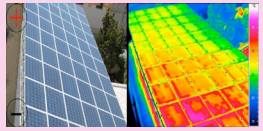


I-V curve

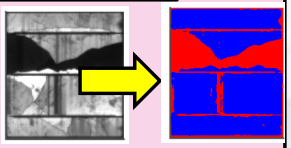


Reflectograms

Images



IRT

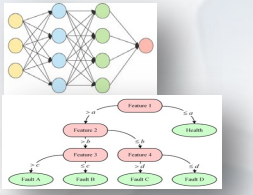


EL [3]

Features Analysis

Machine Learning Techniques, Control theory techniques, Decision theory, Pattern analysis, …

Preprocessing Features extraction



Machine Learning Techniques, Control theory techniques, Decision theory, Pattern analysis, …

[3] S. Spataru. Characterization and Diagnostics for Photovoltaic Modules and Arrays, Department of Energy Technology, Aalborg University, 2015. 141 p. Research output: Book/Report › Ph.D. thesis

2. Application to PV modules

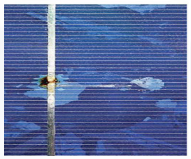
- **Fault diagnosis using I-V curves**

Modeling | Pre-process | Feature extraction | Feature analysis

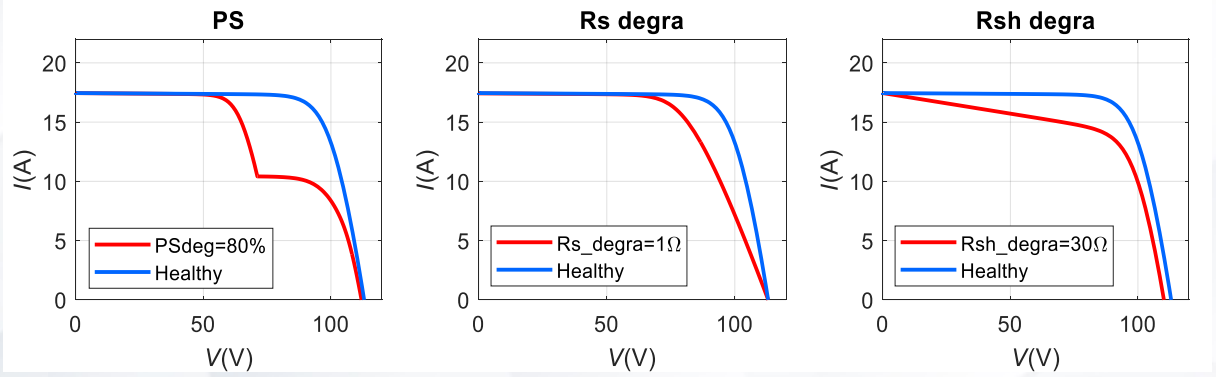
Fault effects on the I-V curves

Partial Shading

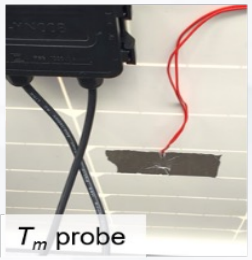
Degradation of the contacts



Delamination



(Reference cell RG100)



(Pt100)

(FTV200)

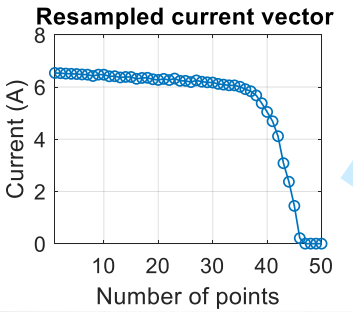
2. Application to PV modules

Feature extraction from I-V curve

Extract key parameters (G, T_m, V_{MPP}, I_{MPP}, V_{OC}, I_{SC}, R_s and R_{sh}, called ***8paras***)

Corrected I-V curves

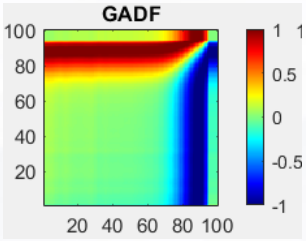
Resampled current vector (50 points)



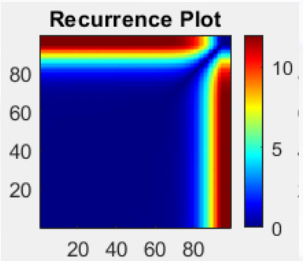
1 **Use directly as input** (called **direct I-V**)

2 **Transform** to matrix

2.1 **GADF**



2.2 **RP**



Dimension reduction

Principal component analysis (PCA)

Features for analysis

Vector transformed to matrix by:

- **GADF:** Gramian Angular Difference Field [11]
- **RP:** Recurrence Plot [12]

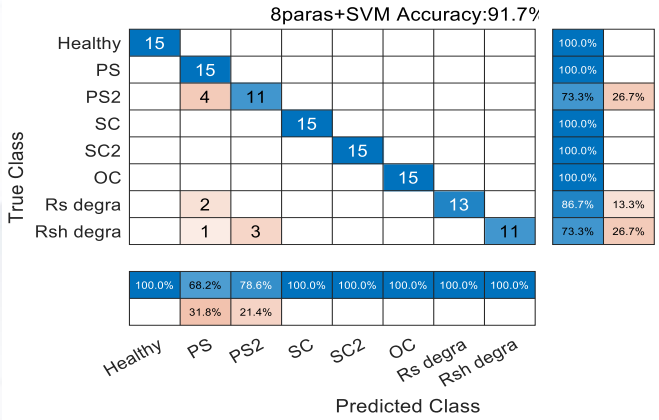
[11] Wang Zhiguang, IJCAI-2015, 2015

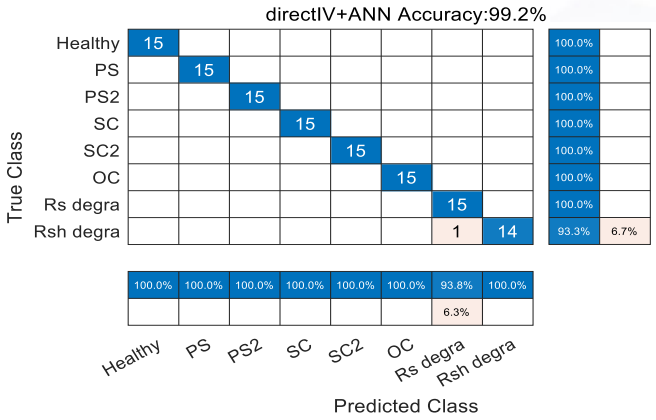
[12] Marwan N, Physics reports, 2007, 438(5-6): 237-329

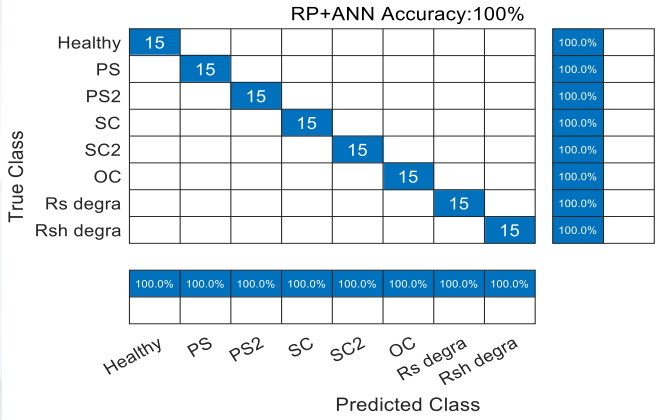
2. Application to PV modules

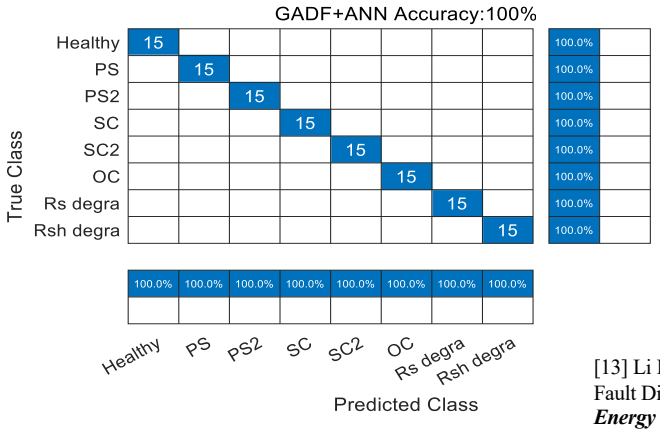
- Test results using field-measured data [13]

Modeling | Pre-process | Feature extraction | **Feature analysis**







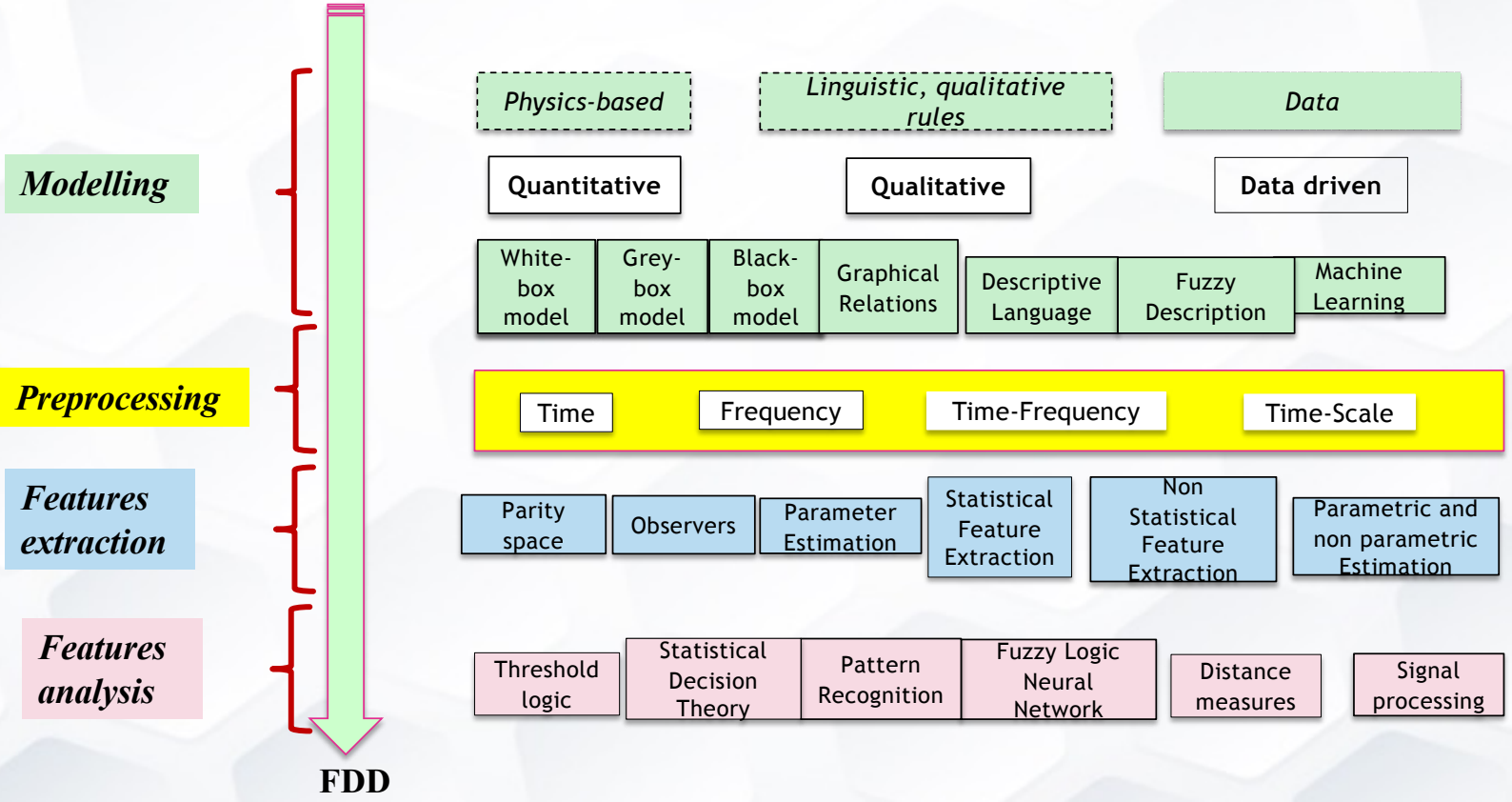


ANN	**Artificial Neural Network**
SVM	**Support Vector Machine**
NBC	**Naive Bayes Classifier**
DT	**Decision Tree**
RF	**Random Forest**
kNN	**k-Nearest Neighbors**

[13] Li B., Delpha C., Migan A., Diallo D.
Fault Diagnosis of Photovoltaic Panels Using Full I-V Characteristics and Machine Learning Techniques.
Energy Conversion and Management 248 (2021). doi: 10.1016/j.enconman.2021.114785

3. Conclusion

In summary: a 4-step FDD methodology



[1] Delpha, C.; Diallo, D. Kullback–Leibler divergence for incipient fault diagnosis. In Signal Processing for Fault Detection and Diagnosis in Electric Machines and Systems; Benbouzid, M., Ed.; IET, The Institution of Engineering and Technology, 2020

Thank you!

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