



Robust and reliable general management tool for performance and durability improvement of fuel cell stationary units

Data-driven and model-based diagnosis of PEMFC & SOFC

Balance of Plants

ALFONSO PANDOLFI*

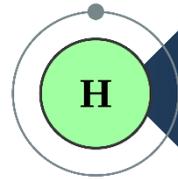
RUBY WORKSHOP, LUCERNE (CH)

5 JULY 2022

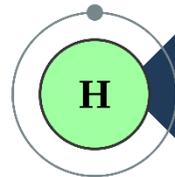
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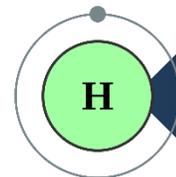
INTRODUCTION



MODEL-BASED METHODOLOGY AND RESULTS



DATA-DRIVEN METHODOLOGY AND RESULTS



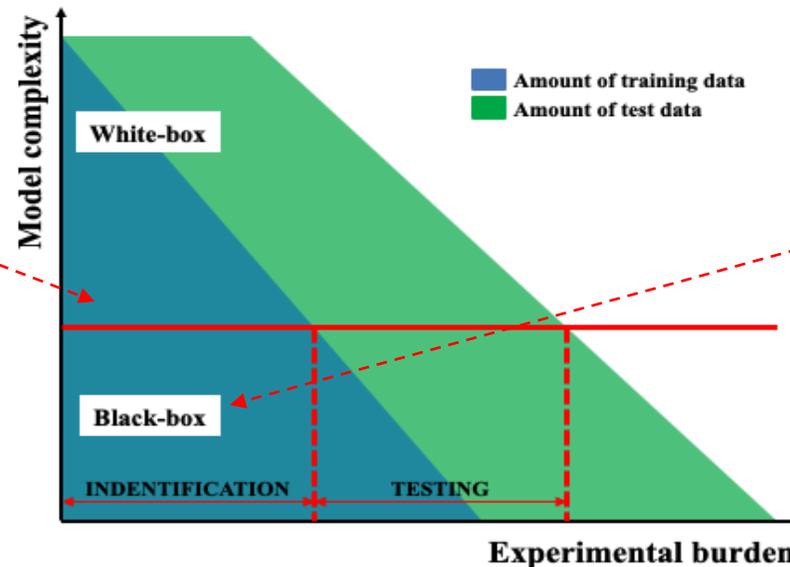
CONCLUSIONS

Introduction

Within the objectives of the RUBY project regarding the procedures for **diagnosis and prognosis** of fuel cell systems, based on the data provided by Sunfire, **two different methodologies** were constructed in order to explore its different potentials.

A **model-based methodology** that starts from **gray box models** of the system components.

- It requires some degree of physical knowledge of the system.
- May be computationally heavier.
- It may not be generalizable.



A **data-driven methodology**

- Generally faster.
- Requires a high amount of data.
- Typically, more generalizable.

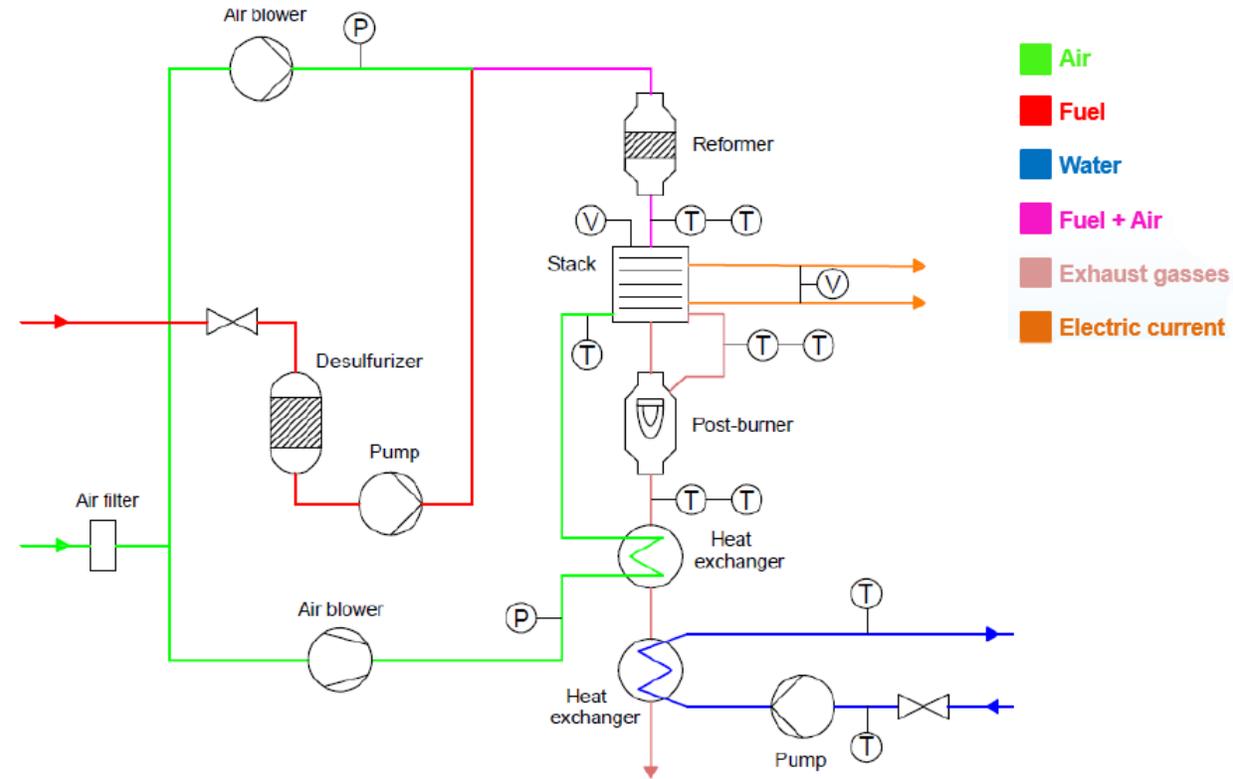
It is intended to provide solutions that have a high degree of **generalizability** and therefore are not too systems-specific, as well as being **cost-effective**. The goal is to have a tool that can be **easily implemented** on board and used in **industrial contexts**.

System description

The system studied is a **micro-CHP plant**, based on solid oxide fuel cell technology, developed by project partner Sunfire. Specifically, the system analyzed is the **Sunfire-Home 750**, which is a micro-CHP system for residential use.

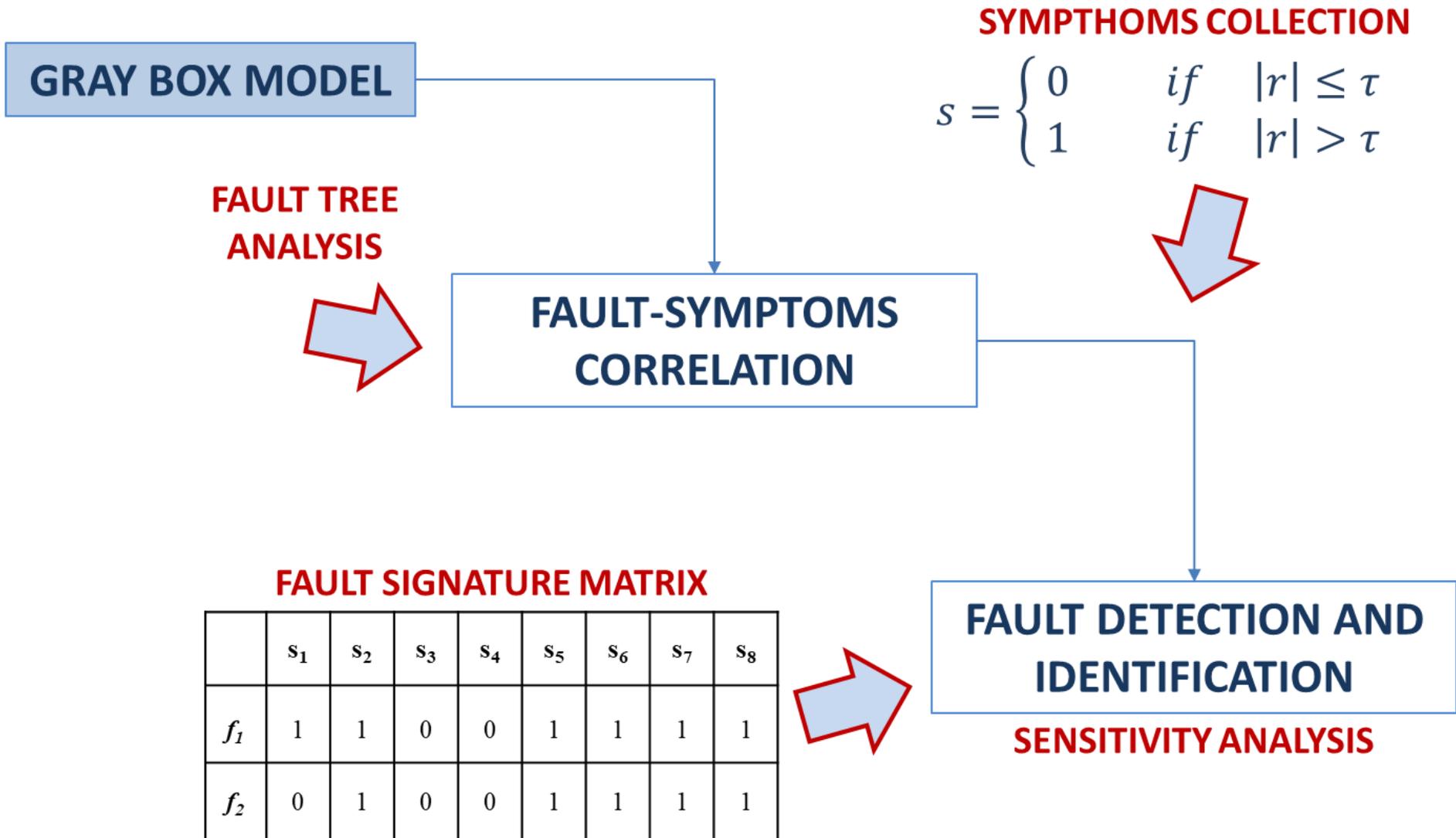


SUNFIRE HOME - 750



Technology	SOFC
# of cells	57
Single cell area	127 cm ²
Nominal voltage	45 Vdc
Nominal current	19 A

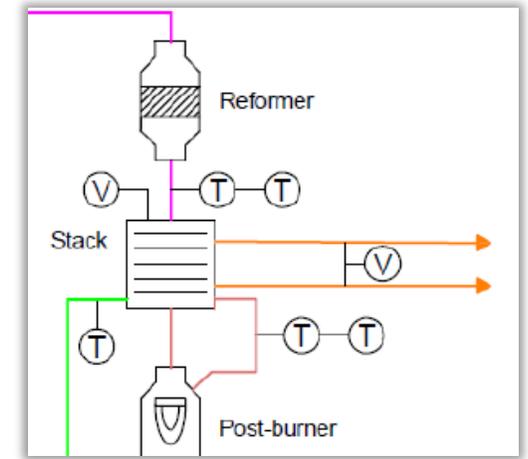
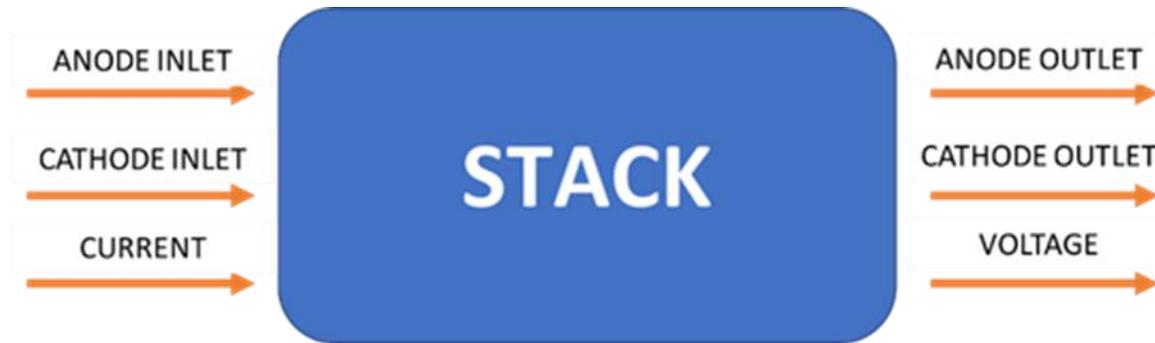
Model-Based methodology



Stack temperature model

To obtain the model, the following assumptions were made:

- The model is with lumped parameters.
- The operating temperature of the cell is assumed to be that of the flow leaving the stack at the cathode side.
- The outlet temperatures at the anode and cathode are the same.



$$k_s \cdot \frac{dT}{dt} = \frac{\dot{m}_{H_2}^{st}}{FU} \cdot c_{PH_2}^{IN} \cdot T_{an}^{IN} + \frac{\dot{m}_{O_2}^{st}}{x_{O_2} \cdot AU} \cdot c_{Pair}^{IN} \cdot T_{ca}^{IN} - \left\{ \dot{m}_{H_2O}^{st} \cdot c_{PH_2O}^{OUT} + \dot{m}_{H_2}^{st} \cdot \left(\frac{1}{FU} - 1 \right) \cdot c_{PH_2}^{OUT} + \dot{m}_{O_2}^{st} \cdot \left[\left(\frac{1}{AU} - 1 \right) \cdot c_{PO_2}^{OUT} + \left(\frac{1 - x_{O_2}}{x_{O_2} \cdot AU} \right) \cdot c_{PN_2}^{OUT} \right] \right\} \cdot T + \dot{m}_{H_2}^{st} \cdot HHV - \left\{ \left[1,274 - 2,765 \cdot 10^{-4} \cdot T + \frac{RT}{2F} \cdot (0,5 \cdot \ln(p_{amb} + \bar{p}_2) + A_{medio}) \right] - I \cdot \frac{ASR_{medio}}{A_{cella}} \right\} \cdot N_c \cdot I$$

Voltage model (V_{stack})

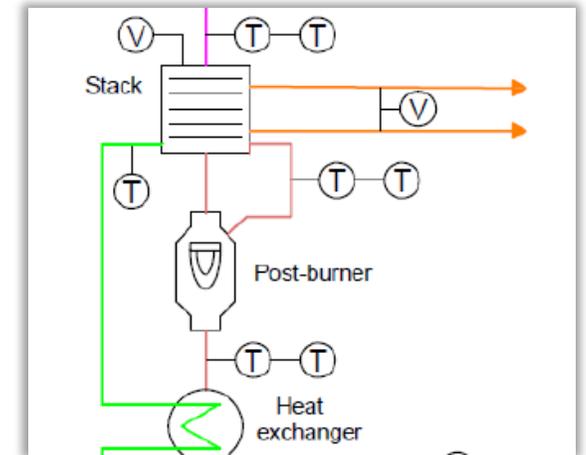
Post-Burner temperature model

This component was modeled using the following assumptions:

- Only hydrogen, from the anode, and a mixture of oxygen and nitrogen from the cathode are present at the inlet.
- The enthalpy values of the exhaust gases from the anode and the cathode are equal.
- In the post-burner, complete combustion of the residual hydrogen takes place.



$$T_{PB}^{out} = T_{STACK} + \frac{\dot{m}_{an} H_i \eta_b}{\dot{m}_{out} c_{p,air}}$$

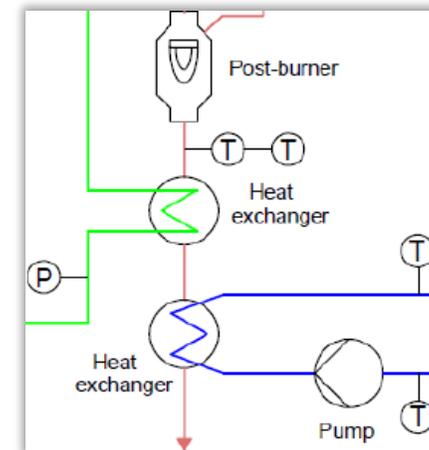
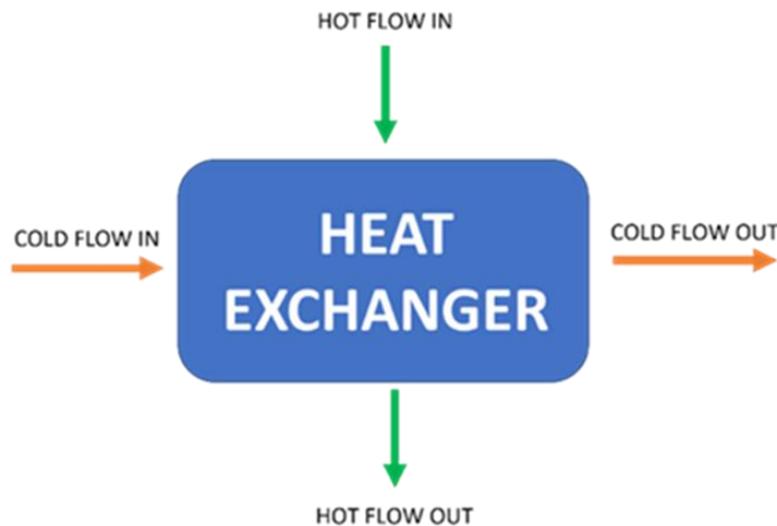


Heat exchanger temperature model

The assumptions made for the purpose of building the heat exchanger model were:

- Steady-state conditions.
- The specific heats of both fluids are constant between inlet and outlet and are considered the same and equal to the specific heat at constant air pressure.

$$\begin{cases} T_h^{OUT} \cdot \left(c_{p,air} \cdot \dot{m}_h + \frac{hA}{2} \right) - \frac{hA}{2} \cdot T_c^{OUT} = T_h^{IN} \cdot \left(c_{p,air} \cdot \dot{m}_h - \frac{hA}{2} \right) + \frac{hA}{2} \cdot T_c^{IN} \\ -T_h^{OUT} \cdot \frac{hA}{2} + T_c^{OUT} \cdot \left(c_{p,air} \cdot \dot{m}_c + \frac{hA}{2} \right) = T_c^{IN} \cdot \left(c_{p,air} \cdot \dot{m}_c - \frac{hA}{2} \right) + \frac{hA}{2} \cdot T_h^{IN} \end{cases}$$



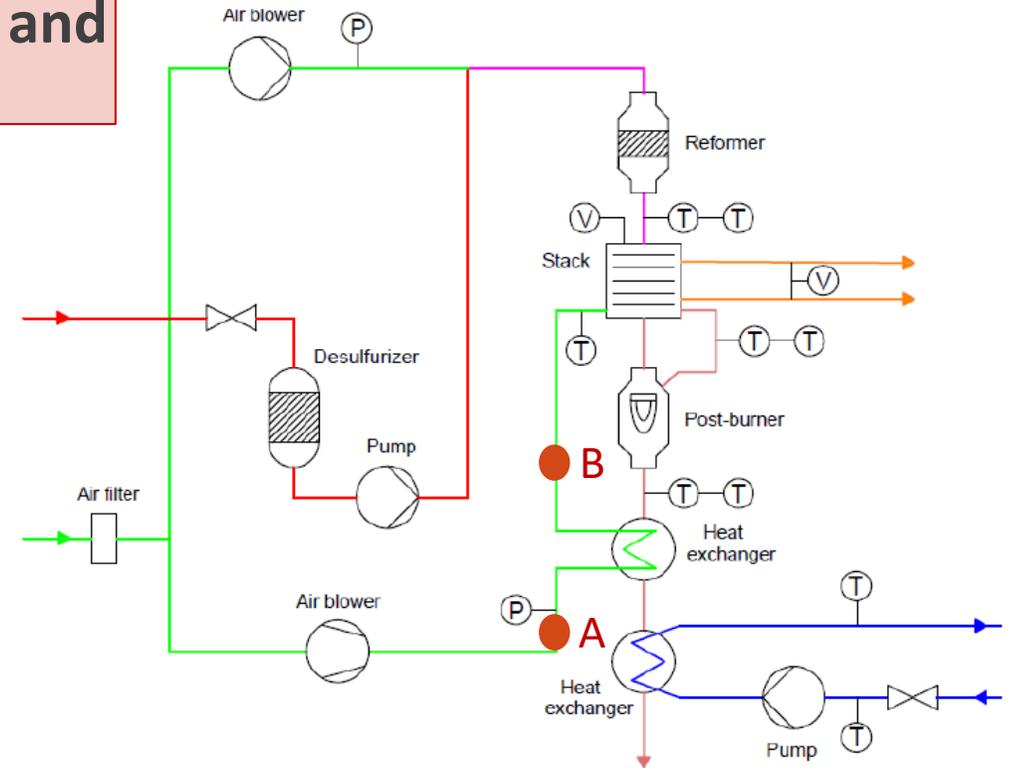
Failure introduction

The fault analyzed on the proposed model consists of a **leakage of inlet air** at the cathode evaluated at two different positions of the system: **upstream and downstream of the heat exchanger**.

Mathematically, this fault, is studied by introducing a **loss coefficient ξ** . The expected effect is a **reduction in air density and pressure** caused by a reduction in flow rate:

$$\dot{m}_{air} = \rho_{air} A v_{air}$$

$$\underbrace{p_{air}^F}_{\text{Faulty}} = RT \rho_{air}^N \cdot (1 - \xi) = \underbrace{p_{air}^N}_{\text{Normal}} \cdot (1 - \xi)$$

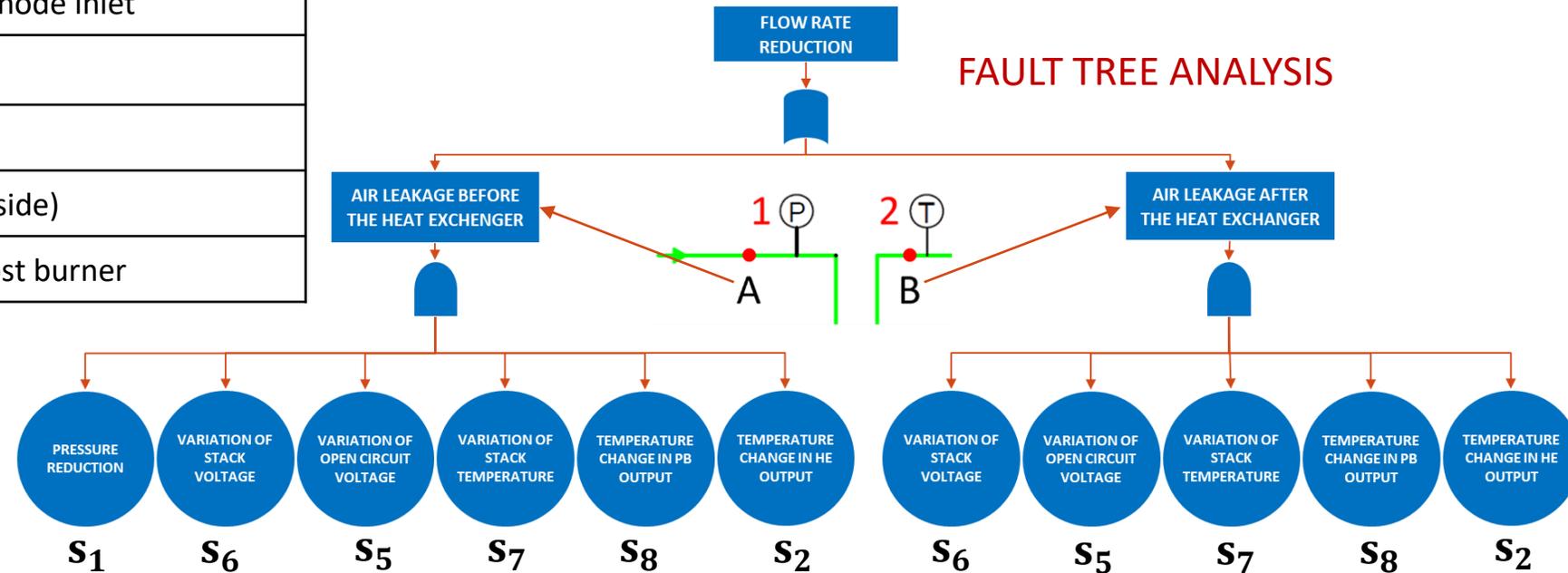


Fault Detection and Isolation

VARIABLES REPRESENTING SYMPTOMS

	MONITORED VARIABLE
S_1	Inlet air pressure of the heat exchanger
S_2	Cathode inlet air temperature
S_3	Inlet air pressure to the reformer
S_4	Temperature of hydrogen at the anode inlet
S_5	Single cell open circuit voltage
S_6	Stack voltage
S_7	Outlet gas temperature (cathode side)
S_8	Temperature of gas leaving the post burner

Qualitative analysis aimed at constructing a **qualitative FSM** and then on the recognition of the **symptoms expected** in relation to the simulated faults.



Qualitative results

STACK:

A reduction in flow rate due to a loss of air will cause observable changes in **stack temperature** (s_7) since air, in addition to providing oxygen for the reaction, also has a cooling function. In addition, the **stack voltage** (s_6) and consequently also the open **circuit voltage** (s_5) depend on temperature.

POST BURNER:

If the stack temperature increases, as the flow rate decreases, there is an increase in the **temperature of the gases leaving the Post Burner** (s_8). If the temperature of the stack decreases, it is not possible to determine how the temperature of the gases leaving the Post Burner varies because changes in stack temperature and flow rate leaving the stack have opposite effects on the temperature leaving the Post Burner.

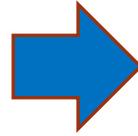
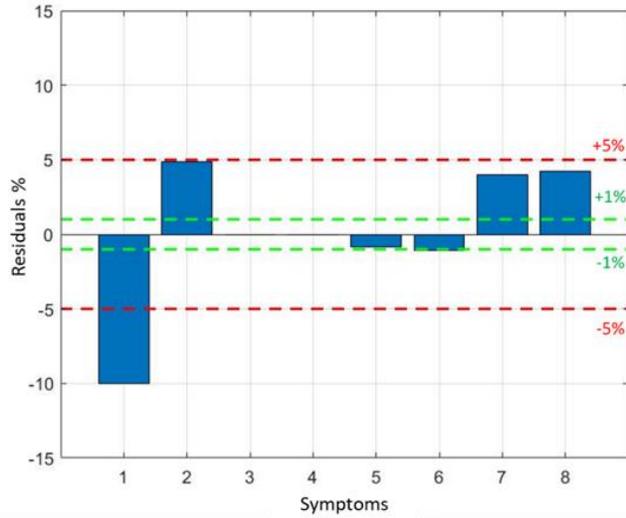
HEAT EXCHANGER:

A loss of air causes a change in the **temperatures of the gases leaving the exchanger** (s_2), both in the case of failure at point A and in the case of failure at point B. In case A, the fault will also be detected by the **pressure sensor** (s_1).

	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8
f_A	1	1	0	0	1	1	1	1
f_B	0	1	0	0	1	1	1	1

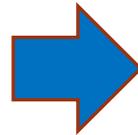
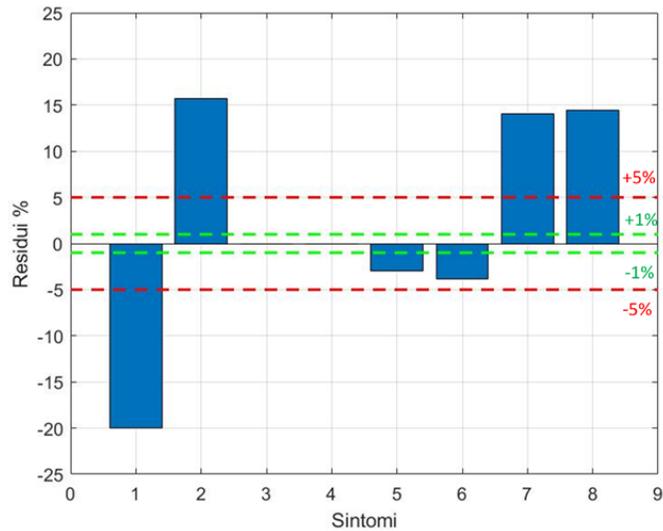
Quantitative results f_A

FAULT MAGNITUDE 10%



Fault f_A	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8
FSM	1	1	0	0	1	1	1	1
$\tau = 1\%$	1	1	0	0	0	1	1	1
$\tau = 5\%$	1	0	0	0	0	0	0	0

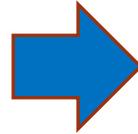
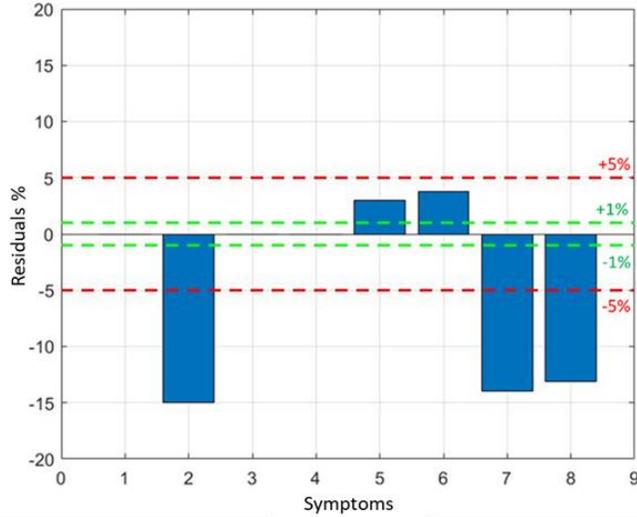
FAULT MAGNITUDE 20%



Fault f_A	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8
FSM	1	1	0	0	1	1	1	1
$\tau = 1\%$	1	1	0	0	1	1	1	1
$\tau = 5\%$	1	1	0	0	0	0	1	1

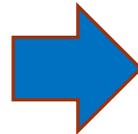
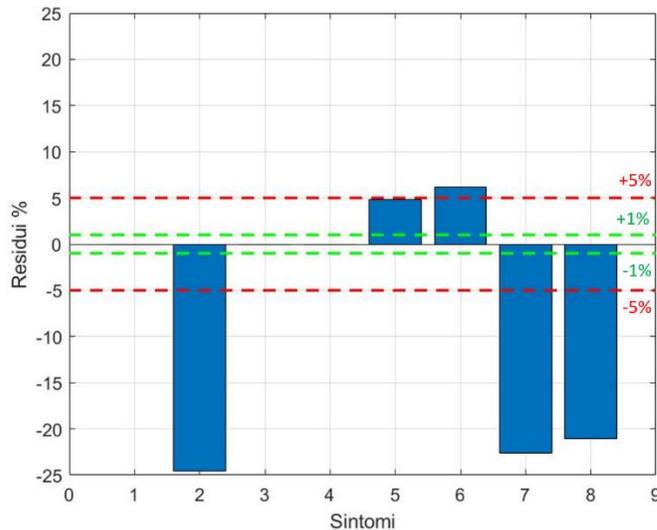
Quantitative results f_B

FAULT MAGNITUDE 10%



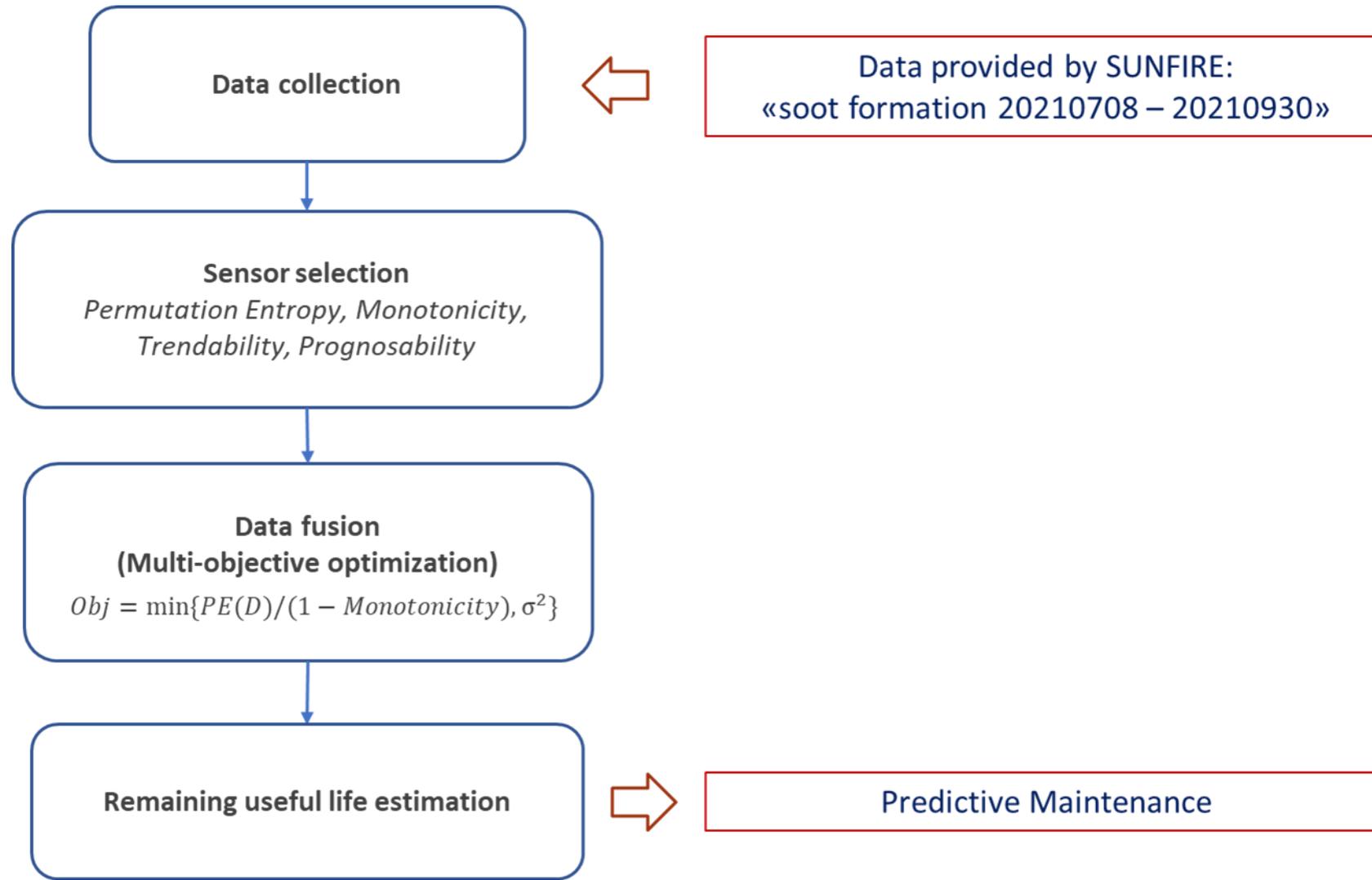
Fault f_B	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8
FSM	0	1	0	0	1	1	1	1
$\tau = 1\%$	0	1	0	0	1	1	1	1
$\tau = 5\%$	0	1	0	0	0	0	1	1

FAULT MAGNITUDE 20%



Fault f_B	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8
FSM	0	1	0	0	1	1	1	1
$\tau = 1\%$	0	1	0	0	1	1	1	1
$\tau = 5\%$	0	1	0	0	0	1	1	1

Data-driven methodology



Sensor selection functions

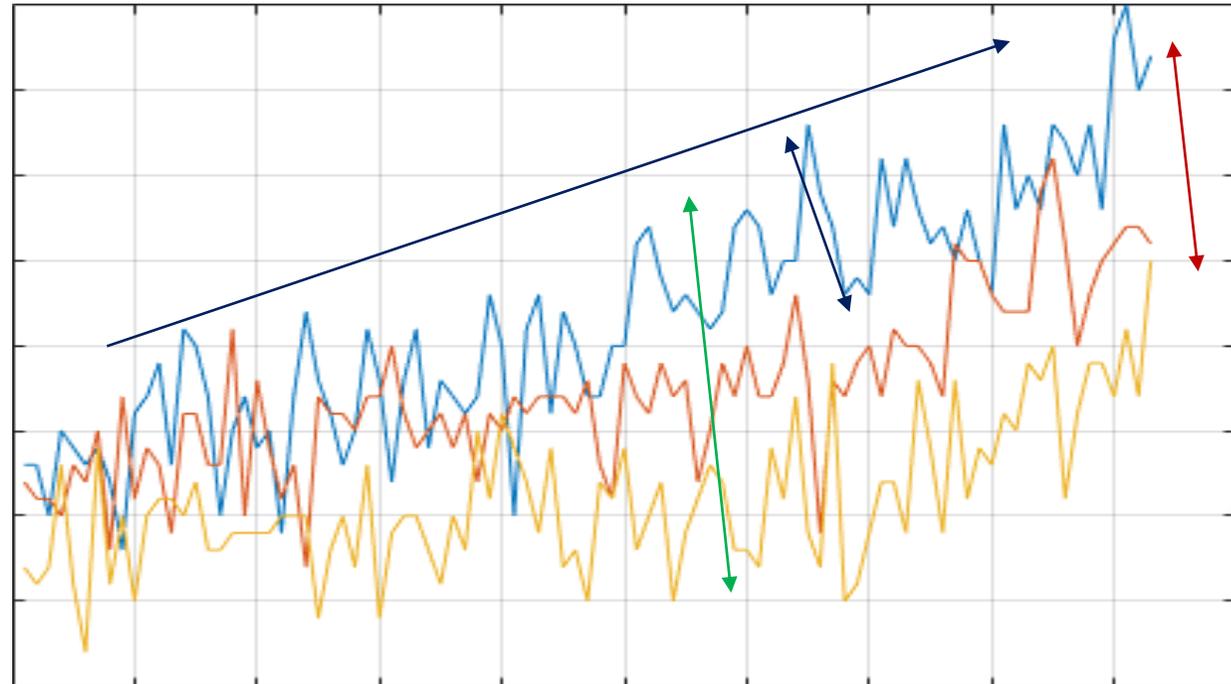
A variety of suitable indicators can be used for the sensor selection activity:

Permutation Entropy

Monotonicity

Trendability

Prognosability



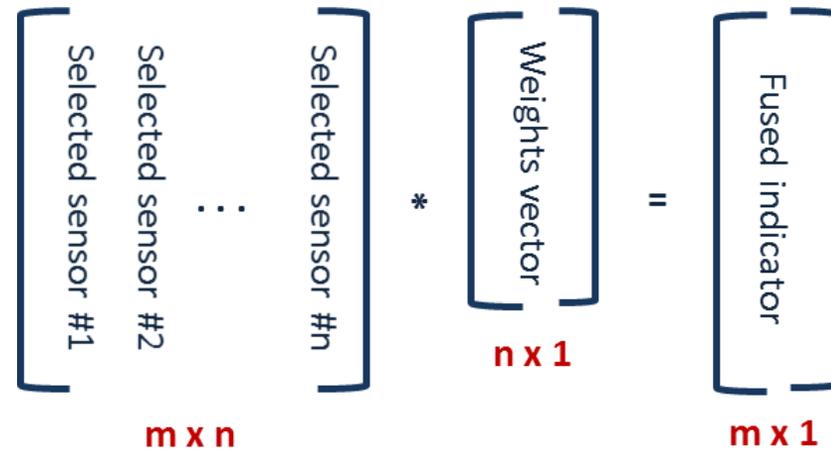
Each of these indicators measures **different characteristics**.

Data Fusion

The sensors selected based on the sensor selection algorithms can be used in **data fusion**, which allows to obtain a health indicator with more **evident trends**, allows us to observe **multiple sensors** simultaneously.

$m = \#$ of experiments

$n = \#$ of sensors



The objective of data fusion is to calculate a **vector of weights** which when multiplied by the **matrix containing the chosen sensors** allows us to obtain a fused indicator.

Multi-objective optimization problem

The vector of weights is calculated from the matrix of selected sensors with the aim of minimizing two objective functions: **variance** and **permutation entropy/1-Monotonicity**.

$$Obj = \{PE(D)/(1 - Monotonicity), \sigma^2\} \quad \min_w Obj$$

The variance is calculated according to the following formula:

$$\sigma^2 = \frac{(Y_W - \frac{1_M Y_W}{M})^T (Y_W - \frac{1_M Y_W}{M})}{M - 1}$$

Where Y is the matrix of selected sensors, but it only contains a **limited number** of the latest observations. M is the number of units.

This allows the algorithm to update itself and follow new trends in the data.

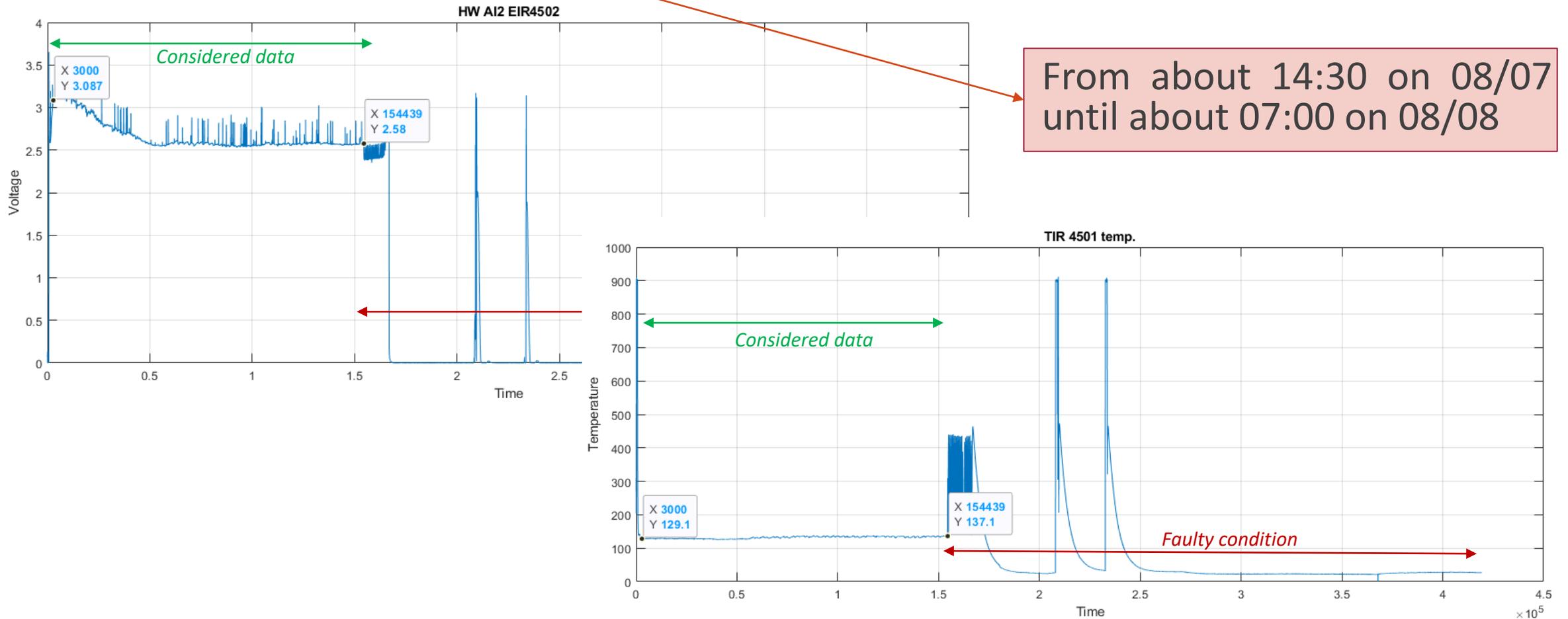
Source: Zhang, H., Jiang, J., Mo, Z., and Miao, Q., A Remaining Useful Life Prediction Framework for Multi-sensor System. *2019 IEEE 19th International Conference on Software Quality, Reliability and Security Companion (QRS-C)*, pp. 255-259, Bulgaria, July 2019.

Sunfire-Home 750 sensors

CONSIDERED MEASUREMENTS			
2	HW AI0 MP UB	43	TIR6001 Temp.
3	HW AI1 EIR4501	44	TIR6002 Temp.
4	HW AI2 EIR4502	45	TIR6101 Temp.
5	HW AI3	46	TIR6102 Temp.
30	P1 PIR1201 Druck	47	TIR6103 Temp.
31	P2 PIR1401 Druck	48	TIR6104 Temp.
32	P3 PIR4501 Druck	49	HW AO1 MV3301
33	TIR3401a Temp.	50	HW AO2 MV6001
34	TIR3401b Temp.	51	HW AO3 GB1201
35	TIR3201a Temp.	52	HW AO4 GB2101
36	TIR3201b Temp.	53	HW AO5 GB1201
37	TIR4502a Temp.	54	HW AO6
38	TIR4502b Temp.	55	GB1401 PWM
39	TIR4501 Temp.	56	GB6001 PWM
40	TIR3301a Temp.	57	GB6001 Status
41	TIR3301b Temp.	58	FIR6001 Fluss
42	PCB Temp.		

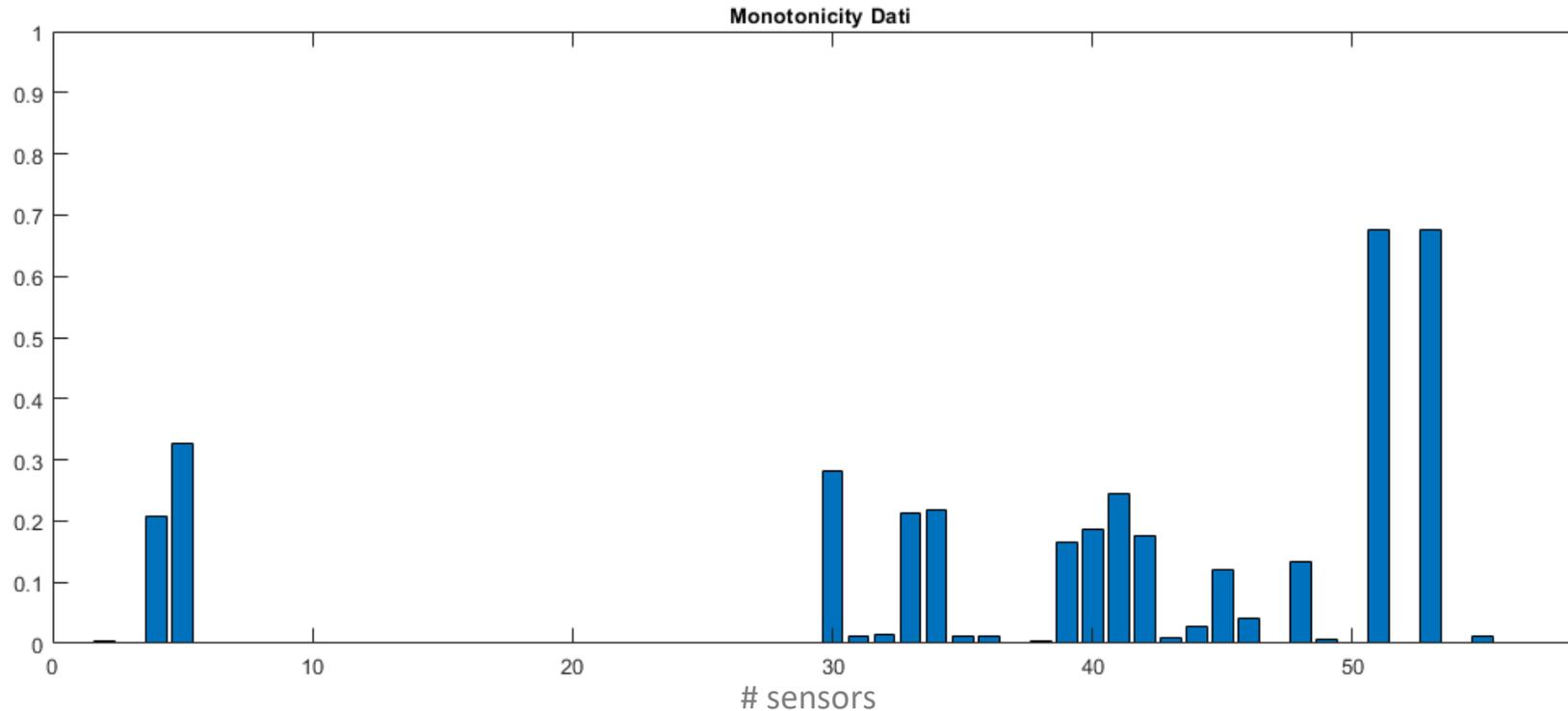
Dataset description

The analysis focused on the last data set before failure ("soot formation 20210708 - 20210930"). From these data, only values **from 3000 to 154439** were considered.



Sensor selection 1/2

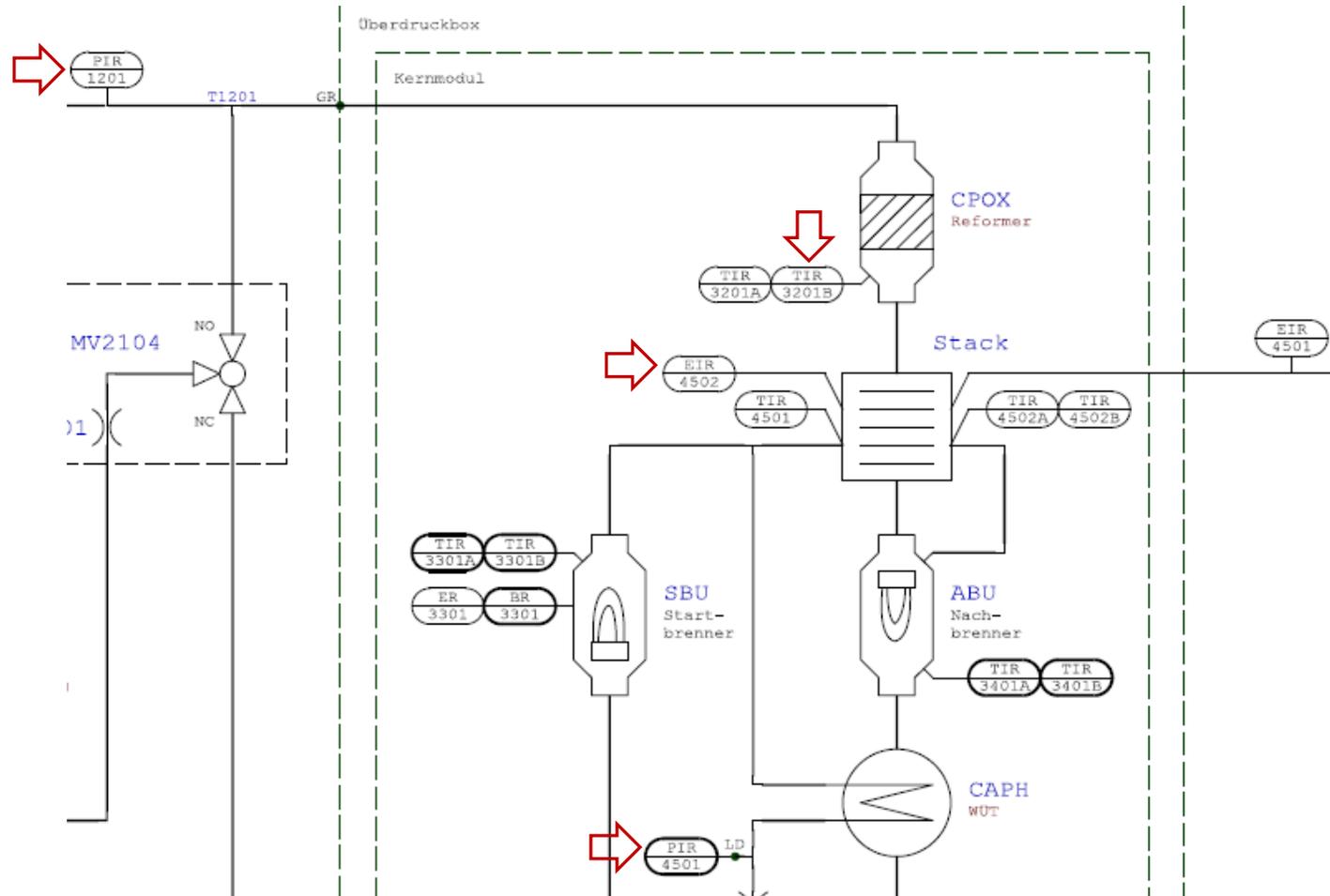
Using the “**Monotonicity**” function, the presence of monotonic trends in the data was assessed.



The sensors with the **highest Monotonicity** value are potentially the ones of greatest interest.

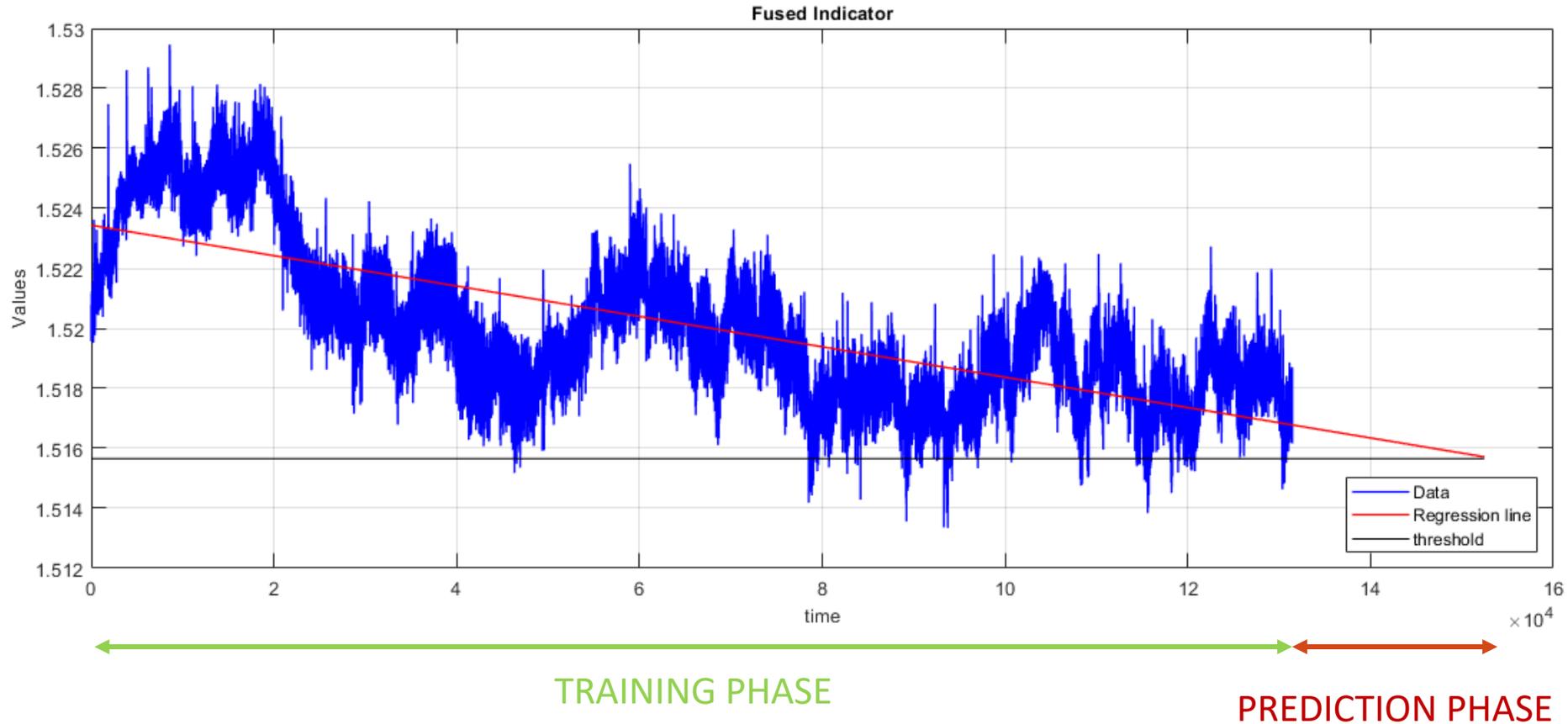
Sensor selection 2/2

The sensors most **affected by stack operation** and with the **highest monotonicity values** were selected (#30, #4, #32, #36).



Fused health indicator

The **fused health indicator** created has the trend shown in the graph.



The last 20000 values of the fused indicator were eliminated to evaluate the **prediction capability**.

Conclusions

- Two different methodologies were used on that system to carry out diagnostic and prognostic activities: a **model-based methodology** and a **data-driven methodology**.
- The model-based methodology has proven effective, especially for higher values of fault magnitude, in diagnosis and **fault identification**. In fact, the **fault signature matrix** turn out to be an effective tool in correlating symptom sets exhibited by a specific system to specific degradation mechanisms.
- The data-driven methodology, on the other hand, in addition to being usable for diagnostic purposes, has been shown to **predict** with some accuracy the **remaining useful life** of the system through a regression analysis performed on the **fused health indicator**.
- The proposed techniques are still being studied and refined. In fact, it is intended to expand the model-based analysis to other **different types of faults at different locations** in the plant. Regarding the data-driven methodology, the aim is to make the fused health indicator **more stable** by avoiding spikes that could lead to premature end-of-life assessments.
- Black-box models of **recurrent neural networks** (RNNs) are also under development with the goal of having models capable of reproducing system behavior and making predictions with high accuracy, even in the transient phase.

THANKS FOR YOUR ATTENTION



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