Prognostics aware control design for extended remaining useful life: Application to Liquid Propellant Reusable Rocket Engine

HAC Meeting 22th November 2023

Julien Thuillier, Mayank Shekhar Jha,
Sebastien Le Martelot, and Didier Theilliol

Project supported by CNES 2021-2023 supervised by Marco Galeotta (until November 2022) and by Sebastien Le Martelot

DISSEMINATION

12th IFAC Symposium on
Fault Detection, Supervision
and Safety for Technical Processes

IFAC
INTERNATIONAL FEDERATION
OF AUTOMATIC CONTROL

safeprocess 2024

4-7 June 2024
Ferrara, ITALY

NEW

Important dates

- Invited session proposals: November 15, 2023
- Submission of contributions: November 28, 2023
- Tutorial session proposals: January 8, 2024
- Roundtable proposals: January 8, 2024
- Notification of acceptance: March 1, 2024
- Final paper submission: April 1, 2024
- Early registration: April 1, 2024

OUTLINES

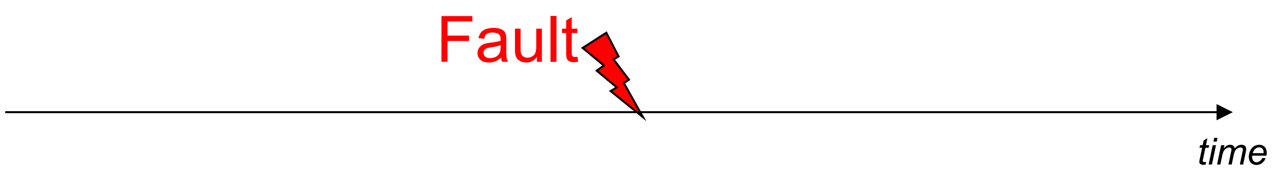
- **Introduction / Context**
- **Problem Statement**
- **Our Solution**
- **Illustrative Examples**
- **Conclusions / Perspectives**

OUTLINES

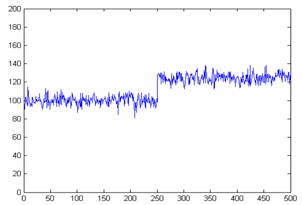
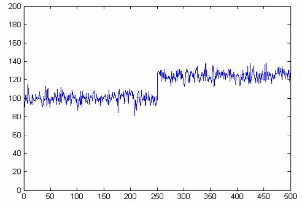
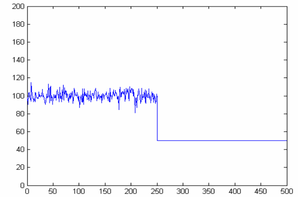
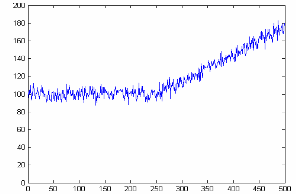
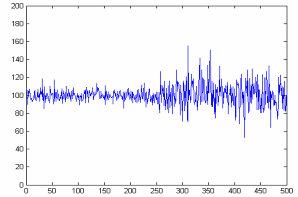
- **Introduction / Context**
- **Problem Statement**
- **Our Solution**
- **Illustrative Examples**
- **Conclusions / Perspectives**

Context

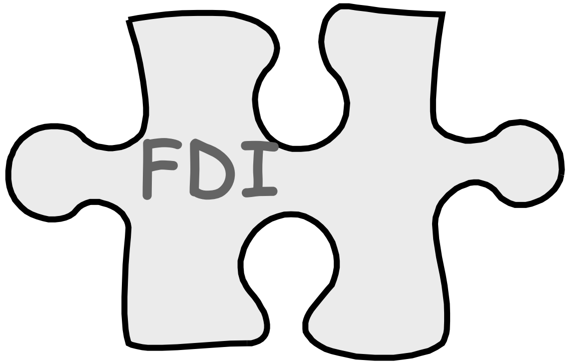
Context



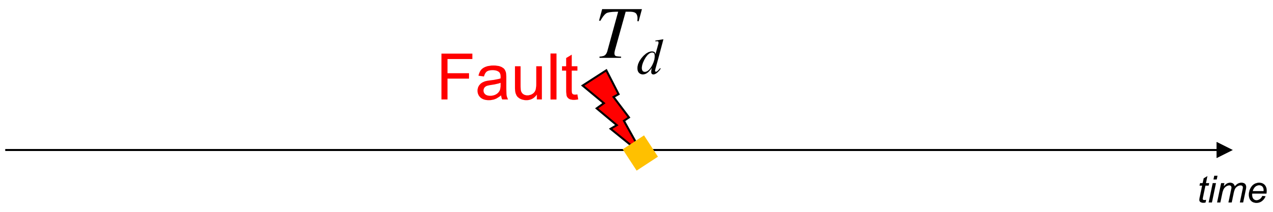
Context

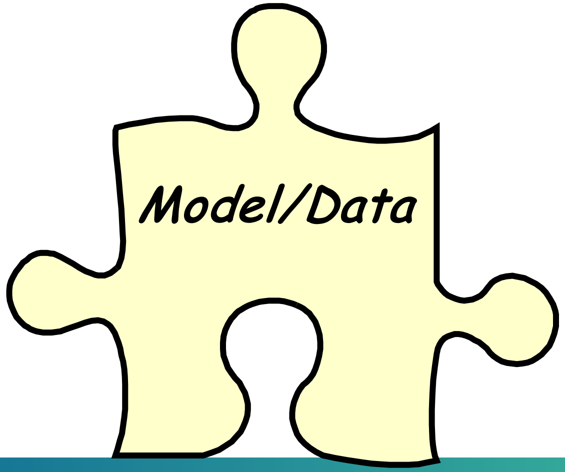
Fault	Equation	Cause	Effect	Graph
Bias	$Y_i(t)=Y_i^*(t)+\varepsilon_i(t)+\alpha\Gamma_\theta$ $\alpha = constant\ value$ $\Gamma_\theta=\begin{cases}0, t<\theta\\ 1, t\geq\theta\end{cases}$ the Heavisides function	• Decalibration	Jump in the mean value	
Gain modification	$Y_i(t)=\alpha\Gamma_\theta Y_i^*(t)+\varepsilon_i(t)$	• Decalibration	Jump in the mean value	
Total breakdown	$Y_i(t)=(1-\Gamma_\theta)[Y_i^*(t)+\varepsilon_i(t)]+k$ $k\in\{Y_{min}, 0, Y_{max}\}$	•Destruction of the sensor •Disconnection of an electrical signal	Signal constant, zero or min/max	
Offset drift Bias drift	$Y_i(t)=Y_i^*(t)+\varepsilon_i(t)+\alpha\, r_{\theta,t}\,\Gamma_\theta$ $r_{\theta,t}=\begin{cases}0 & , t<0\\ t-\theta & , t\geq 0\end{cases}$	•Ageing •Slow destruction of the sensor •Temperature drift	Signal slowly deviates from the true value	
Increased noise	$Y_i(t)=Y_i^*(t)+\varepsilon_i(t)+[\eta_i(t)-\varepsilon_i(t)]\,\Gamma_\theta$ $\eta_i =$ increased noise standard deviation	•Electro-magnetic disturbance •Loss of screening •Disconnection of the ground signal	Small signal to noise ratio	

Context

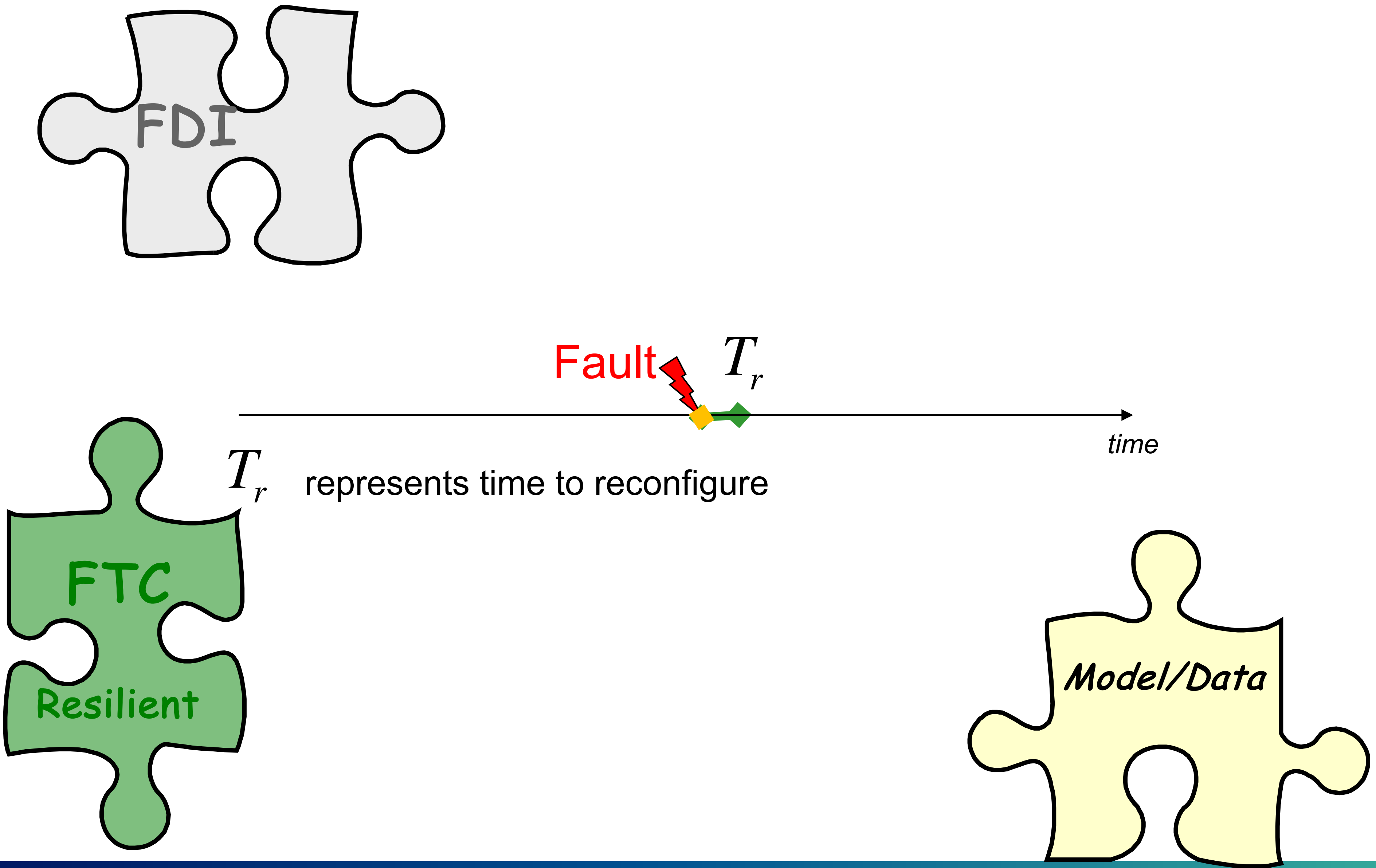


T_d represents time to detect, isolate and to estimate

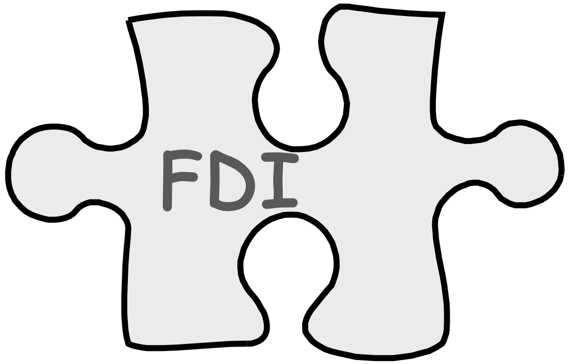


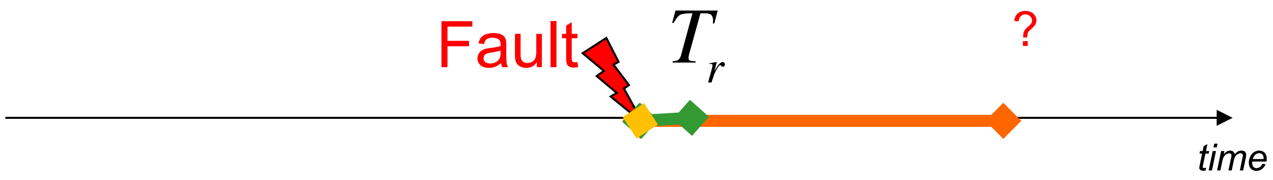


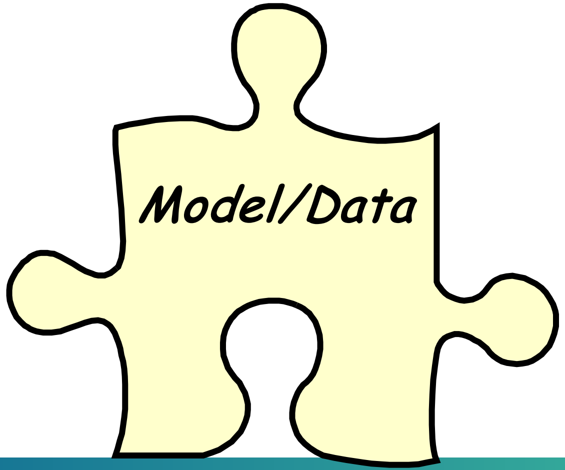
Context


FDI
Fault
T_r
time
T_r represents time to reconfigure
FTC
Resilient
Model/Data

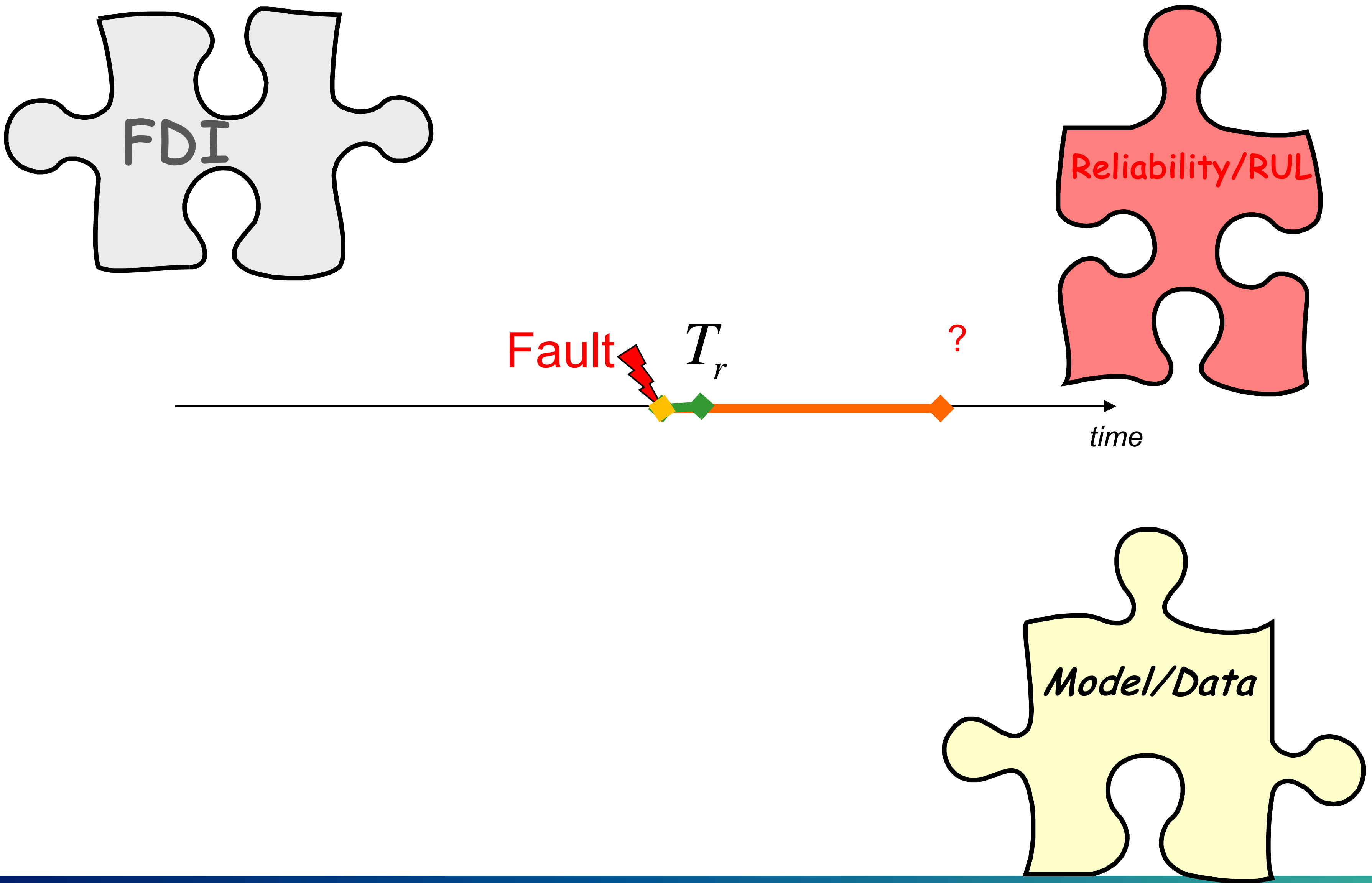
Context



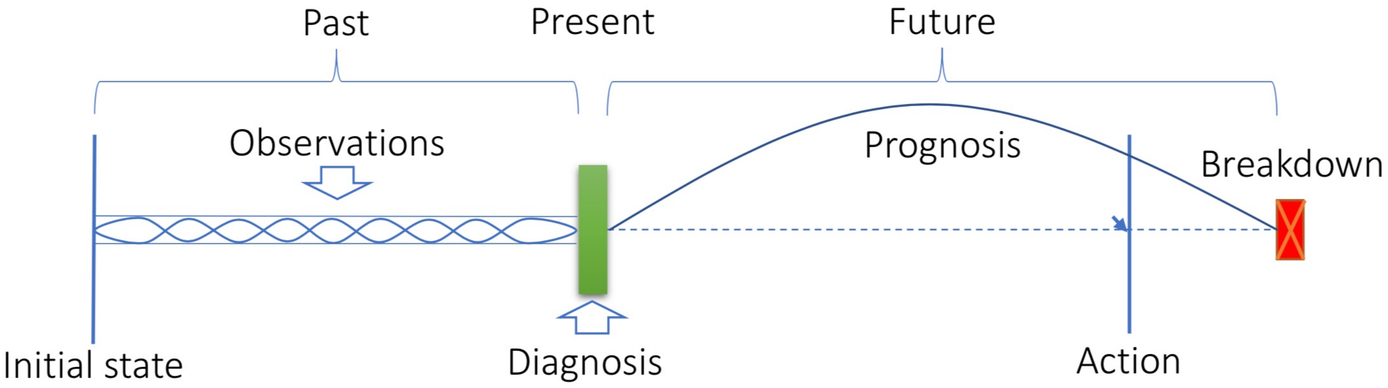




Context

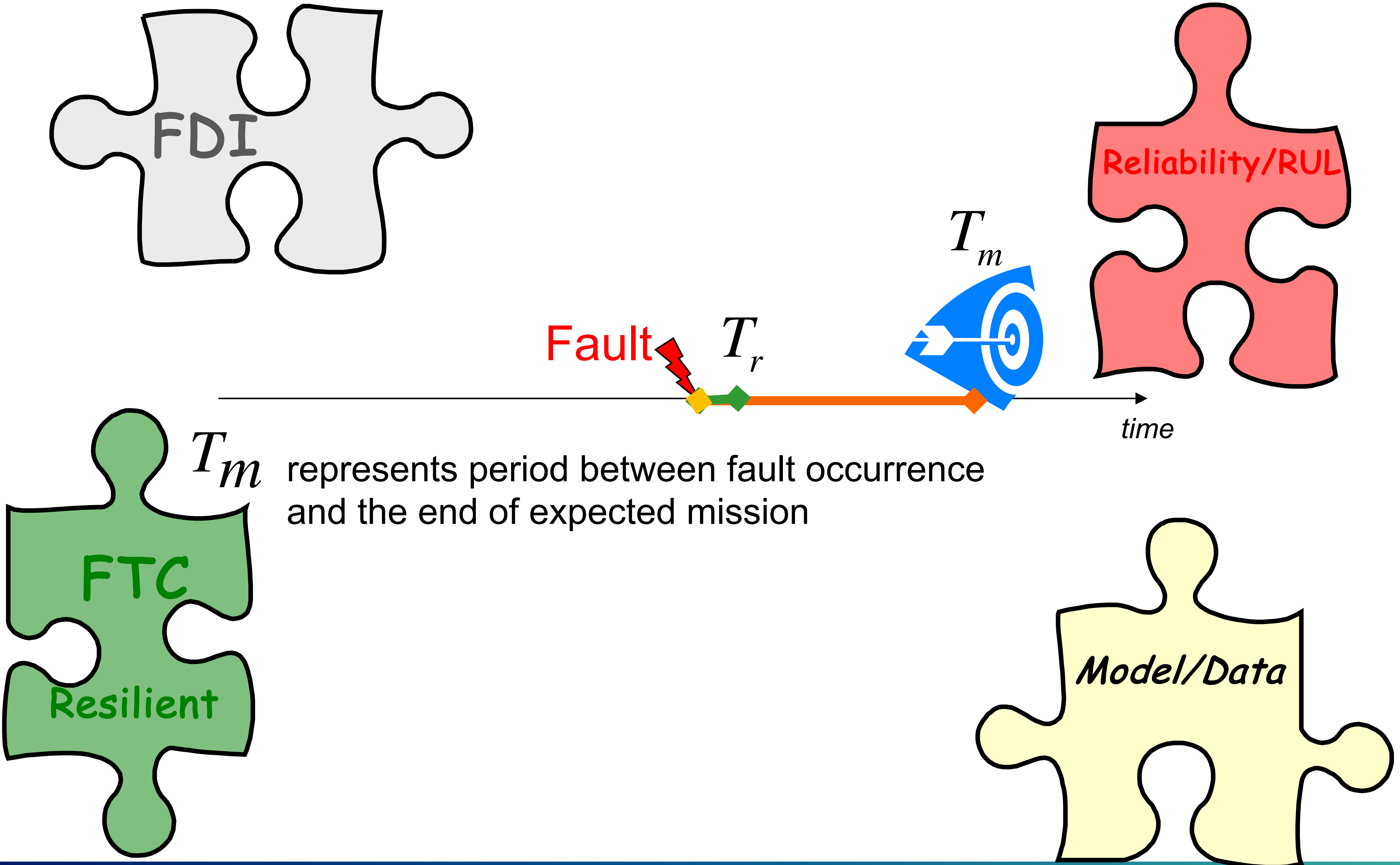


DIAGNOSIS & PROGNOSIS



- Initial state: State distribution at the beginning.
- Observations: Extracted data from sensors on the complex system.
- Diagnosis: Identifying the current hidden health state of the system based on observations.
- Prognosis: prediction of the future health evolution of the system considering operating conditions.
- Action: Plan maintenance.
- Breakdown: System failure.

Heath Aware Control Design



T_m represents period between fault occurrence and the end of expected mission

PROBLEM STATEMENT

Consider the linear system as follows:

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) + w(k) \\ z(k) = Cx(k) + v(k) \end{cases}$$

with measured output and tracking control loop:

$$\begin{cases} y(k) = Dx(k) \\ u(k) = -K_1 x(k) + K_2(y_{ref}(k) - y(k)) \end{cases}$$

PROBLEM STATEMENT

Consider the degraded linear system as follows:

$$x(k+1) = Ax(k) + B(u(k) - d(k)) + w(k)$$

with Unknown degradation (dimension 1)

$$d(k) = \phi(x(k), u(k), \theta(k))$$

where $\phi(\cdot)$ is a nonlinear function

PROBLEM STATEMENT

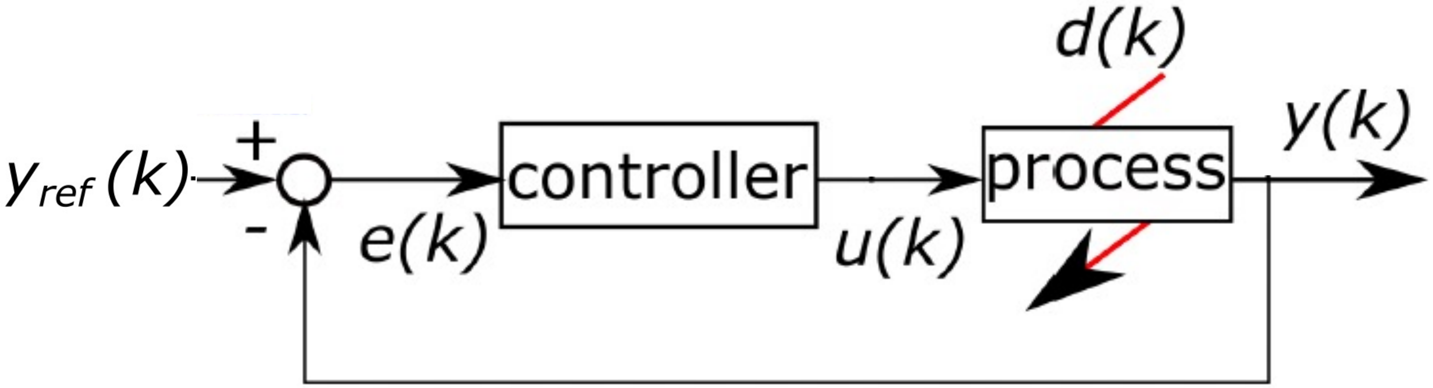
Consider the degraded linear system as follows:

$$x(k+1) = Ax(k) + B(u(k) - d(k)) + w(k)$$

with Unknown degradation

$$d(k) = \phi(x(k), u(k), \theta(k))$$

where $\phi(\cdot)$ is a nonlinear function



Consider the degraded linear system as follows:

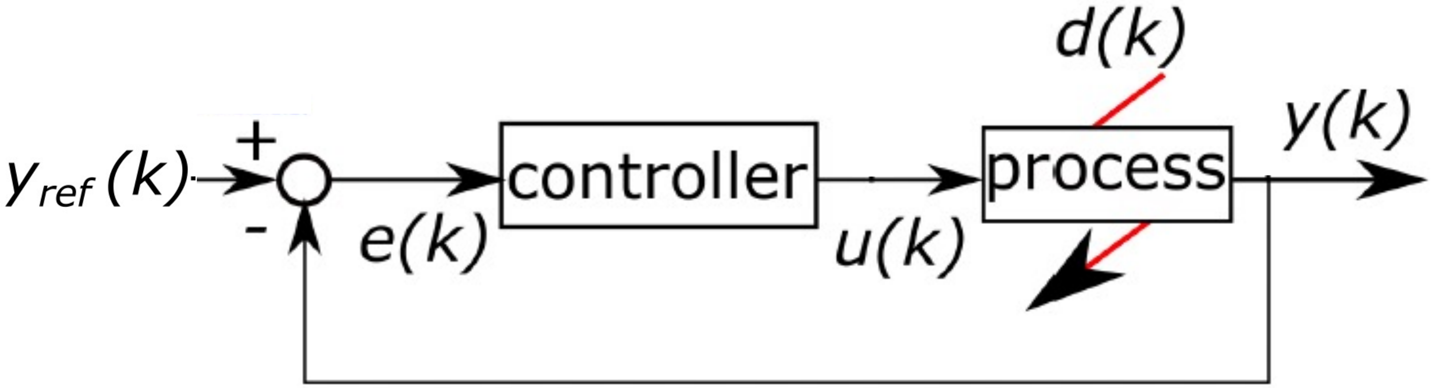
$$x(k+1) = Ax(k) + B(u(k) - d(k)) + w(k)$$

with Unknown degradation

$$d(k) = \phi(x(k), u(k), \theta(k))$$

where $\phi(\cdot)$ is a nonlinear function

Remaining Useful Life
Dynamic Behaviour
Etc …



17

PROBLEM STATEMENT

Consider the degraded linear system as follows:

$$x(k+1) = Ax(k) + B(u(k) - d(k)) + w(k)$$

with Unknown degradation

$$d(k) = \phi(x(k), u(k), \theta(k))$$

where $\phi(\cdot)$ is a nonlinear function

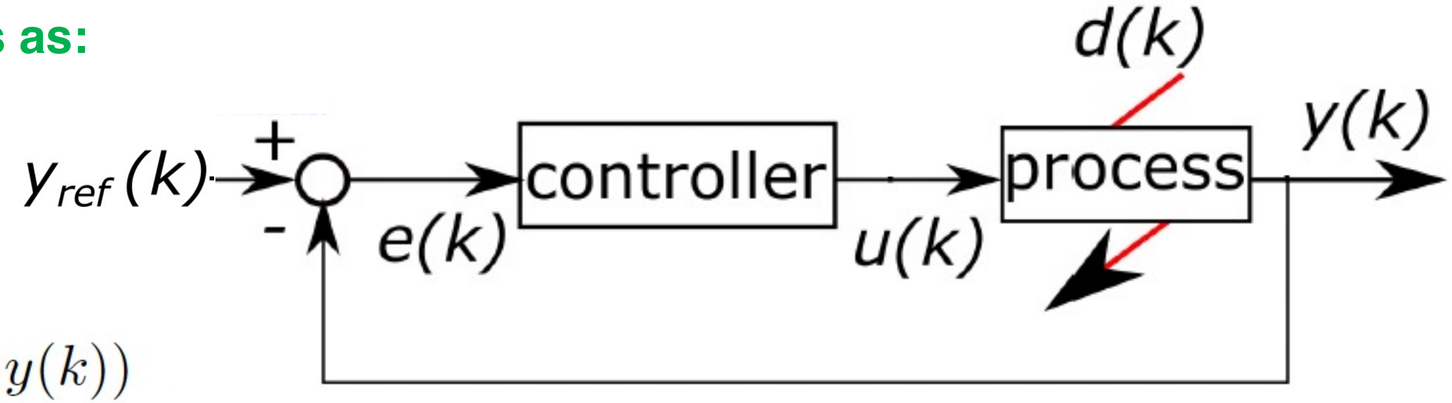
Remaining Useful Life
Dynamic Behaviour
Etc …

Remaining Useful Life dynamics as:

$$\widehat{RUL}(k) = \Phi(\hat{d}(k), u(k))$$

For tracking control as:

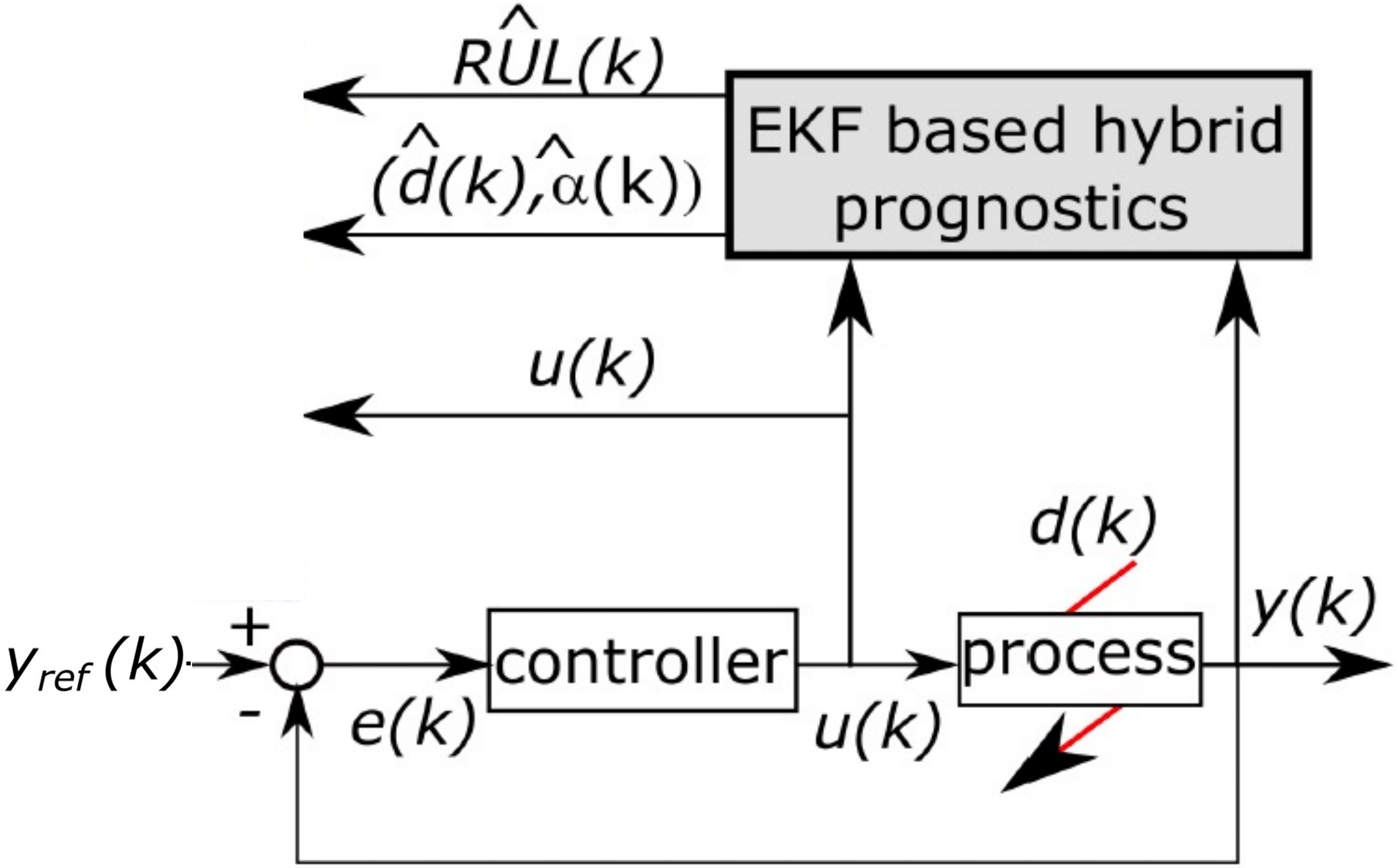
$$\widehat{RUL}(k) = \Phi(\hat{d}(k), (y_{ref}(k) - y(k))$$



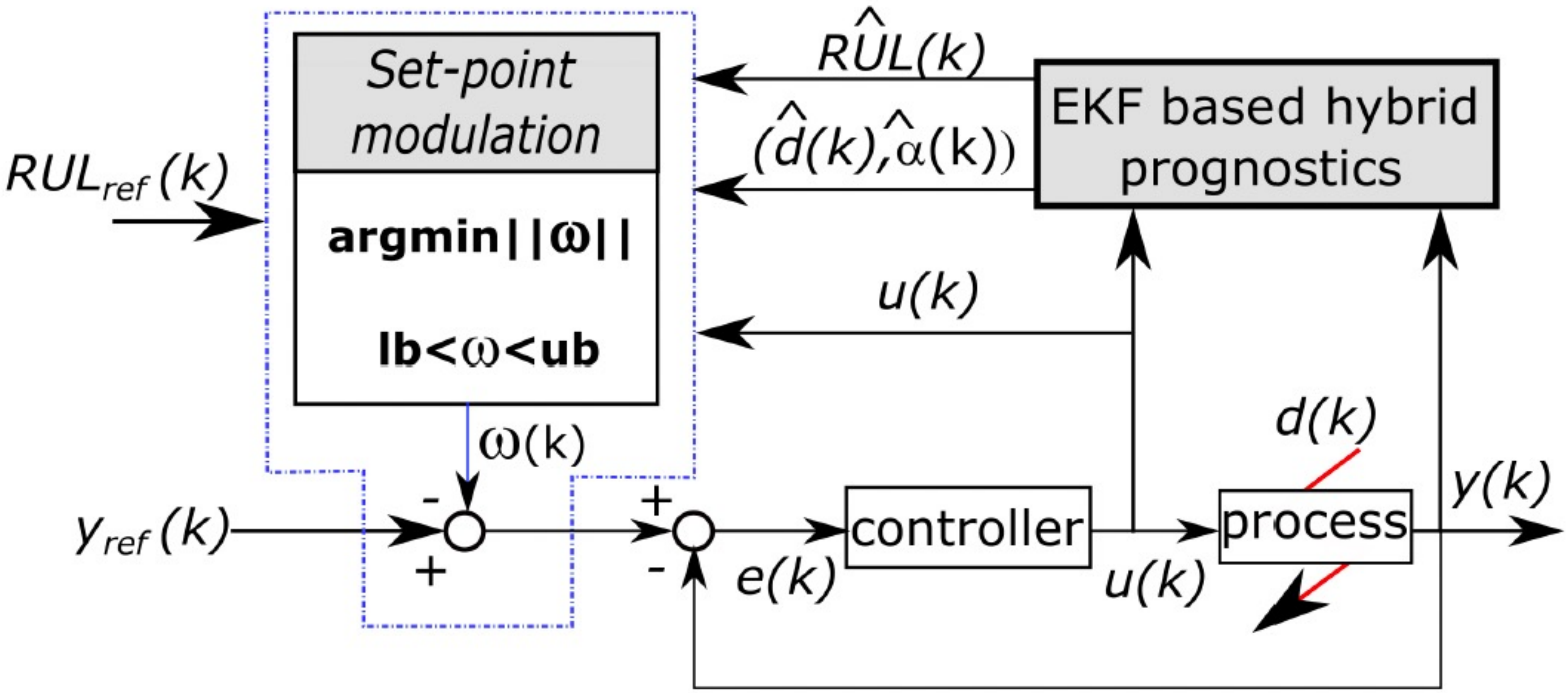
OUTLINES

- Introduction / Context
- Problem Statement
- **Our Solution**
- Illustrative Examples
- Conclusions / Perspectives

HYBRID PROGNOSTICS ENABLED SET POINT MODULATION STRATEGY



HYBRID PROGNOSTICS ENABLED SET POINT MODULATION STRATEGY



Degradation model *sensitive* to system input but unknown $\phi(\cdot)$ so approximated by:

$$d(k) = e^{(\sum_{i=1}^{k} u(i).\alpha(i-1).T_s)} + w_d(k)$$

Time + Cumulative « Energy »

$$\begin{cases} d(k+1) = e^{(\sum_{i=1}^{k+1} u(i).\alpha(i-1).T_s)} + w_d(k+1) \\ \quad = e^{(\sum_{i=1}^{k} u(i).\alpha(i-1).T_s)} \times e^{(u(k+1).\alpha(k).T_s)} \\ \quad\quad + w_d(k+1) \\ \quad = d(k)e^{(u(k+1).\alpha(k).T_s)} + w_d(k+1) \\ \\ \alpha(k+1) = \alpha(k) + w_\alpha(k+1) \end{cases}$$

Recurrent formulation

$$\begin{cases} d(k+1) = d(k)(1 + u(k+1).\alpha(k).T_s) + w_d(k+1) \\ \alpha(k+1) = \alpha(k) + w_\alpha(k+1) \end{cases}$$

State space representation included degradation becomes as:

$$\begin{pmatrix} x(k+1) \\ x_d(k+1) \end{pmatrix} = \begin{pmatrix} A & 0_{n,2} \\ 0_{2,n} & A_d(k) \end{pmatrix} \begin{pmatrix} x(k) \\ x_d(k) \end{pmatrix} + Bu(k) + w(k)$$

$$\begin{pmatrix} z(k) \\ z_d(k) \end{pmatrix} = \begin{pmatrix} C \\ C_d \end{pmatrix} \begin{pmatrix} x(k) \\ x_d(k) \end{pmatrix} + v(k)$$

where $x_d(k) = \begin{bmatrix} d(k) & \alpha(k) \end{bmatrix}^T$

with
$$\begin{cases} d(k+1) = d(k)(1 + u(k+1).\alpha(k).T_s) + w_d(k+1) \\ \alpha(k+1) = \alpha(k) + w_\alpha(k+1) \end{cases}$$

DEGRADATION ESTIMATION

Algorithm 1 Algorithm for degradation estimation using EKF

Input: $z_{d_k}, P_{k|k}, u_k$

Output: $\hat{x}_{d_{k+1|k+1}}$

Initialisation : $z_{d_0}, \hat{x}_{0|0}, P_{0|0}$

if $(i \neq 0)$ **then**

$\hat{x}_{d_{k+1|k}} = A_d(k) x_{d_{k|k}}$

$P_{k+1|k} = J(k) P_{k|k} J(k) + Q$

$z_{d_{k+1|k}} = C_d x_{d_{k+1|k}}$

$S_{k+1} = H_{k+1} P_{k+1|k} H_{k+1}^T + G R_{k+1} G^T$

$K_{k+1} = P_{k+1|k} H_{k+1}^T S_{k+1}^{-1}$

$\hat{x}_{d_{k+1|k+1}} = \hat{x}_{k+1|k} + K_{k+1|k}(z_{d_{k+1}} - z_{dk+1|k})$

$P_{k+1|k+1} = P_{k+1|k} - K_{k+1} S_{k+1} K_{k+1}^T$

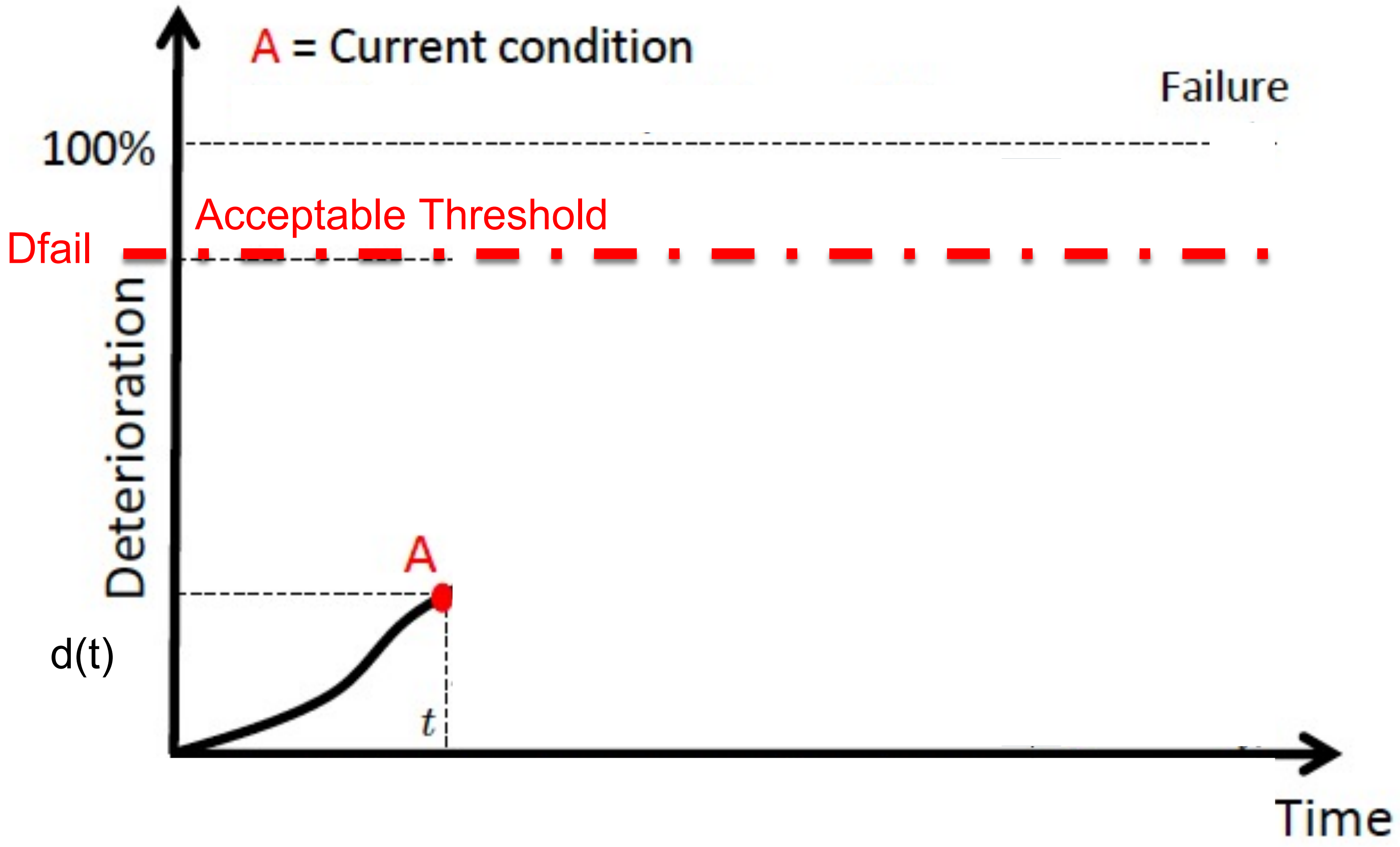
$z_{d_{k+1|k+1}} = C_d \hat{x}_{d_{k+1|k+1}}$

end if

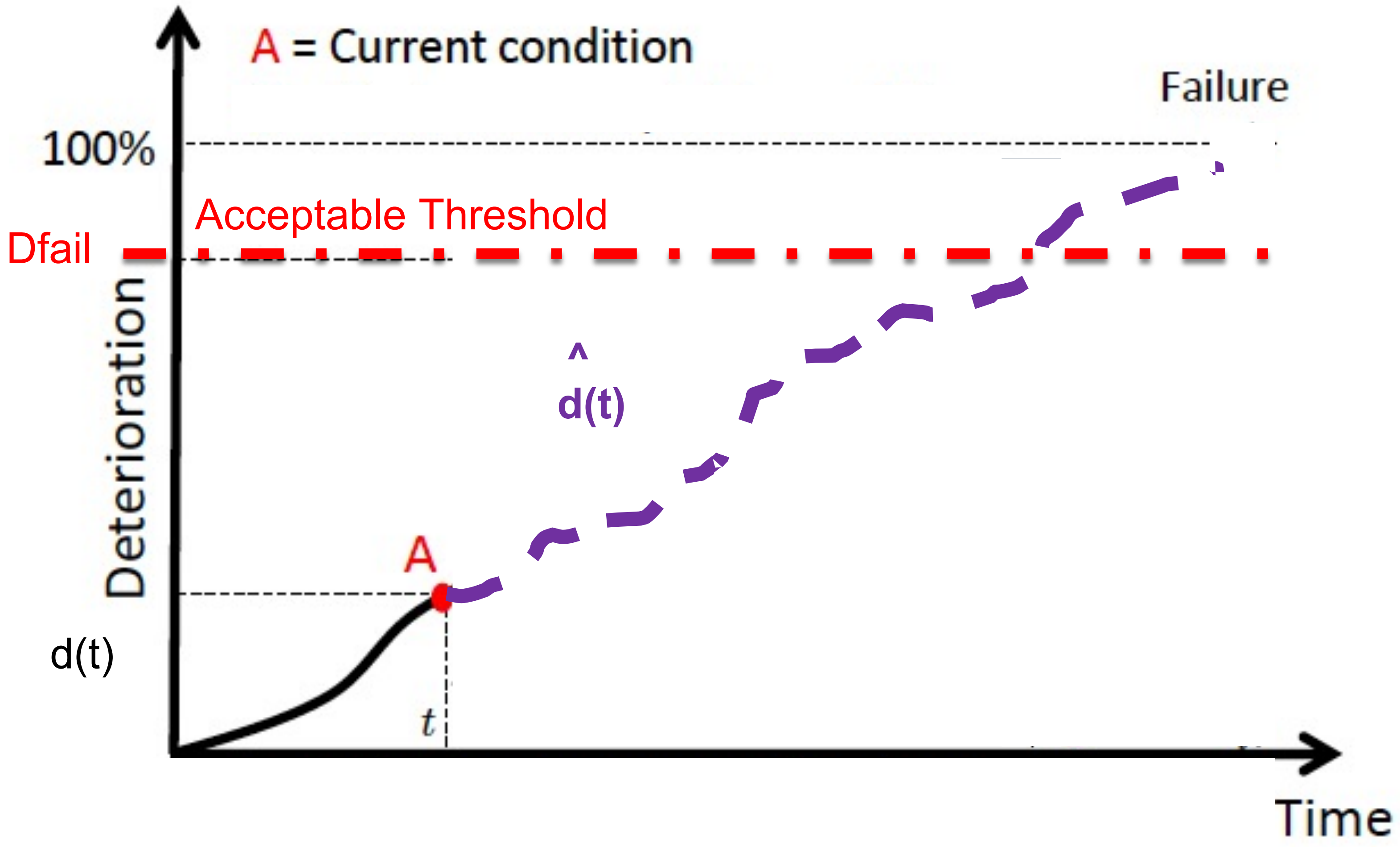
return $\hat{x}_{d_{k+1|k+1}}$

RUL PREDICTION OVER LONG TIME HORIZON

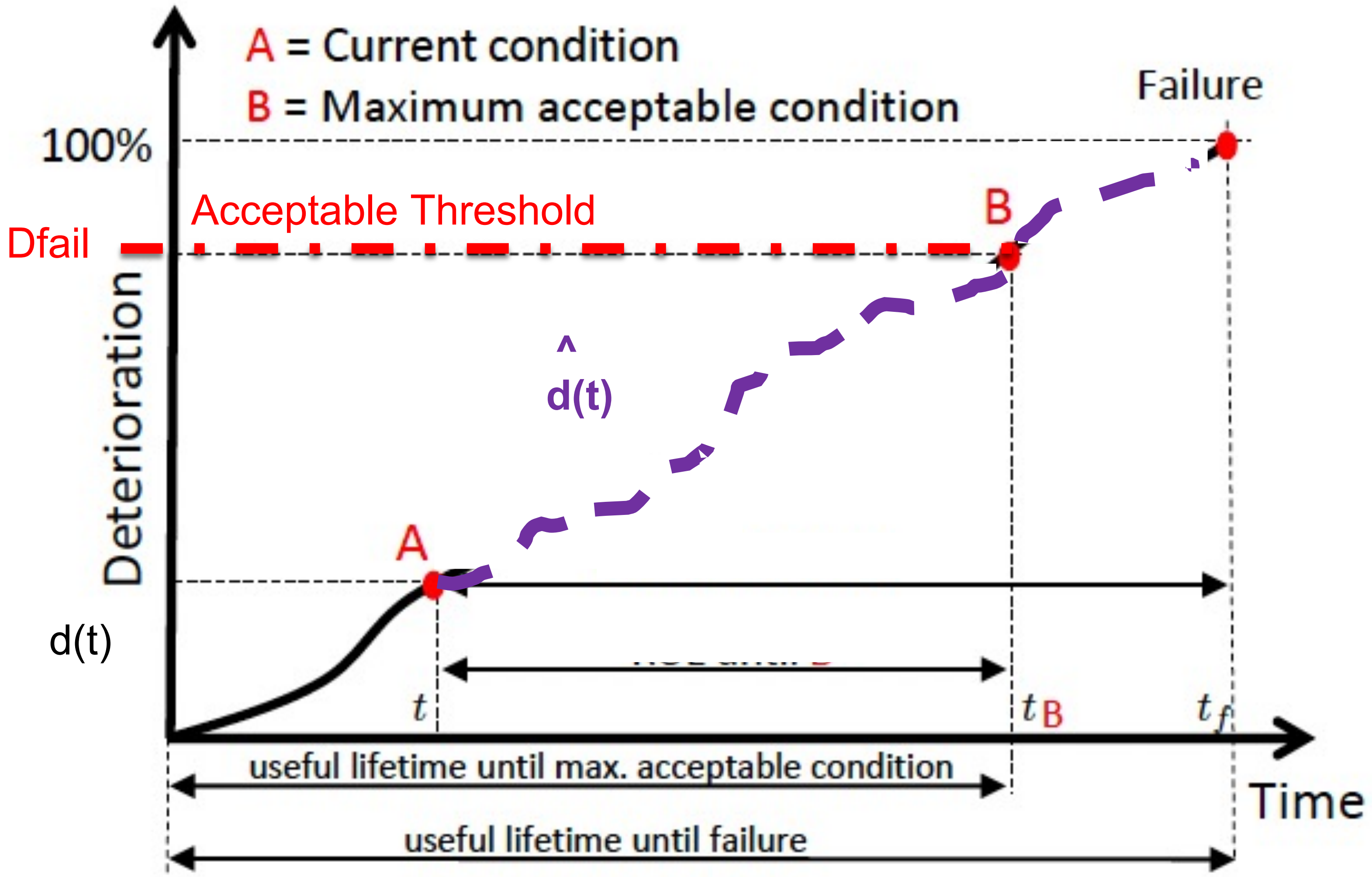
RUL DEFINITION



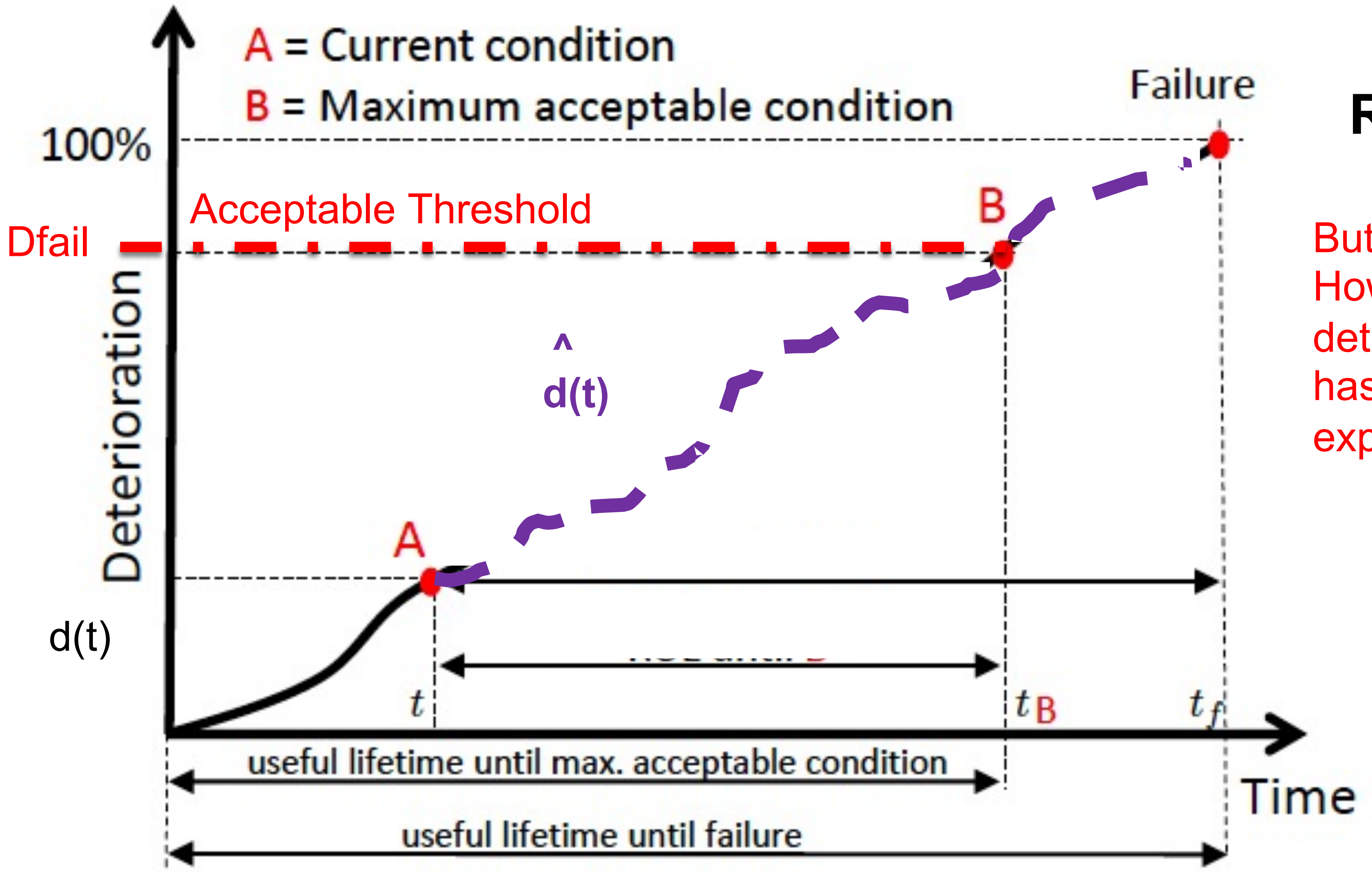
RUL DEFINITION



RUL DEFINITION



RUL DEFINITION



$RUL(t)=t_B-t$

But t_b is unknown
However only deterioration level has been fixed by expert

RUL PREDICTION OVER LONG TIME HORIZON

Algorithm 2 L-step ahead RUL prediction

Input: u_k

Output: $R\hat{U}L$

$Initialisation : L = 0$

$[\hat{d}(i), \hat{\alpha}(i)] =$ Algorithm $1(z_{d_k}, P_{k|k}, u_k)$

$d_L(i) = \hat{d}(i)$

while $d_L(i) \leq \boxed{D_{fail}}$ **do**

  $d_L(i) = d_L(i).(1 + \hat{\alpha}(i).u(i).T_s))$

  $L = L + T_s$

end while

$R\hat{U}L = L$

return $R\hat{U}L$

or based on
formal equations

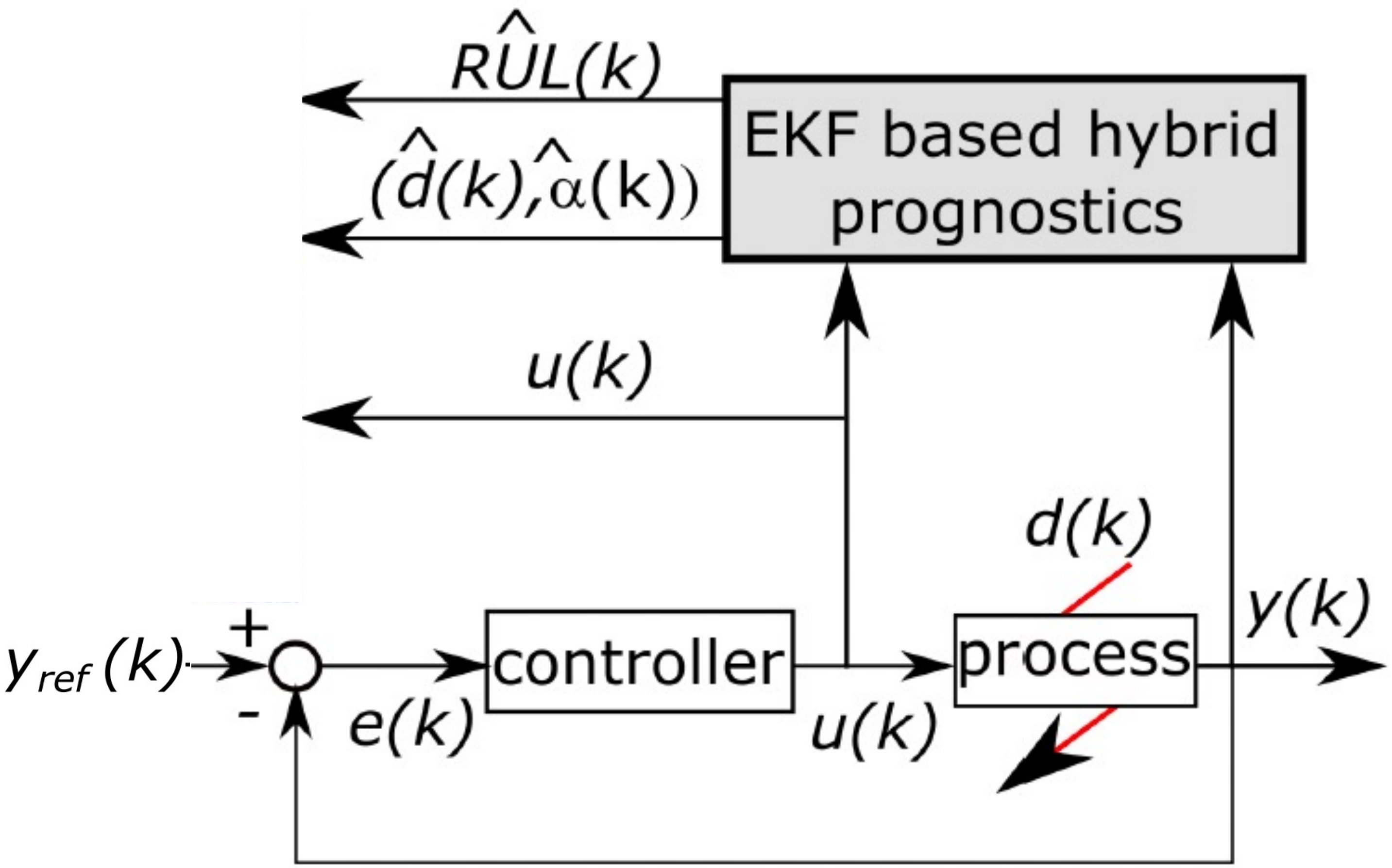
$$RUL(k) = (n_{fail} - k_p).T_s$$

$$d(n_{fail}) = d(k).(1 + \alpha(k).u(k).T_s)^{n_{fail}-k}$$

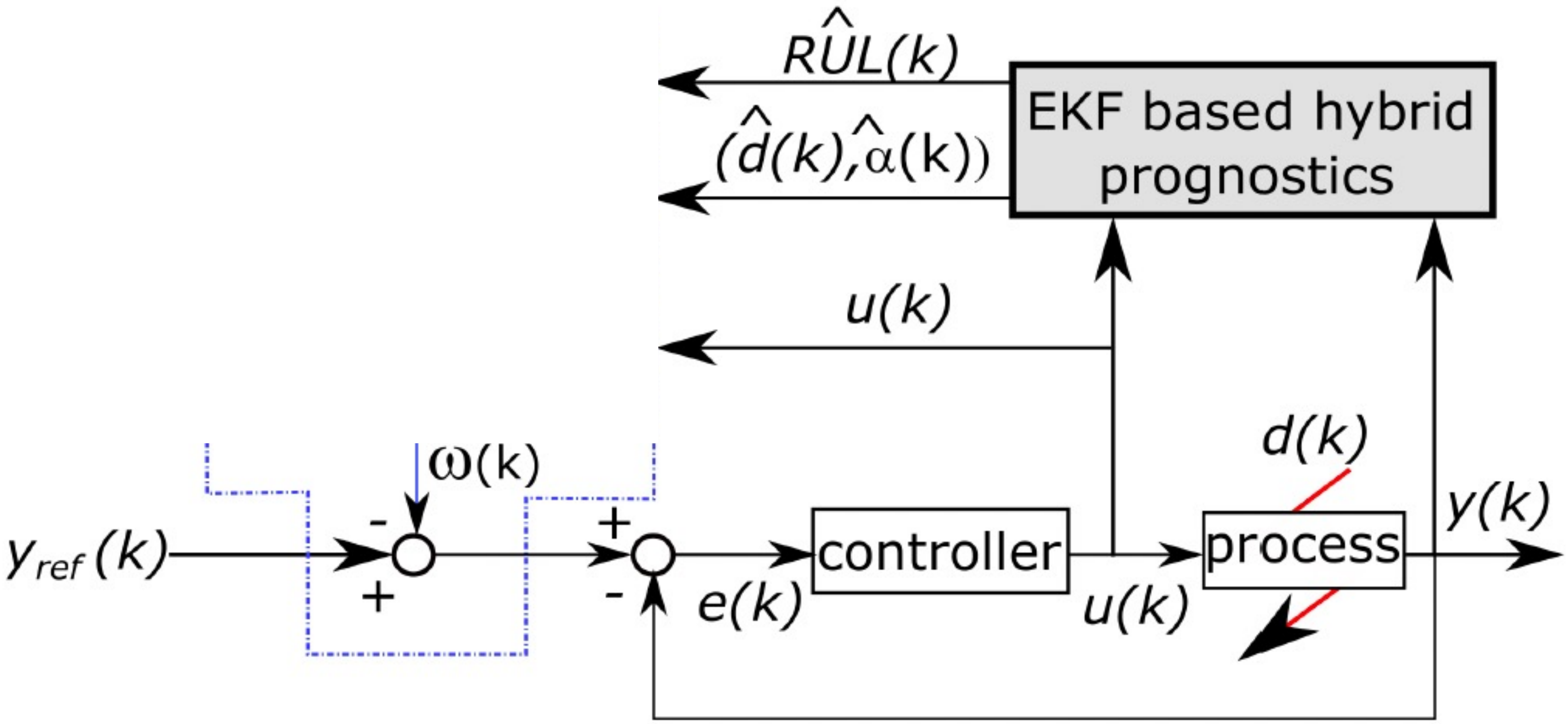
$$d(n_{fail}) = d(k).(1 + \alpha(k).u(k).T_s)^{L} \qquad d(n_f) < D_{fail}$$

$$L > \frac{log\left(\frac{D_{fail}}{d(k)}\right)}{log\left(1 + \alpha(k).u(k).T_s\right)}$$

$$\widehat{RUL}(k) = L$$


$\widehat{RUL}(k)$
EKF based hybrid prognostics
$(\hat{d}(k),\hat{\alpha}(k))$
$u(k)$
$d(k)$
$y(k)$
$y_{ref}(k)$
+
-
$e(k)$
controller
$u(k)$
process

HYBRID PROGNOSTICS ENABLED SET POINT MODULATION STRATEGY



OPTIMIZATION-BASED SET- POINT MODULATION

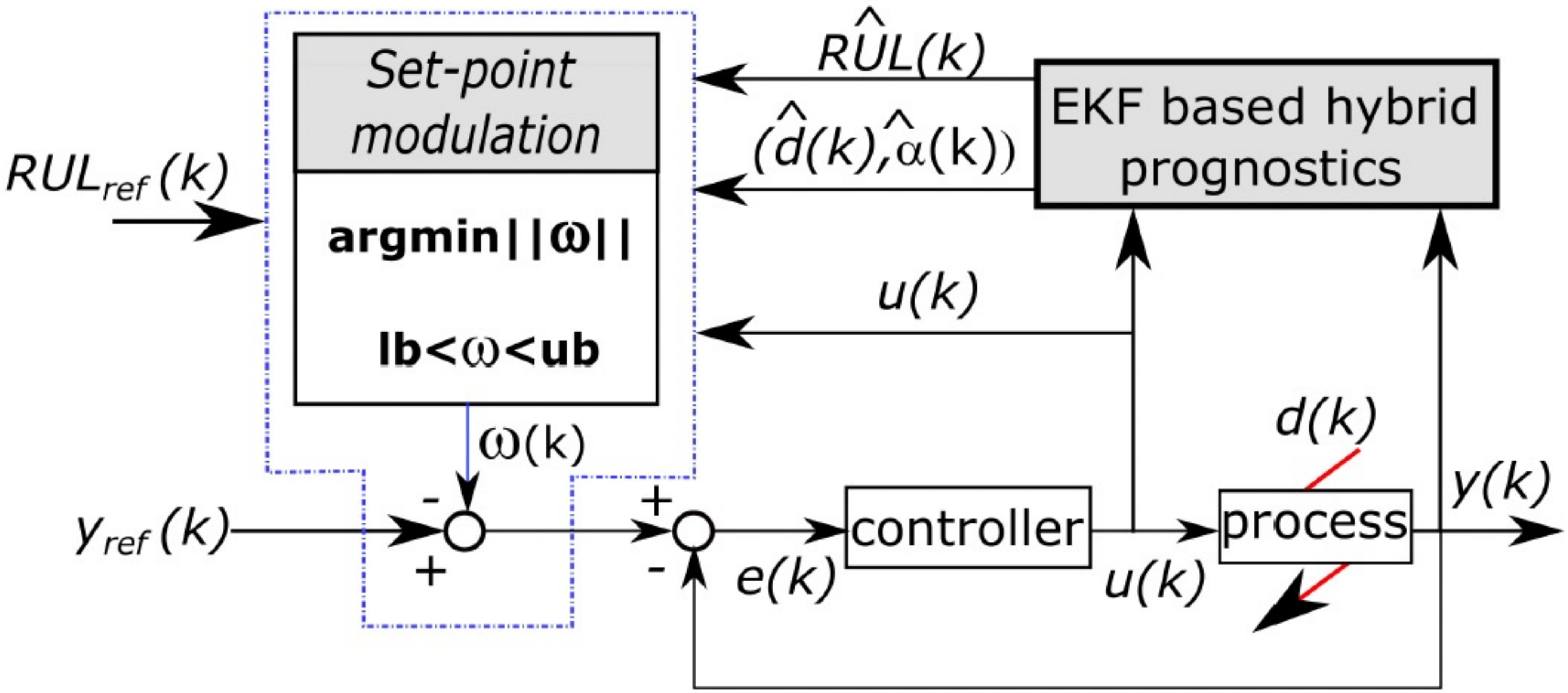
$$\omega^*(k) = \text{argmin} \quad J(k) \quad \Longrightarrow \quad J(k) = \gamma.\omega(k)^2 + (1-\gamma).\left(RUL_{ref}(k) - \widehat{RUL}(k)\right)^2$$

$$\widehat{RUL}(k) = \Phi(\hat{d}(k), ((y_{ref}(k) - \omega(k)) - y(k)))$$

Algorithm 3 Set point modulation based reconfiguration strategy

Input: $RUL_{ref}, y_{ref}, y, u_k,$
Output: ω^*

$[\hat{d}(k), \alpha(\hat{k})] =$Algorithm 1$(z_{d_k}, P_{k|k}, u_k)$
if $R\hat{U}L(k) < RUL_{ref}(k)$ **then**
  $J(k) = \gamma.\omega(k)^2 + (1-\gamma).(RUL_{ref}(k) -$ Algorithm 2$(u(k))^2$
  such $lb \leq \omega \leq ub$
  $\omega^*(k) = \text{argmin}(J(k))$
end if
return $\omega^*(k)$


Set-point modulation
argmin||ω||
lb<ω<ub
$\hat{RUL}(k)$
$(\hat{d}(k),\hat{\alpha}(k))$
EKF based hybrid prognostics
$RUL_{ref}(k)$
u(k)
ω(k)
$y_{ref}(k)$
-
+
+
-
e(k)
controller
u(k)
d(k)
process
y(k)

OUTLINES

- Introduction / Context
- Problem Statement
- Our Solution
- **Illustrative Examples**
- Conclusions / Perspectives

EXAMPLE 1 – SYSTEM DESCRIPTION

Please consider the following academic example:

$$\begin{cases} \begin{pmatrix} x_1(k+1) \\ x_2(k+1) \end{pmatrix} = \begin{pmatrix} -12 & -20.02 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} x_1(k) \\ x_2(k) \end{pmatrix} + \begin{pmatrix} 1 \\ 0 \end{pmatrix} u(k) + w(k) \\ z(k) = \begin{pmatrix} 0 & 2 \end{pmatrix} \begin{pmatrix} x_1(k) \\ x_2(k) \end{pmatrix} + v(k) \end{cases}$$

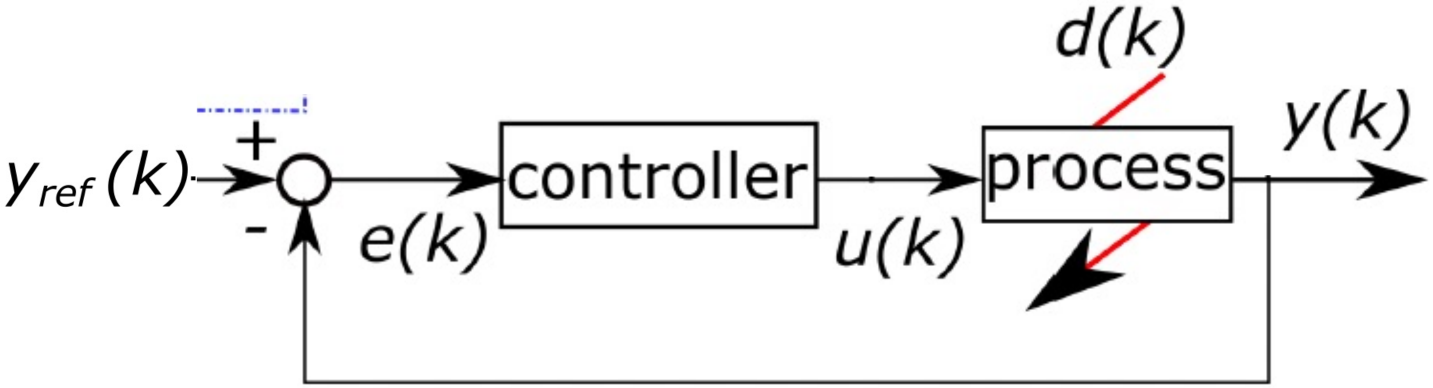
With degradation $x(k+1) = Ax(k) + B(u(k) - d(k)) + w(k)$

where $d(k) = \begin{cases} 0 & \textbf{if} \Phi(k) < K_{lim} \\ (\Phi(k) - K_{lim})^{K_{exp}} & \textbf{if} \Phi(k) > K_{lim} \end{cases}$

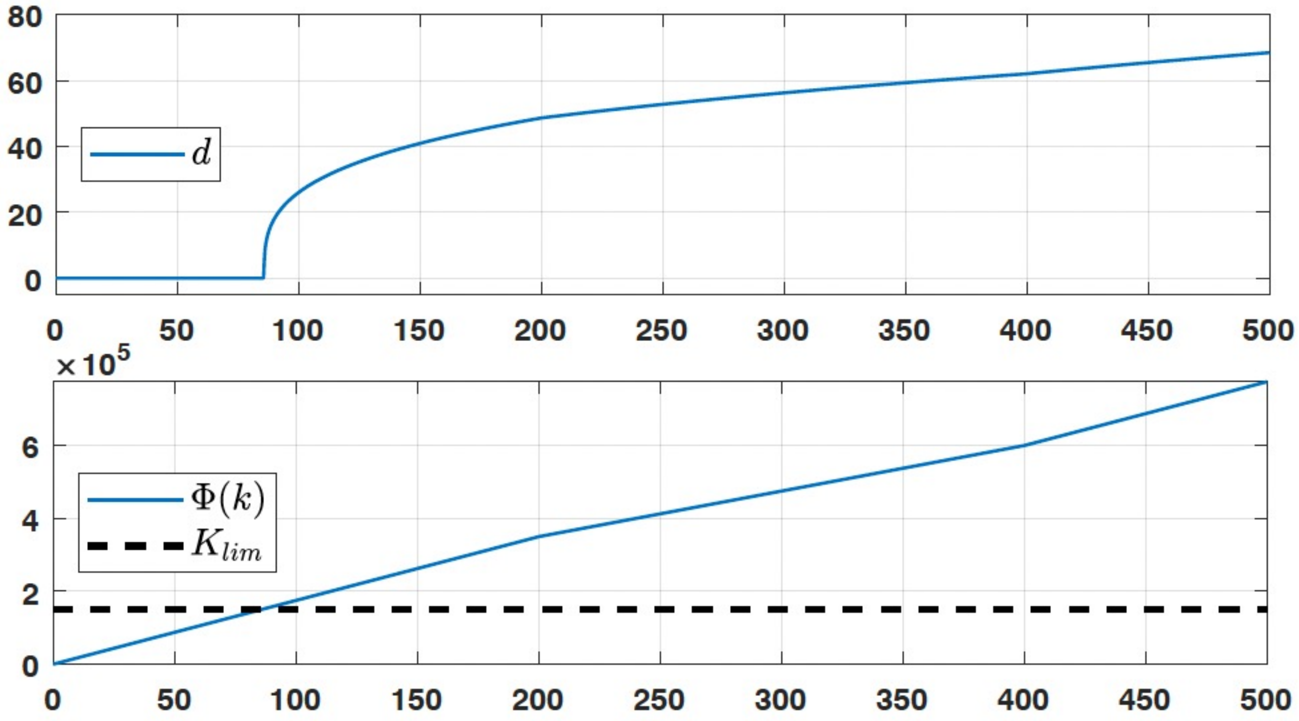
with $\Phi(k)$ defined as:

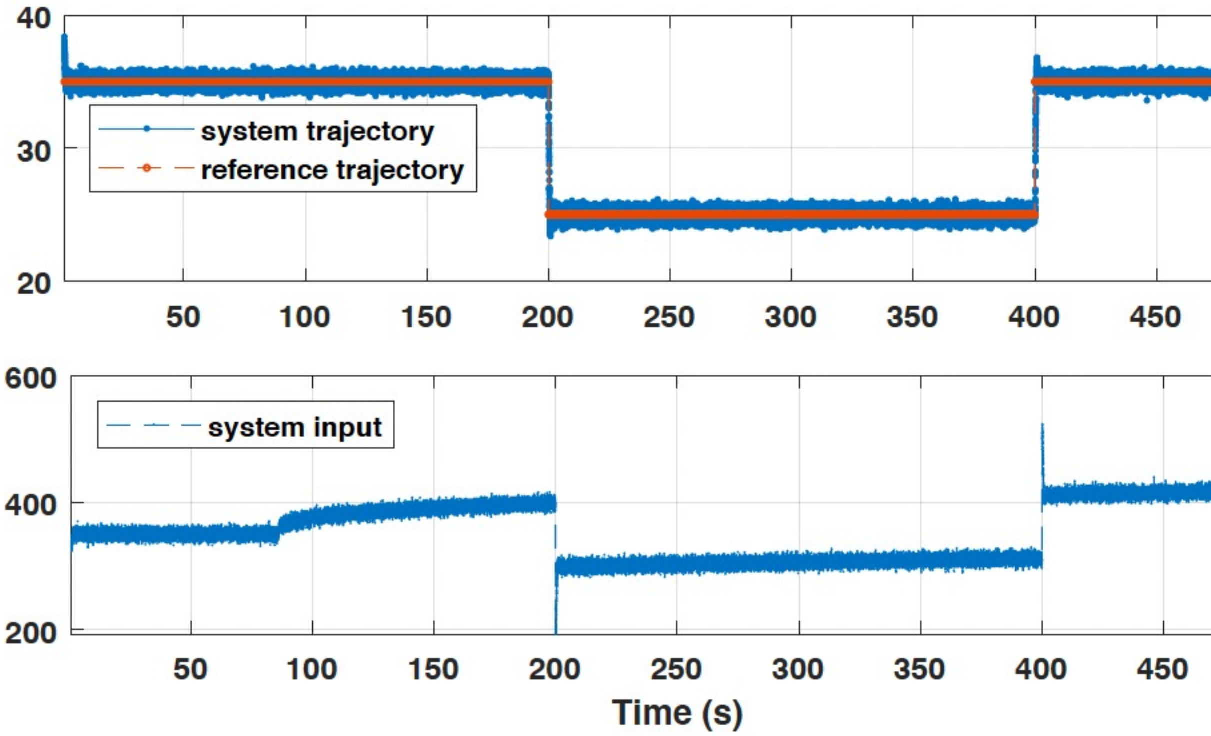
$$\Phi(k) = \sum_{k=1}^{N} x_1(k)$$

EXAMPLE 1 – CLOSED LOOP

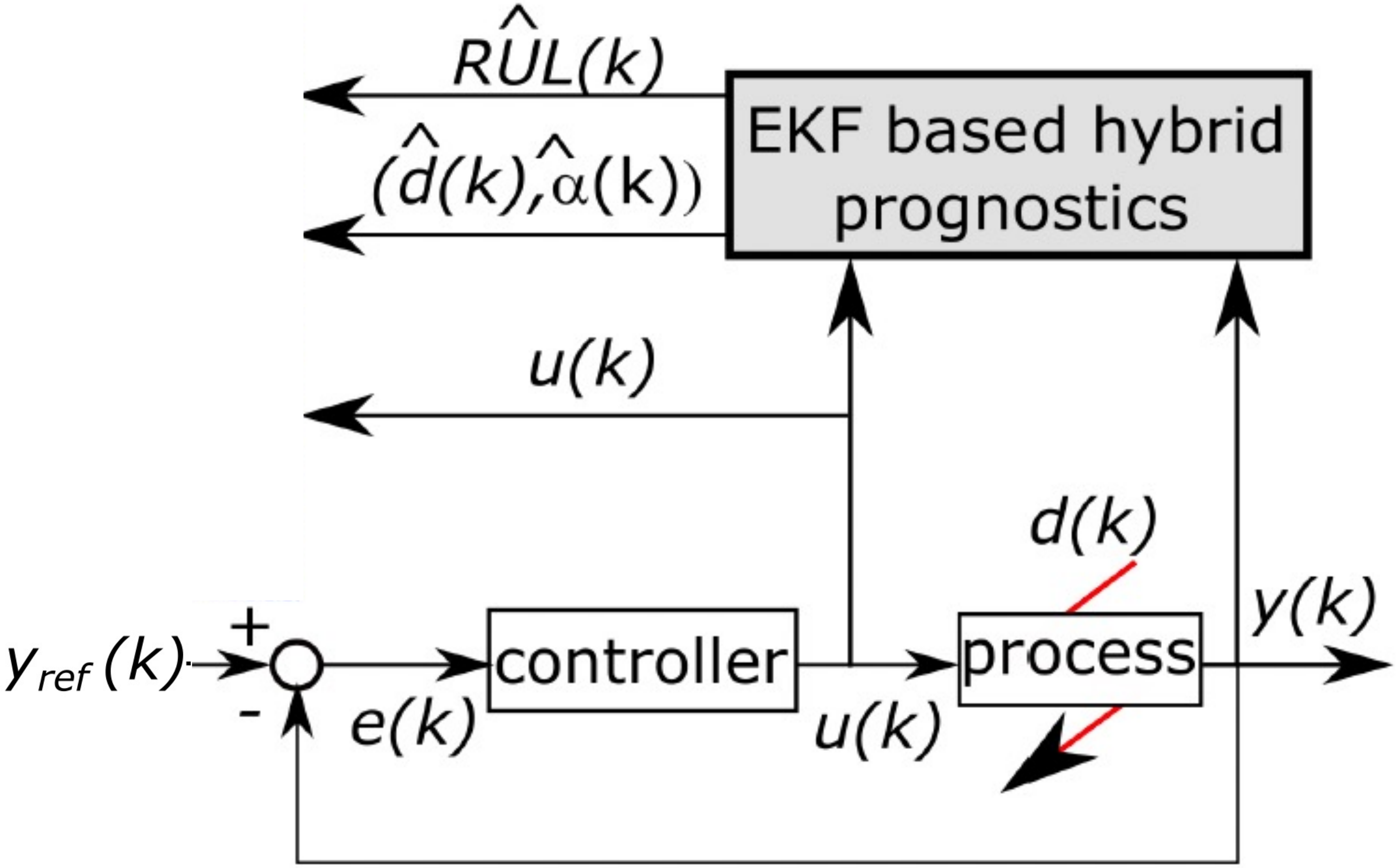


EXAMPLE 1 – DYNAMIC BEHAVIOR IN CLOSED LOOP

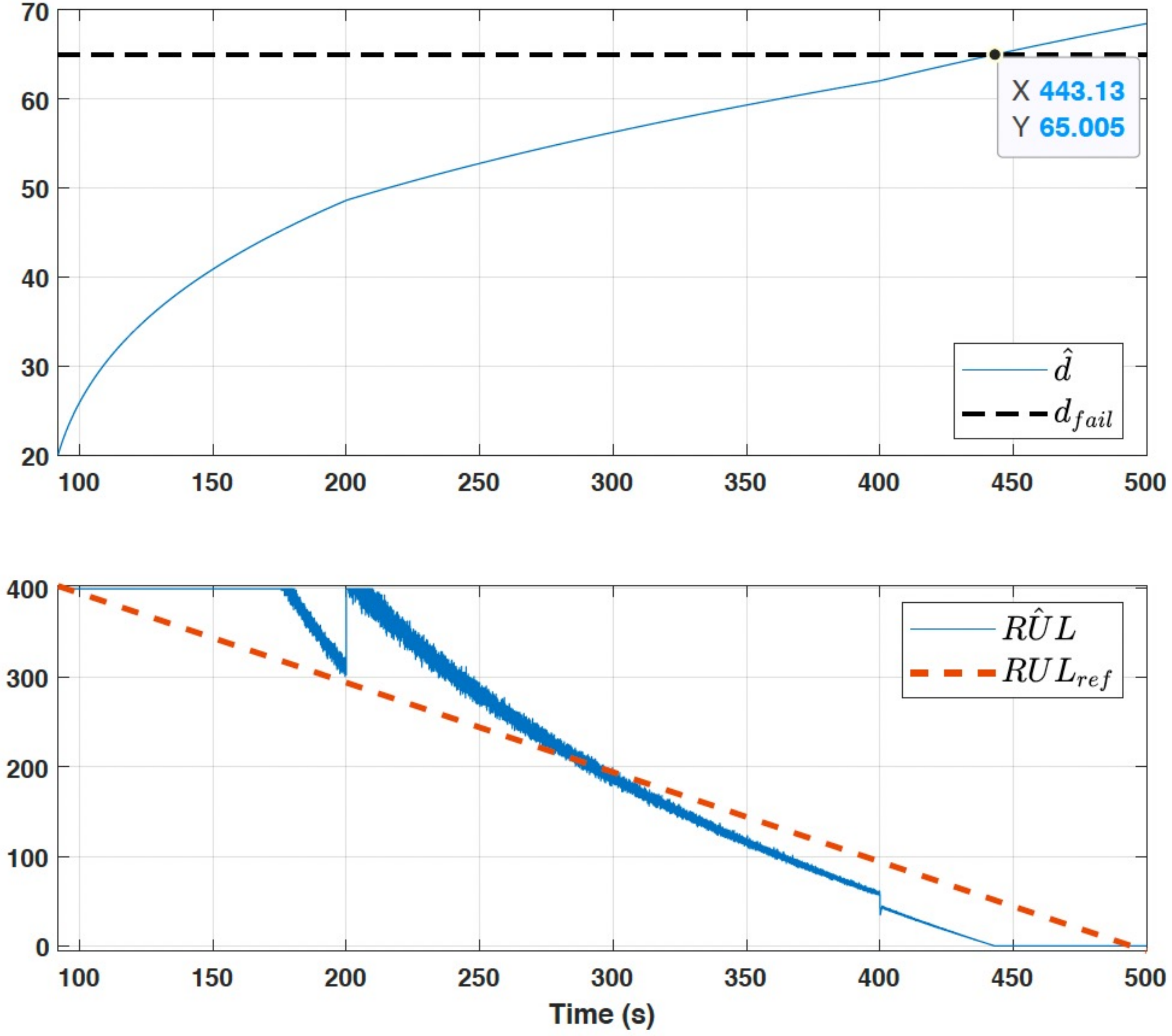




EXAMPLE 1 – EKF

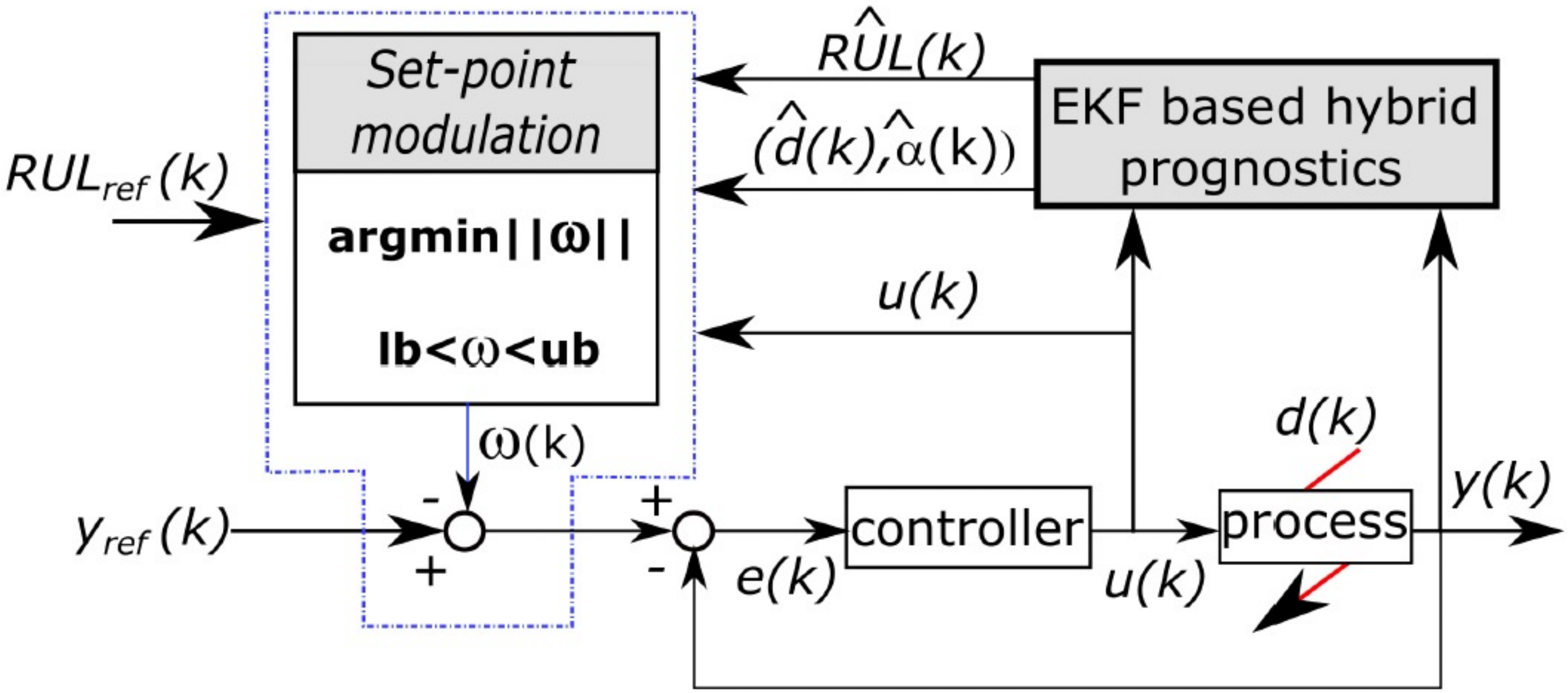


EXAMPLE 1 – DEGRADATION ESTIMATION & RUL

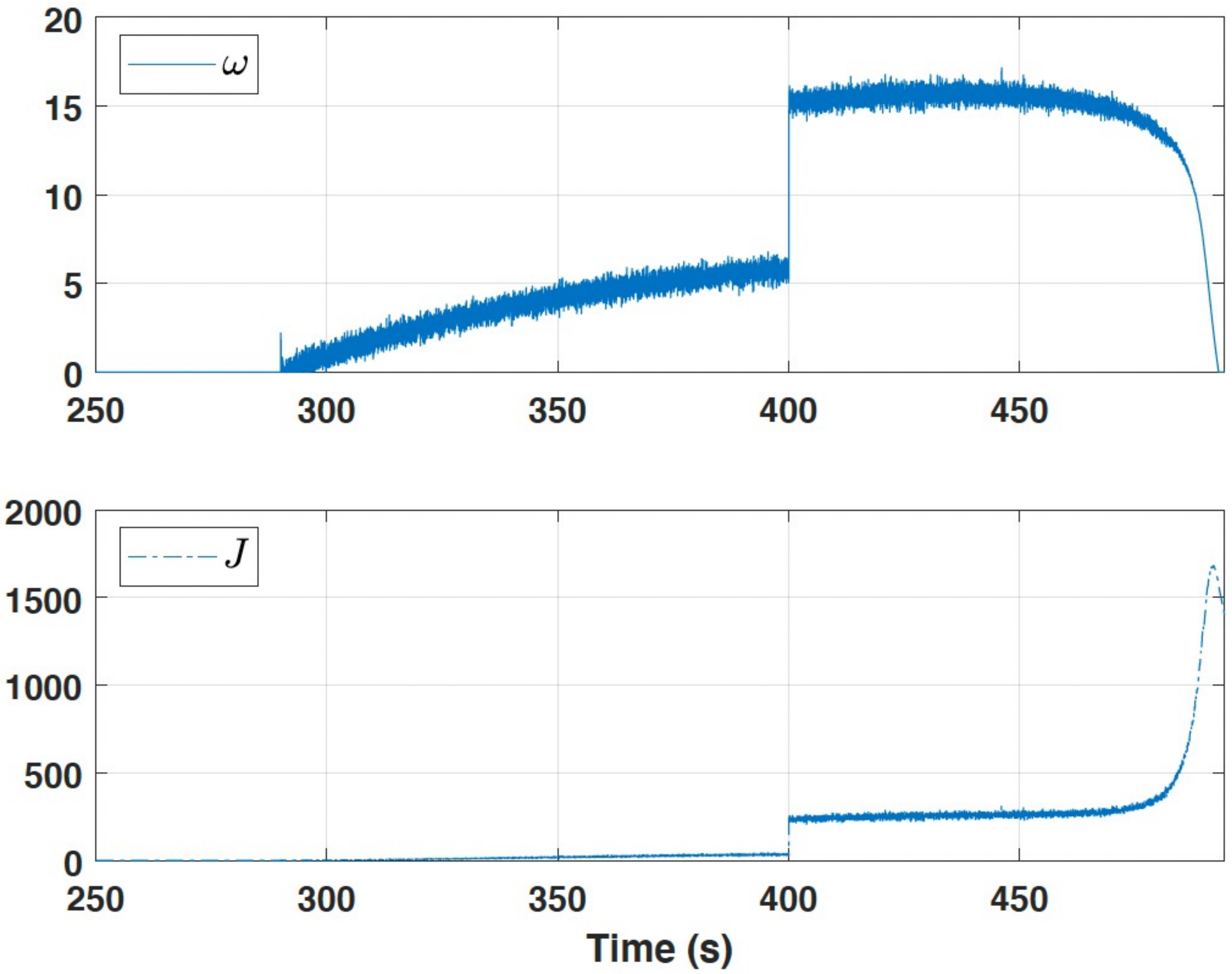


41

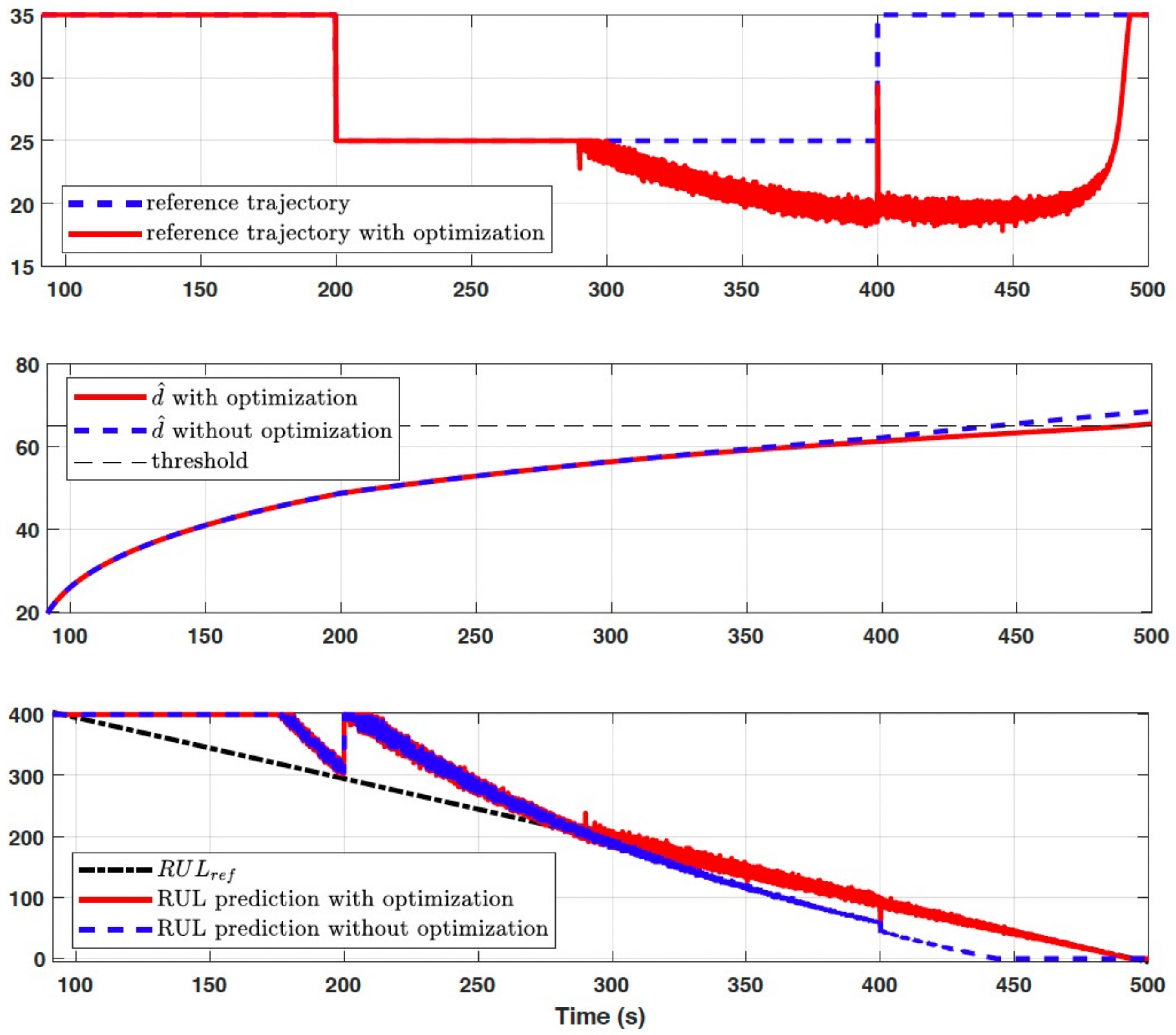
HYBRID PROGNOSTICS ENABLED SET POINT MODULATION STRATEGY



EXAMPLE 1 – DESIGN PARAMETER & CRITERIA



EXAMPLE 1 – DYNAMIC BEHAVIOR & DEGRADATION & RUL



Two Criteria are defined:

$$I_H(\gamma, ub) = \frac{EOL_{WithStrategy}}{EOL_{WithoutStrategy}} \times 100$$

$$\omega^*(k) = \text{argmin} \quad J(k)$$

$$I_P(\gamma, ub) = (\sum_{i=1}^{N} \frac{y_{ref}(i) + \omega(i)}{y_{ref}(i)}) \times 100$$

$$J(k) = \gamma.\omega(k)^2 + (1-\gamma).\left(RUL_{ref}(k) - \widehat{RUL}(k)\right)^2$$

Parameter Sensitivies

test	1	2	3	4	5	6	7	8
γ	0.001	0.01	0.1	0.25	0.5	0.75	0.9	0.99

test	1	2	3	4	5	6	7	8
ub	1.5	3	4.5	6	7.5	9	10.5	12

45

EXAMPLE 1 – ANAYSIS

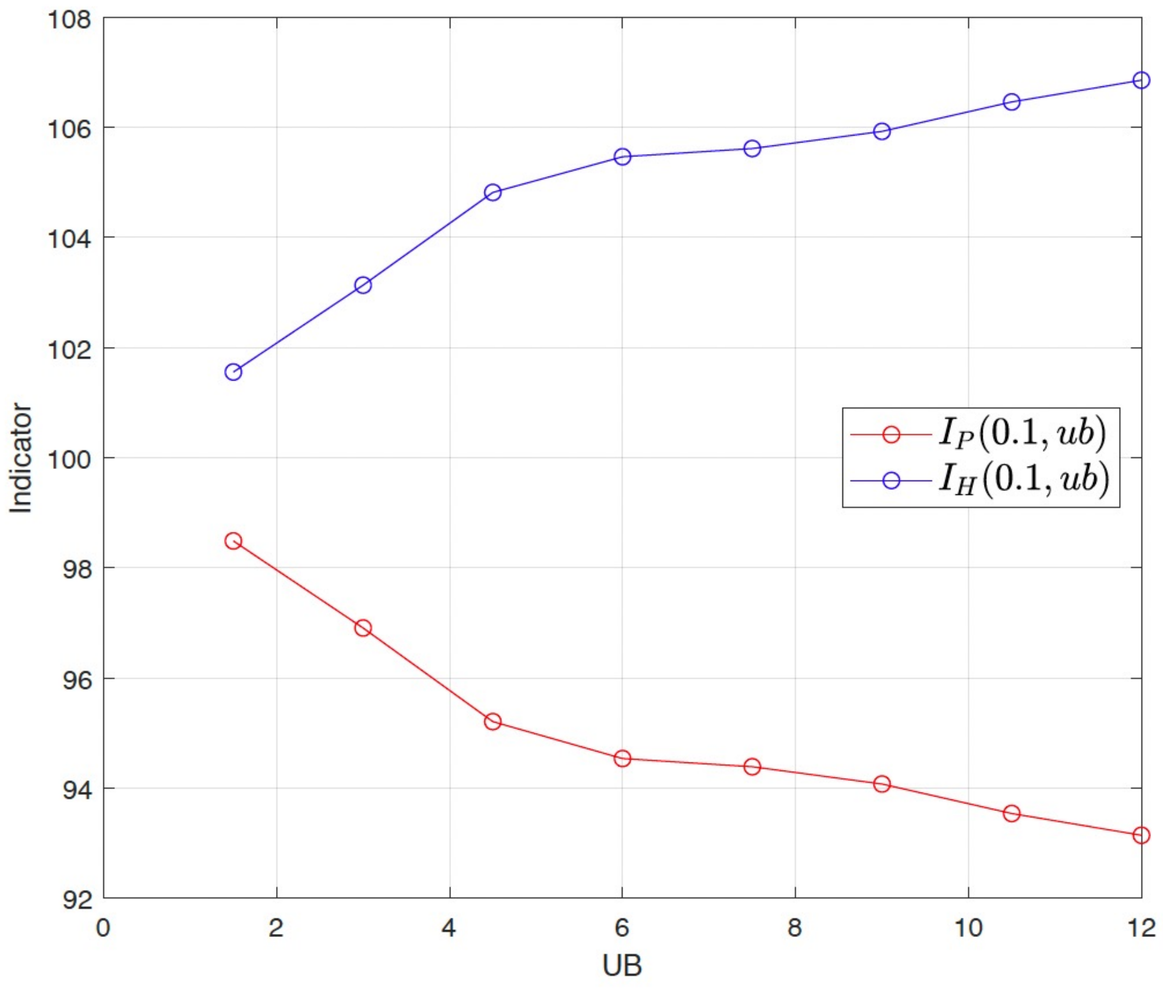


Figure 8. Indicators evolution for ub variations

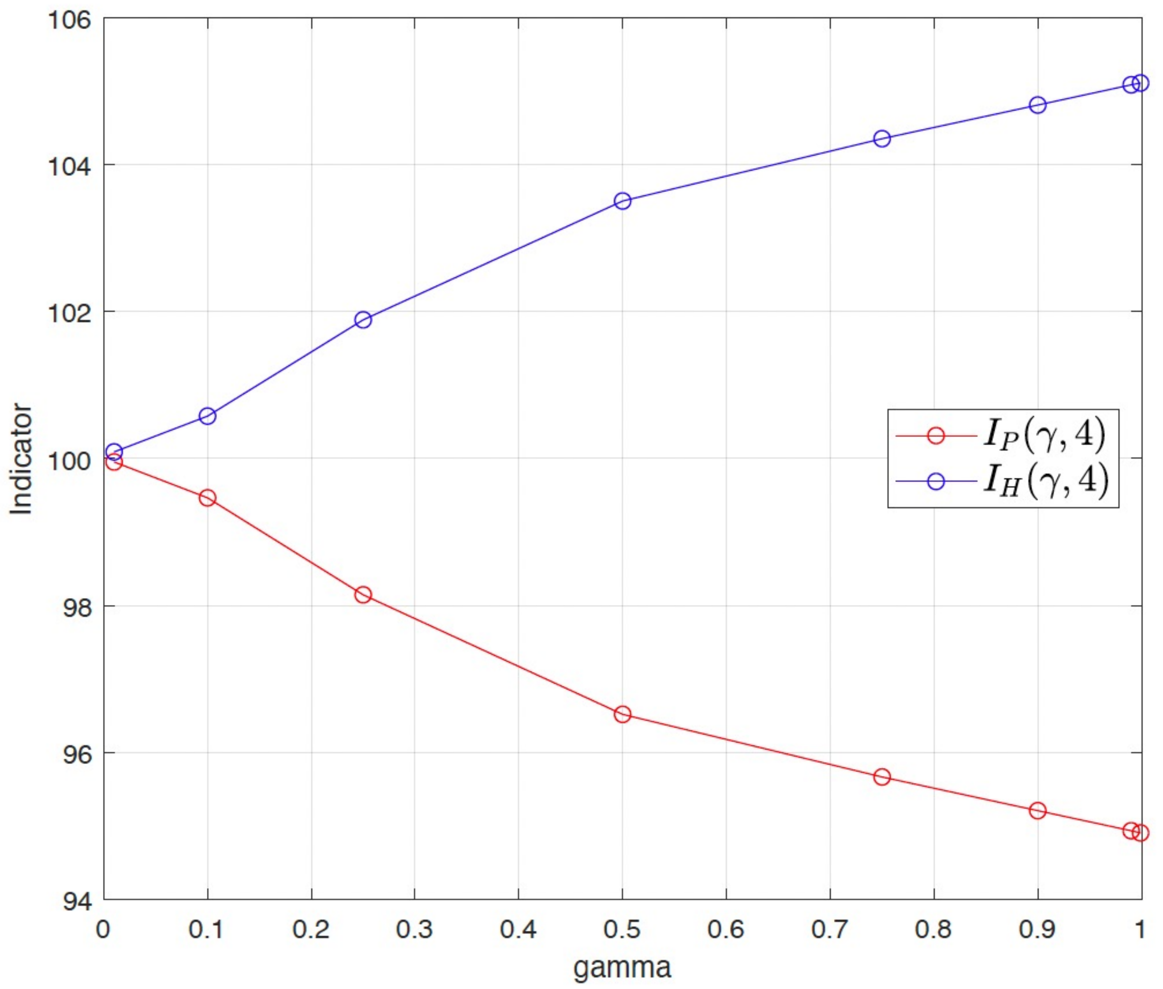
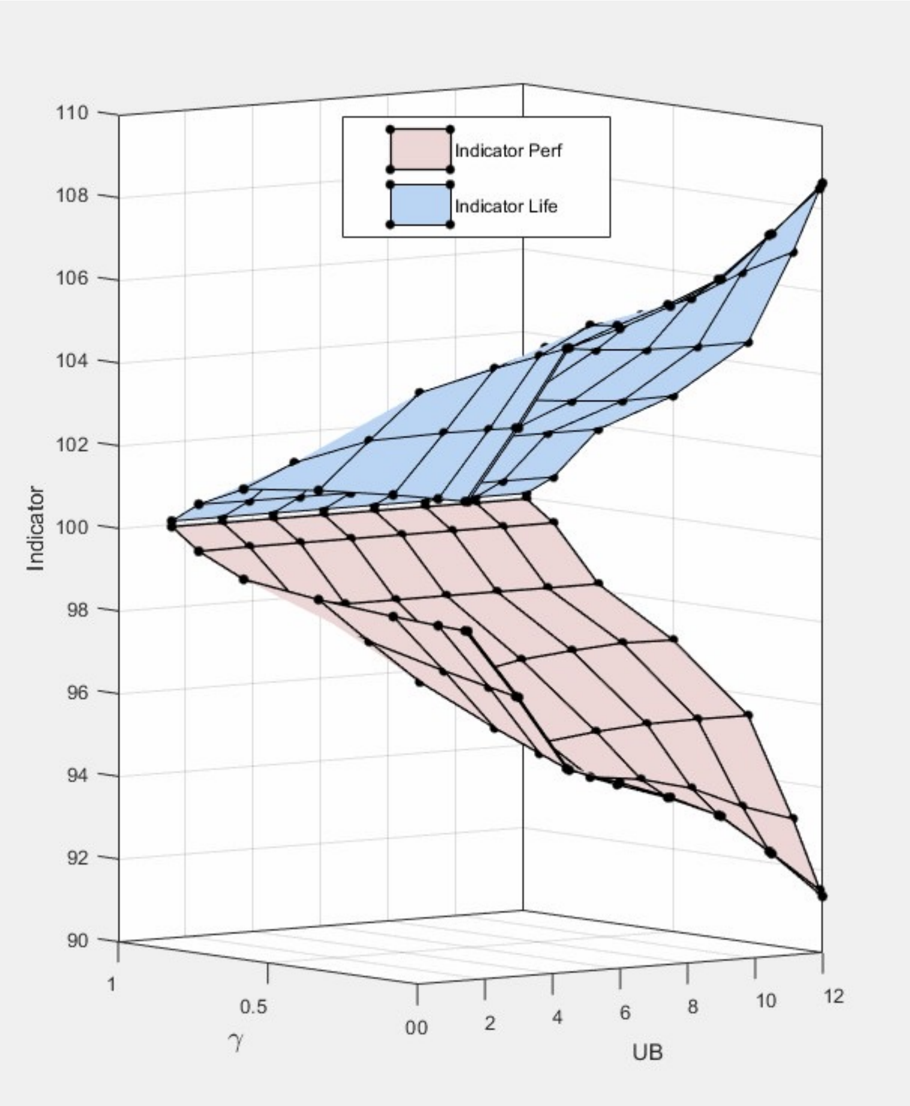


Figure 10. Indicators evolution for γ variations

Combinaison of both parameters



EXAMPLE 1 – ANAYSIS

Extension in seconds of system life for various combinaisons

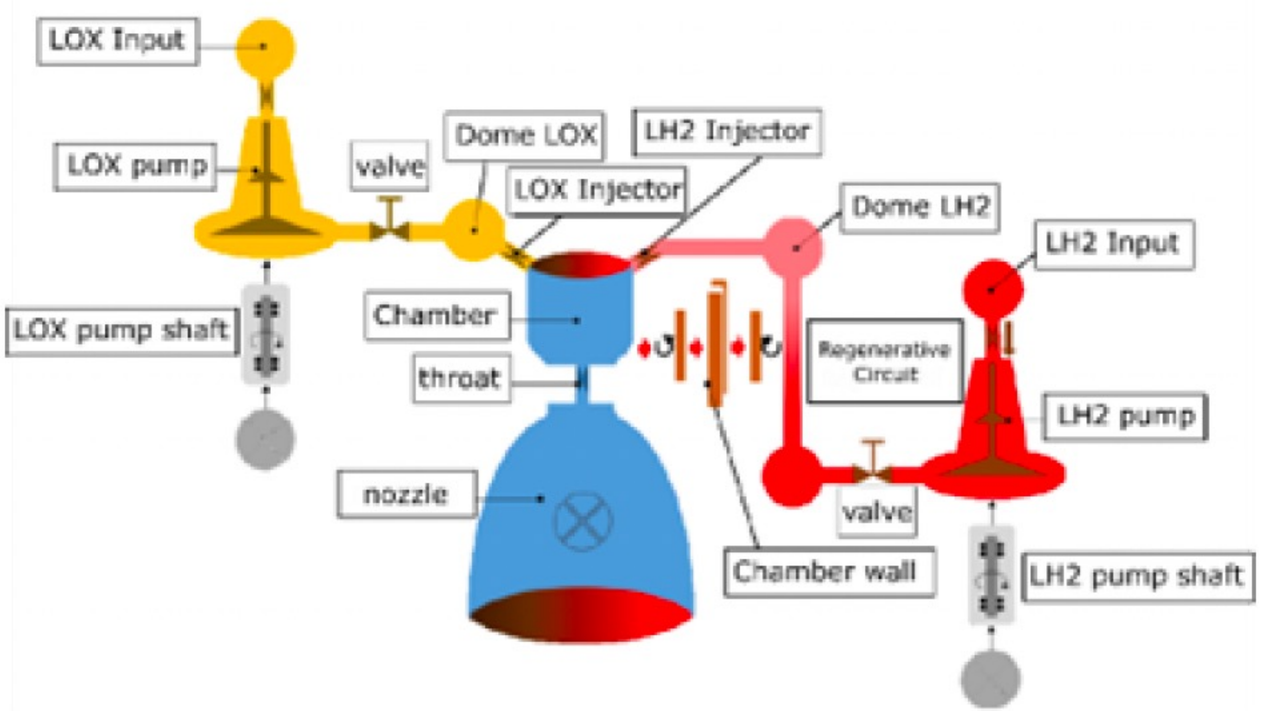
γ / UB	1.5	3,0	4.5	6,0	7.5	9,0	10.5	12,0
0.010	6.49	12.7	18.30	22.53	26.10	30.07	34.53	39.54
0.100	6.49	12.69	18.25	22.40	25.87	29.70	33.89	38.41
0.250	6.43	12.40	17.44	20.64	23.24	25.77	28.13	30.06
0.500	6.29	11.76	15.64	17.18	18.28	18.88	18.91	18.92
0.750	5.88	9.77	10,00	10,00	10,00	10,00	10,00	10,00
0.900	4.64	4.75	4.75	4.75	4.75	4.75	4.75	4.75
0.990	1.85	1.81	1.81	1.81	1.81	1.81	1.81	1.81
0.999	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17

Legen

<10s	<20s	<30s	<40s

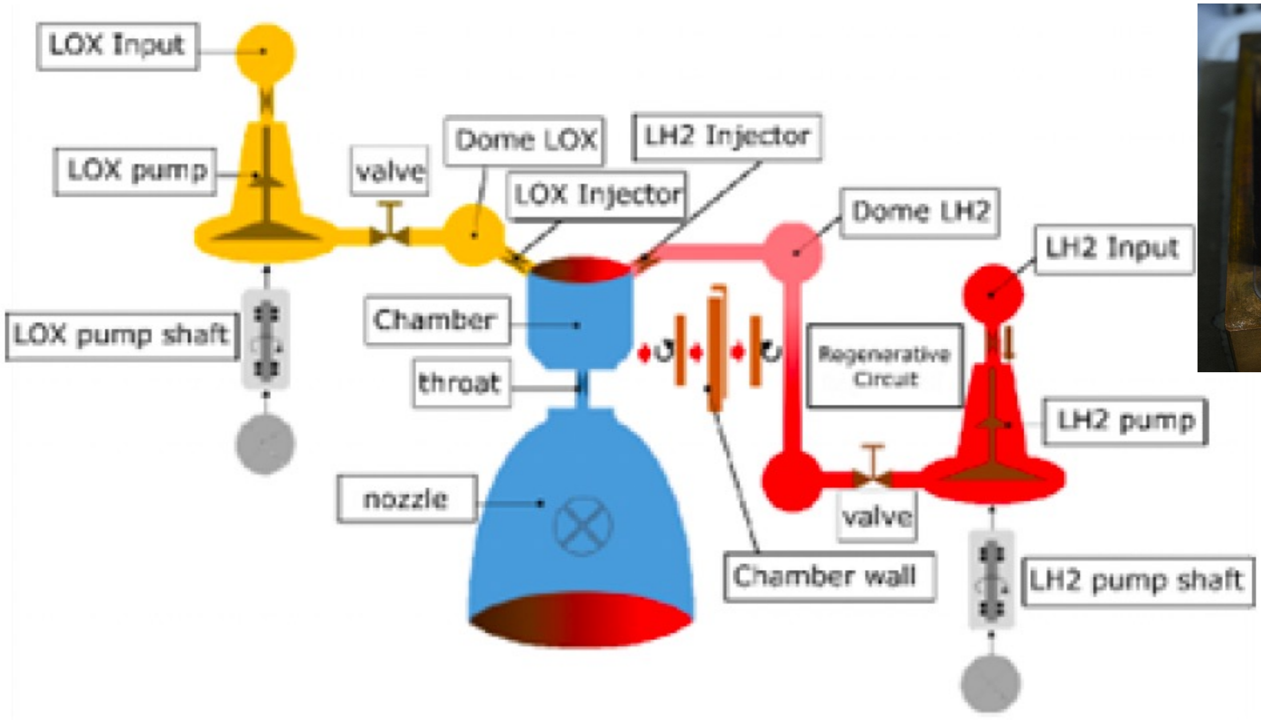
Note: The system without HAC fails after 443s.

REUSABLE LIQUID ROCKET ENGINE - RLRE

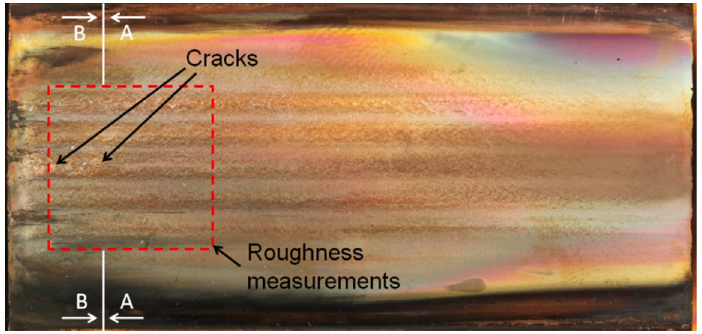


Simulation Engine: CNES RT-NT-2510000-CNES

RLRE - DEGRADATION



Degradation

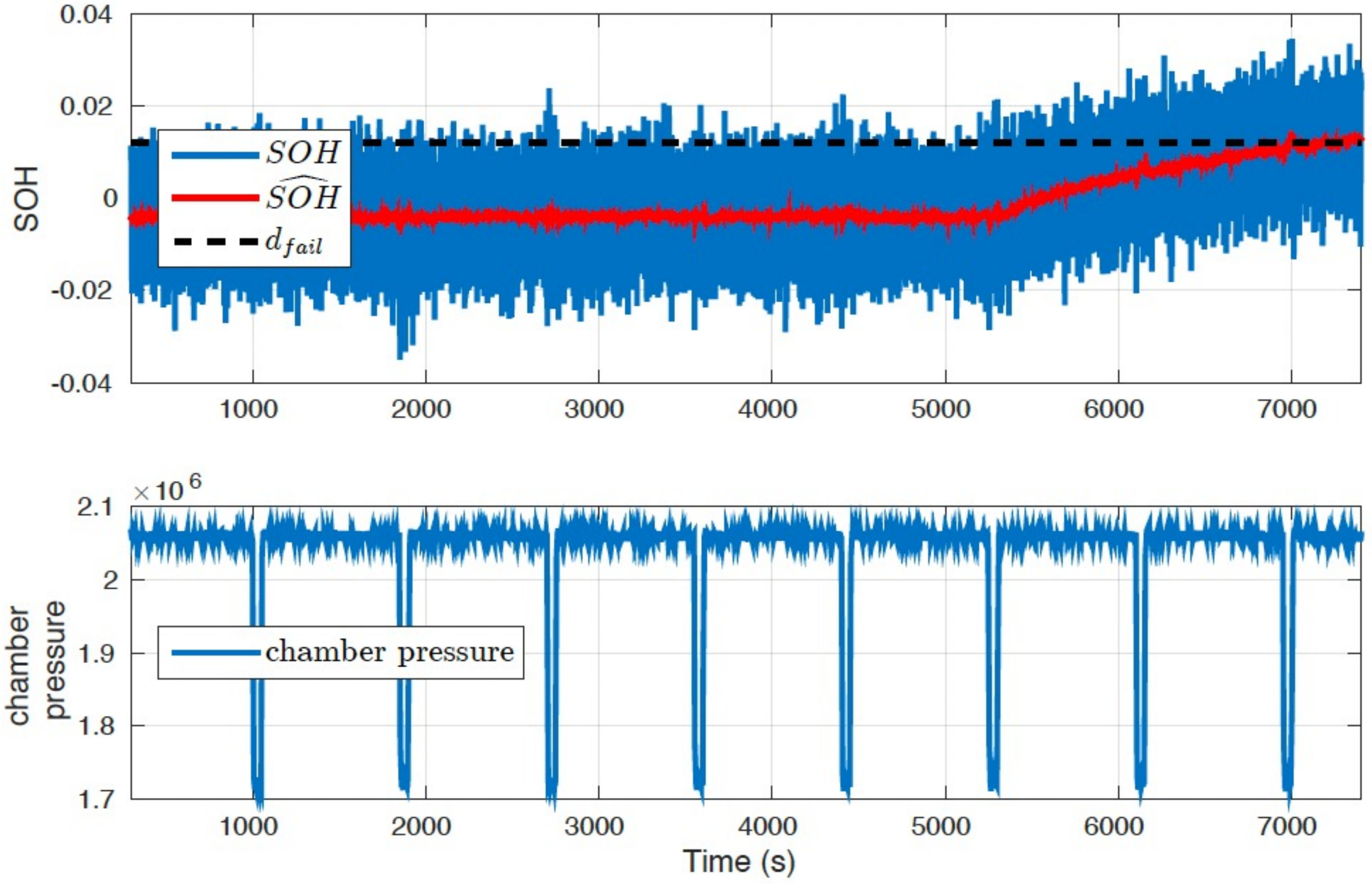


Hötte, F., Sethe, C. V., Fiedler, T., Haupt, M. C., Haidn, O. J., & Rohdenburg, M. (2020). Experimental lifetime study of regeneratively cooled rocket chamber walls. *International Journal of Fatigue*, *138*, 105649.

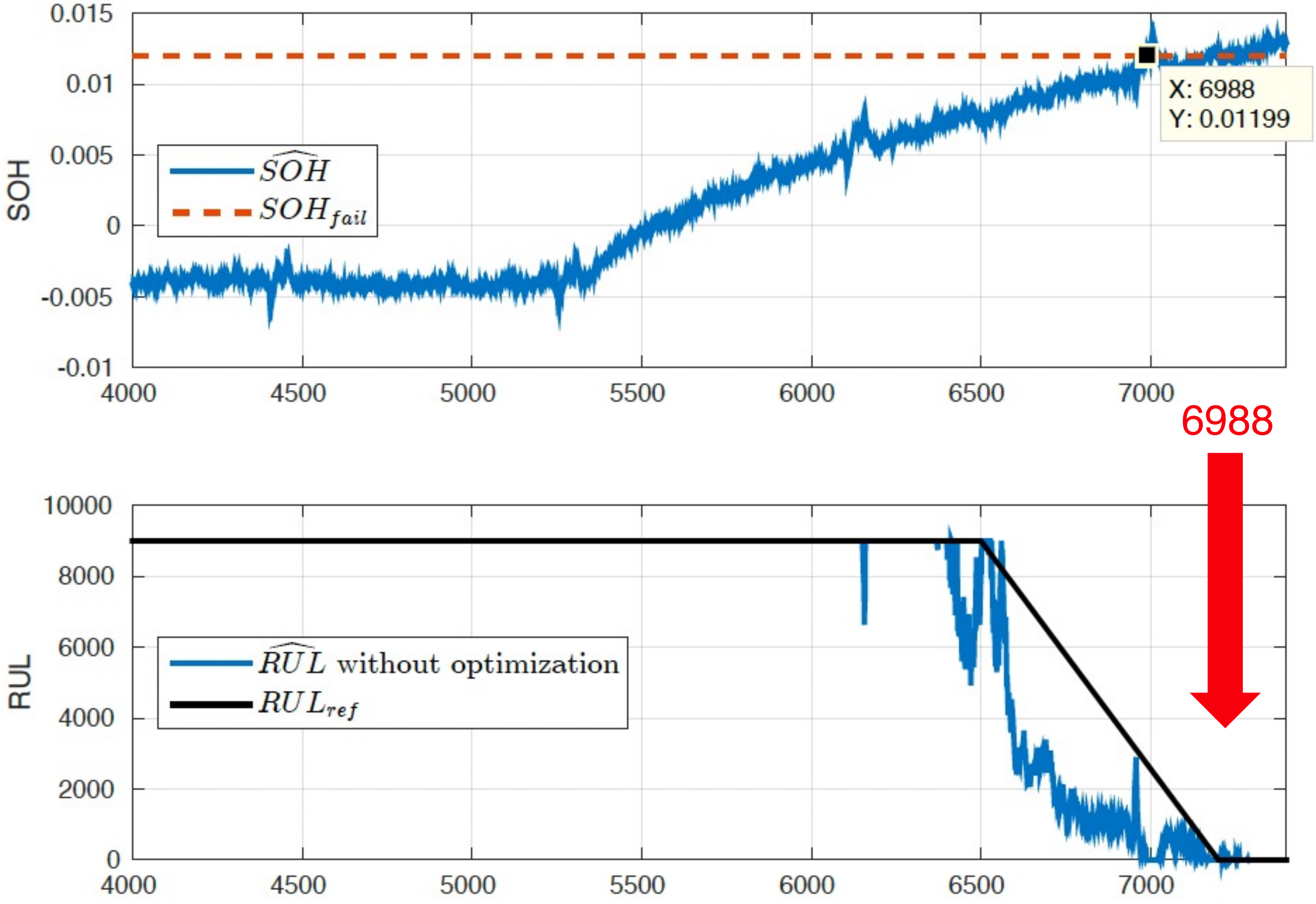
Degradation is the appearance of cracks in the combustion chamber.
This leads to fuel leaking from the regenerative circuit into the combustion chamber.

Leak will affect the efficiency on combustion and so the dynamic performance of the closed loop

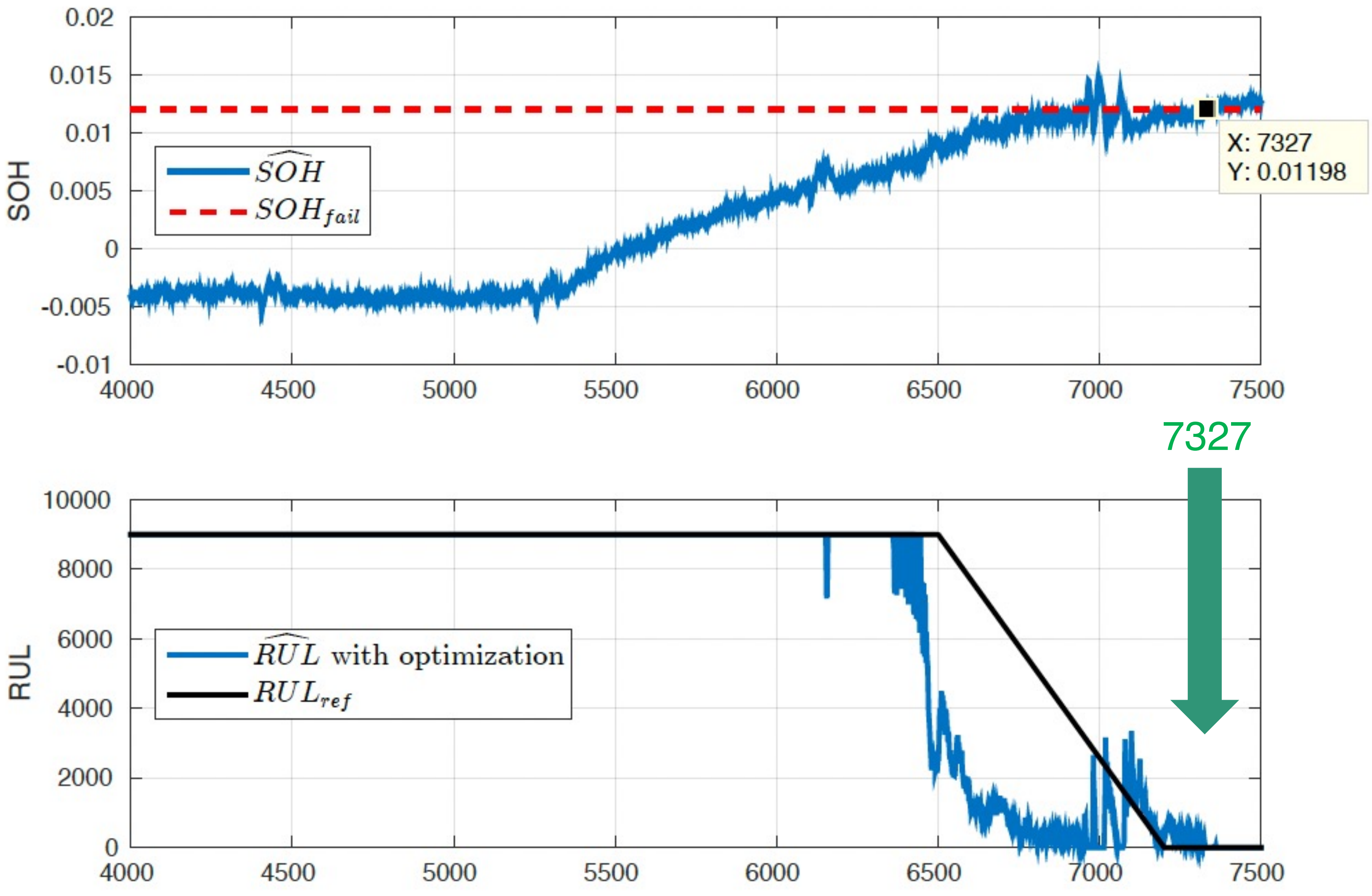
RLRE - DEGRADATION



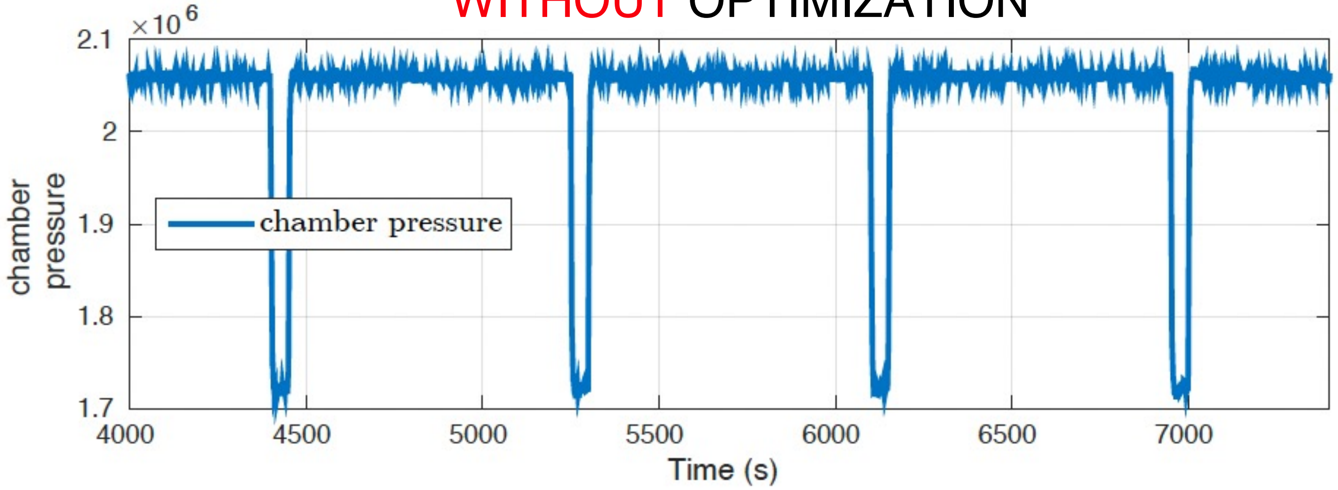
RLRE - WITHOUT OPTIMIZATION



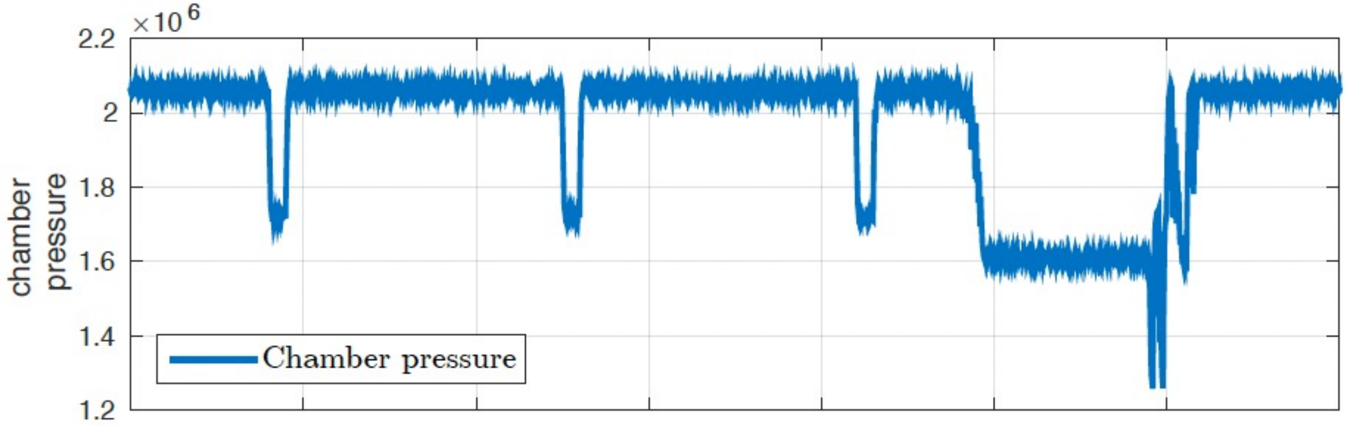
RLRE - WITH OPTIMIZATION



WITHOUT OPTIMIZATION



WITH OPTIMIZATION



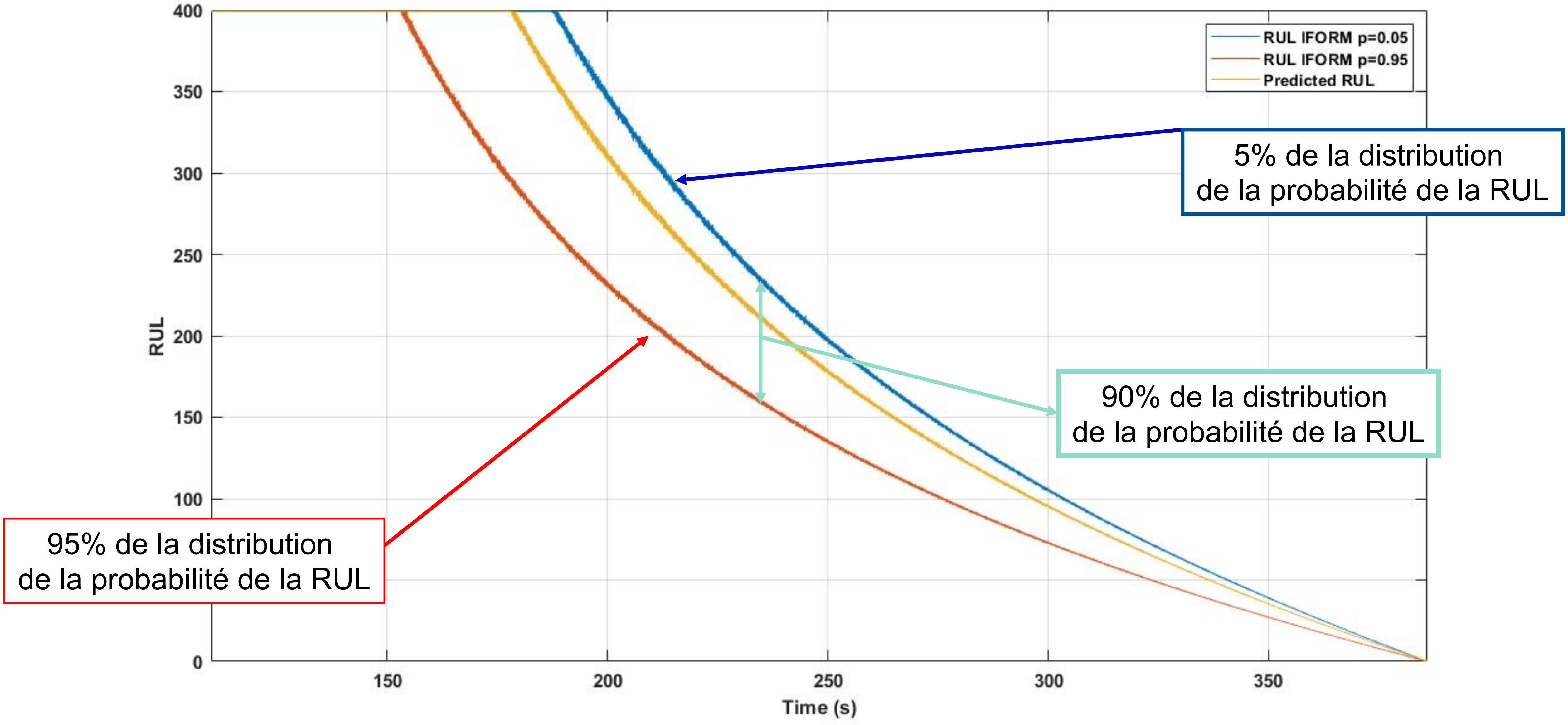
OUTLINES

- Introduction / Contexte
- Problem Statement
- Our Solution
- Illustrative Examples
- **Conclusions / Perspectives**

CONCLUSIONS

- **Trade-off between dynamic performance and RUL has been proposed**
- **Degradation model estimation**
- **FDI Robustness has been assumed**
- **Uncertainties on RUL estimation have been omitted**
- **…**

PERSPECTIVES – RUL with uncertainties



Assessing a Statistical and a Set-based Approach for Remaining Useful Life Prediction.

Khoury Boutrous[1]; Julien Thuillier[2]; Mayank Shekhar Jha[3]; Vicenc Puig[1] and Didier Theilliol[3] **.

MED 2023

[1] Research Center for Supervision, Safety, and Automatic Control (CS2AC), (UPC), Barcelona, Spain.

[2] Centre National d'Etudes Spatiales (CNES), France.

[3]Centre de Recherche en Automatique de Nancy (CRAN), Universite de Lorraine, France.

Prognostics aware control design for extended remaining useful life: Application to Liquid Propellant Reusable Rocket Engine

HAC Meeting 22th November 2023

Julien Thuillier, Mayank Shekhar Jha,
Sebastien Le Martelot, and Didier Theilliol