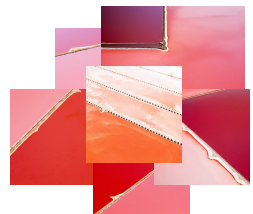


Safe Reinforcement Learning, Resilient/Fault Tolerant and Health Aware Control Strategies for Autonomous Systems

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<http://www.cran.univ-lorraine.fr>

Safe Reinforcement Learning, Resilient/Fault Tolerant and **Health Aware Control** Strategies for Autonomous Systems

Seminar on Health Aware Control !!!

Action



Health Aware Control Design in Dynamic Systems

Soumis par THEILLIOL le mer 15/03/2023 - 23:43

Initiateur [Didier THEILLIOL](#)

Porteur(s) [Mayank Shekhar JHA](#) [John Jairo MARTINEZ MOLINA](#) [Didier THEILLIOL](#) [Philippe Weber](#) [Christophe BERENGUER](#)

Type d'action [Création et animation d'une communauté scientifique](#)

November 22rd, 2023

Ensam, Le Cnam

Arts et Métiers, Ensam, Paris

151, boulevard de l'Hôpital,

75013, Paris

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 Dr. R. Schacht Rodríguez (Mexique)
 Dr. J.A. Vazquez (Mexique)
 Prof. P. Weber (France)
 Prof. Y. Zhang (Canada)

Experimental platform from:



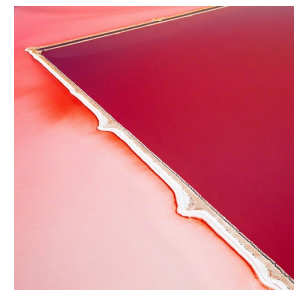
Shenyang Institute
of Automation - RPC



(*) alphabetic order

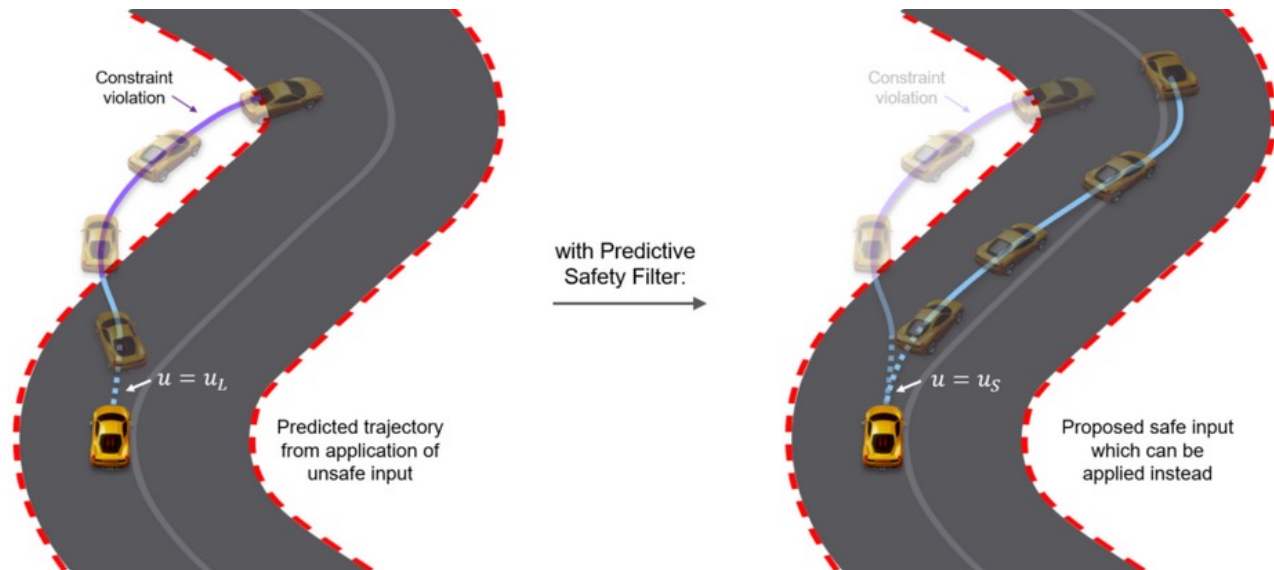
OUTLINES

Context



Safe Unmanned Vehicles

Motivations: Ensure safety



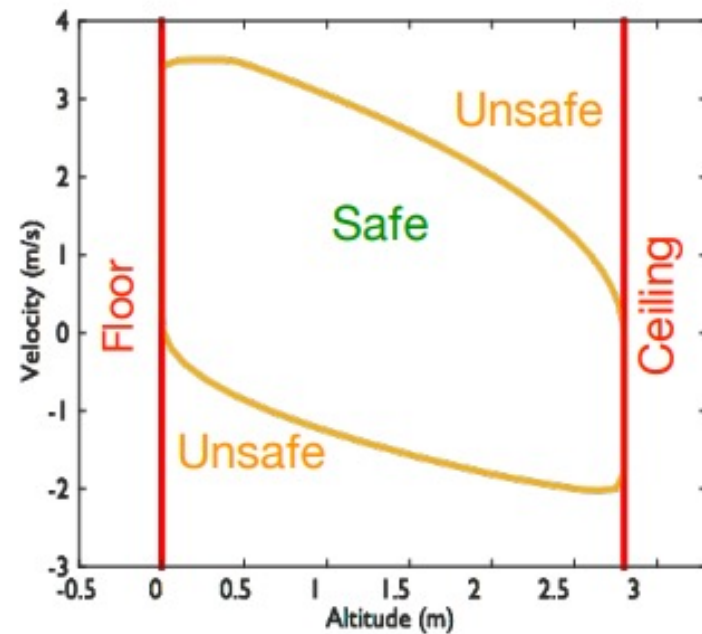
Wabersich, K. P., & Zeilinger, M. N. (2021). A predictive safety filter for learning-based control of constrained nonlinear dynamical systems. *Automatica*, 129, 109597.

Safe Unmanned Vehicles

Motivations: Ensure safety



$$x_{k+1} = f(x_k, u_k) + d(\bullet)$$

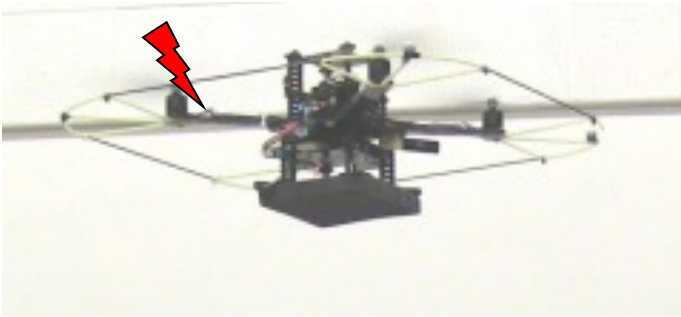


Gillula, J. H., & Tomlin, C. J. (2012, May). Guaranteed safe online learning via reachability: tracking a ground target using a quadrotor. In *2012 IEEE ICRA* (pp. 2723-2730). IEEE.

Safe Unmanned Vehicles

Motivations:

Ensure operational safety



 **Fault / Degradation/ Failure**

Scope... IFAC TC 6.1. SAFEPROCESS



International Federation of Automatic Control

“Complex systems are vulnerable to **faults or failures** such as defects in components and/or instruments or in controllers or in control loop. **Faults or failures** can cause undesired reactions, consequences as damage to technical parts of the plant, to human life, to the environment and great significance of the vested economic value....”

Scope... IFAC TC 6.1. SAFEPROCESS



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Sensor or actuator failure, equipment fouling, feedstock variations, may affect controller performance and as many as 60% of industrial controllers problem [*] .

[*] Harris, T. J., Seppala, C., and Desborough, L. D., *A review of performance monitoring and assessment techniques for univariate and multivariate control systems*. Journal Process of Control 9, 1-17 (1999)

Dependability Norms

IEC 60812 Analysis techniques for system reliability - Procedure for failure mode and effects analysis (FMEA)

IEC 60863 Presentation of reliability, maintainability and availability predictions

IEC 61014 Programmes for reliability growth

IEC 61025 Fault tree analysis (FTA)

IEC 61070 Compliance test procedures for steady-state availability

IEC 61078 Analysis techniques for dependability - Reliability block diagram method

IEC 61123 Reliability testing - Compliance test plans for success ratio

IEC 61124 Reliability testing - Compliance tests for constant failure rate and constant failure intensity

IEC 61164 Reliability growth - Statistical test and estimation methods

IEC 61165 Application of Markov techniques

IEC 61508 Functional Safety of Electrical/Electronic/Programmable Electronic Safety-related Systems

IEC 61703 Mathematical expressions for reliability, availability, maintainability and maintenance support terms

IEC 61709 Electronic components - Reliability - Reference conditions for failure rates and stress models for conversion

...

Scope... IFAC TC 6.1. SAFEPROCESS



International Federation of Automatic Control

“

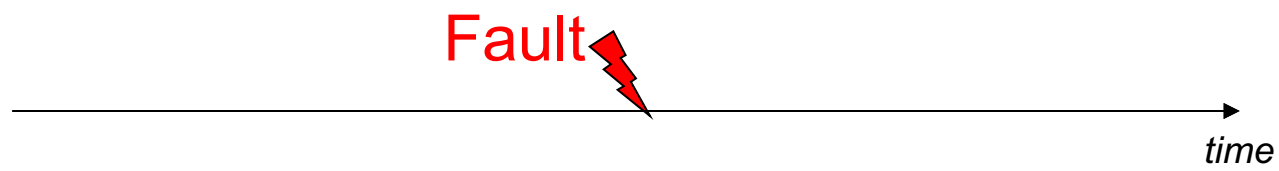
The main objective of the **Fault Detection and Isolation (FDI)** research area, widely addressed from several points of view in the last years, is to study methodologies for identifying and exactly characterizing possible incipient faults arising in predetermined parts of the plant. After accurate diagnosis, the next natural step is to design new control law in order to tolerate the fault, namely to guarantee pre-specified performances for the faulty system. This is the main aim of a **Fault Tolerant Control (FTC)** system.”

FTC as industrial standards and guidelines ?

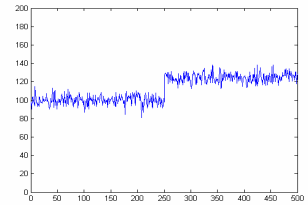
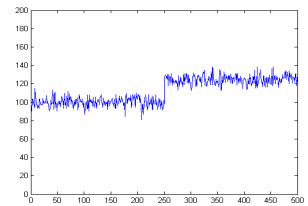
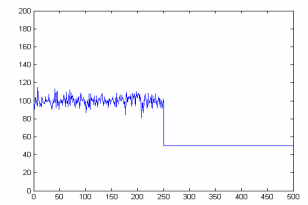
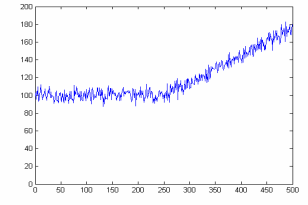
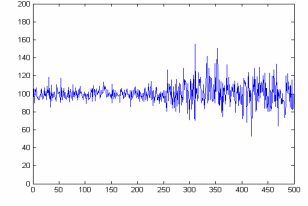
[*] « A series of industrial safety standards and guidelines have been issued for the safety of industrial processes. International standard IEC 61508 (IEC, 2010) « **IEC 61508 Functional Safety of Electrical/Electronic/Programmable Electronic Safety-related Systems** » is a general standard for design, construction, and operation of safety related systems, from which more specific sets of safety standards are developed for various industrial fields. For instance, IEC 62061 (IEC, 2005), IEC 61513 (IEC, 2011), and IEC 62425 (IEC, 2007) are industrial standards especially for machinery systems, NPPs, and railway signaling systems, respectively. In avionics industry, a series of guidelines for the design and manufacture of airplanes has also been issued (RTCA, 1992, 2000; SAE, 1996). **One needs to follow the industrial rules, regulations, and standards when designing an active FTC.**»

[*] X. Yu and J. Jiang A survey of fault-tolerant controllers based on safety-related issues, Annual Reviews in Control , 2016

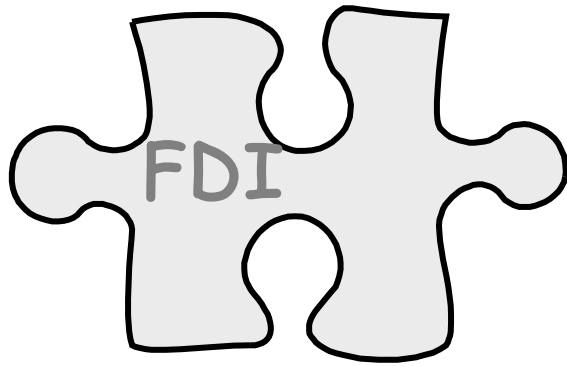
Context and aim



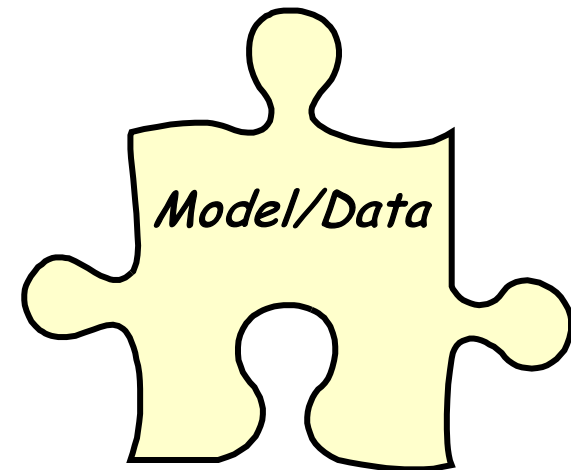
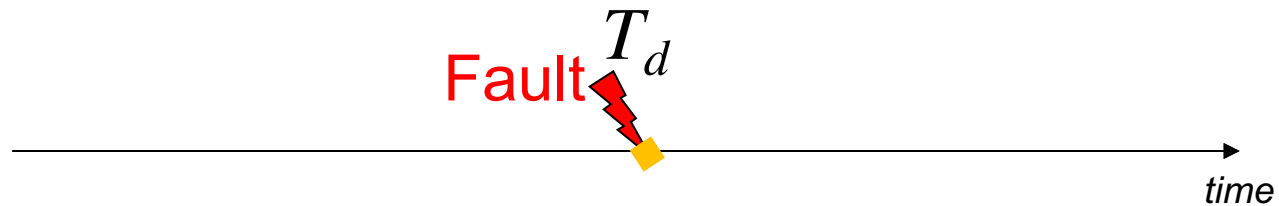
Fault/ Degradation/ Failure

Fault	Equation	Cause	Effect	Graph
Bias	$Y_i(t) = Y_i^*(t) + \varepsilon_i(t) + \alpha \Gamma_\theta$ $\alpha = \text{constant } t \text{ value}$ $\Gamma_\theta = \begin{cases} 0, & t < \theta \\ 1, & t \geq \theta \end{cases}$ the Heavisides function	<ul style="list-style-type: none"> Decalibration 	Jump in the mean value	 <p>The graph shows a noisy signal that starts at a mean value of approximately 100. At t=250, the signal jumps to a new mean value of approximately 120 and continues with the same level of noise until t=500.</p>
Gain modification	$Y_i(t) = \alpha \Gamma_\theta Y_i^*(t) + \varepsilon_i(t)$	<ul style="list-style-type: none"> Decalibration 	Jump in the mean value	 <p>The graph shows a noisy signal that starts at a mean value of approximately 100. At t=250, the signal jumps to a new mean value of approximately 120 and continues with the same level of noise until t=500.</p>
Total breakdown	$Y_i(t) = (1 - \Gamma_\theta) [Y_i^*(t) + \varepsilon_i(t)] + k$ $k \in \{Y_{min}, 0, Y_{max}\}$	<ul style="list-style-type: none"> Destruction of the sensor Disconnection of an electrical signal 	Signal constant, zero or min/max	 <p>The graph shows a noisy signal that starts at a mean value of approximately 100. At t=250, the signal drops to zero and remains constant at zero until t=500.</p>
Offset drift Bias drift	$Y_i(t) = Y_i^*(t) + \varepsilon_i(t) + \alpha r_{\theta,t} \Gamma_\theta$ $r_{\theta,t} = \begin{cases} 0 & , t < \theta \\ t - \theta & , t \geq \theta \end{cases}$	<ul style="list-style-type: none"> Ageing Slow destruction of the sensor Temperature drift 	Signal slowly deviates from the true value	 <p>The graph shows a noisy signal that starts at a mean value of approximately 100. At t=250, the signal begins to slowly deviate from the true value, showing a clear upward trend until t=500.</p>
Increased noise	$Y_i(t) = Y_i^*(t) + \varepsilon_i(t) + [\eta_i(t) - \varepsilon_i(t)] \Gamma_\theta$ $\eta_i = \text{increased noise standard deviation}$	<ul style="list-style-type: none"> Electro-magnetic disturbance Loss of screening Disconnection of the ground signal 	Small signal to noise ratio	 <p>The graph shows a noisy signal that starts at a mean value of approximately 100. At t=250, the signal becomes significantly noisier, with the noise level increasing and the signal-to-noise ratio decreasing until t=500.</p>

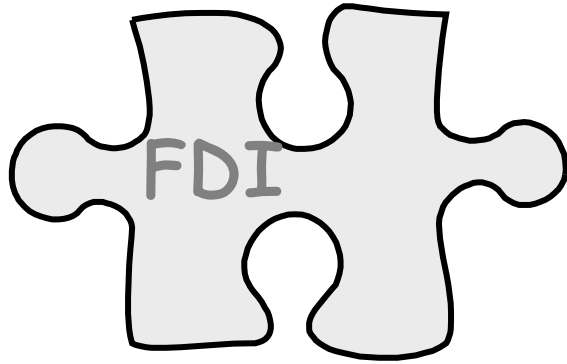
Context and aim



T_d represents time to detect, isolate and to estimate



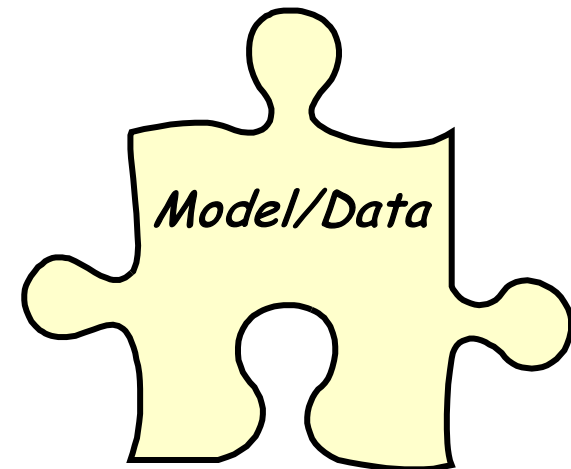
Context and aim



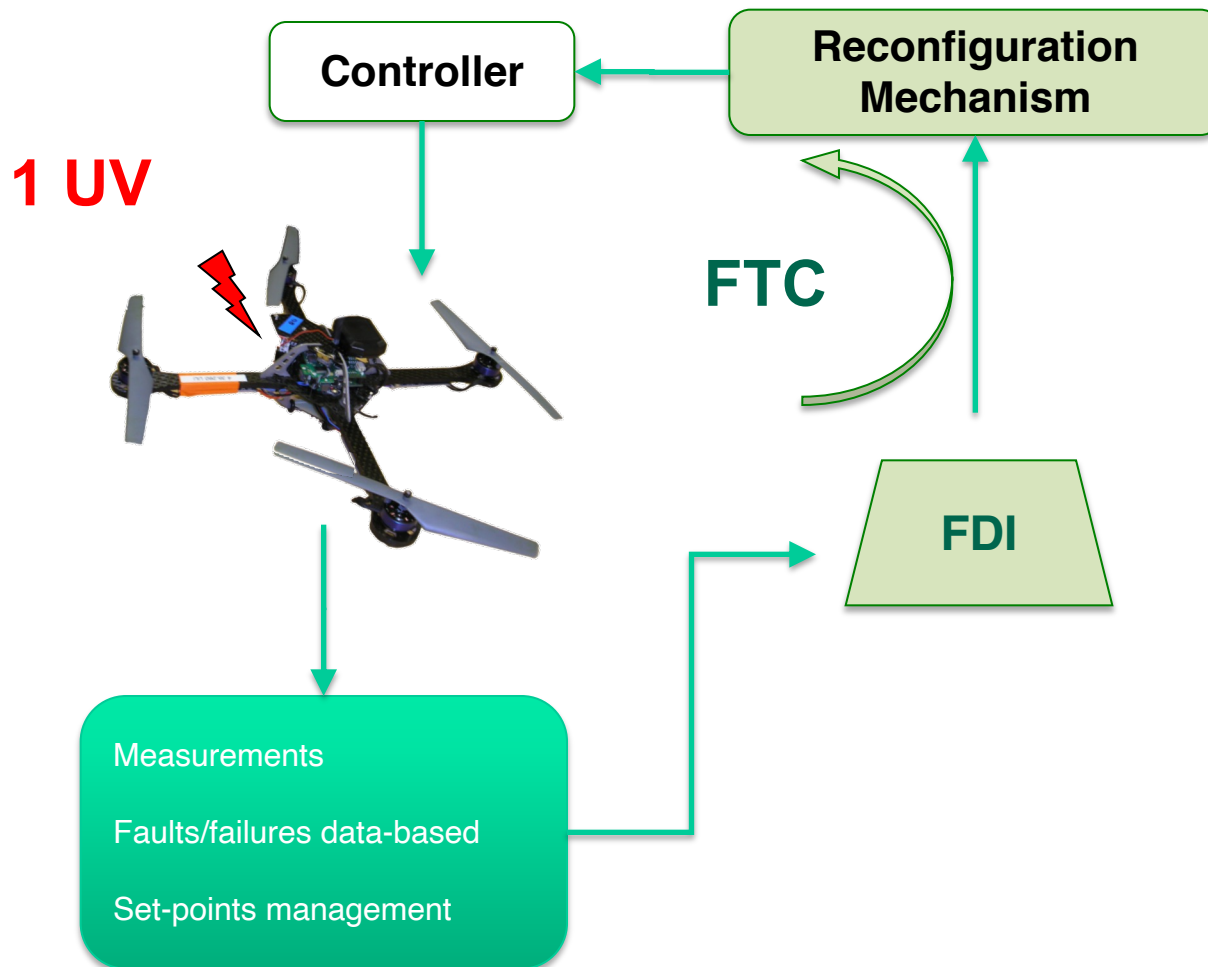
Fault T_r



T_r represents time to reconfigure

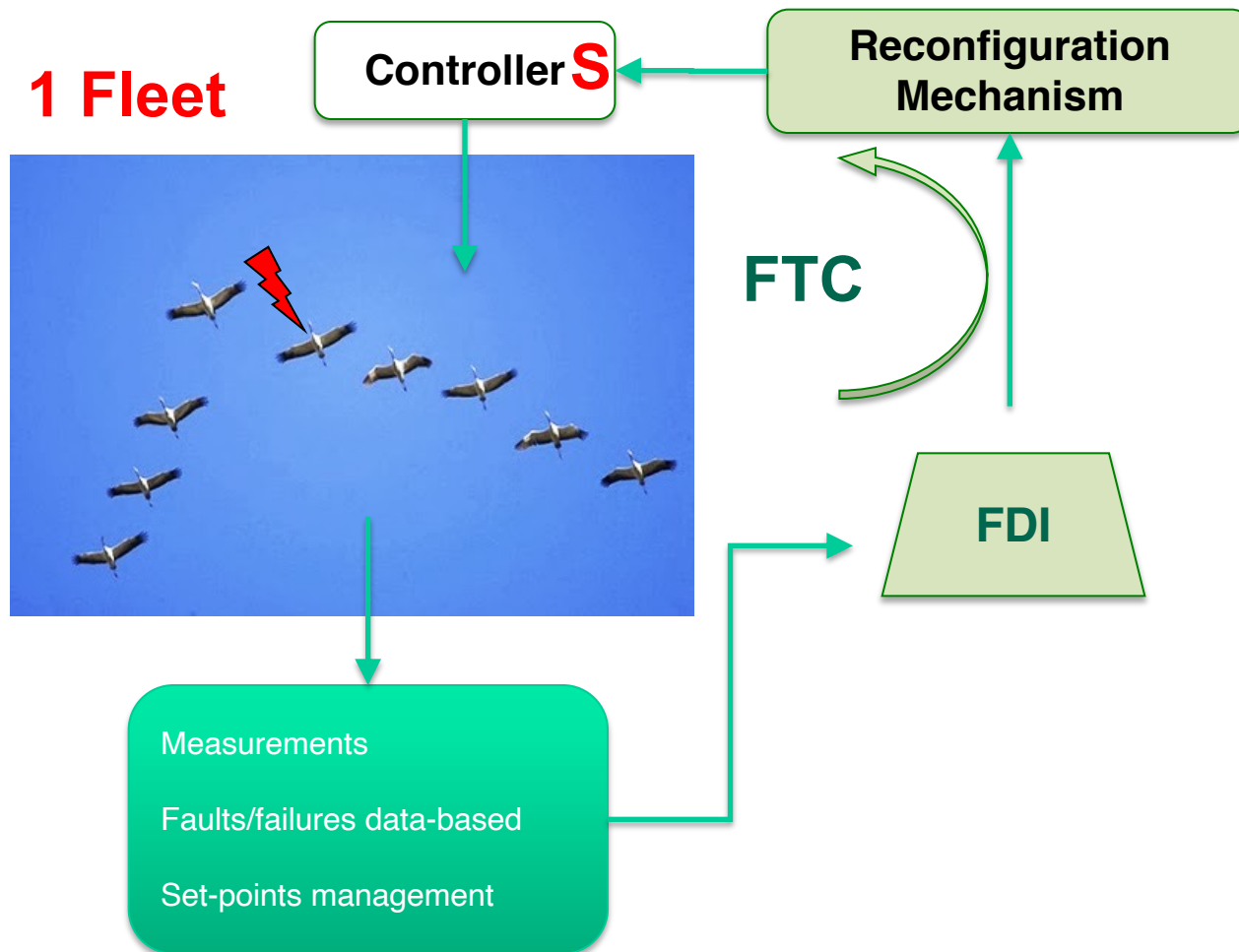


FDI / FTC & Prognosis Health Management



FDI / FTC & Prognosis Health Management

Multi Agent System (Consensus...)



FDI / FTC & Prognosis Health Management

Multi Agent System (Consensus...)

1 Fleet

Controller S

**Reconfiguration
Mechanism**

FTC

FDI

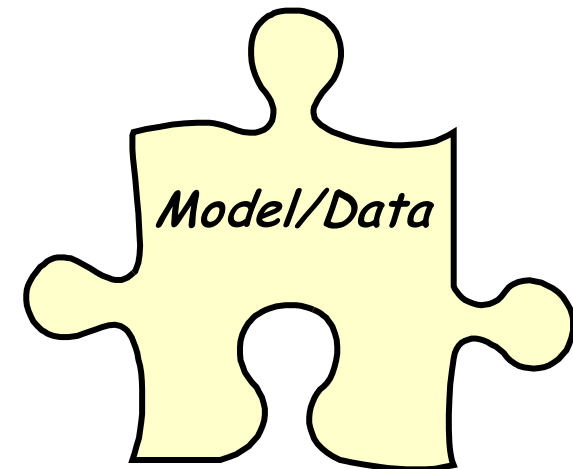
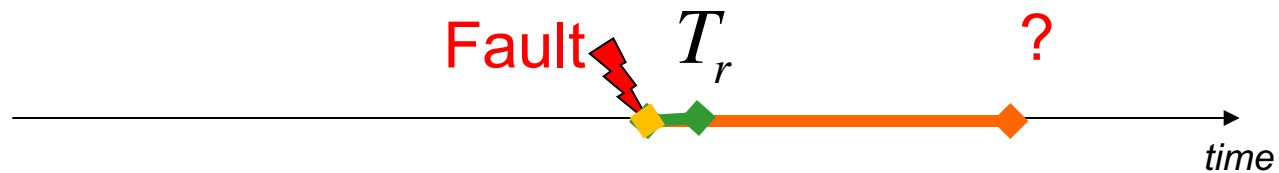
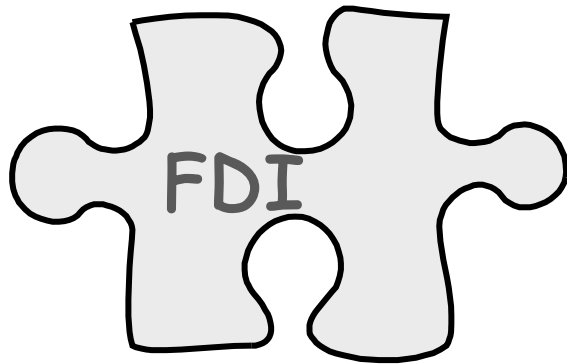
Measurements

Faults/failures data-based

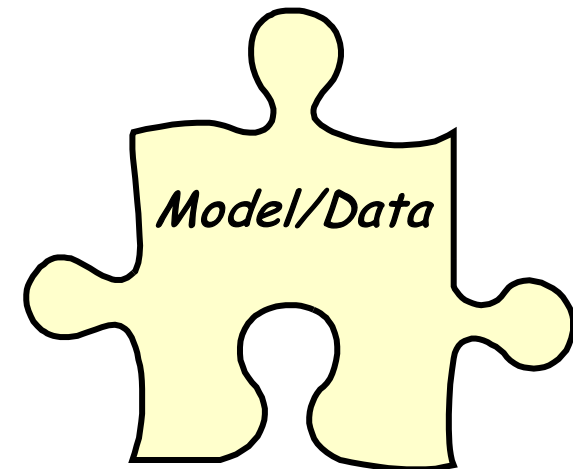
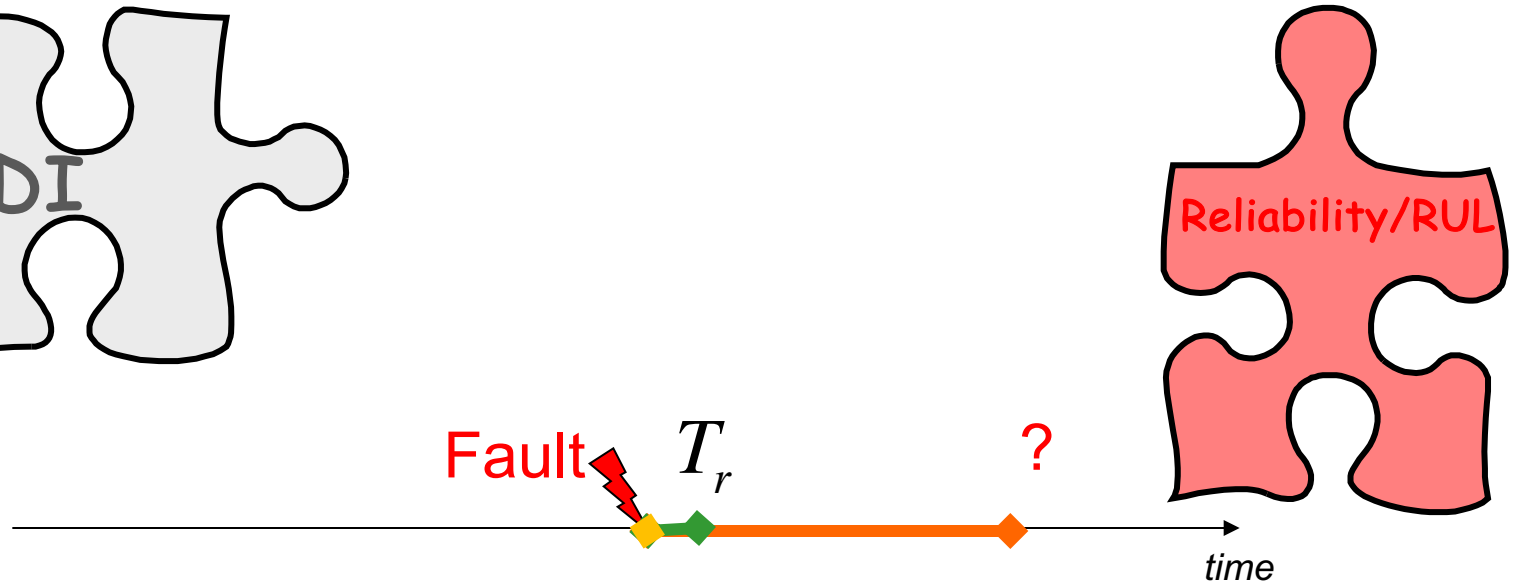
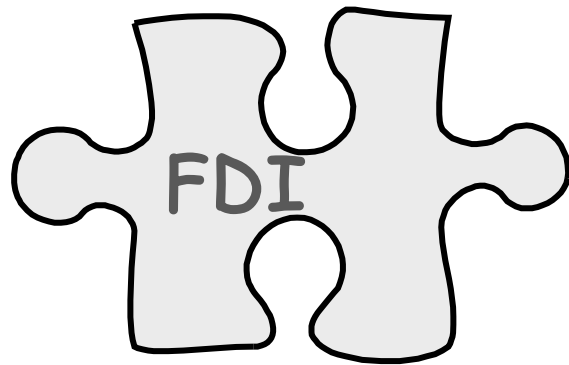
Set-points management

**Research Activities NOT
Presented during this Plenary**

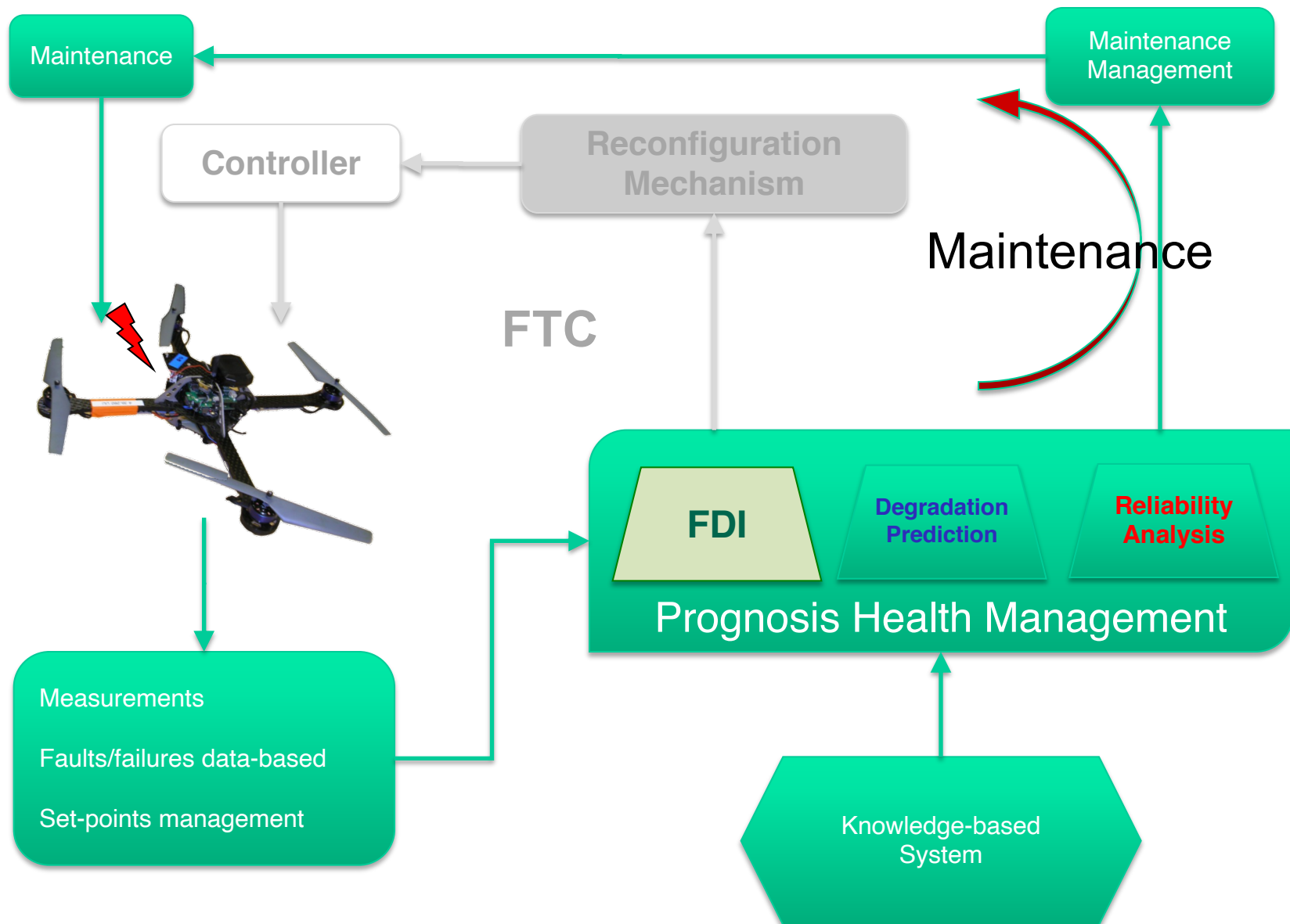
Diagnosis and



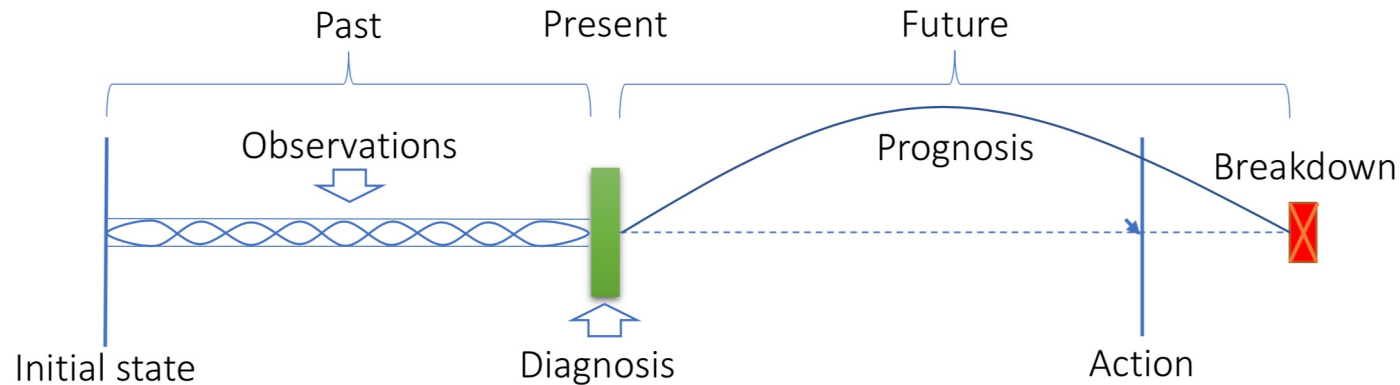
Diagnosis and Prognosis



FDI / FTC & Prognosis Health Management

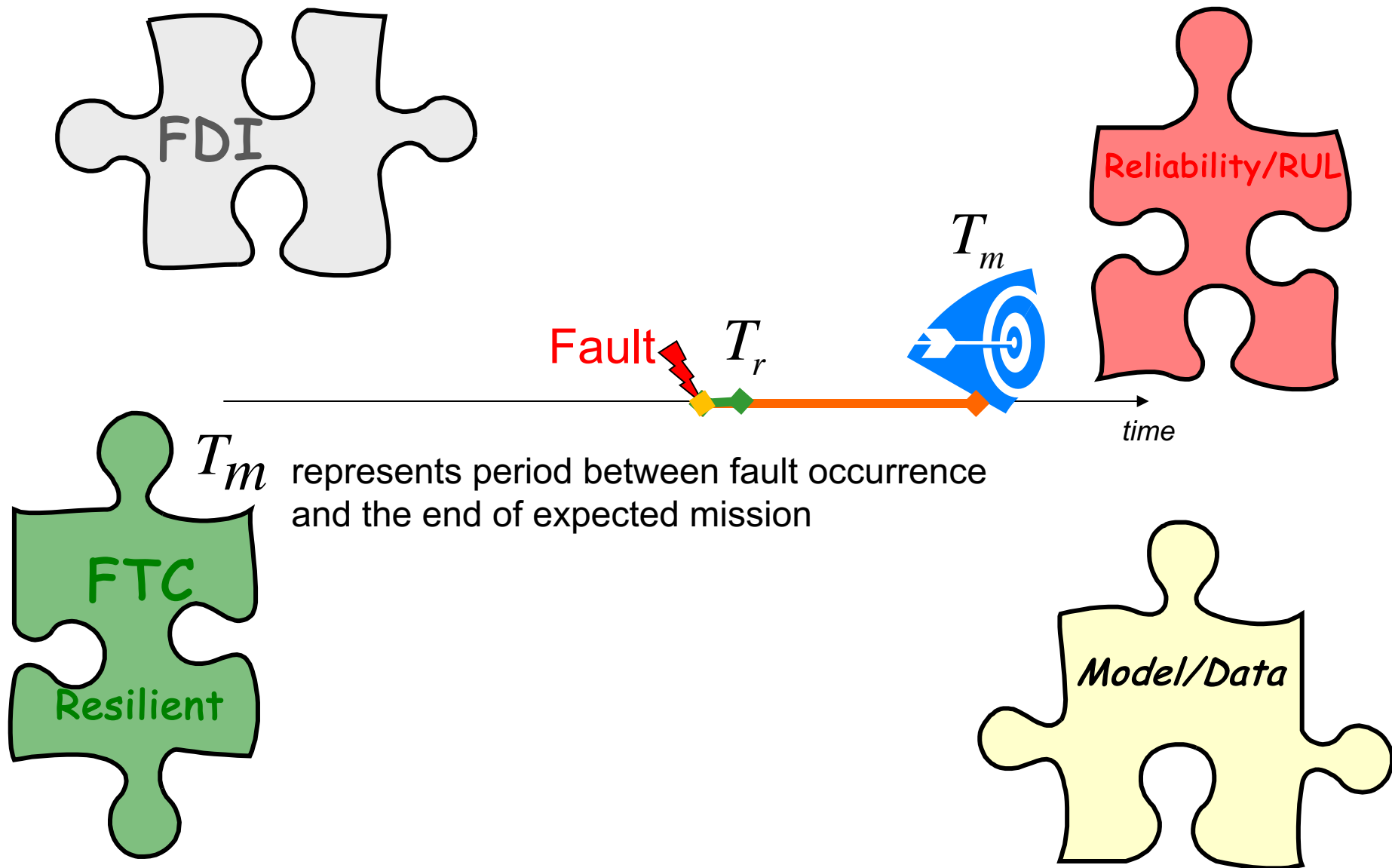


Diagnosis (FDI) & Prognosis

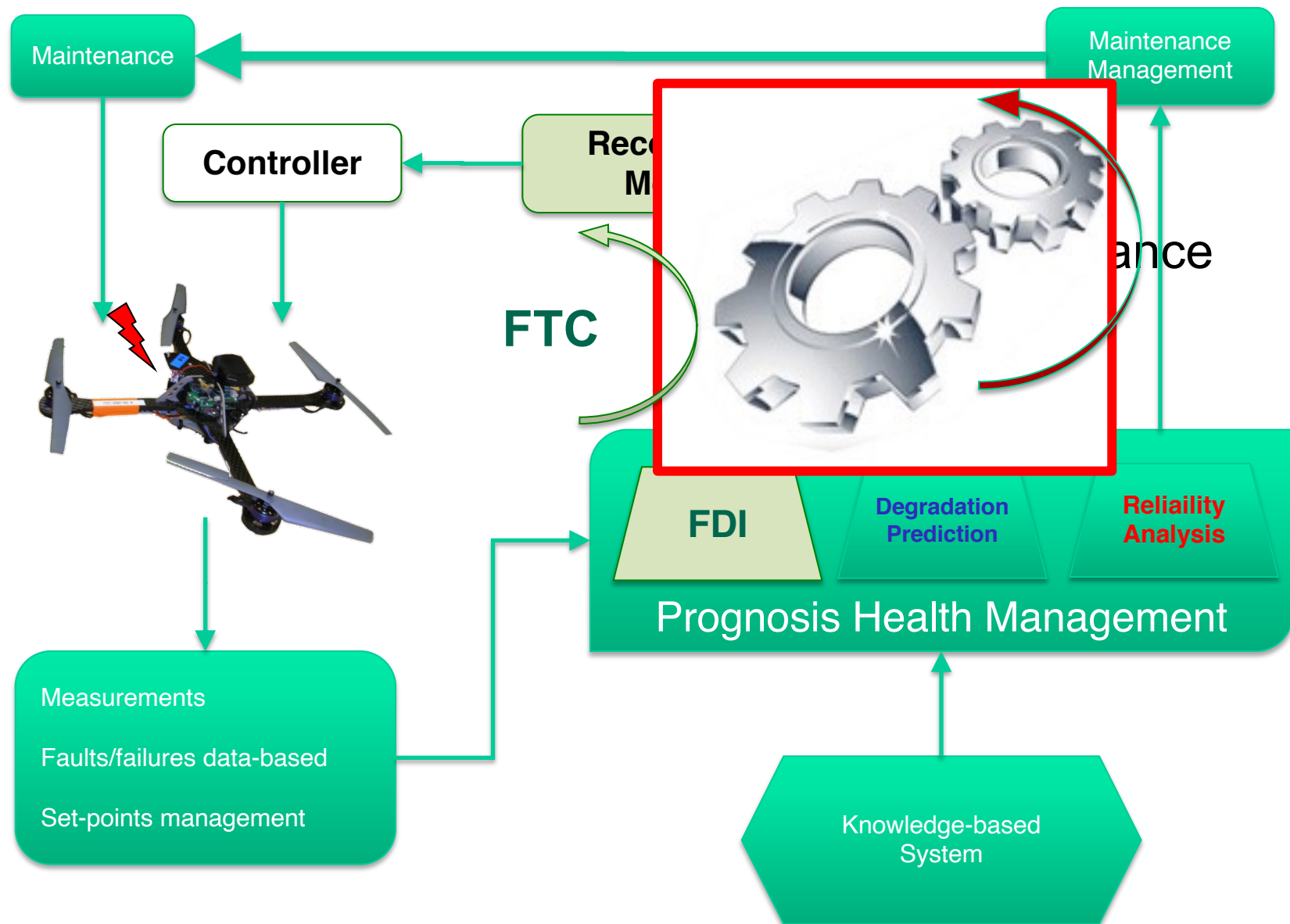


- Initial state: State distribution at the beginning.
- Observations: Extracted data from sensors on the complex system.
- Diagnosis: Identifying the current hidden health state of the system based on observations.
- Prognosis: prediction of the future health evolution of the system considering operating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

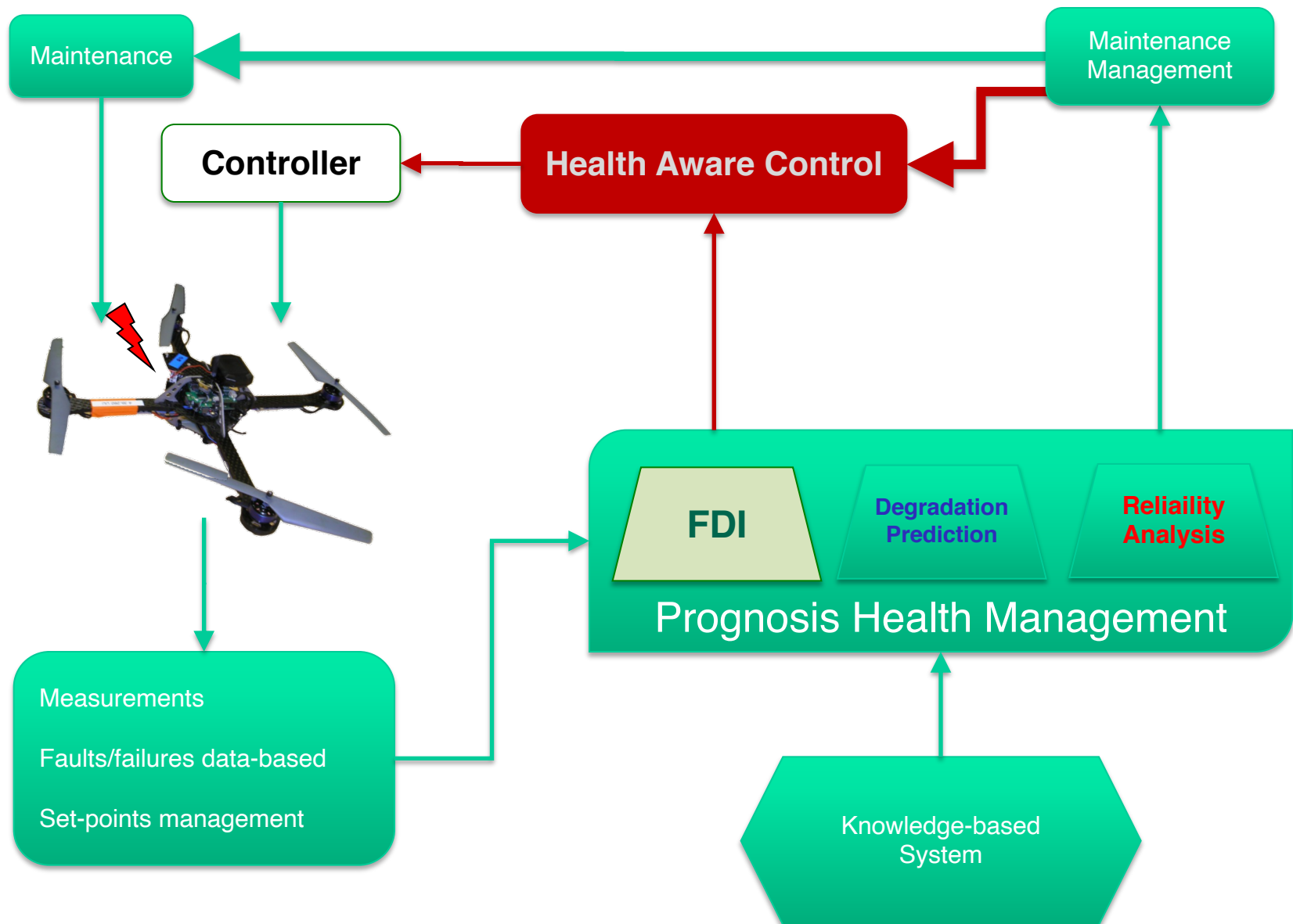
Consider prognosis in the closed-loop ... Why not !!!



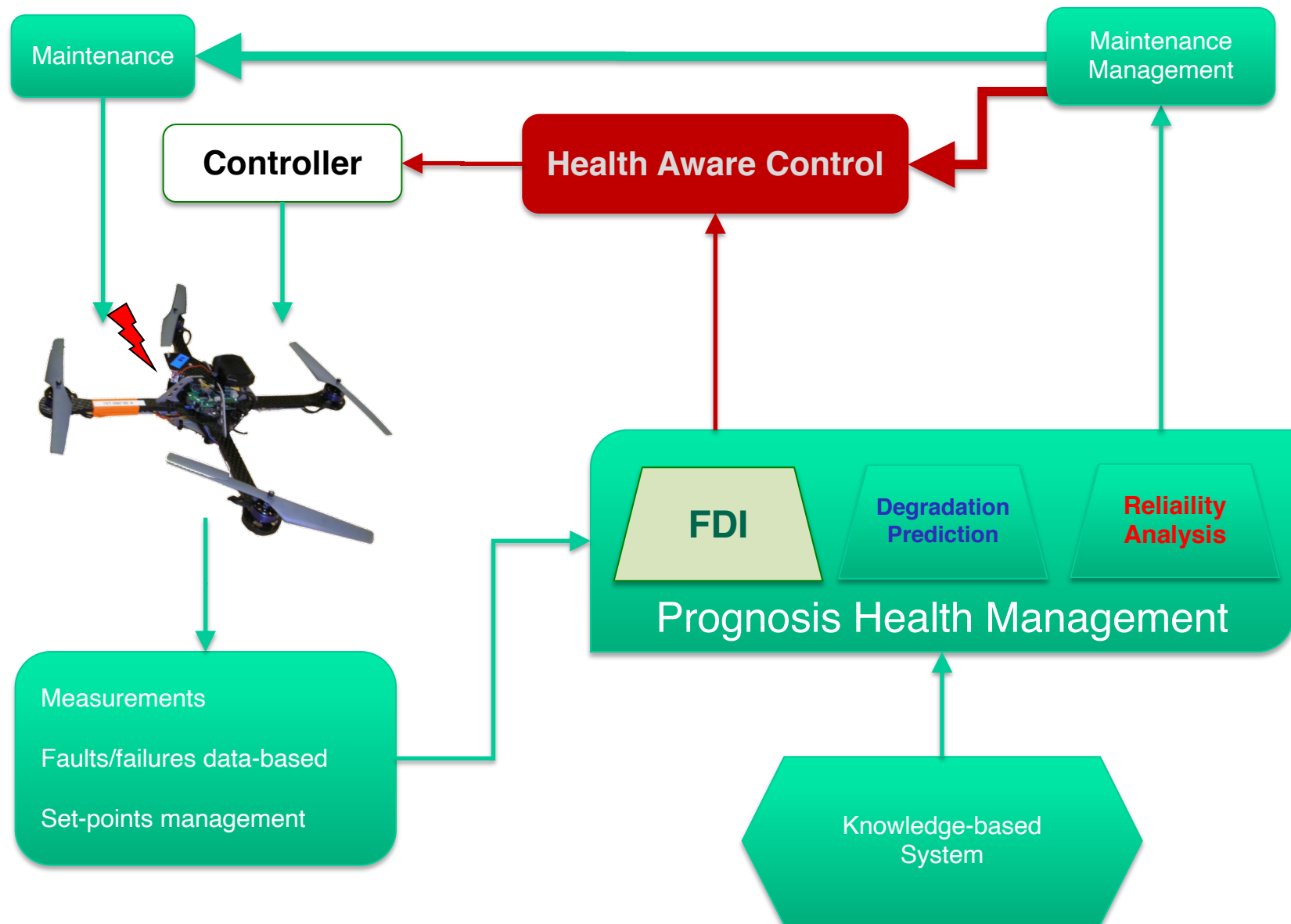
FDI / FTC & Prognosis Health Management



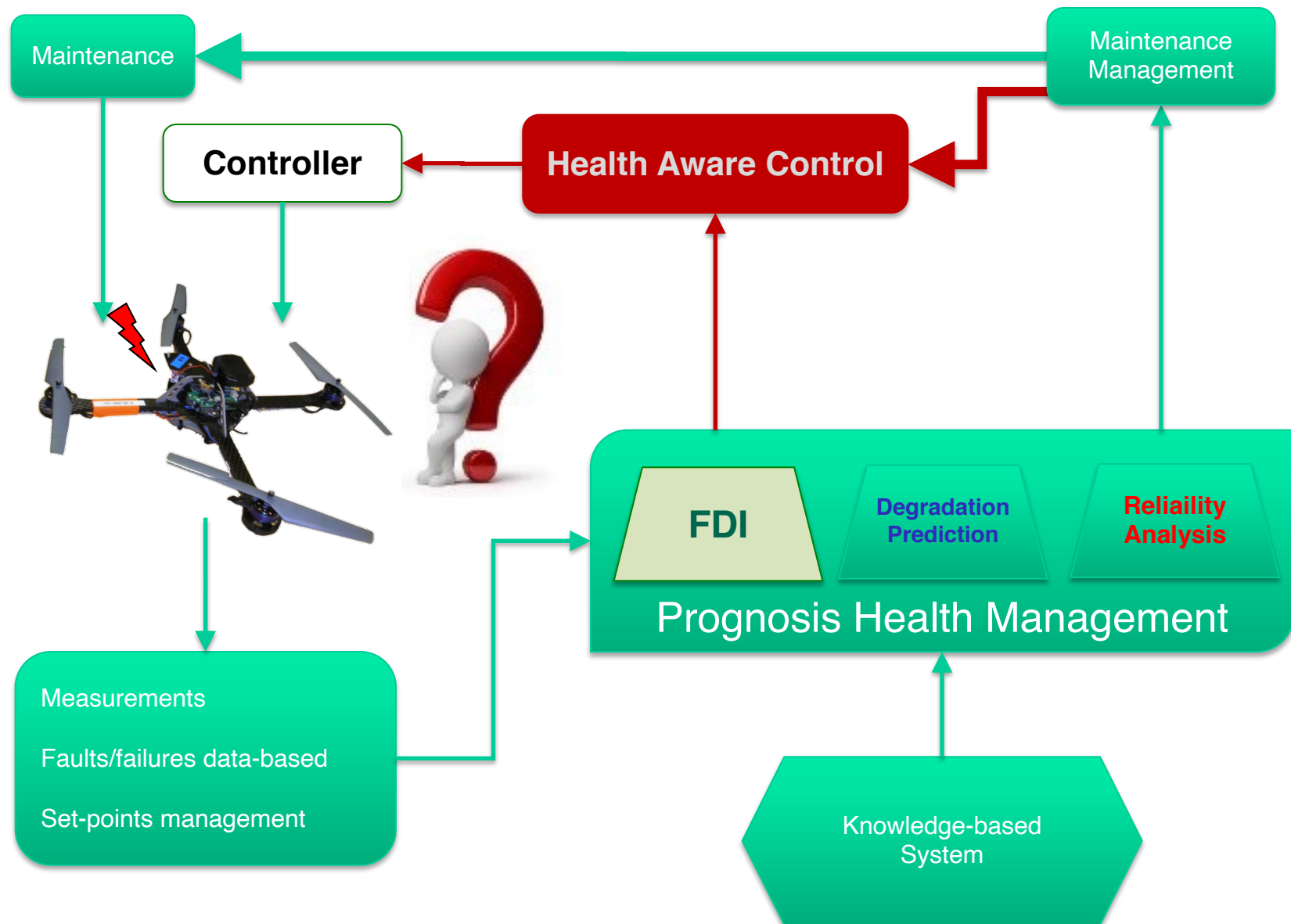
Health Aware Control Design



Health Aware Control Design – **Model Based Approach**



Health Aware Control Design – ~~Model-Based Approach~~



Reinforcement Learning – RL

RL : Rich History

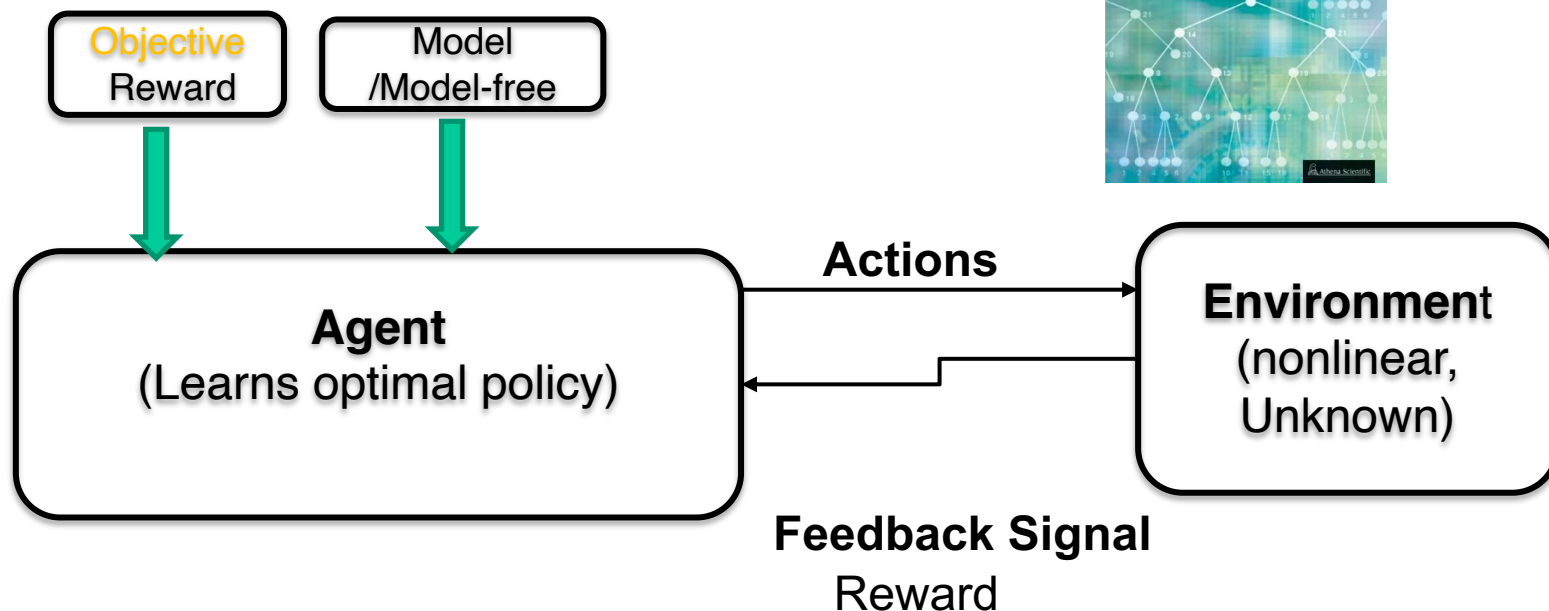
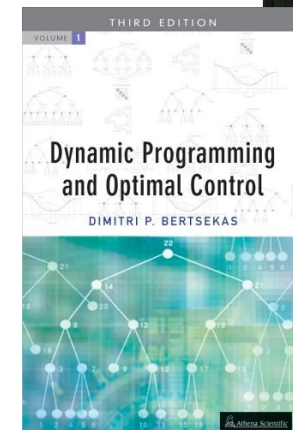
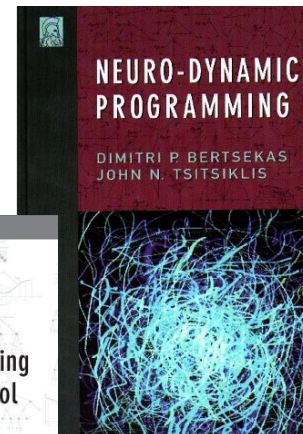
Psychology: Ivan Pavlov 1890 (Classical conditioning vs Instrumental conditioning , Dog experiments....)

Optimal control and Dynamic programming (1950) Richard Bellman, MIT)

Dynamic programming + Neuro-dynamic programming (Neural Networks) 1980-...

RL + Deep Learning = Deep RL (2010-...)

Supervised learning --- Unsupervised Learning --- Reinforcement Learning



OUTLINES

Context

Fault Tolerant Control

- Problem statement & Principle

Health Aware Control

- Reliability and RUL Definitions

- Heuristic approach - Optimal “reliable FTC” method

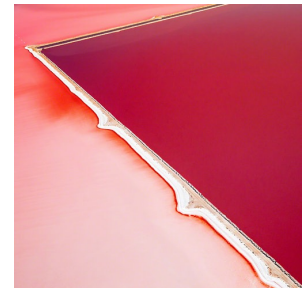
- HAC based on RUL estimation

Safe Reinforcement Learning (*)

- Reinforcement Learning

- Safe Reinforcement Learning

Conclusions and Perspectives

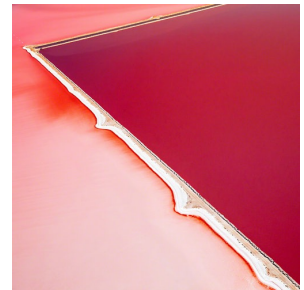


(*) *new results from main contributor Dr. MS JHA*

OUTLINES

Fault Tolerant Control

Problem statement & Principle



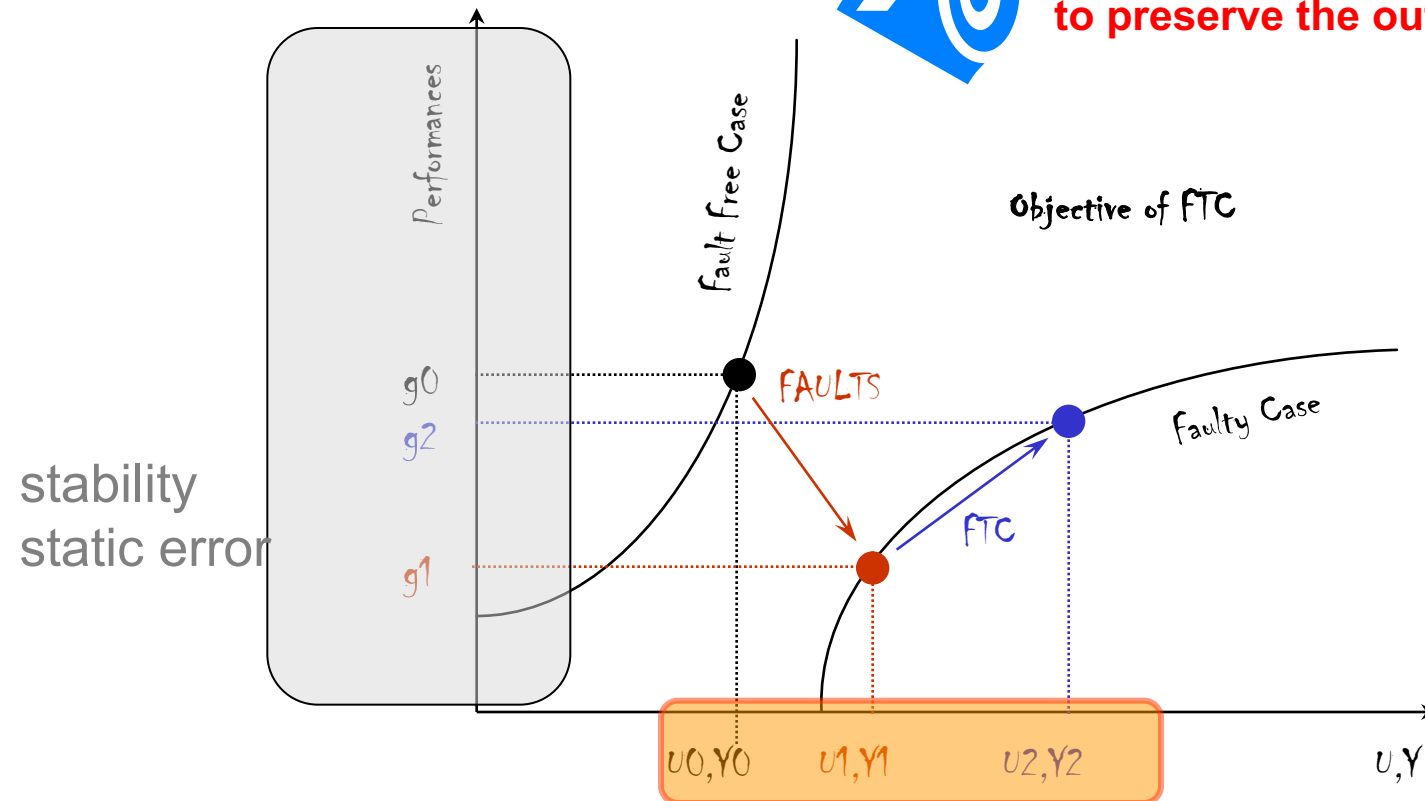
General Principle of FTC

✓ *Fault Tolerant Control system* (1980)

System capable to maintain current performances closed to desirable performances and stability conditions in the presence of component and/or instrument faults ;
Accept reduced performance as a trade-off.



to limit the energy of control inputs
to preserve the output dynamic properties



Definition

✓ *Fault Tolerant Control system* (1980)

System capable to maintain current performances closed to desirable performances and stability conditions in the presence of component and/or instrument faults ;
Accept reduced performance as a trade-off.

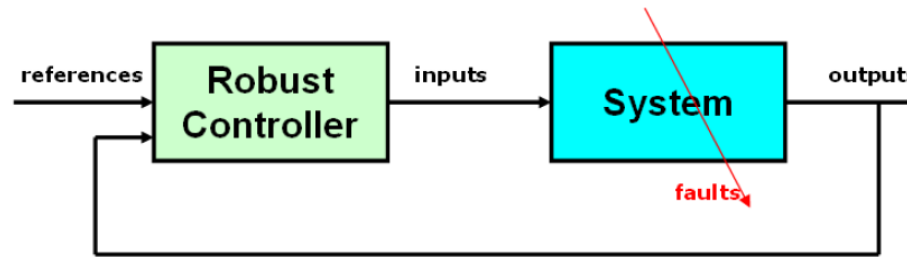
RESISTANCE U RENAISSANCE

✓ *Resilient system or resilience* (2006)

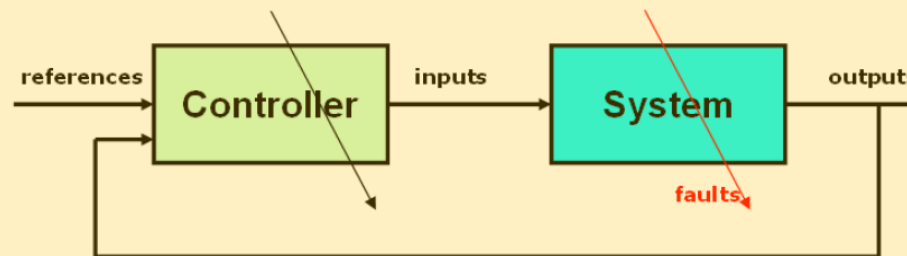
System able to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions. Resilience includes the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incident .

Definitions

Passive FTC:

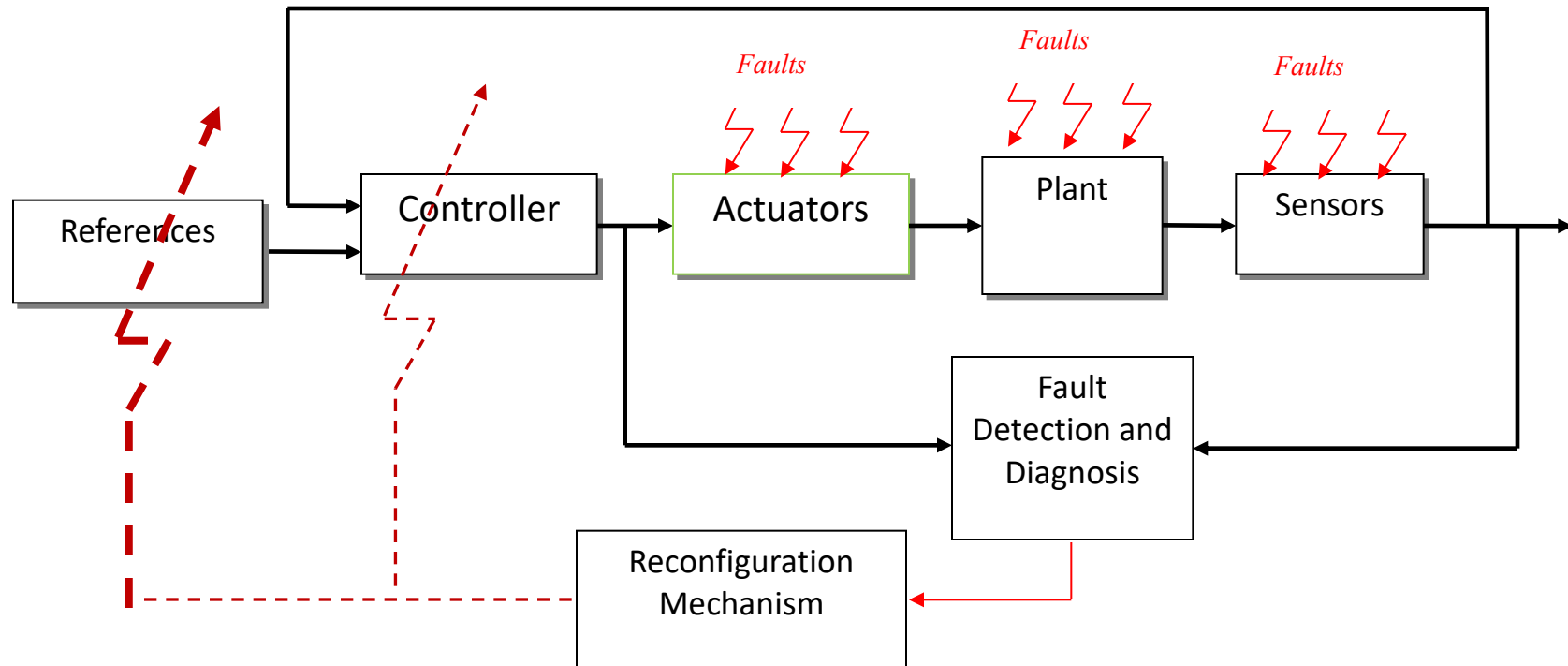


Active FTC:



- **Passive FTC** are mainly based on **robust control** theory. Non require on-line detection, it could be very conservative, and only for small failures.
- **Active FTC** integrates a re-configurable mechanism (**adaptation**) intended to preserve both *stability* and *performance*.

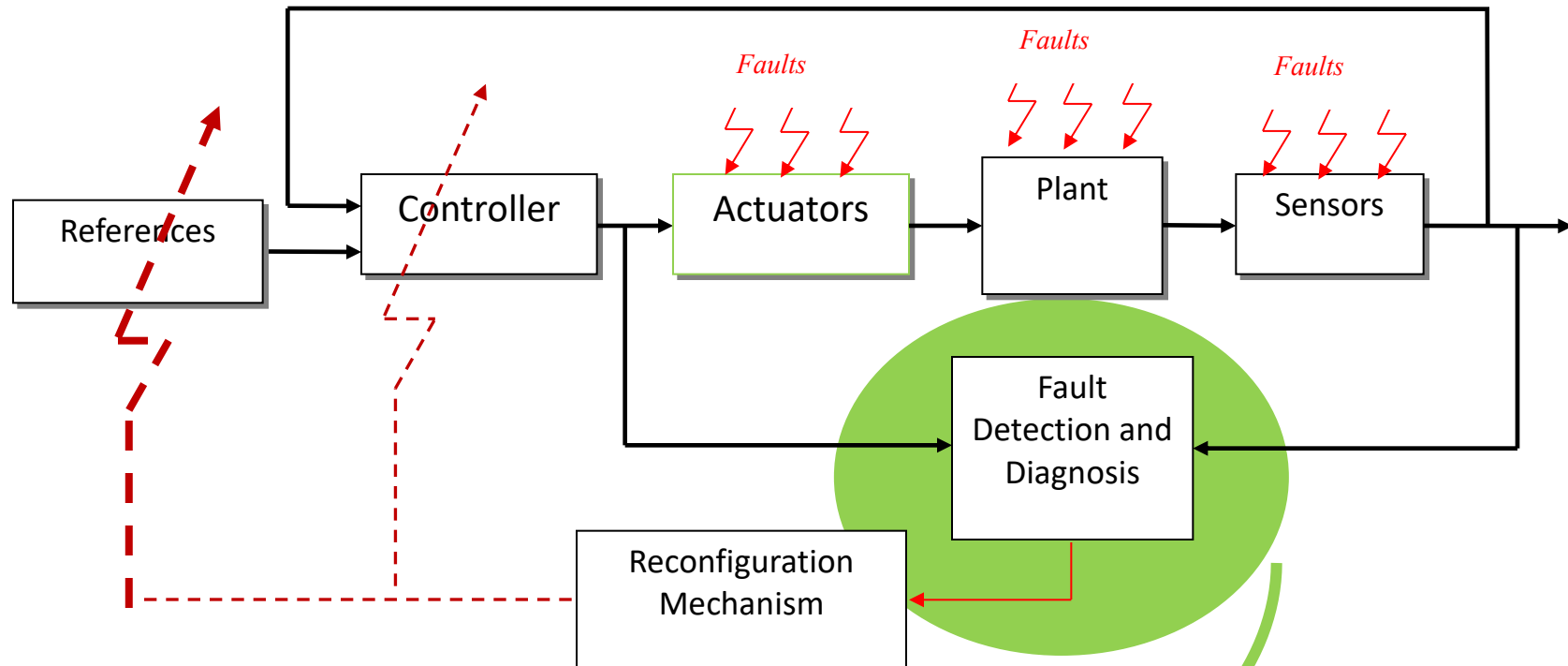
FTC - General Scheme - Reconfiguration



Caution: Controllability, Detectability and **reconfigurability** properties (Structure Analysis can be considered) should be studied before to synthesize FTC.

Remark 1: Adaptive methods and Predefined Faulty Multiple models Adaptive approaches(MMAE Family) have been omitted in the presentation

FTC - General Scheme - Reconfiguration

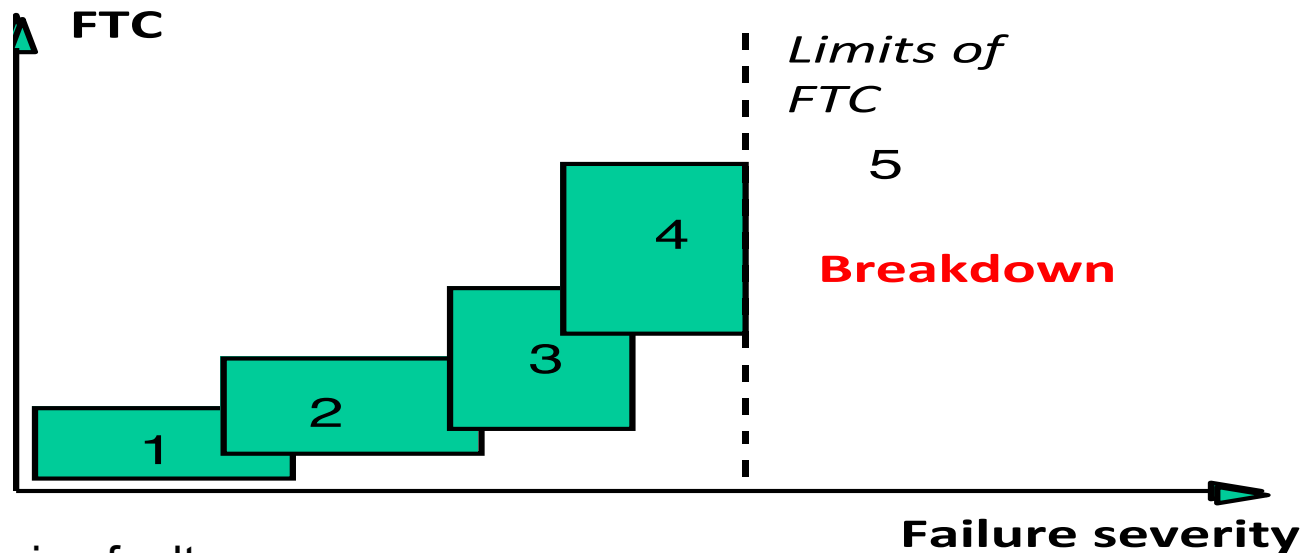


Caution: Controllability, Detectability and **reconfigurability** properties (Structure Analysis can be considered) should be studied before to synthesize FTC.

Remark 1: Adaptive methods and Predefined Faulty Multiple models Adaptive approaches(MMAE Family) have been omitted in the presentation

Remark 2: *Damage compensation in robotics without diagnosis* – JEAN-BAPTISTE MOURET, PhD / Inria Senior Researcher - Nancy

FTCS: What is possible to do ?



1 : Small size faults

Robust control (no FDI module)

2 : Non critical faults: bias, drifts, loss of actuating effectiveness

Disturbance rejection , adaptive control,.. Interaction Control-FDI

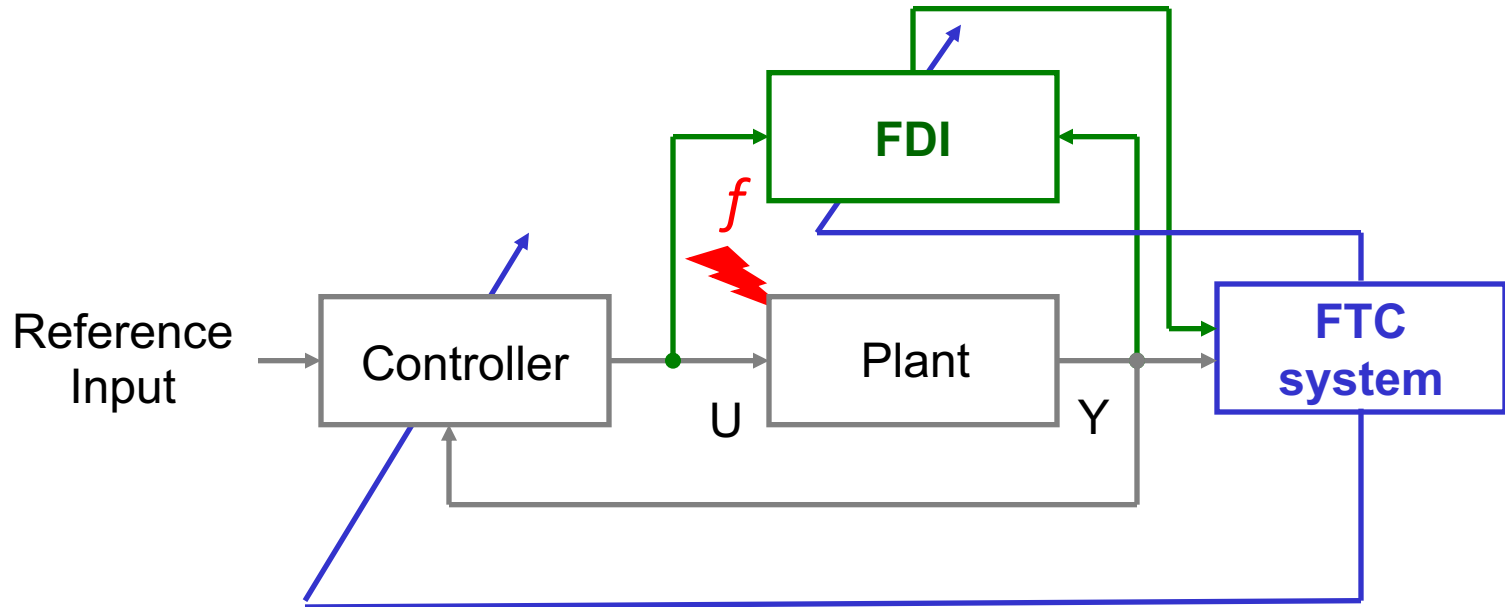
Pseudo-Inverse Method (PIM)

● Principle

Basic Idea: To redesign the controller so that the closed-loop system matrix of the reconfigured system as close as possible to that of the nominal system

- **Advantages:** Simplicity in calculating the reconfigurable control Law
- **Requirement:** Perfect information on FDD (fault time) and post-fault system (post-fault model)

Pseudo-Inverse Method (PIM)



Pseudo-Inverse Method (PIM)

● Method

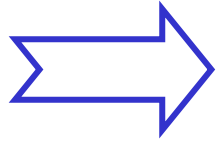
Let the nominal system be given as:

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y(t) = Cx(t) \end{cases} \quad \begin{cases} \dot{x}(t) = (A + BK)x(t) \\ y(t) = Cx(t) \end{cases}$$

and the multiplicative faulty mode:

$$\begin{cases} \dot{x}(t) = A_f x(t) + B_f u(t) \\ y(t) = Cx(t) \end{cases} \quad \begin{cases} \dot{x}(t) = (A_f + B_f K_f)x(t) \\ y(t) = Cx(t) \end{cases}$$

Pseudo-Inverse Method (PIM)



• Solution: $\min J(K_f) = \|(A_f + B_f K_f) - (A + BK)\|_F$

$$K_f^* = (B_f)^+ (A - A_f + BK)$$

• Model matching:
$$\begin{cases} \dot{x}(t) = Mx(t) + Nr(t) \\ u(t) = -Kx(t) + Gr(t) \end{cases} \quad G_f^* = (B_f)^+ N$$

The control reconfiguration is based on the minimization of the Frobenius norm of the difference of two system matrices

« without connection with system stability measure, e.g., eigenvalues »

— **lack of a stability guarantee** —

=> Overcome by a **modified PIM (MPIM)** ([*])

[*] Gao, Z. and P.J Antsaklis (1991). Stability of the pseudo-inverse method for reconfigurable control. International Journal of Control, vol. 53, n° 3, pp. 717-729.

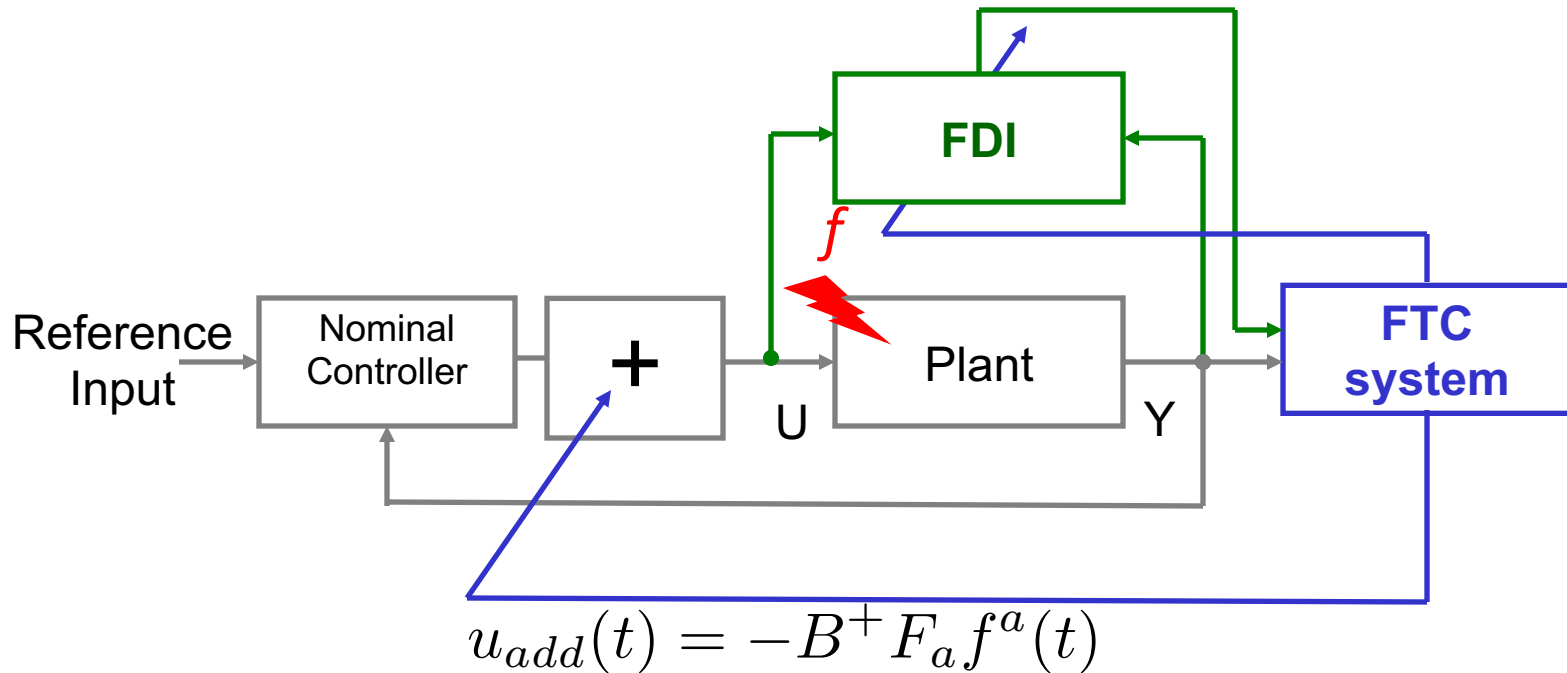
Fault Compensation (FC)

● Principle

Basic Idea: To compensate the fault effect based on an additive control law so that the reconfigured closed-loop system is closed as possible to the nominal one

- **Advantages:** Simplicity in calculating the reconfigurable control Law and **do not modify the controller**
- **Requirement:** Perfect information on FDD (fault time) and post-fault system (post-fault model)

Fault Compensation (FC)



Fault Compensation (FC)

● Method

Let the nominal open-loop system be given again as

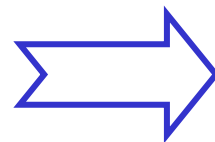
$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) \\ y(t) = C(t) \end{cases}$$

and the additive faulty mode :

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + F_a f^a(t) \\ y(t) = C(t) \end{cases}$$

• Solution :

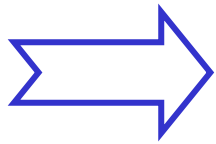
$$\begin{cases} u_{comp}(t) = u_{nom}(t) + u_{add}(t) \\ Bu_{add}(t) + F_a f^a(t) = 0 \end{cases}$$



$$u_{add}(t) = -B^+ F_a f^a(t)$$

Fault Compensation (FC)

● Method



$$u_{add}(t) = -B^+ F_a f^a(t)$$

Remark 1: if B is square $u_{add}(t) = -B^{-1} F_a f^a(t)$

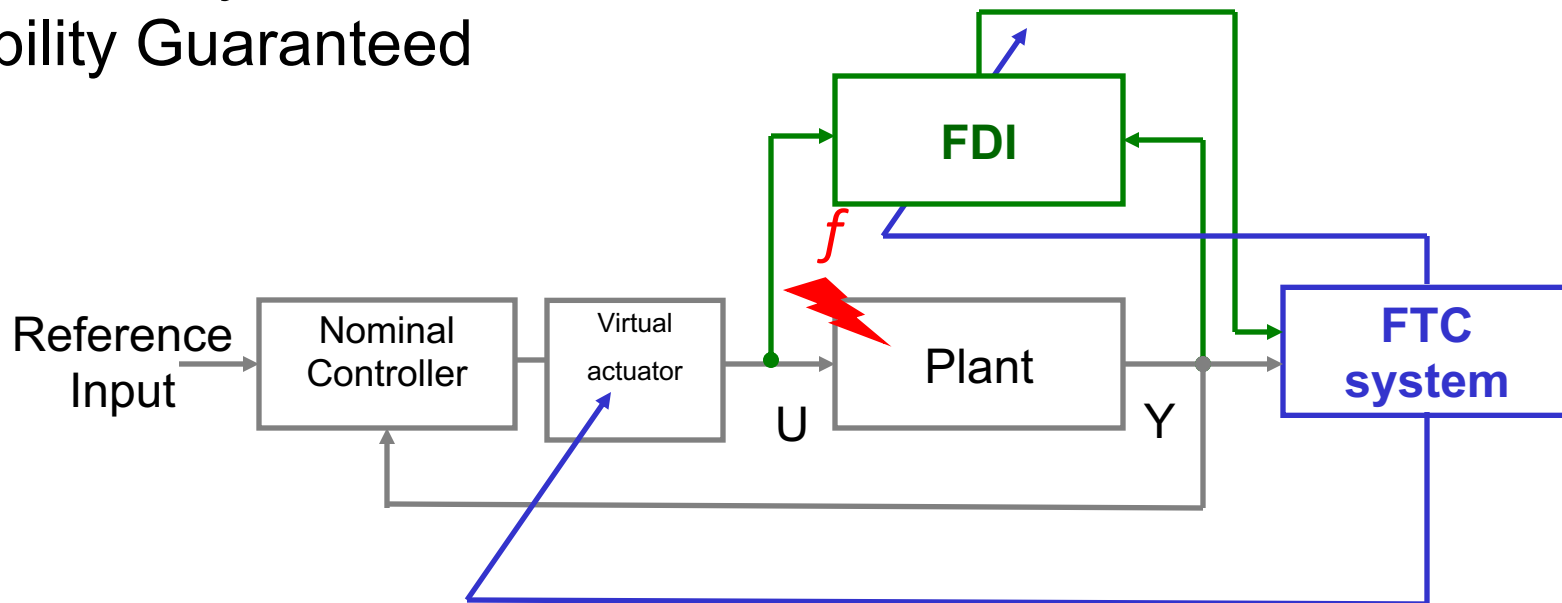
Remark 2: if B is not a full row rank matrix (nb of state less than input). A SVD can be applied to the matrix B.

The stability is not guaranteed and can not be studied off-line !!!

“Virtual Actuator” since 2010 ...

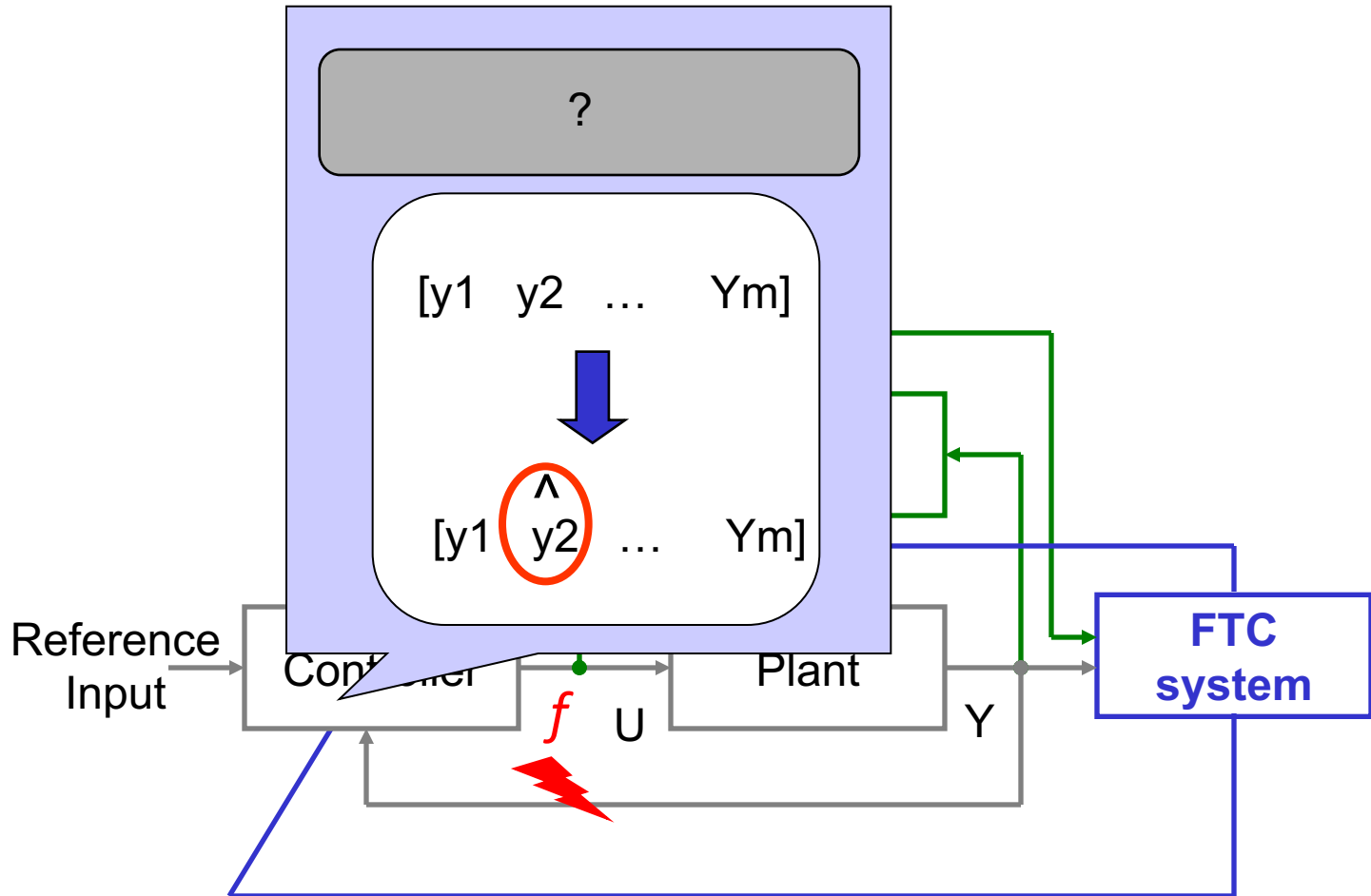
- **(Gain Redesign) + (Fault Compensation)= Virtual Actuator**

Excellent Dynamic Performance
Stability Guaranteed



Certification Validated

Sensor FTC = “Sensor Fault Masking”





Annual Reviews in Control 32 (2008) 229–252

*Annual Reviews
in Control*

www.elsevier.com/locate/arcontrol

Bibliographical review on reconfigurable fault-tolerant control systems

Youmin Zhang^{a,*}, Jin Jiang^{b,1}

^a *Department of Mechanical and Industrial Engineering, Concordia University, Montreal, Quebec H3G 1M8, Canada*

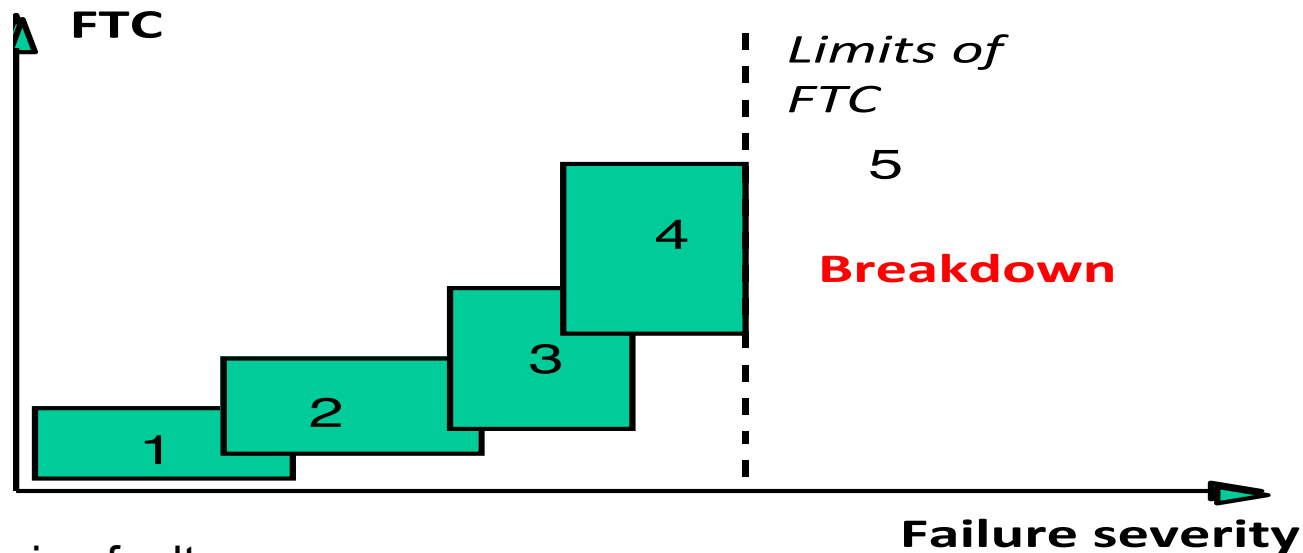
^b *Department of Electrical and Computer Engineering, The University of Western Ontario, London, Ontario N6A 5B9, Canada*

Received 15 July 2007; accepted 23 March 2008

[*] More than **300** papers have been classified, defined, identified

“FTC design applied on Various Models
(LTI, LPV, nonlinear...)”

FTCS: What is possible to do ?



1 : Small size faults

Robust control (no FDI module)

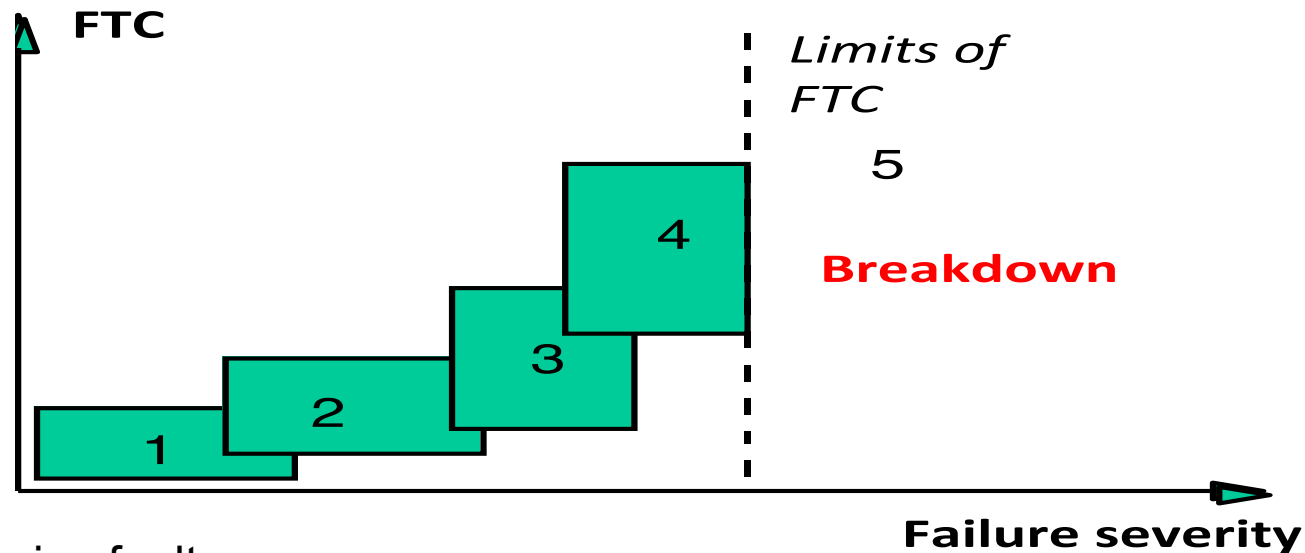
2 : Non critical faults: biais, drifts, loss of actuating effectiveness

Disturbance rejection , adaptive control,.. Interaction Control-FDI

3 : Critical faults leading to saturations or unstability ;

Control reconfiguration ; *Modified objective, still acceptable*

FTCS: What is possible to do ?



1 : Small size faults

Robust control (no FDI module)

2 : Non critical faults: bias, drifts, loss of actuating effectiveness

Disturbance rejection, adaptive control,.. Interaction Control-FDI

3 : Critical faults leading to saturations or instability ;

Control reconfiguration ; Modified objective, still acceptable

4 : Severe faults : inoperant actuator, loss of a sensor ;

Modified objective, degraded performances

Experiments on real quadrotor (indoor)

Self-Healing Control Design for Quadrotors: One motor failure case

Xin Qi, Didier Theilliol, Yuqing He and Jianda Han

Autonomous Robot Lab, Shenyang Institute of Automation, CAS
CRAN, CNRS, Université de Lorraine



中国科学院沈阳自动化研究所
SHENYANG INSTITUTE OF AUTOMATION, CHINESE ACADEMY OF SCIENCES



Resilient/Fault Tolerant Control

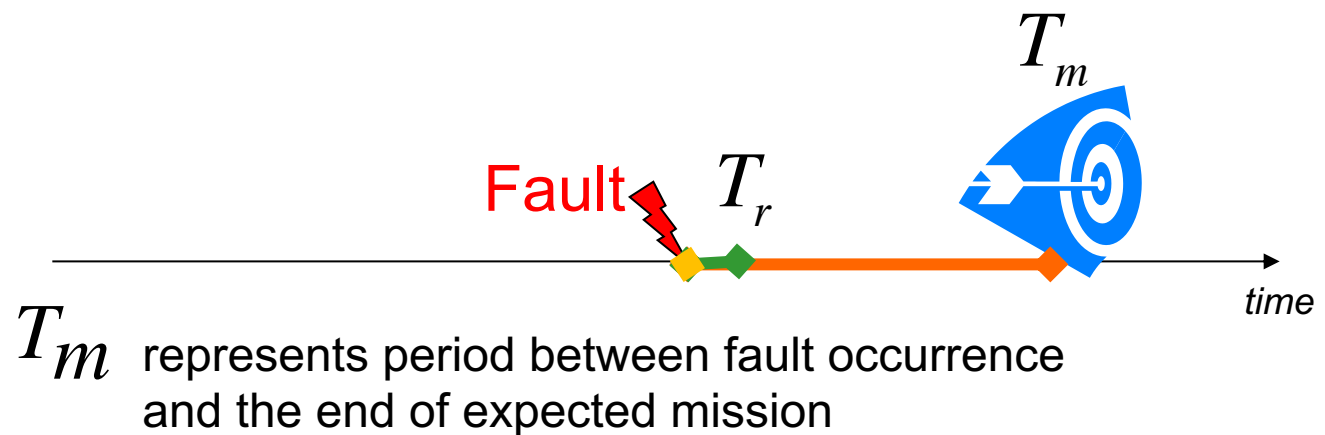
FTC, Reconfiguration, accommodation, recovery !!!!

Health Aware Control Design

FTC, Reconfiguration, accommodation, recovery !!!!

some contributions to increase the safety of the system ...

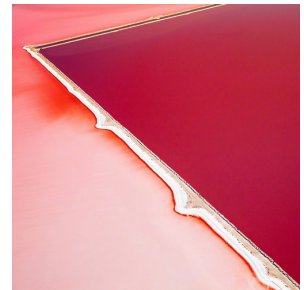
**but not the global reliability (or health) of the system
in order to guarantee to achieve the end of the mission**



OUTLINES

Health Aware Control

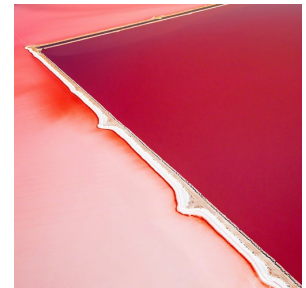
Heuristic approach - Optimal “reliable FTC” method
HAC based on RUL estimation



OUTLINES

Health Aware Control

Heuristic approach - Optimal “reliable FTC” method

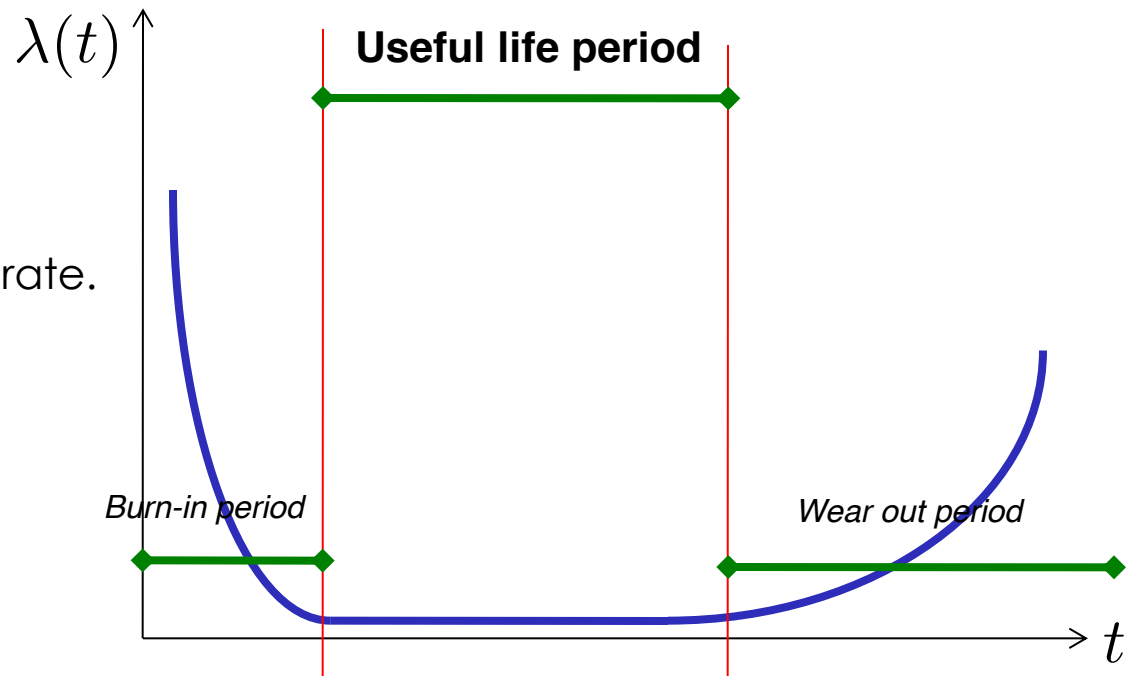


Reliability: “mathematic” definitions

Reliability $R(t)$ is defined as the probability **a priori** that units, components, equipments and systems **will accomplish their intended function for a specified period of time t** under some operating conditions and specific environments [*].

$$R(t) = e^{-\int_0^t \lambda(t) dt}$$

where $\lambda(t)$ presents the failure rate.



[*] I. Gertsbakh. Reliability Theory with Applications to Preventive Maintenance. Springer, 2000.

Reliability analysis for actuator component

Nominal Reliability $R_i^0(t) = \exp(-\lambda_i^0 t), \quad i = 1, \dots, m$

Failure rate $\lambda_i(t) = \lambda_i^0(1 + g(\ell_i)), \quad i = 1, \dots, m$

Load function $g(\ell_i) = \frac{\beta_i}{t} \int_0^t u_i^2(\tau) d\tau, \quad i = 1, \dots, m$

Reliability analysis for actuator component

Nominal Reliability $R_i^0(t) = \exp(-\lambda_i^0 t), \quad i = 1, \dots, m$

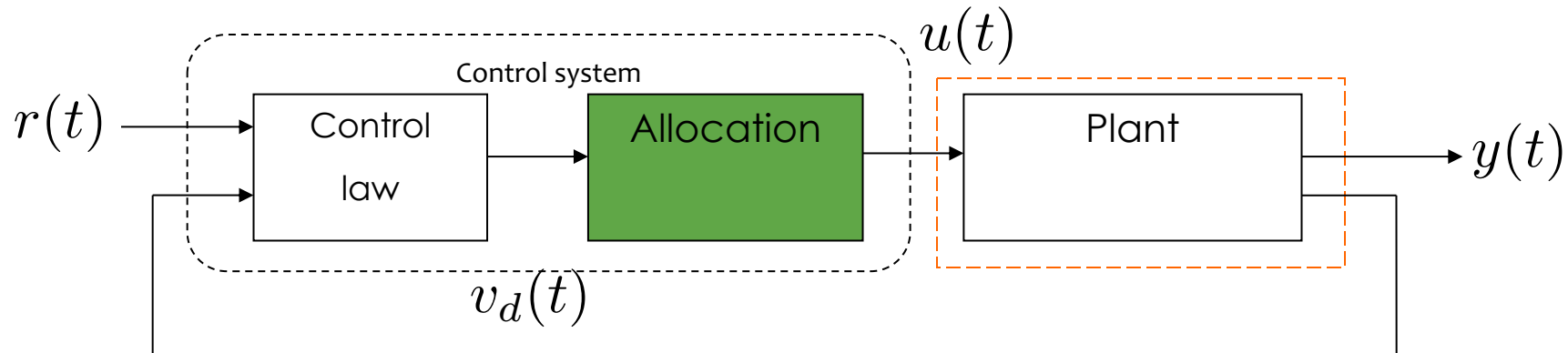
Failure rate $\lambda_i(t) = \lambda_i^0(1 + g(\ell_i)), \quad i = 1, \dots, m$

Load function $g(\ell_i) = \frac{\beta_i}{t} \int_0^t u_i^2(\tau) d\tau, \quad i = 1, \dots, m$

At time $t \in [t_1, t_M]$

$$R_i(t) = \exp(-\lambda_i(t_1) \times (t - t_1)), \quad i = 1, \dots, m$$

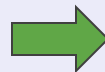
Control Method for Overactuated Systems



Problem description of Control Allocation

How to allocate and distribute the desired efforts to the set of actuators?

$$u(t) = ?$$



$$\dot{x}(t) = Ax(t) + B_v v_d(t)$$



Contents lists available at [SciVerse ScienceDirect](https://www.sciencedirect.com)

Automatica

journal homepage: www.elsevier.com/locate/automatica



Control allocation—A survey[☆]

Tor A. Johansen¹, Thor I. Fossen

Department of Engineering Cybernetics, Center for Autonomous Marine Operations and Systems, Norwegian University of Science and Technology, Trondheim, Norway

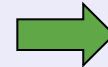


Control Allocation Method

Allocation problem **without** actuators saturations

$$u^* = \arg \min_{u \in \psi} \|W_u u\|_2$$

$$\psi = \arg \min_{u_{\min} \leq u \leq u_{\max}} \|Bu - v_d\|_2$$



$$\begin{aligned} \min_u J &= \|W_u u(t)\|_2 \\ \text{s.t.} \quad & Bu(t) = v_d(t) \end{aligned}$$

A simple control allocation method is the Pseudo-Inverse approach with the following explicit solution

$$u(t) = W_u^{-1} (BW_u^{-1})^+ v_d(t)$$

$W_u = \text{diag}([w_1, w_2, \dots, w_q]^T)$ a positive definite weighting diagonal matrix

Control Allocation Method

Allocation problem **WITH** actuators saturations

- Mixed optimization problem $\epsilon \in [0, 1]$

$$u = \arg \min_{u_{\min} \leq u \leq u_{\max}} (1 - \epsilon) \|Bu - v_d\|_2 + \epsilon \|W_u u\|_2$$

- Fixed point algorithm (among 8 others)

$$u^k = \text{sat}[(1 - \epsilon)\eta B^T v_d + (I_m - \eta H)u^{k-1}], \quad k = 1, \dots, N$$

with $H = (1 - \epsilon)B^T B + \epsilon Q_2$

$$Q_2 = W_u(t)^T W_u(t)$$

$$\eta = \|H\|_F^{-1}$$

where $\text{sat}_i(u) = \begin{cases} \underline{u}_i, & u_i < \underline{u}_i \\ u_i, & \underline{u}_i \leq u_i \leq \bar{u}_i, \\ \bar{u}_i, & u_i > \bar{u}_i \end{cases} \quad i = 1, \dots, m$

Problem statement

Optimal approaches of Control Allocation or Reallocation Method

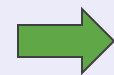
Optimization problem $u^* = \arg \min_{u \in \psi} \|W_u u\|_2$

W_u gives some specific priority to the actuators

Choice of the weighting matrix

Generally, the current choice :

- Equal distribution
- Heuristic priority of the actuators
- Min and Max properties



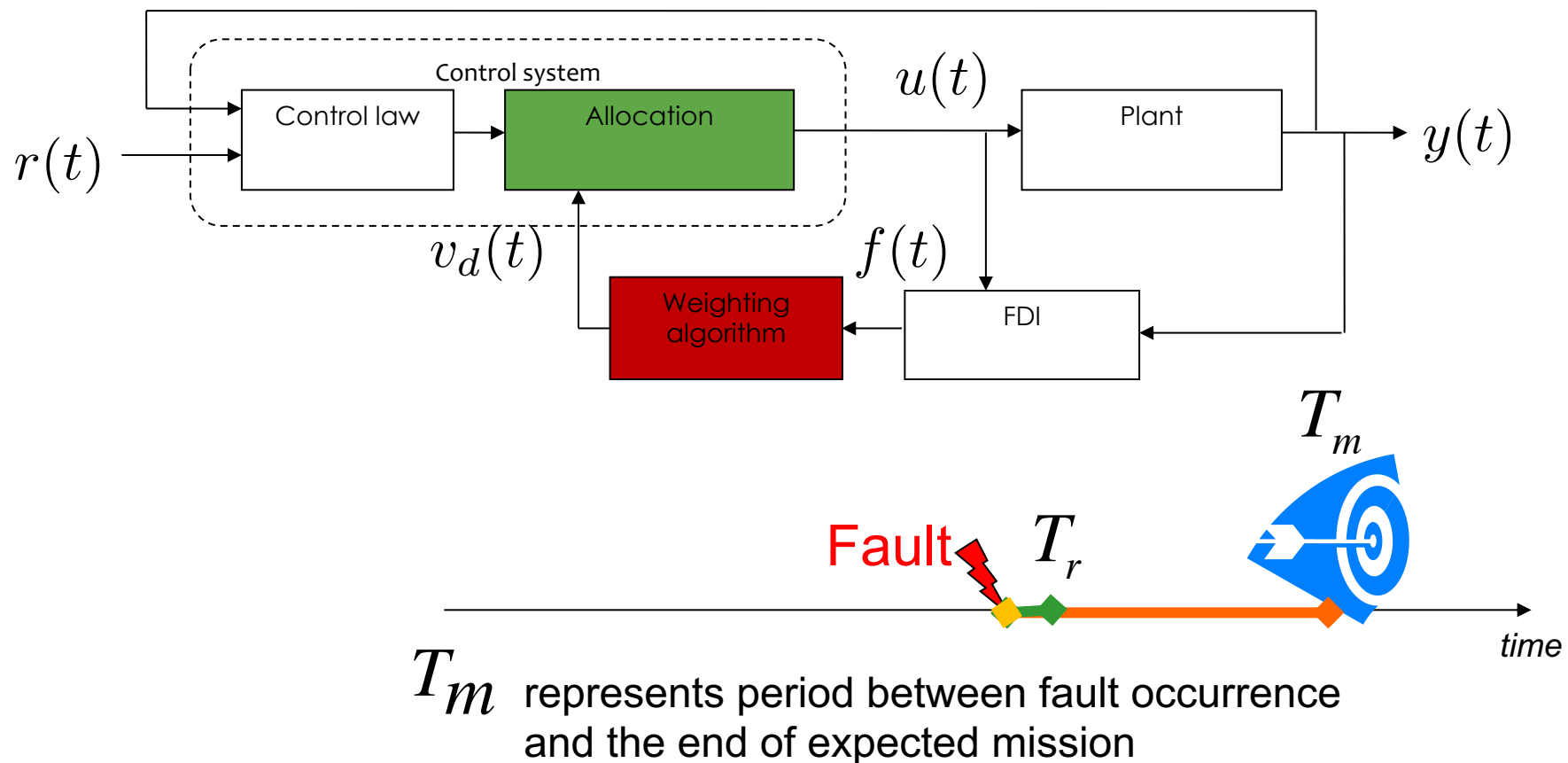
$W_u = I$ A useful solution

weighting matrix (Idea)!

W_u is chosen in order to improve the system dependability

Control (re) allocation method

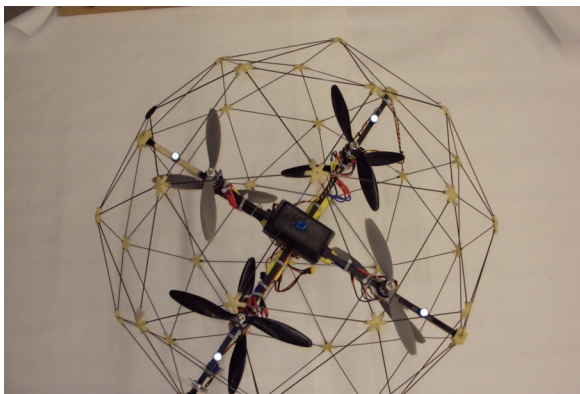
To summarize: For overactuated systems, the reconfigurable control allocation, or called control re-allocation is to provide an admissible management of the redundant actuators through the re-distribution of the desired control efforts among the remaining healthy actuators.



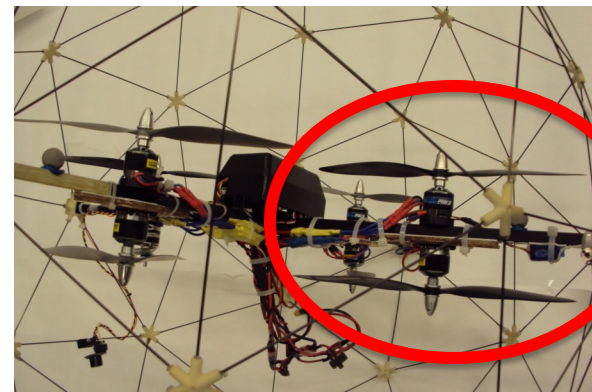
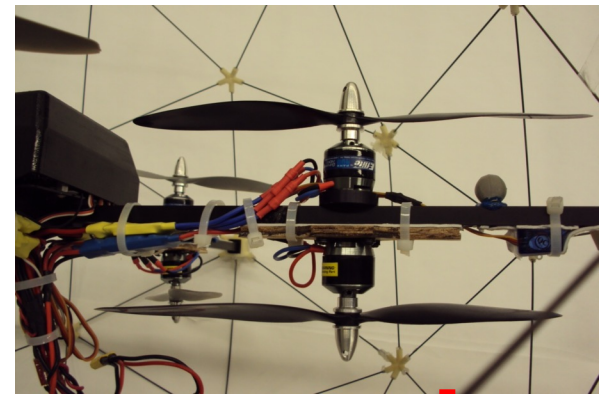
Application Qball-X8

Why to modify the Qball-X4 ?

To increase system's reliability, safety and capability, four additional actuators are added.



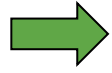
Top view



Side view

Control allocation: Weighting Functions

The objective is to increase the global reliability of the system. This is achieved by adjusting the weighting matrix W to penalize the least reliable actuators and reduce their duties, and consequently increase the duties of the most reliable actuators. To this end, the weighting matrix W is defined as:



$$W_u = \begin{pmatrix} \frac{\lambda_1}{\lambda_{max}} & \dots & 0 \\ & \ddots & \\ \vdots & \frac{\lambda_i}{\lambda_{max}} & \vdots \\ & & \ddots & \\ 0 & \dots & & \frac{\lambda_m}{\lambda_{max}} \end{pmatrix}$$

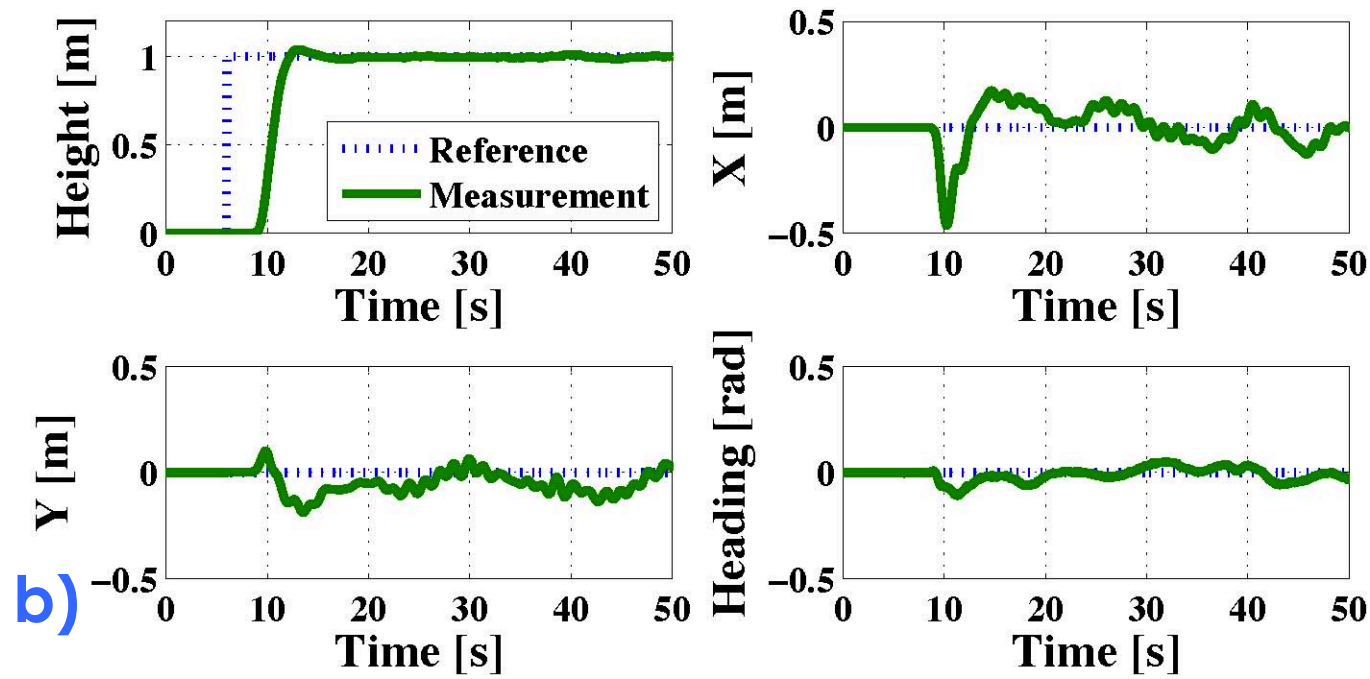
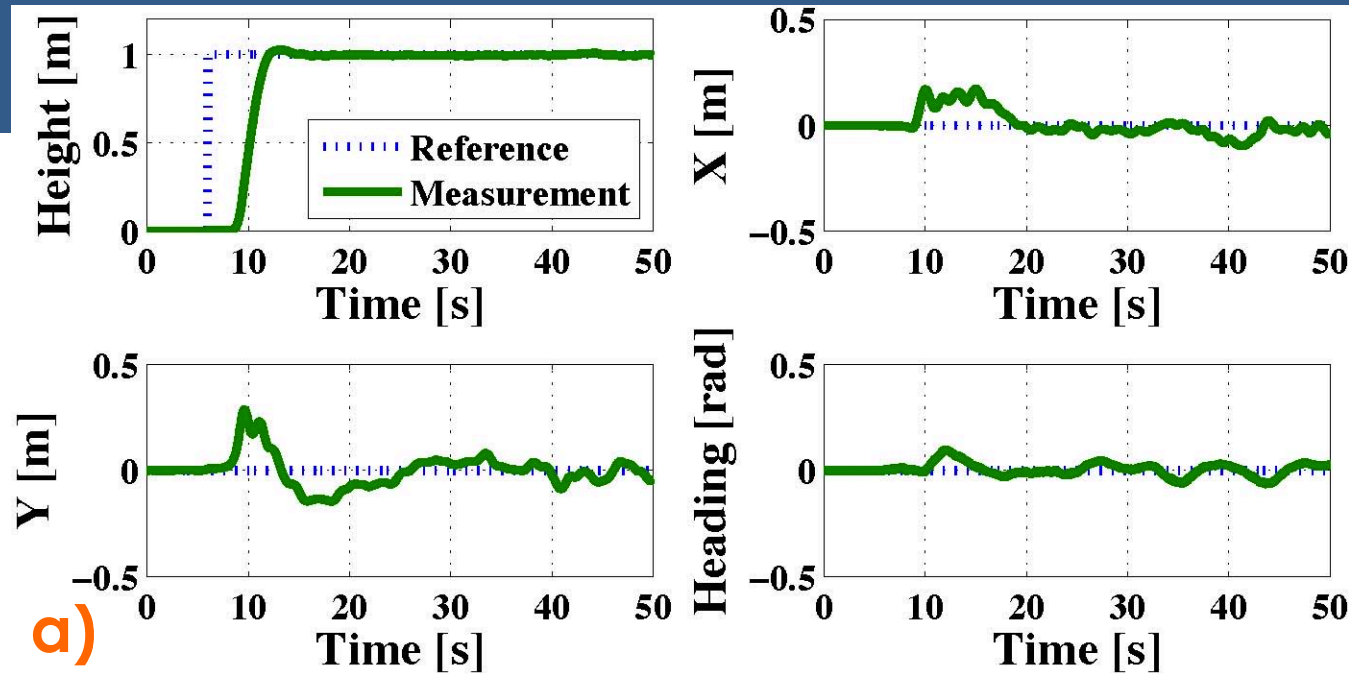
When $\lambda_i < \lambda_{max}$ **then** $w_i < 1$ higher control input is allowed for the i^{th} actuator.

When $\lambda_i \mapsto \lambda_{max}$ **then** $w_i \mapsto 1$ and the i^{th} element of $u(t)$ is more penalized compared with the previous case: a lower control input is then allowed for the i^{th} actuator.

λ_{max} represents the maximal failure rate corresponding to the least reliable actuator.

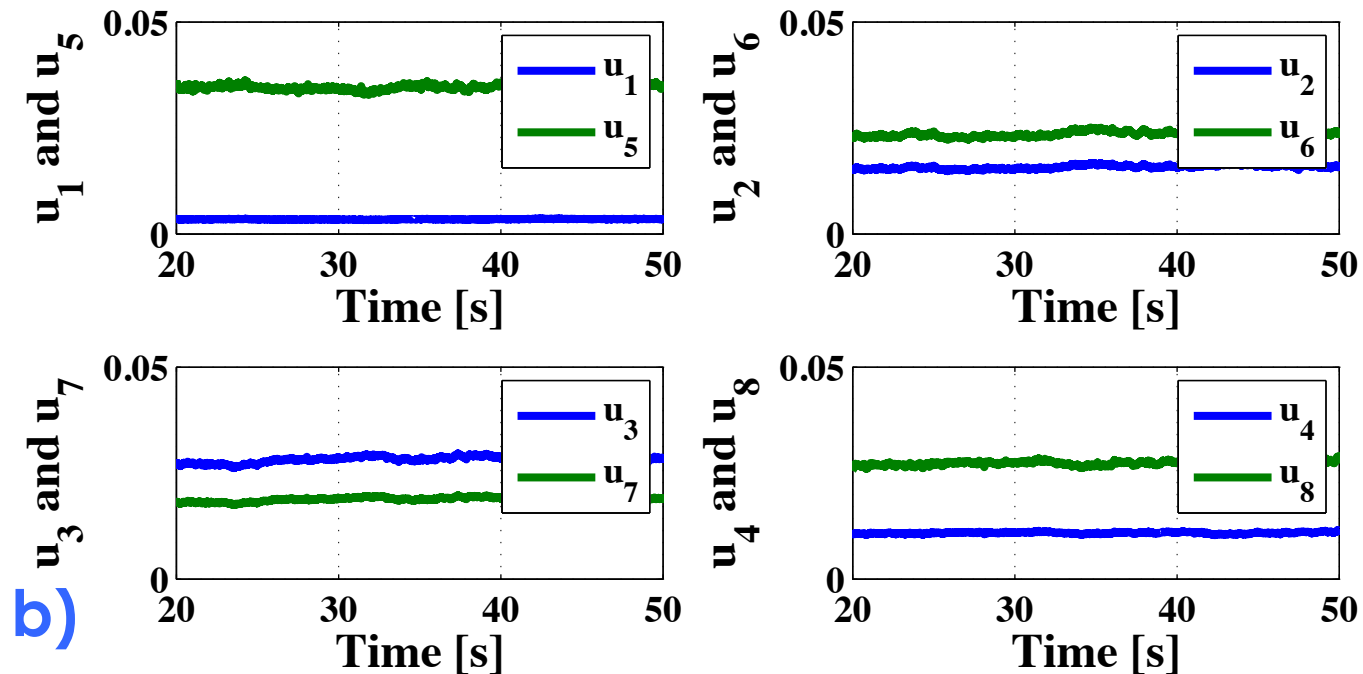
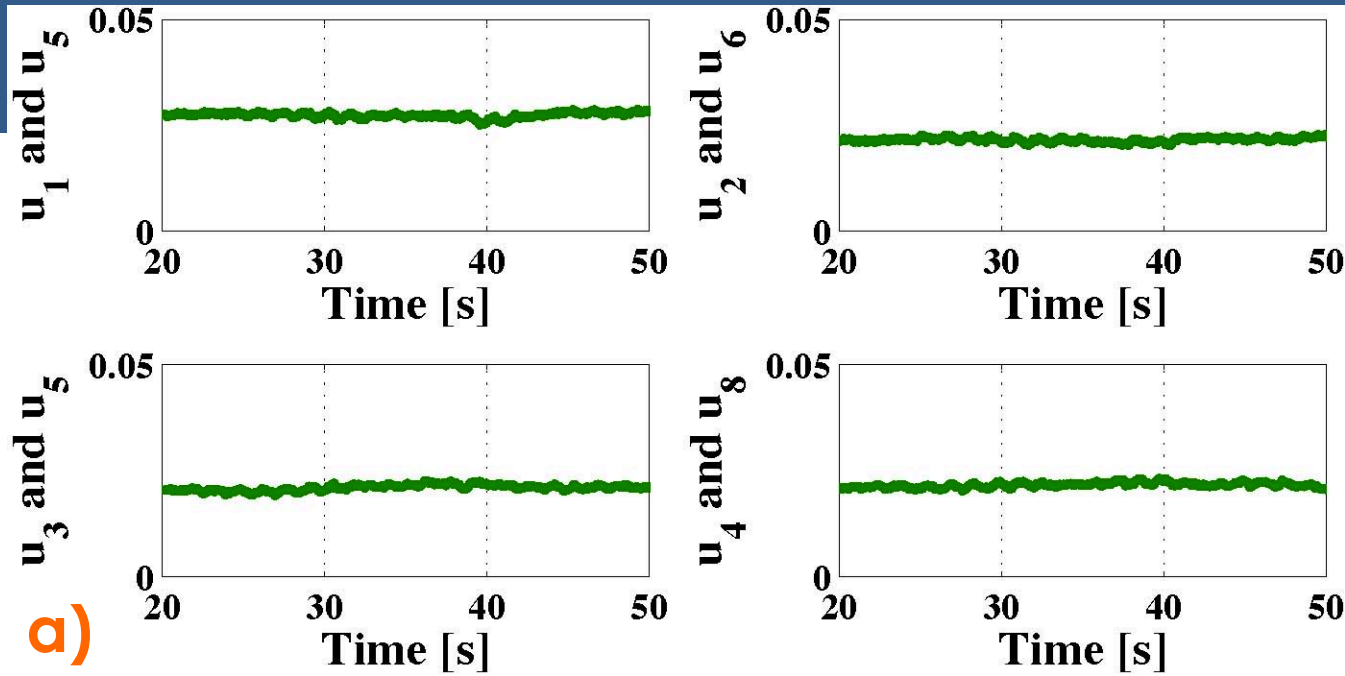
Outputs :

The system states remain similar in both cases **a)** $W=I$ and **b)** $W=f(R)$.



Inputs :

The PWM control inputs are not the same
 a) $W=I$ and
 b) $W=f(R)$.



Quantitative comparison

Top Motors				
	M_1	M_2	M_3	M_4
Rate λ_i	10×10^{-3}	6×10^{-3}	2×10^{-3}	5×10^{-3}

Without reliability
With reliability

Top Motors			
$\ u_1\ $	$\ u_2\ $	$\ u_3\ $	$\ u_4\ $
2.106	1.642	1.603	1.656
0.2654	1.1989	2.1720	0.8331

Bottom Motors				
	M_5	M_6	M_7	M_8
Rate λ_i	1×10^{-3}	4×10^{-3}	3×10^{-3}	2×10^{-3}

Without reliability
With reliability

Bottom Motors			
$\ u_5\ $	$\ u_6\ $	$\ u_7\ $	$\ u_8\ $
2.106	1.642	1.603	1.656
2.6541	1.7984	1.4480	2.0828

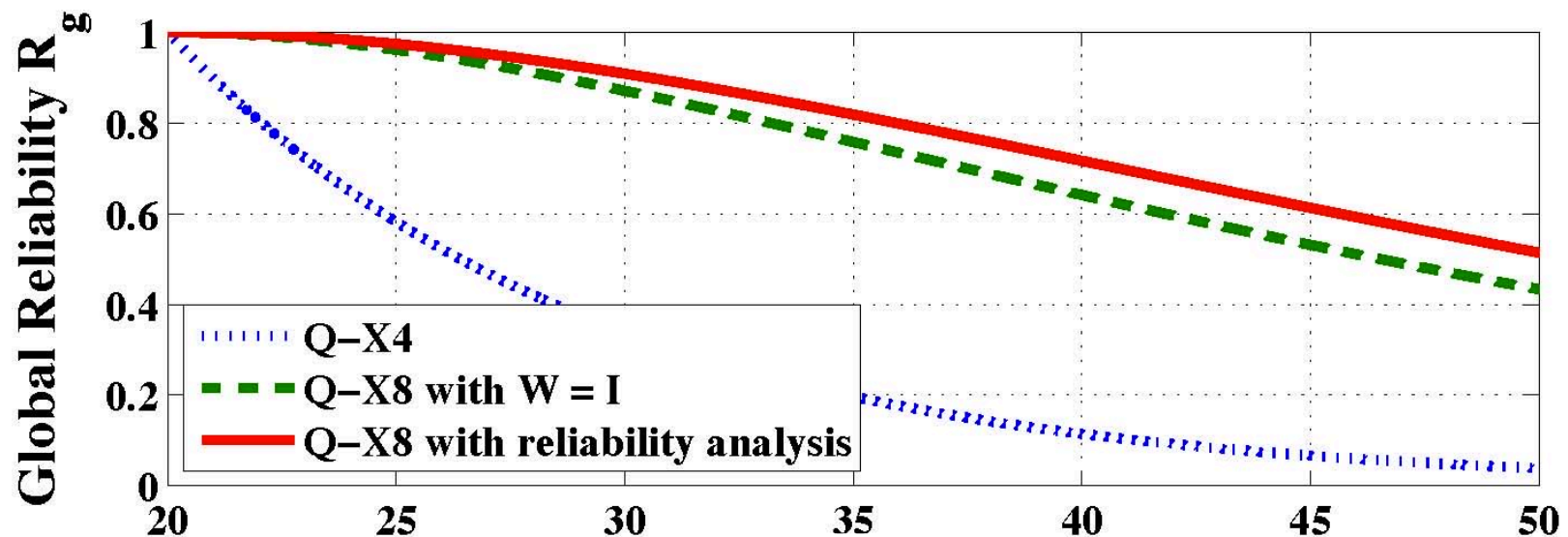
Without reliability analysis, the control inputs to the redundant motors are the same.

With reliability analysis, the control inputs to the most reliable actuators are larger than those to the least reliable actuators.

Global Reliability “a posteriori”

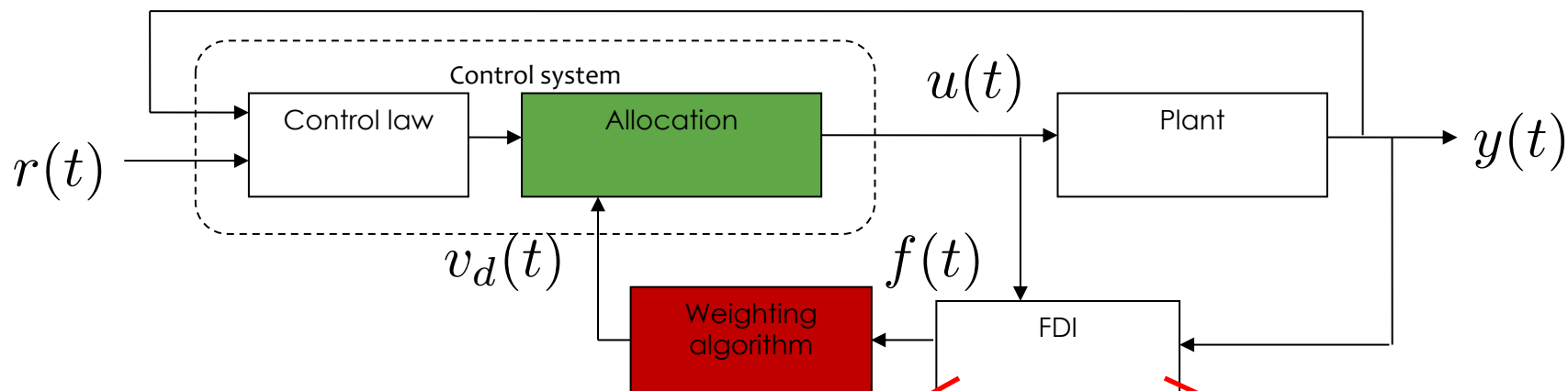
The reliability of the Qball-X4 dramatically drops down (**blue** line) because of the series configuration of its actuators and the lack of redundancy.

Actuator redundancy in the Qball-X8 greatly increases the overall system's reliability (**green** line). Moreover, taking into consideration the actuator failure rates in the control allocation helps to further improve the global reliability (**red** line).



Application Qball-X8 – Actuator faulty-case

Control (re) allocation method



• Faulty system

• Faulty system

$$\begin{cases} \dot{x}(t) &= Ax(t) + B_v v_d(t) \\ v_d(t) &= \diamond B_f u(t) \\ y(t) &= Cx(t) \end{cases}$$

$$B_f = B(I_m - \Gamma)$$

$$\diamond B_f = B(I_m - \Gamma)$$

$$\Gamma = \text{diag}(\gamma_1, \gamma_2, \dots, \gamma_m)$$

Application Qball-X8 – Actuator faulty-case

Second try:

70% of propeller damage
without
control re-allocation
(unstable)

Optimal Solution

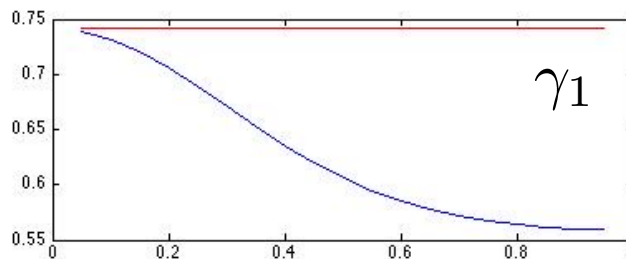
(Re)Allocation Solution **WITHOUT** explicit solution

$$\left\{ \begin{array}{l} u^* = \arg \min_{u \in \psi} \|W_u u\|_2 \\ \psi = \arg \min_{u_{\min} \leq u \leq u_{\max}} \|Bu - v_d\|_2 \end{array} \right.$$

⊕ $\forall t \ W_u(t) = \max_{R_g > (R_g^{W_u=I} + \xi)} R_g(t_m, (\|u\|_2)^2)$

Application to X8 – Simulation - Rg

$$R_g(t_m = 300s, (\|u\|_2)^2) \text{ for } t = 40,000s$$



• Faulty system

$$\rightarrow \begin{cases} \dot{x}(t) &= Ax(t) + B_v v_d(t) \\ v_d(t) &= B_f u(t) \\ y(t) &= Cx(t) \end{cases}$$

$$\rightarrow B_f = B(I_m - \Gamma)$$

$$\Gamma = \text{diag}(\gamma_1, \gamma_2, \dots, \gamma_m)$$

$$\text{---} \quad \forall t \quad W_u(t) = \max_{R_g > (R_g^{W_u=I} + \xi)} R_g(t_m, (\|u\|_2)^2)$$

$$\text{---} \quad u(t) = B^+ V_d(t)$$

Reference

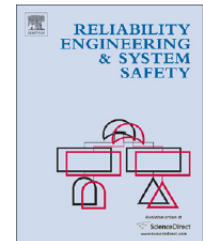
Reliability Engineering and System Safety 132 (2014) 196–206



Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress



Optimal reliability design for over-actuated systems based on the MIT rule: Application to an octocopter helicopter testbed



Abbas Chamseddine^a, Didier Theilliol^{b,*}, Iman Sadeghzadeh^a, Youmin Zhang^a,
Philippe Weber^b

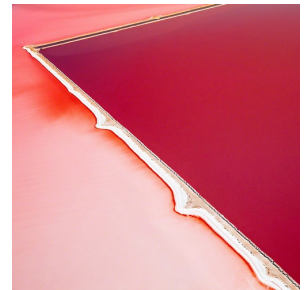
^a Department of Mechanical & Industrial Engineering, Concordia University 1455 Maisonneuve Blvd. West, Montreal, Quebec, Canada H3G 1M8

^b Centre de Recherche en Automatique de Nancy, CRAN CNRS UMR 7039, University of Lorraine, France

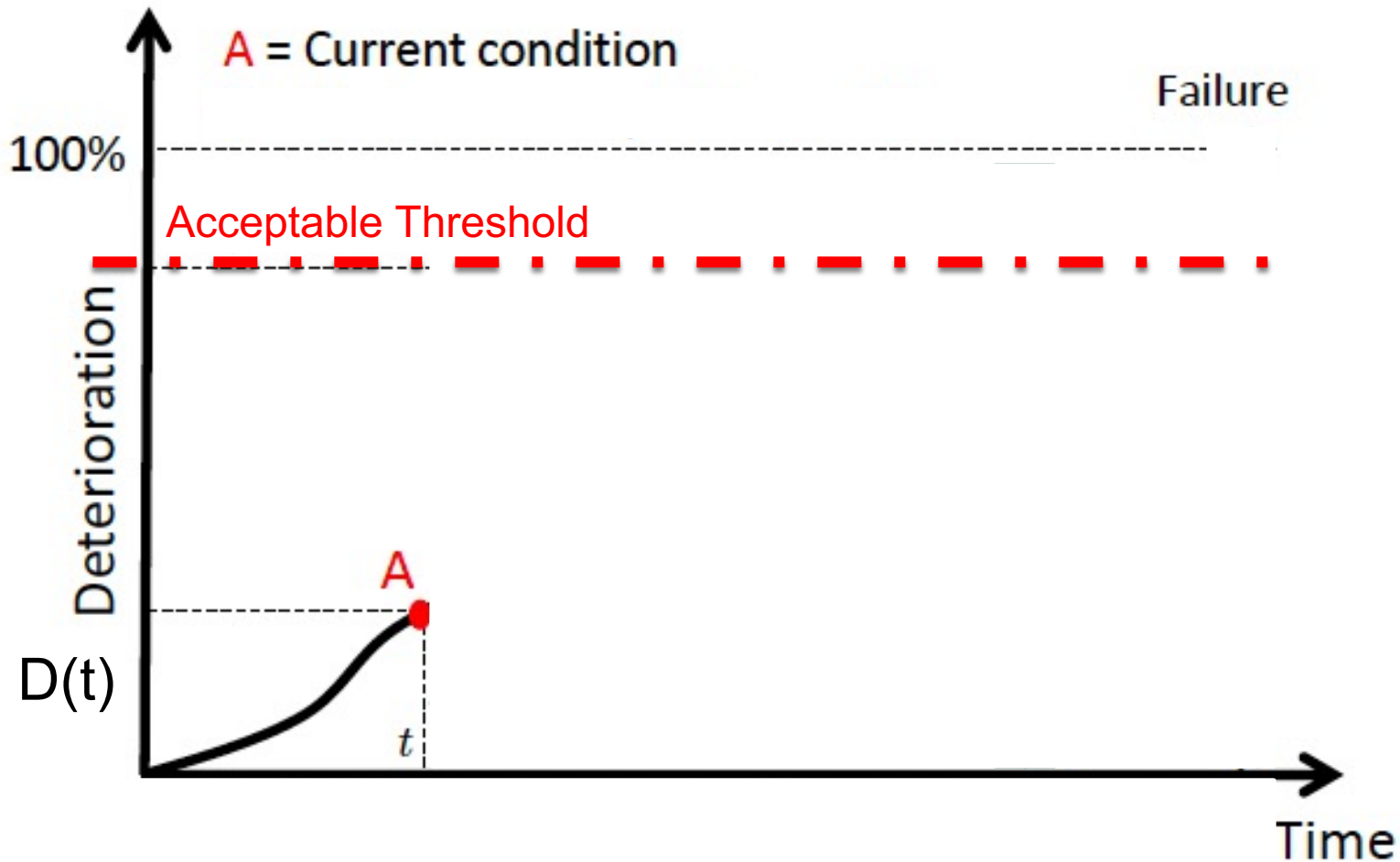
OUTLINES

Health Aware Control

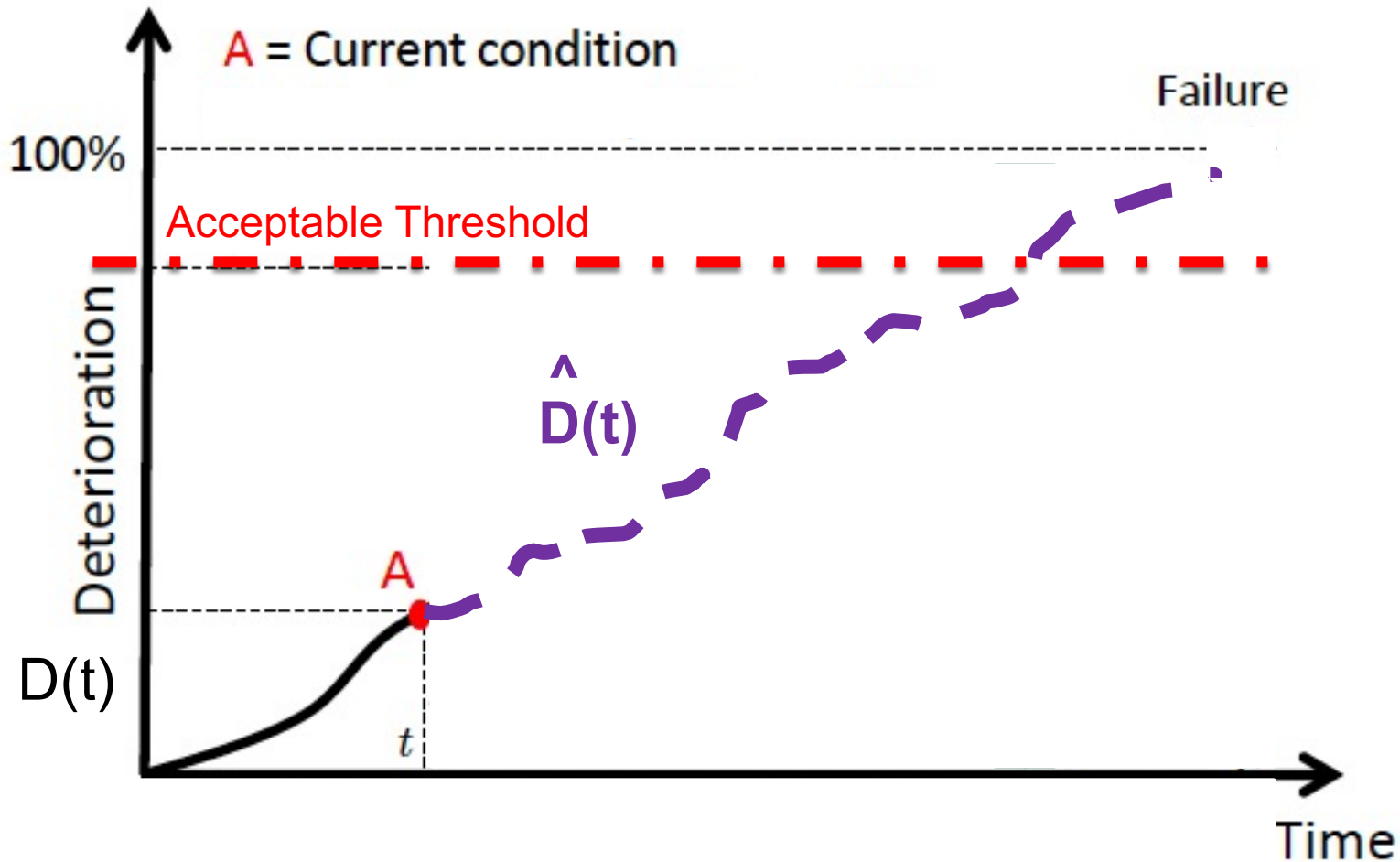
HAC based on RUL estimation



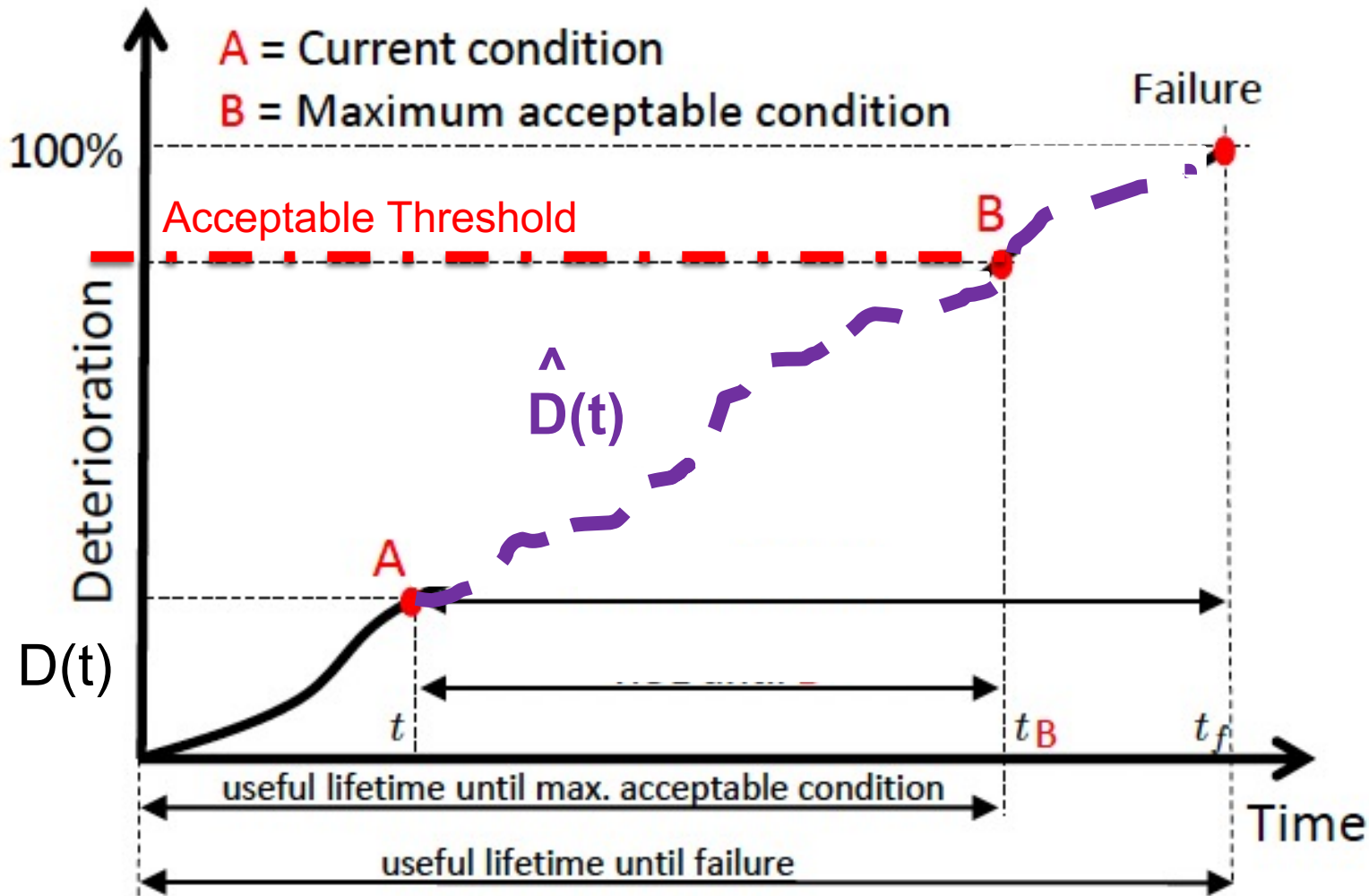
Remaining Useful Life Estimation



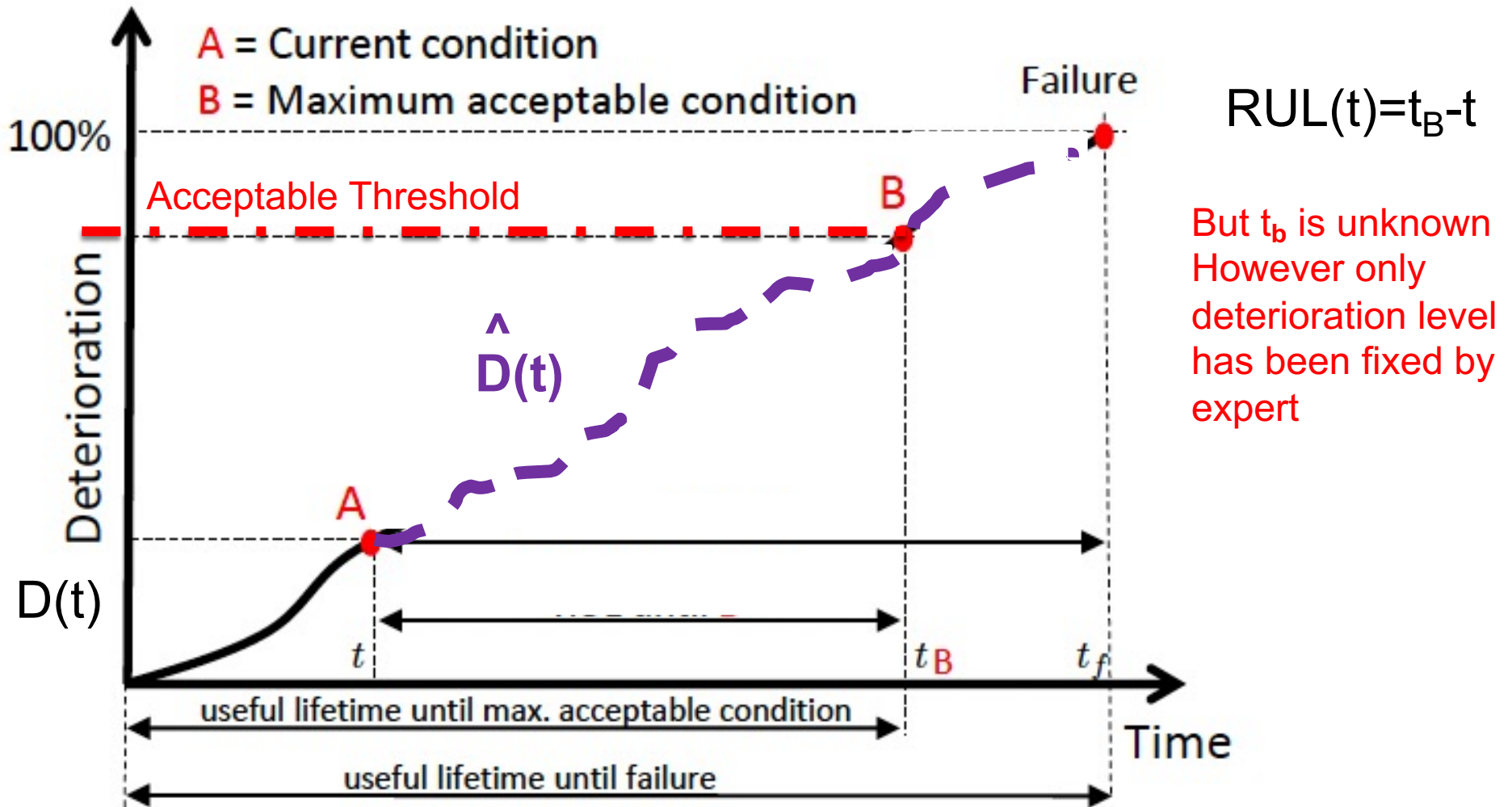
Remaining Useful Life Estimation



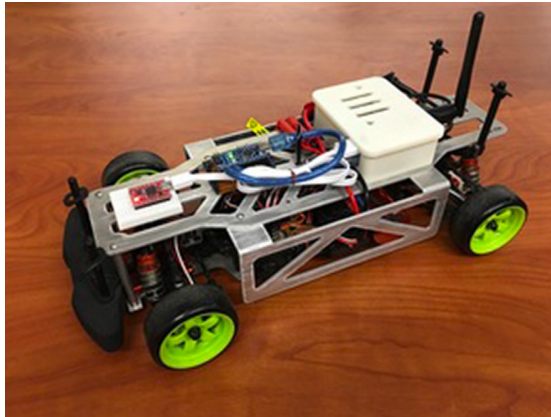
Remaining Useful Life Estimation



Remaining Useful Life Estimation



Unmanned Ground Vehicle



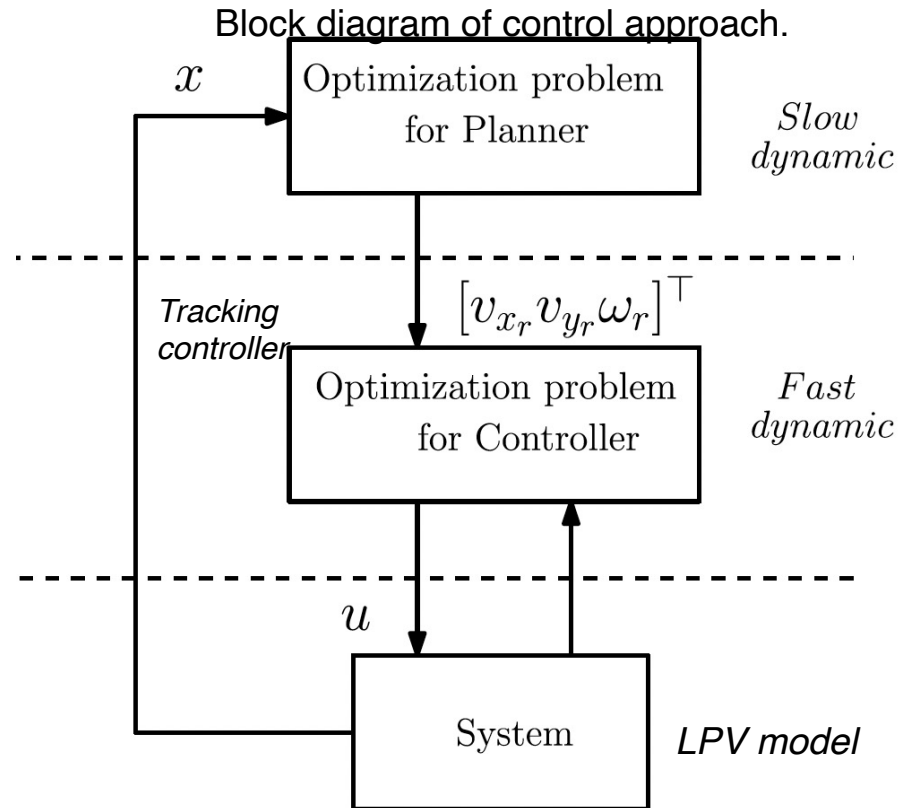
Berkeley Autonomous Vehicle

State of Charge (SoC):

$$SoC(t) = SoC(t_0) - P_{batt}(t),$$

$$P_{batt}(t) = P_{move}(t) + P_{friction}(t),$$

$$P_{batt}(t) = \frac{1}{2} C_d \rho A_r v_x^2 + \mu m g v_x,$$



$$RUL(k) = \frac{SoC_{thresh} - SoC(k)}{-u_b(k)},$$

Unmanned Ground Vehicle



Berkeley Autonomous Vehicle

State of Charge (SoC):

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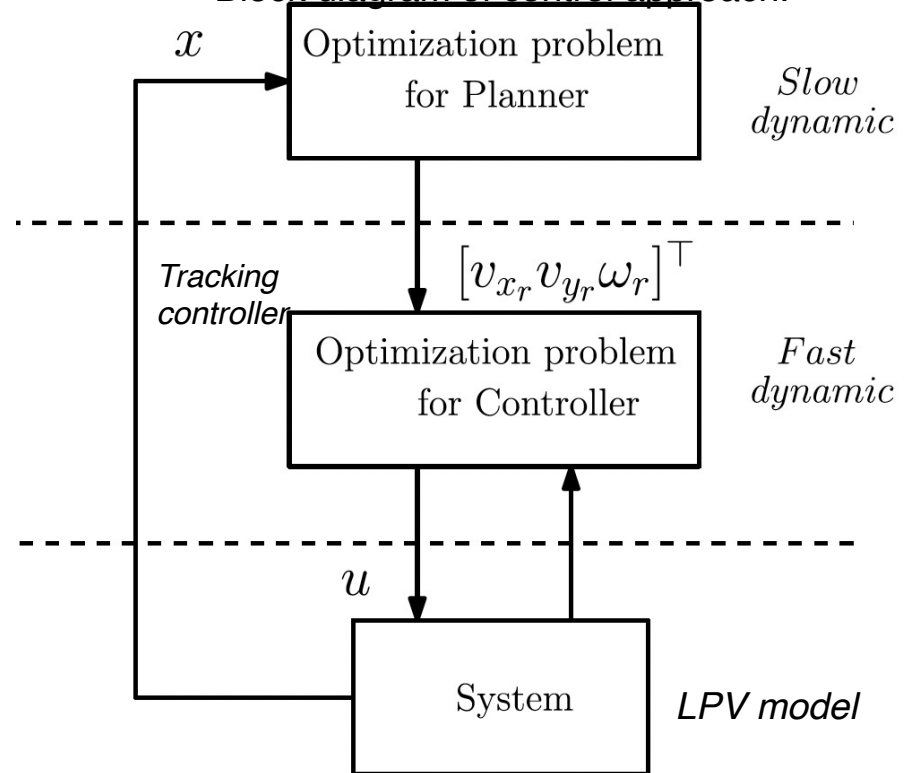
$$P_{batt}(t) = P_{move}(t) + P_{friction}(t),$$

$$P_{batt}(t) = \frac{1}{2} C_d \rho A_r v_x^2 + \mu m g v_x,$$

$$\dot{\tilde{x}}(t) = \tilde{f}(\tilde{x}(t), u(t), w(t), v(t)),$$

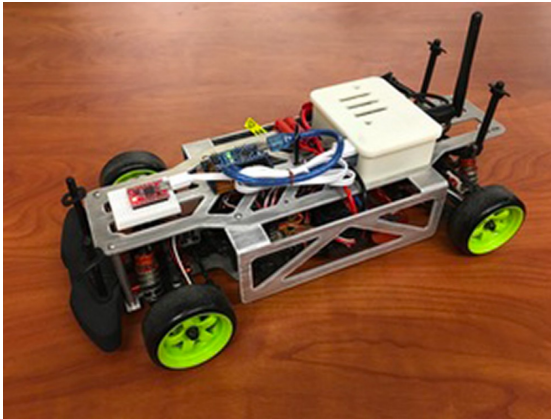
$$\text{with } \tilde{x}(t) = [v_x, v_y, \omega, \tilde{e}_y, \tilde{e}_\theta, \underline{t}, SoC]^\top,$$

Block diagram of control approach.



$$RUL(k) = \frac{SoC_{thresh} - SoC(k)}{-u_b(k)},$$

Unmanned Ground Vehicle



Berkeley Autonomous Vehicle

State of Charge (SoC):

$$SoC(t) = SoC(t_0) - P_{batt}(t),$$

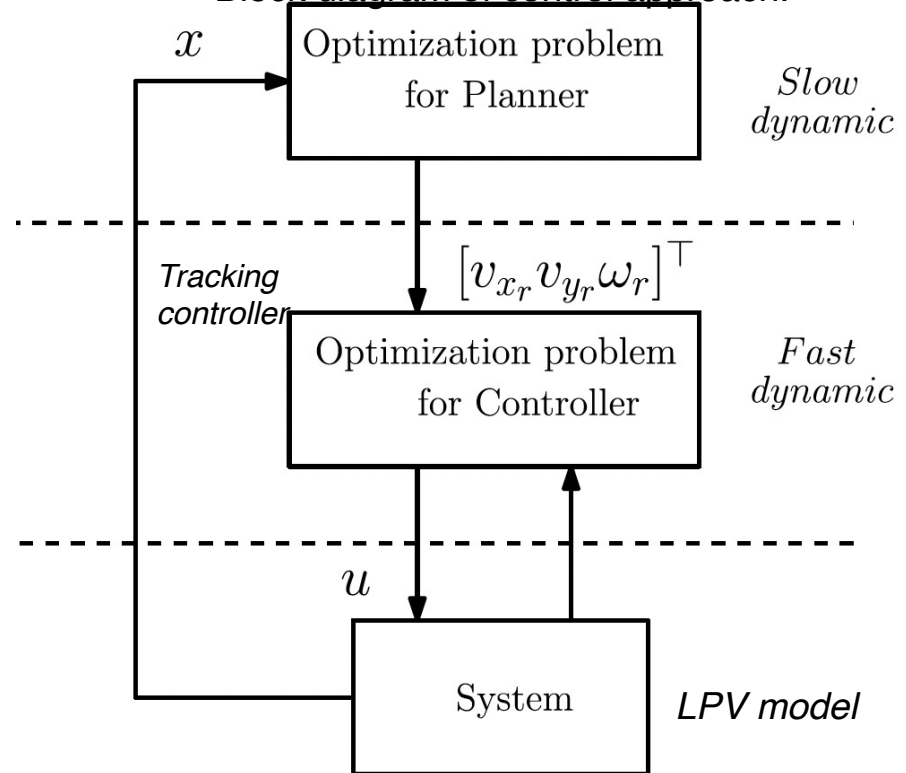
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Block diagram of control approach.

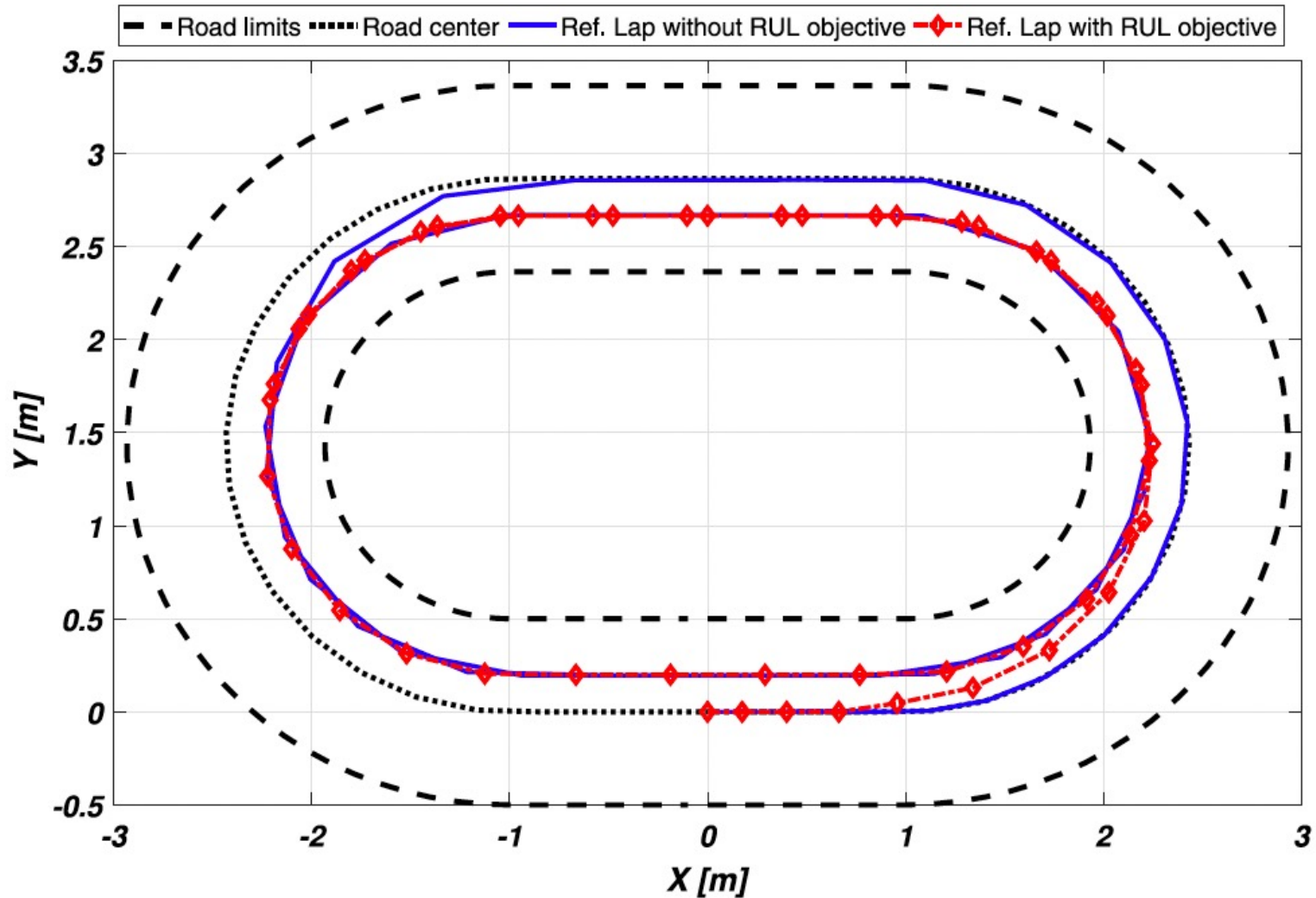


$$RUL(k) = \frac{SoC_{thresh} - SoC(k)}{-u_b(k)},$$

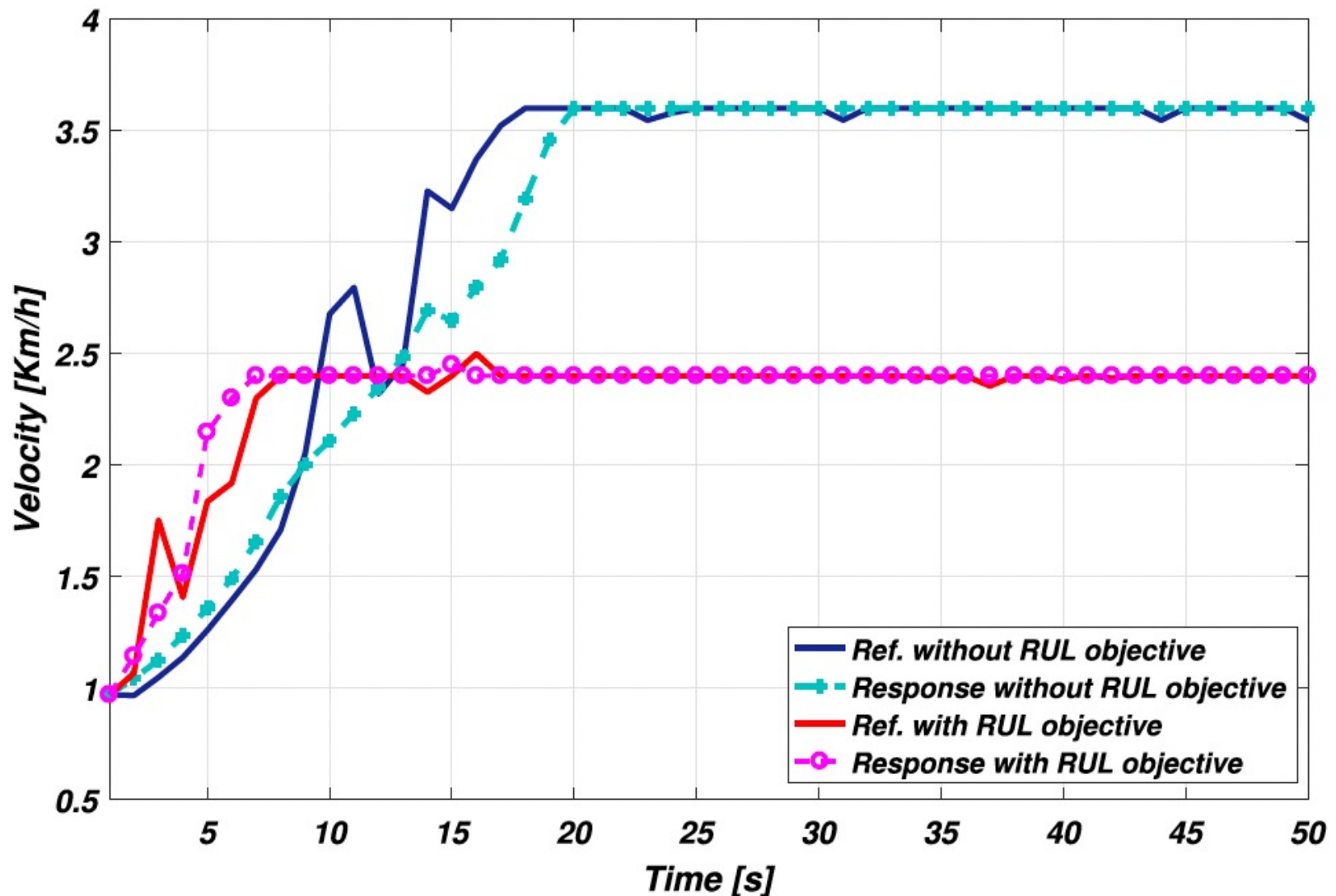


$$\min_{\tilde{u}(k+i|k), i \geq 0} \max_{[A(k+i), B(k+i)] \in \Psi, i \geq 0} J_{g, \infty}(k) = \sum_{i=0}^{\infty} (\|t\|_{\lambda_1}^2 + \|\frac{1}{RUL}\|_{\lambda_2}^2),$$

Simulation Results

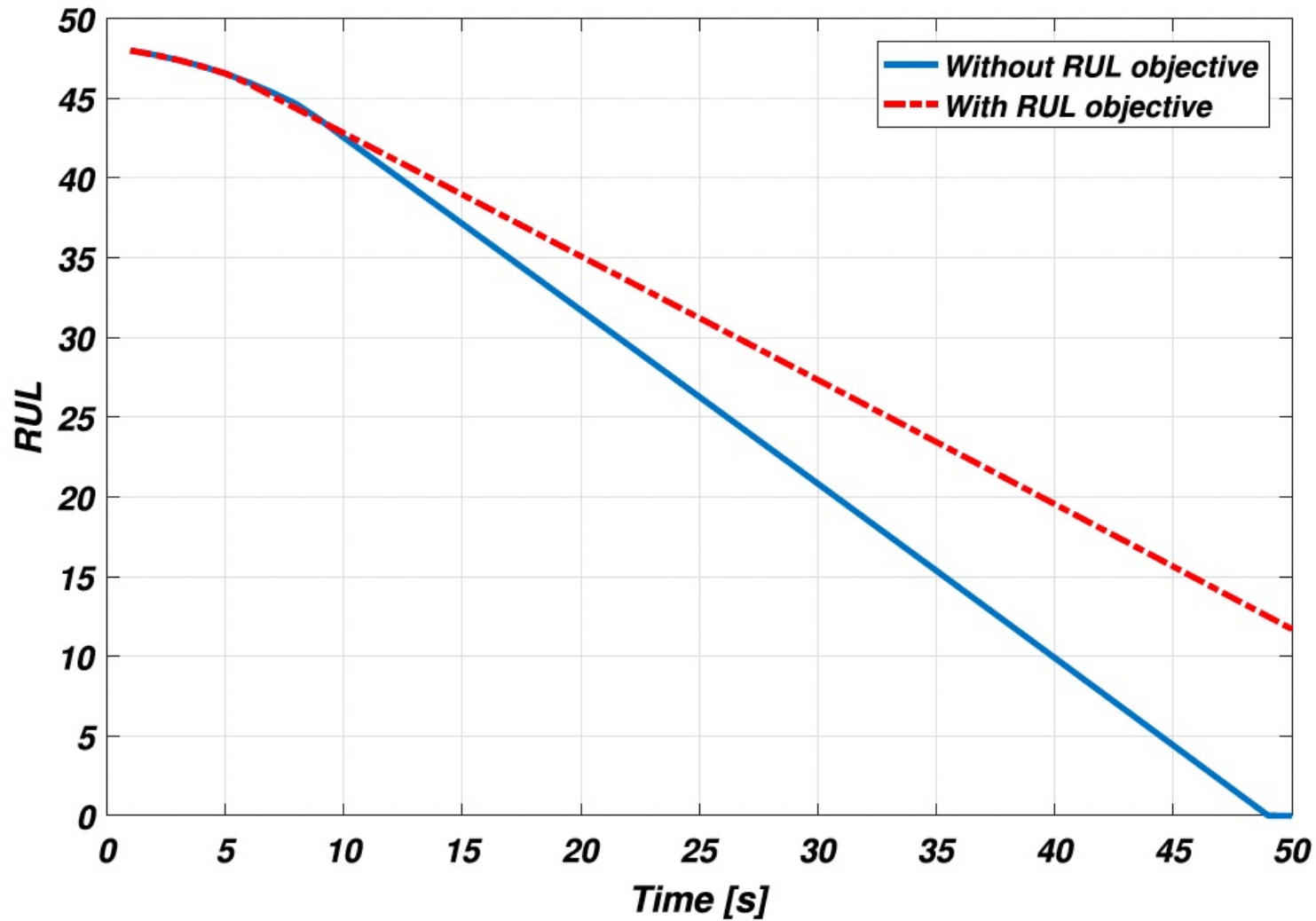


Simulation Results



Simulation Results

Reduce carbon footprint !!



Reference

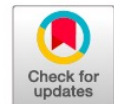
ISA Transactions 113 (2021) 196–209



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ISA Transactions

journal homepage: www.elsevier.com/locate/isatrans



Practice article

Health-aware control design based on remaining useful life estimation for autonomous racing vehicle

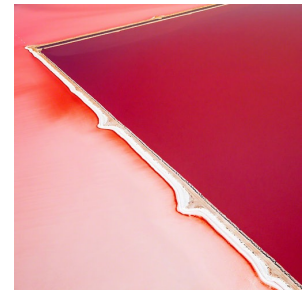
Fatemeh Karimi Pour^{a,*}, Didier Theilliol^b, Vicenç Puig^a, Gabriela Cembrano^a

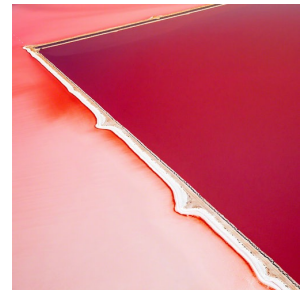
^a Advanced Control Systems Group, Universitat Politècnica de Catalunya, Institut de Robòtica i Informàtica Industrial (CSIC-UPC), C/. Llorens i Artigas 4-6, 08028 Barcelona, Spain

^b Université de Lorraine, CRAN CNRS, UMR 7039, Campus Sciences, B.P. 70239, 54506 Vandoeuvre-les-Nancy Cedex, France

OUTLINES

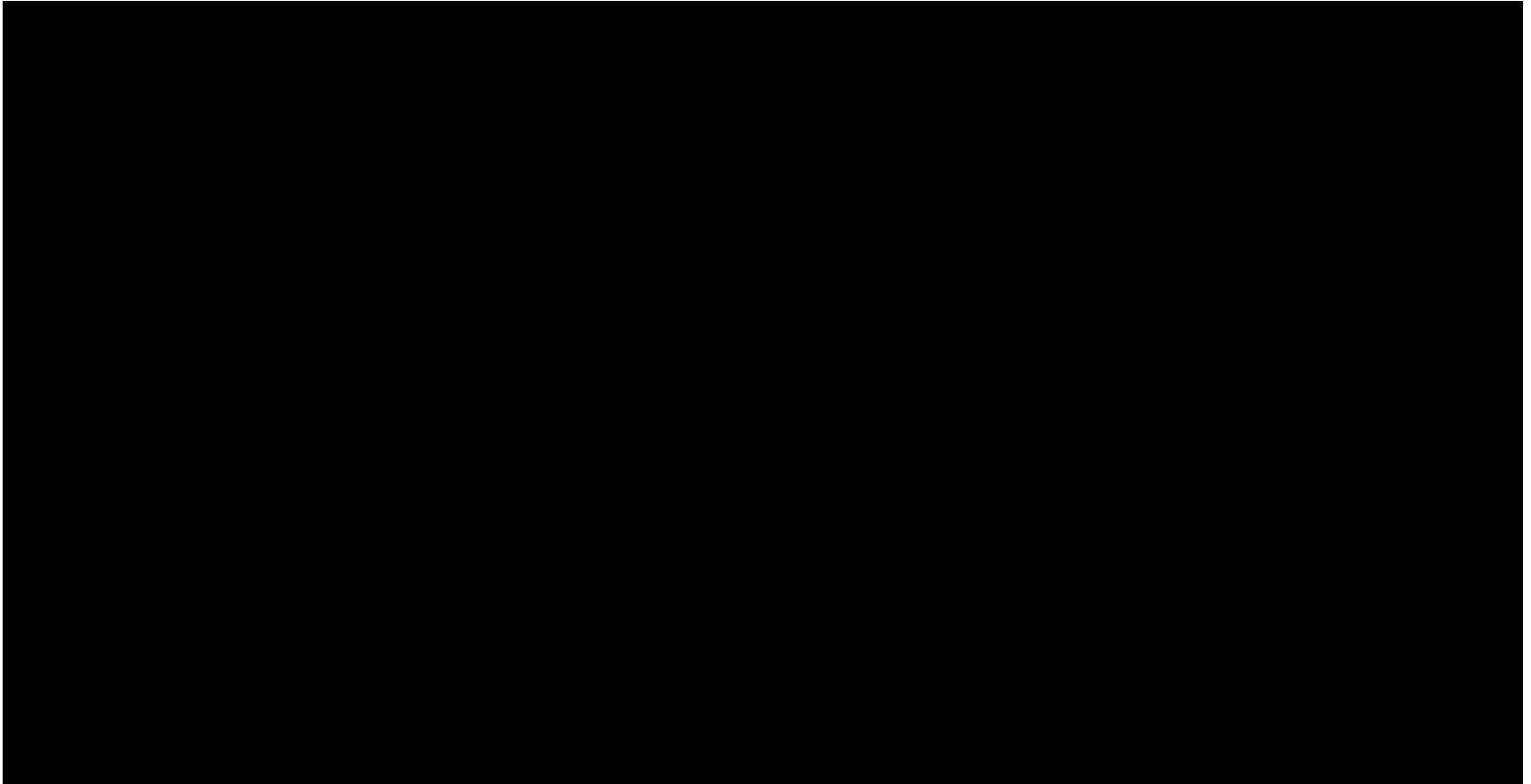
Safe Reinforcement Learning (*)
Reinforcement Learning
Safe Reinforcement Learning





Model free control learning: Q-learning (DDPG)

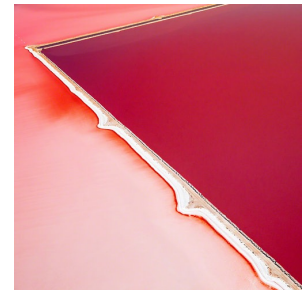
Inverted pendulum: Model free, learning of nonlinear stabilizing optimal control law



George Claudiu Andrei, Mayank Shekhar JHA*, Didier Theilliol, 2022, *Complementary reward function based learning enhancement for Deep Reinforcement learning*, 16th European Workshop on Advanced Control and Diagnosis (ACD 2022), Nancy, France

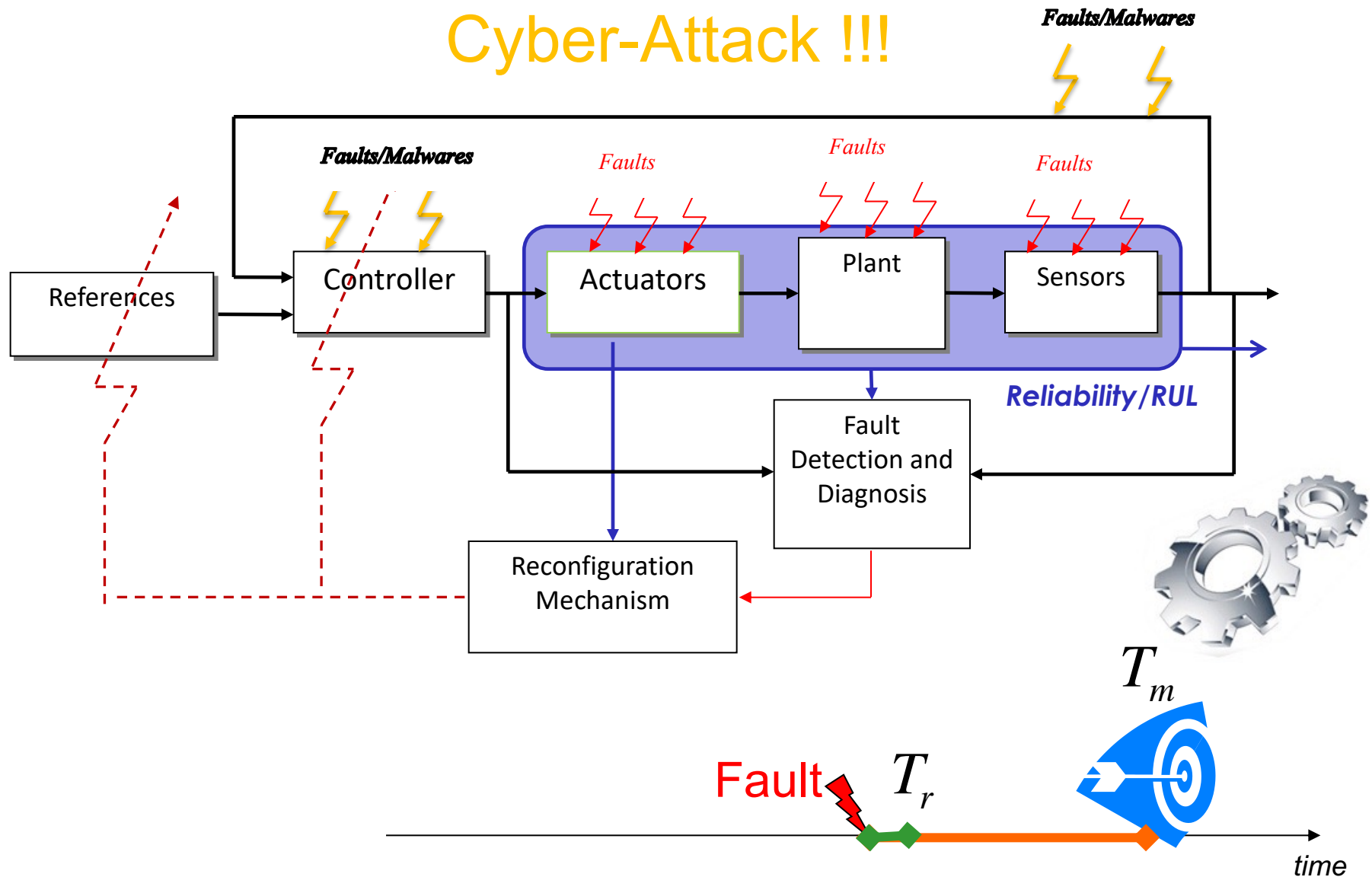
OUTLINES

Conclusions and Perspectives

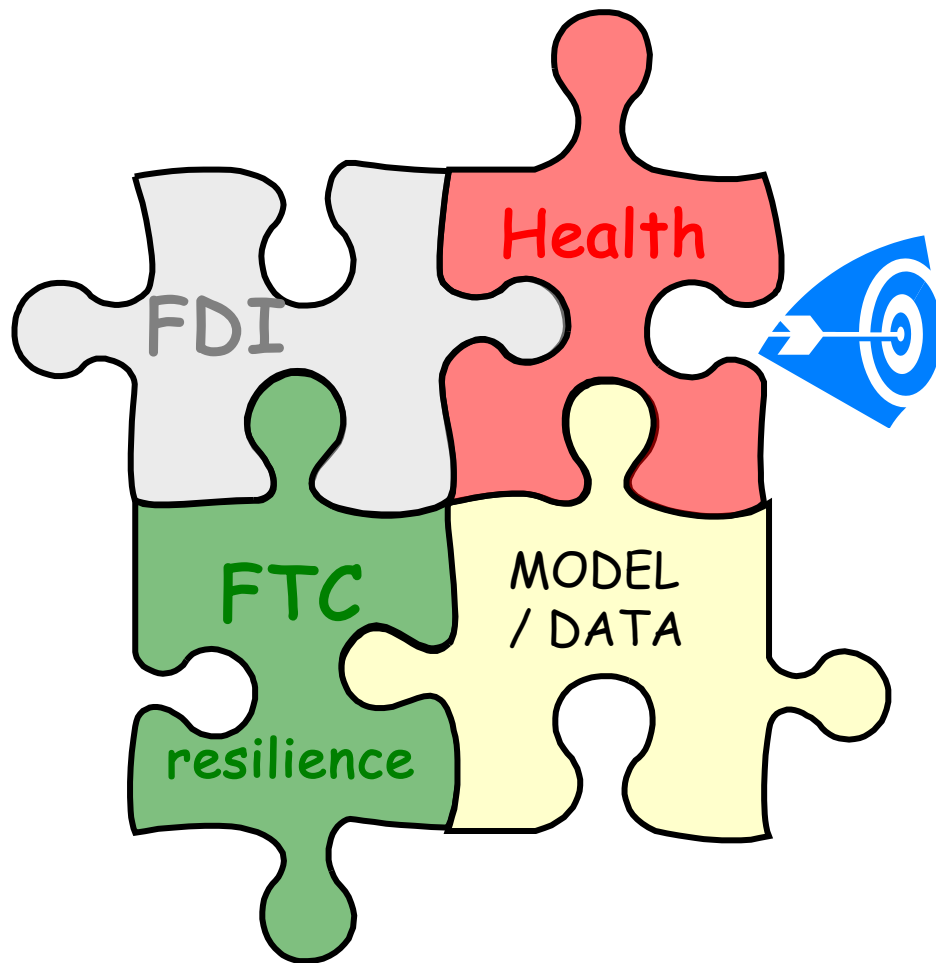


Heath Aware Control Design

Cyber-Attack !!!



Health Aware Control Design



Health Aware Control Strategy

- + Safe Learning
- + Multi Agent Systems on a fleet of Unmanned Vehicles

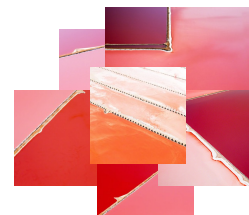


Safe Reinforcement Learning, Resilient/Fault Tolerant and Health Aware Control Strategies for Autonomous Systems

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