

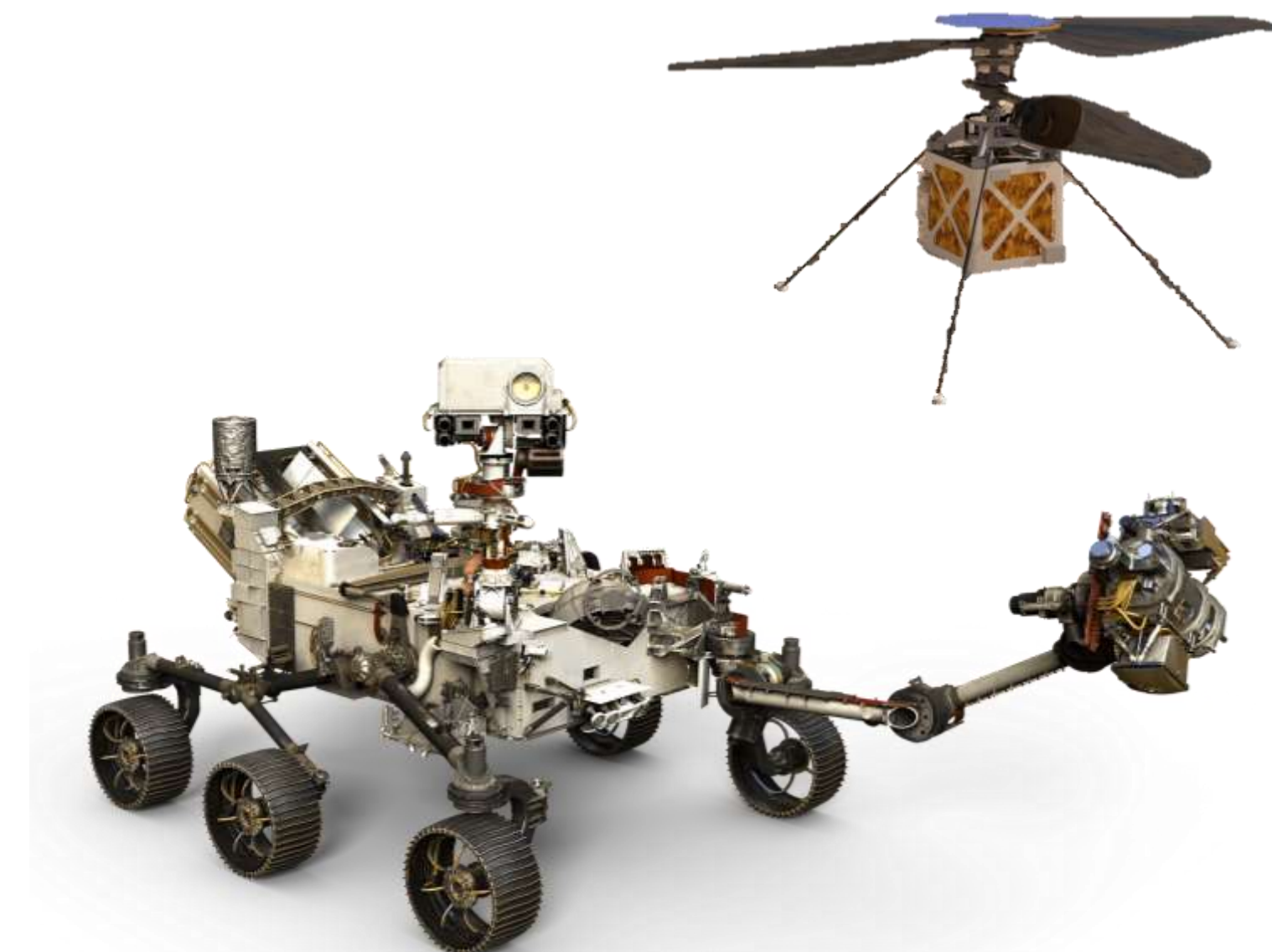
# Dealing with uncertainty in safety-critical cyber-physical systems

A control engineering perspective

dr. ir. Sofie Haesaert

Assistant Professor  
TU Eindhoven

November 27, 2019





# Control engineering — classically

Provide **stability**, **performance** and **robustness** via **feedback** withstanding **physical uncertainty** and **stochasticity**

Mechanical ~1788

Governor & throttle valve

1st automatic control

Analogue

PID control

Digital control

Optimal control

Robust control

Complex systems

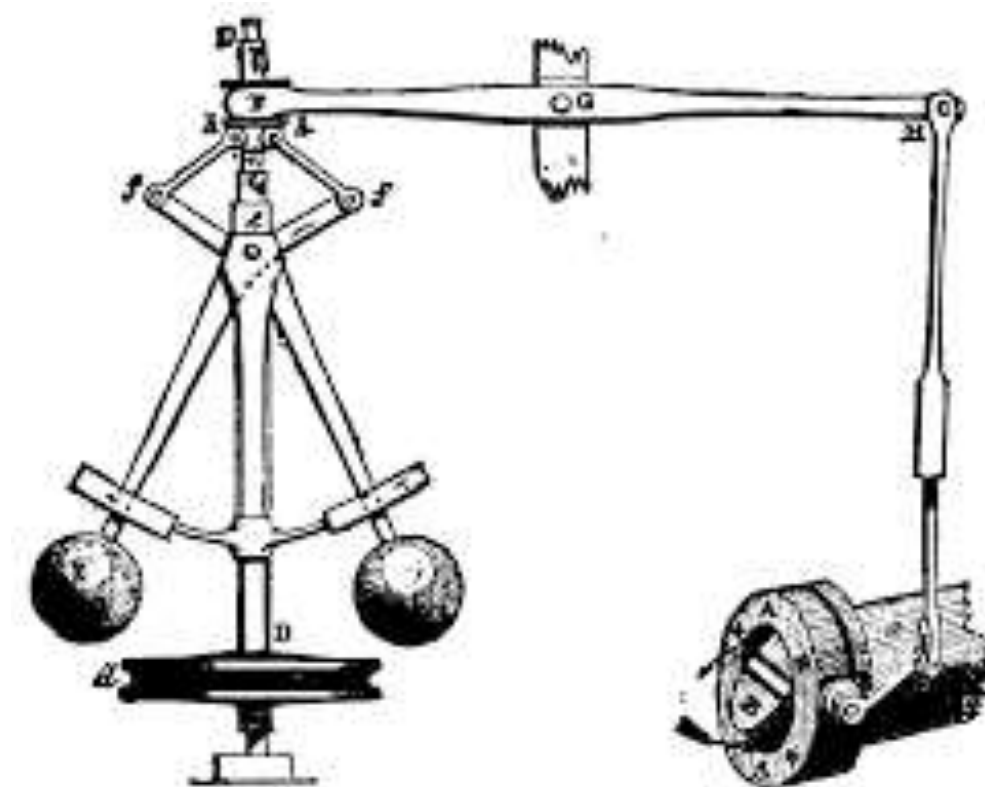
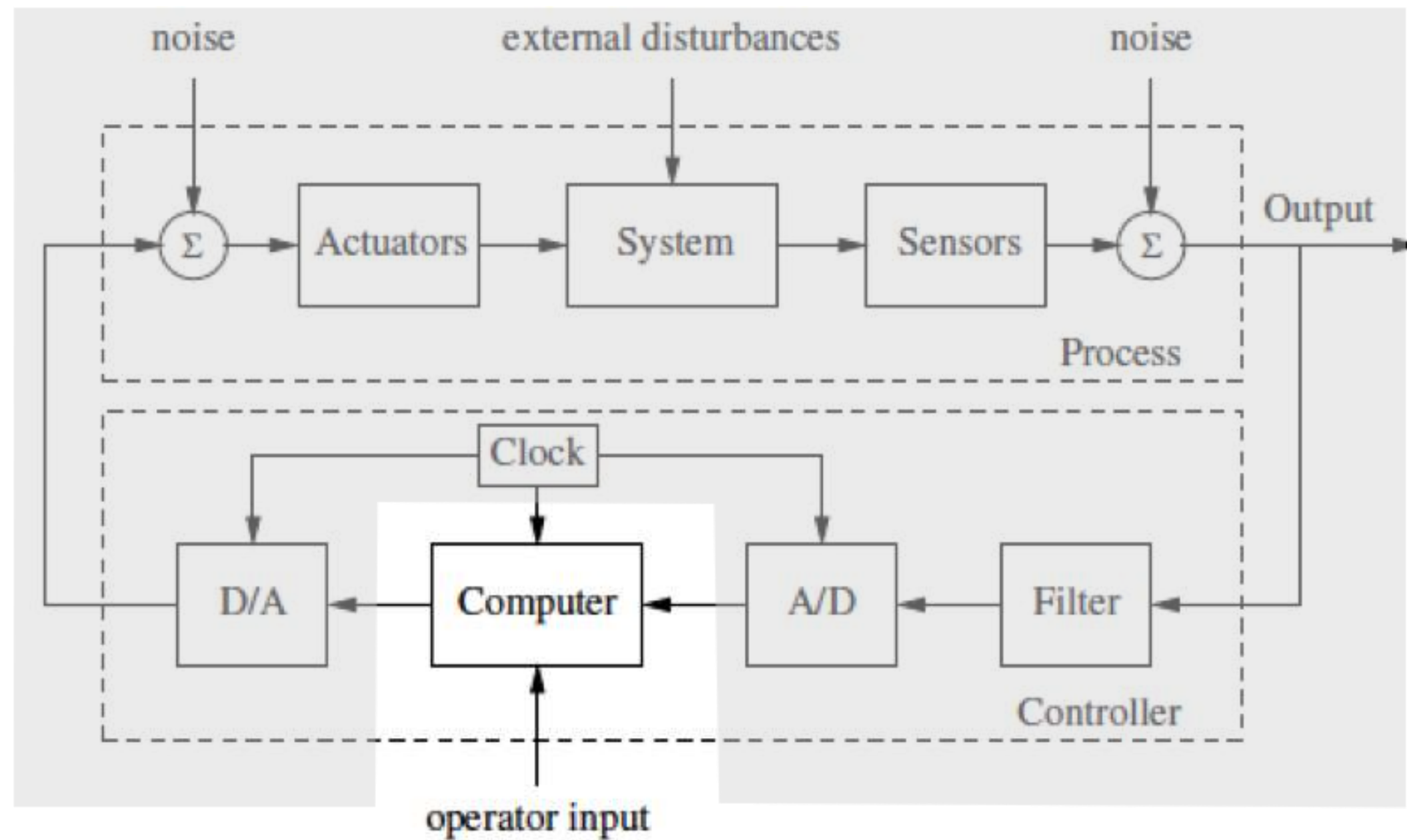


FIG. 4.—Governor and Throttle-Valve.





# Examples of digitally controlled systems



## Models for digital control

**state:**  $x(t+1) = F(x(t), u(t))$  + **disturbances**  
**output:**  $y(t) = H(x(t), u(t))$  + **sensor noise**

## Dynamical systems modeled via ordinary differential equation

**state:**  $\dot{x}(t) = f(x(t), u(t))$  + **disturbances**  
**output:**  $y(t) = h(x(t), u(t))$  + **sensor noise**



# Control engineering — emerging

Technological innovations lead to increased functionality, complexity and autonomy

Waymo's fully autonomous driving





# Cyber-physical systems (CPS)

Complex merging of computation into the physical world

Increase of connectivity, functionality, complexity, and autonomy

Physical systems with software for communications, interactions, sensing, and control.

Delivery drones (amazon)



Credit: [dryve.com](https://www.dryve.com)

Autonomous driving



Credit: Amber

Smart grid



Credit: unsplash

Long-term autonomy on Mars rover missions



Credit: NASA/JPL-Caltech



# Safety-critical cyber-physical systems

Complex merging of computation into the physical world

**Increase** of connectivity, functionality, complexity, and autonomy

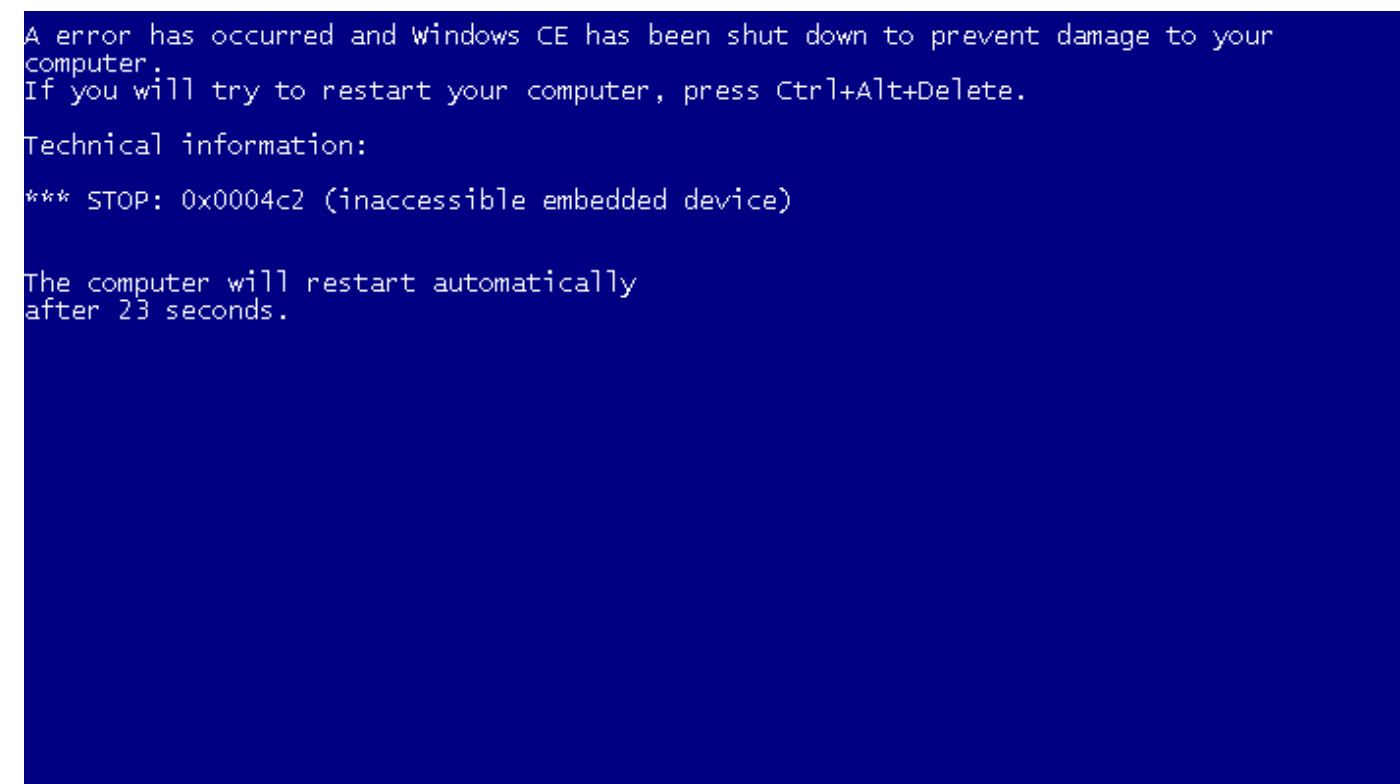
**Physical systems with software** for communications, interactions, sensing, and control.

Software bugs directly affect physical world

**Verify software + physical system**



- Uncertain, continuous space models
- Noisy output measurements
- Stochastic disturbances





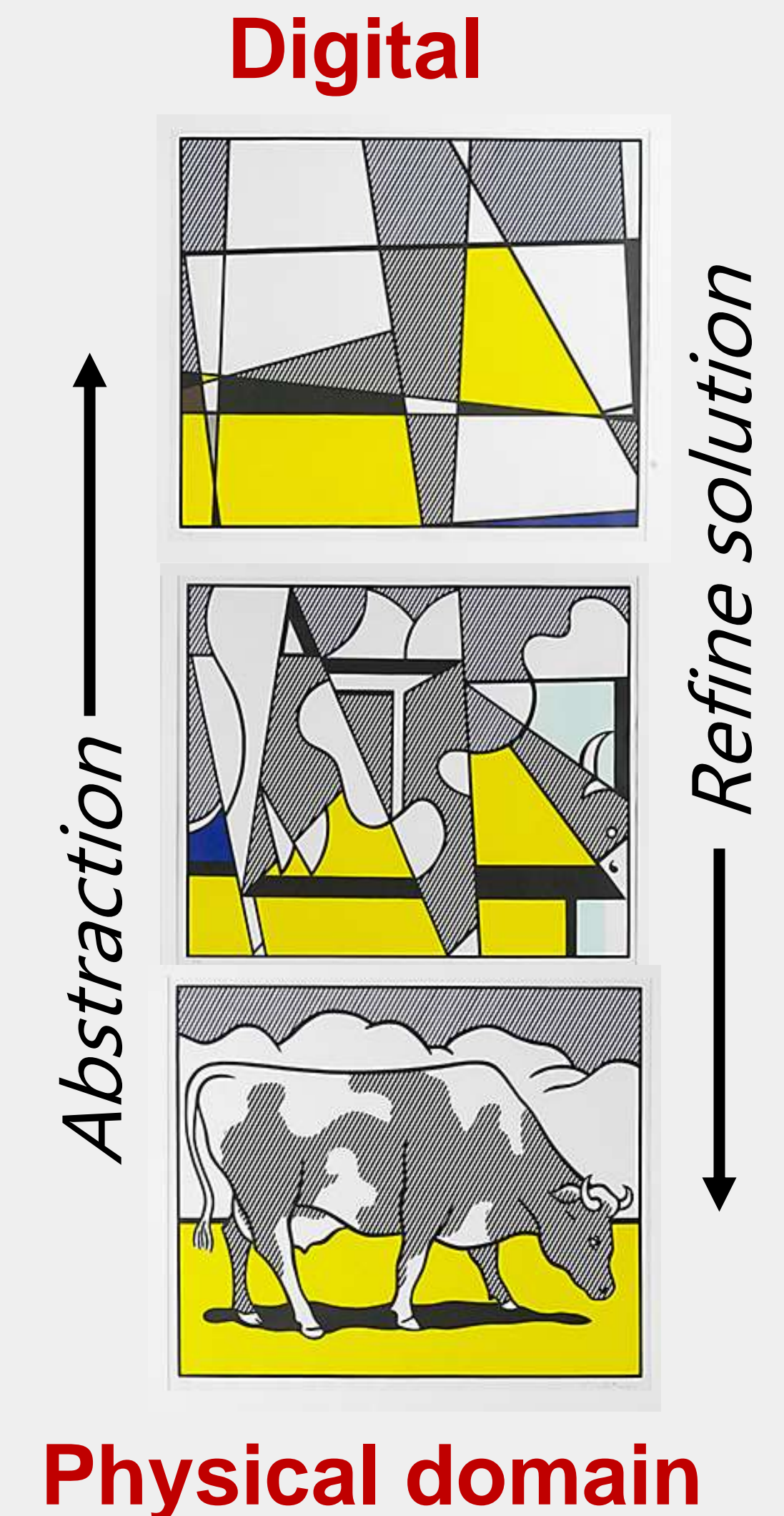
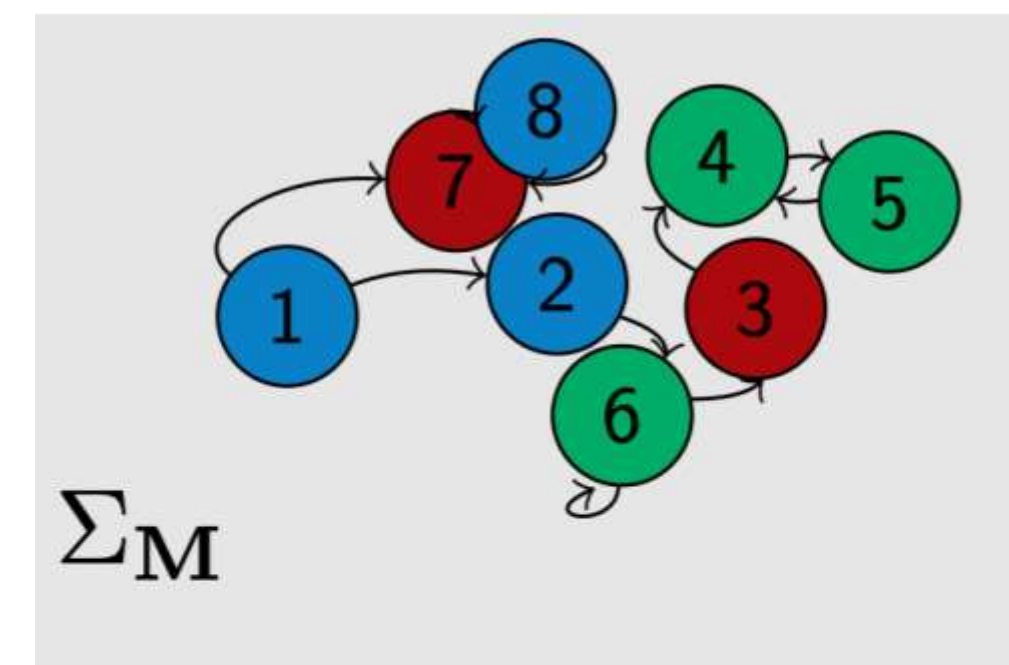
# Dealing with stochasticity in CPS

*How to design and verify digital control?*

High-level specifications  
e.g., Avoid **A** until **K** and  
eventually visit **L** ...

Physical model

- Wind & temperature
- Component failure
- Human behavior





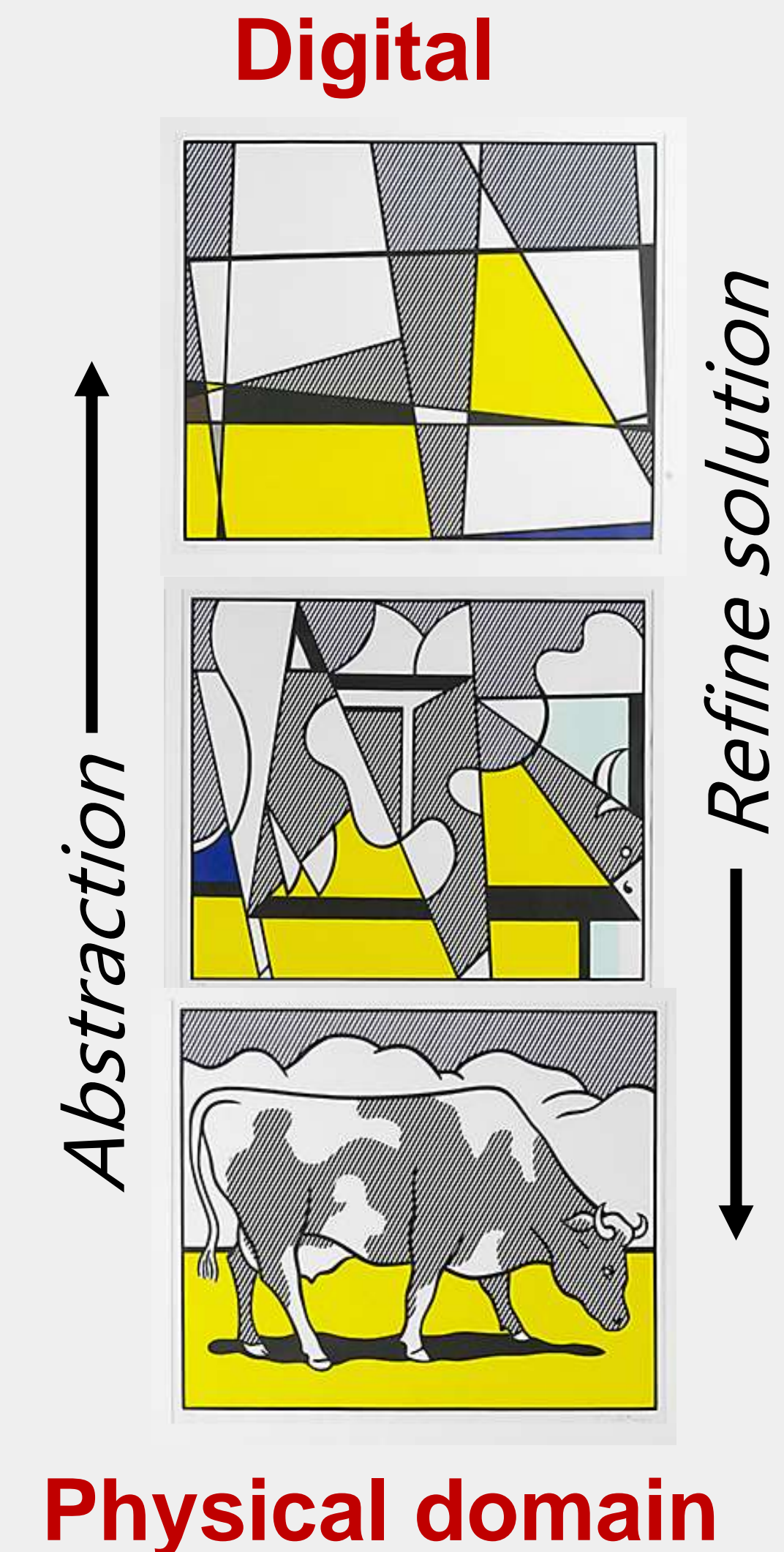
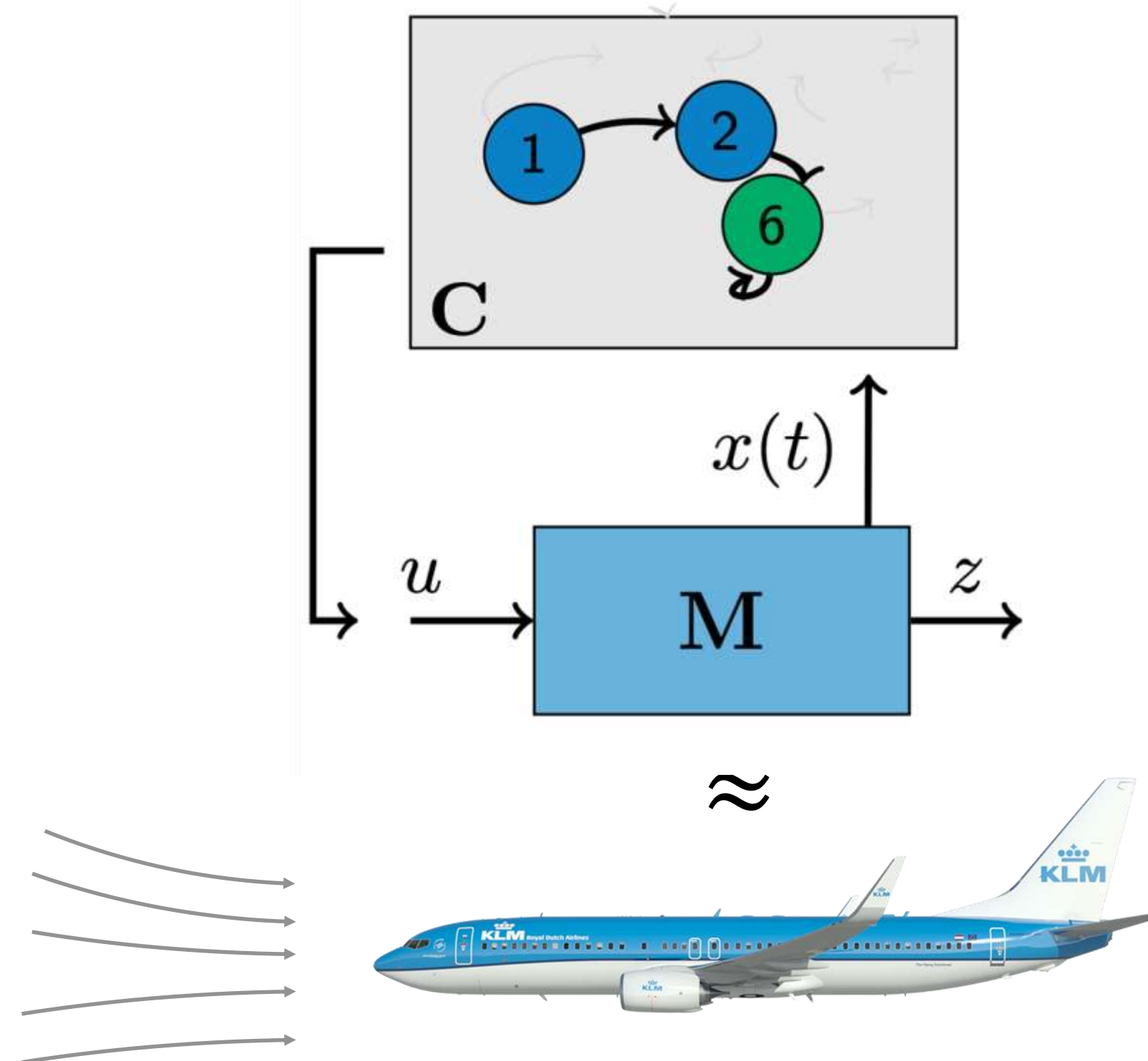
# Dealing with stochasticity in CPS

*How to design and verify digital control?*

High-level specifications  
e.g., Avoid **A** until **K** and  
eventually visit **L** ...

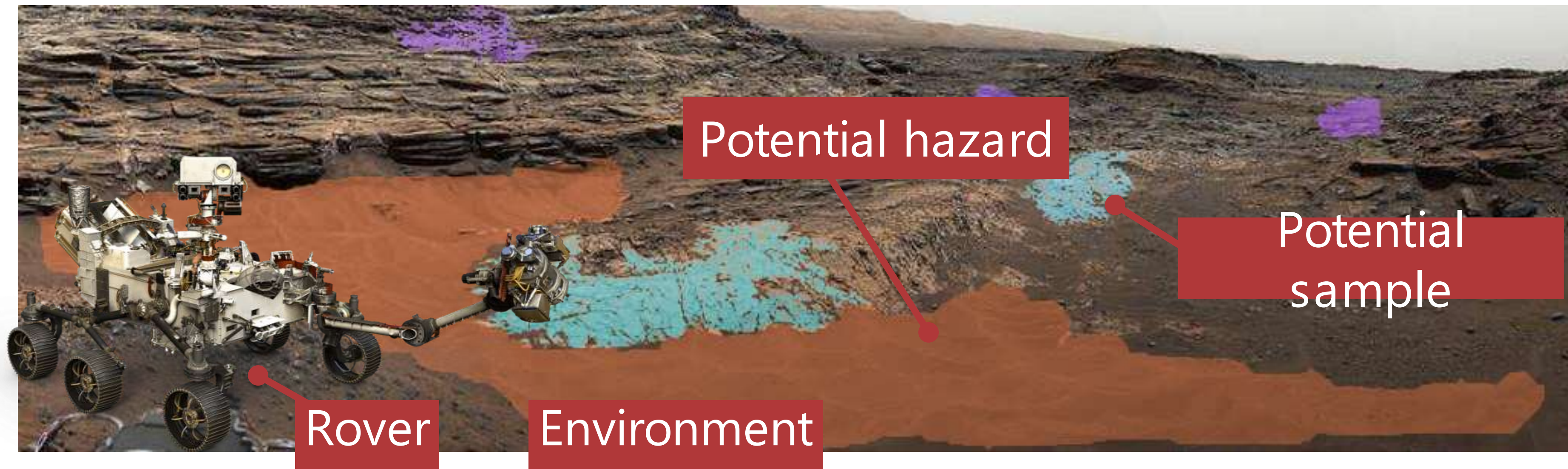
Physical model

- Wind & temperature
- Component failure
- Human behavior





# Dealing with partial & noisy observations



Mission specification

$$\psi := \neg \text{fail} \mathcal{U} \text{ sample}$$



Partially observable MPD

$$x_{t+1} \sim \mathbb{T}(\cdot | x_t, u_t) \leftarrow \text{state}$$
$$z_t \sim \mathbb{R}(\cdot | x_t, u_t) \leftarrow \text{observations}$$

Belief MDP

$$b_t = \mathbb{P}(dx_t | (u_k, y_k)_{k \leq t}) \leftarrow \text{state}$$
$$b_{k+1} \sim \mathbb{T}_b(\cdot | b_k, u_k) \leftarrow \text{belief transitions}$$

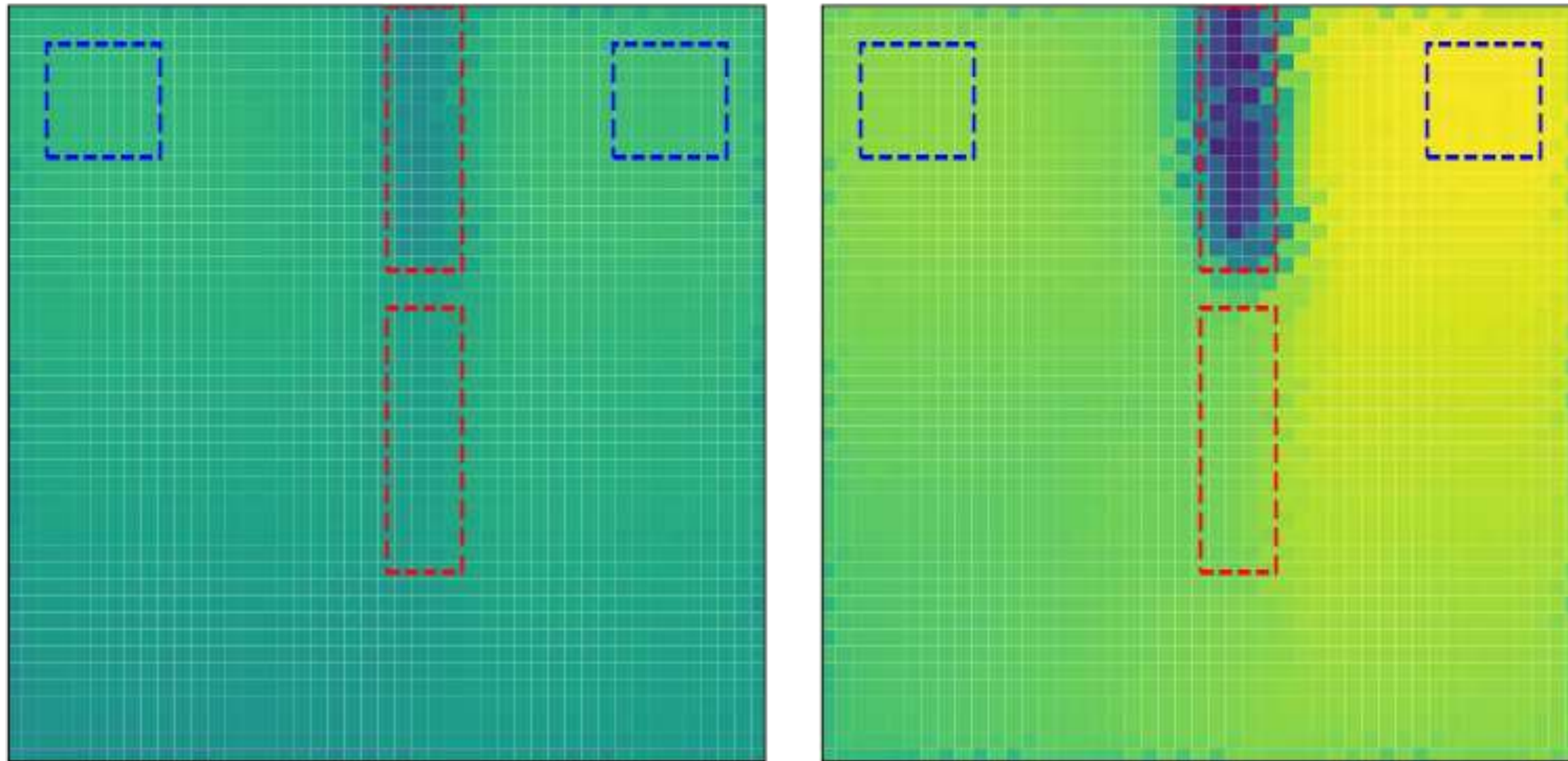
Abstract problem

Finite MDP  $\tilde{\mathbf{M}}$   
+ specification  $\psi$



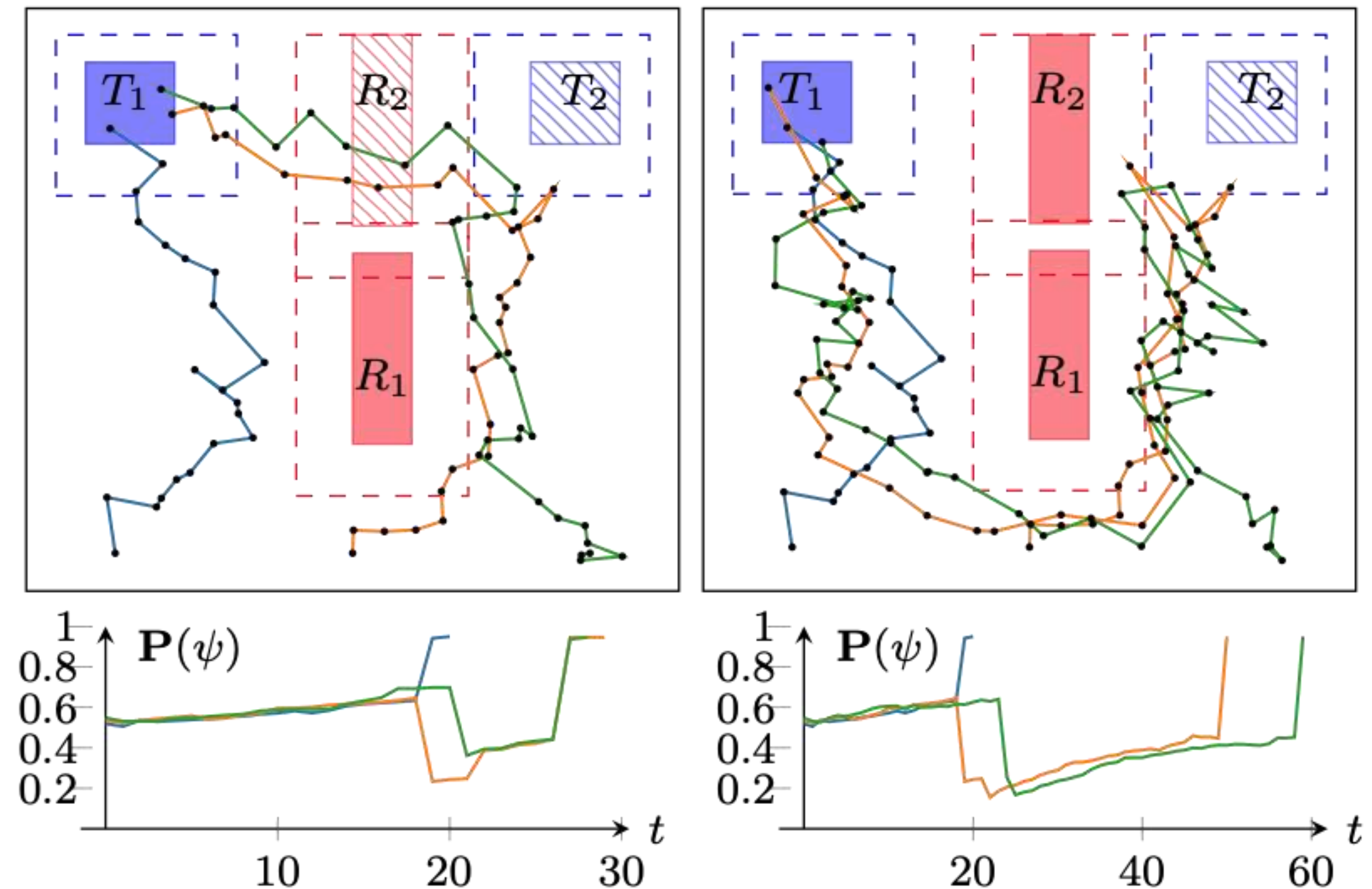
# Dealing with partial & noisy observations

*How to design and verify digital control?*



## Control refinement to gMDP

- Preserves guarantees



## Computations on abstract model

- Value iterations
- Robust temporal logic satisfaction

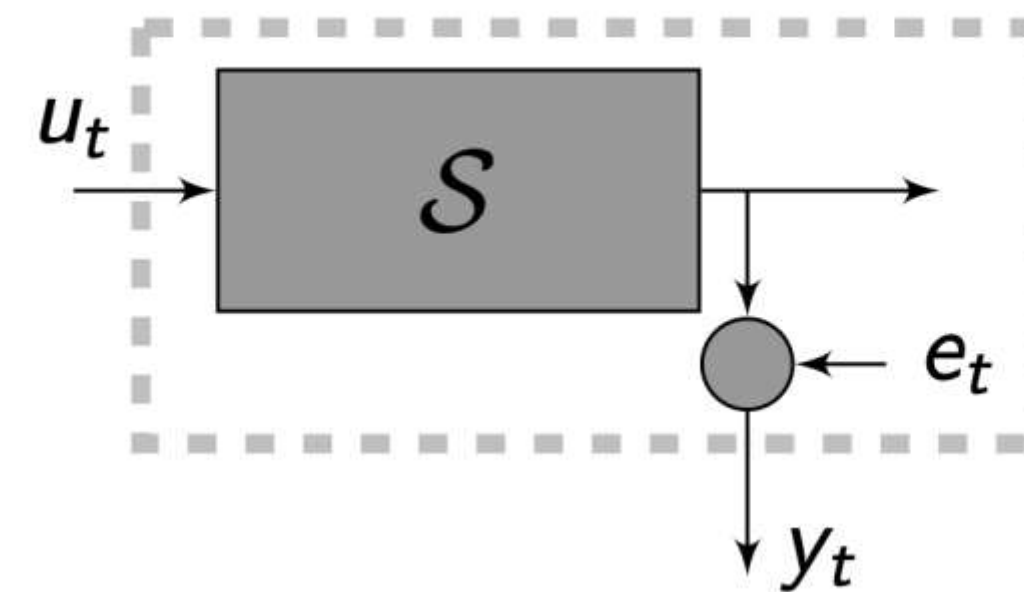


# Dealing with model uncertainty in CPS

*How to verify functionality using data?*



Partially unknown system



$$\left. \begin{aligned} x_{t+1} &= f(x_t, u_t; \theta) + v_t \\ y_t &= h(x_t; \theta) + e_t \end{aligned} \right\} \mathbf{M}(\theta) \text{ Parameterized model}$$

$\theta = \text{unknown parameter}$

Solution: Use prior knowledge and data

Compute confidence with Bayesian inference

$$\mathbf{P} \{ \mathbf{M}(\theta) \models \psi \mid (u, y)_t \}$$

Data obtained from system



# Dealing with model uncertainty in CPS

*How to collect the right data efficiently?*

Design experiment input  
to gain information on  
property satisfaction.

$$\mathbf{P}(\mathbf{M}(\theta) \models \psi \mid \{u, y\}_t)$$

← Data from  
experiment

= Optimal control problem

Maximize probability of reaching decision

$$\mathbf{P}(\mathbf{M}(\theta) \models \psi \mid \{u, y\}_t) \geq 1 - \delta = \text{accept}$$

$$\mathbf{P}(\mathbf{M}(\theta) \models \psi \mid \{u, y\}_t) \leq \delta = \text{reject}$$



Some data is expensive



# Dealing with uncertainty in safety-critical cyber-physical systems

A control engineering perspective

dr. ir. Sofie Haesaert  
Assistant Professor  
TU Eindhoven  
The Netherlands

Contact me at  
Sofiehaesaert.com  
[s.haesaert@tue.nl](mailto:s.haesaert@tue.nl)

# Thank you for your attention