Composition of Scheduling and Control-Theory Techniques

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New Challenges in Scheduling Theory
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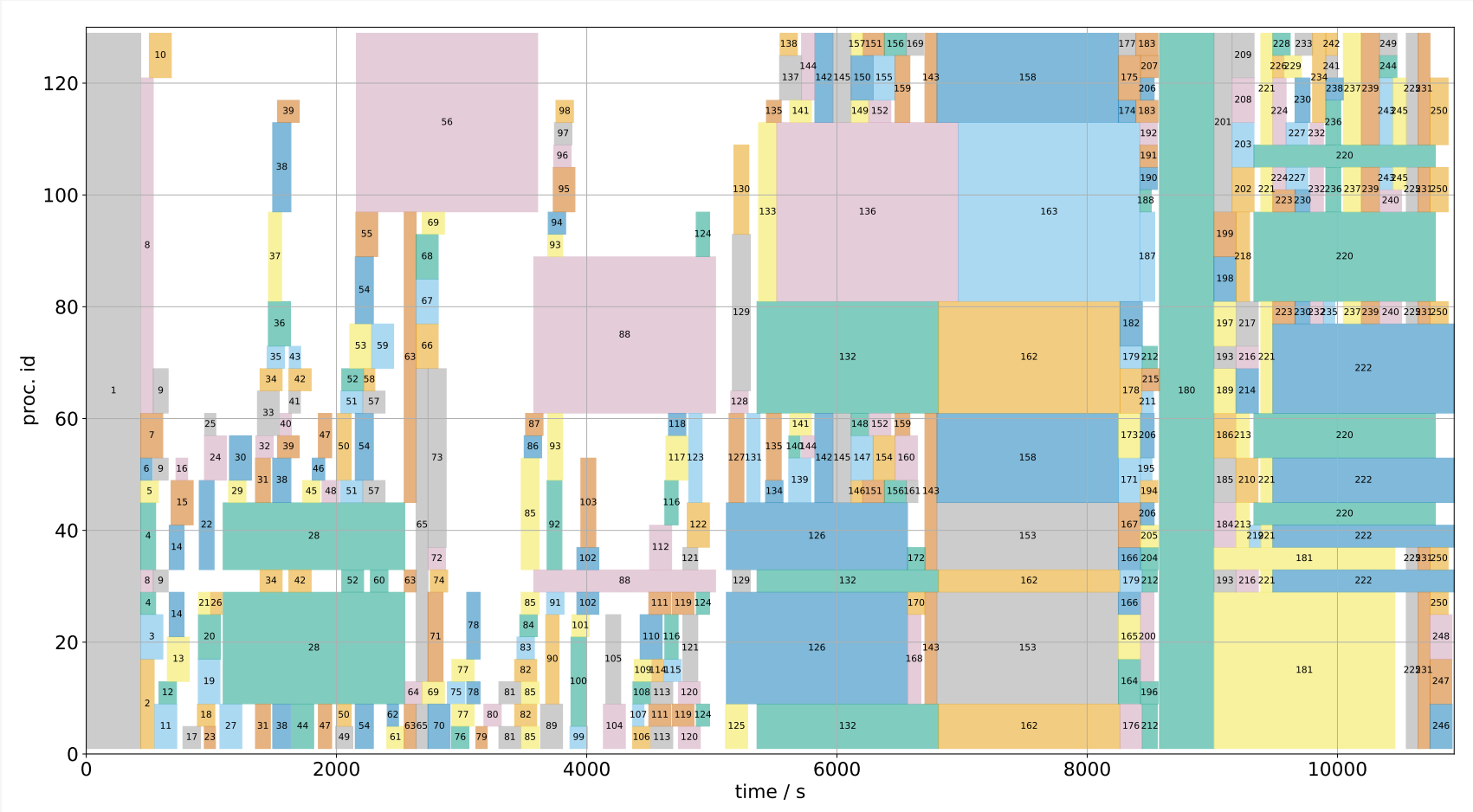
Scheduling (~ Resource Allocation)



platform tasks/jobs objective

$\Longrightarrow$ where? & when?

Coping with reality?

complex systems

- network topology: fat tree, $\star$-fly, torus
- intricate software stacks: kernel, runtimes, application code

complex behaviors

- provisioning/deprovisioning jobs
- sensitive dependence on initial conditions

extrinsic variability

- offline: hardware spec., aging, ...
- online: phases (e.g., I/O, compute), adaptive routing, failures, temperature, ...

Simplistic ∧ Tangled Models

some answers

- ignore the "complex" parts: $1 \mid\mid C_{\max}$, $P \mid\mid C_{\max}$, ...
- offline *vs.* online *vs.* clairvoyant
- introducing uncertainty: stochastic models

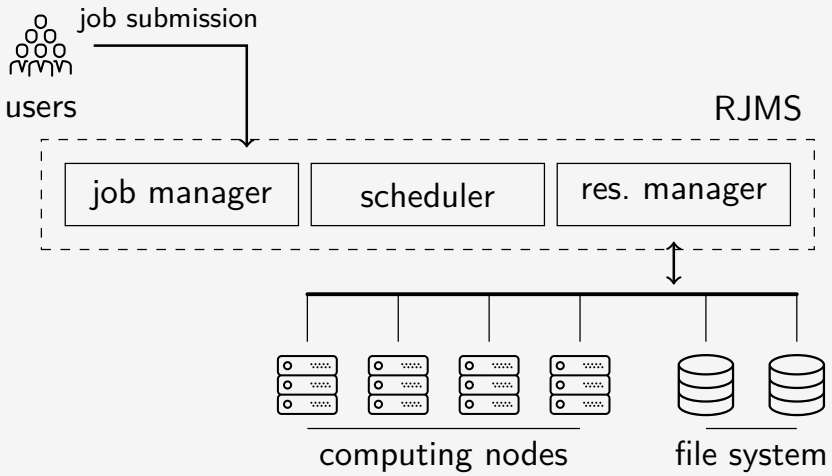
rough spots

- non-representative models (ivory tower?)
- non-instantiable models
- time & dynamics of the system

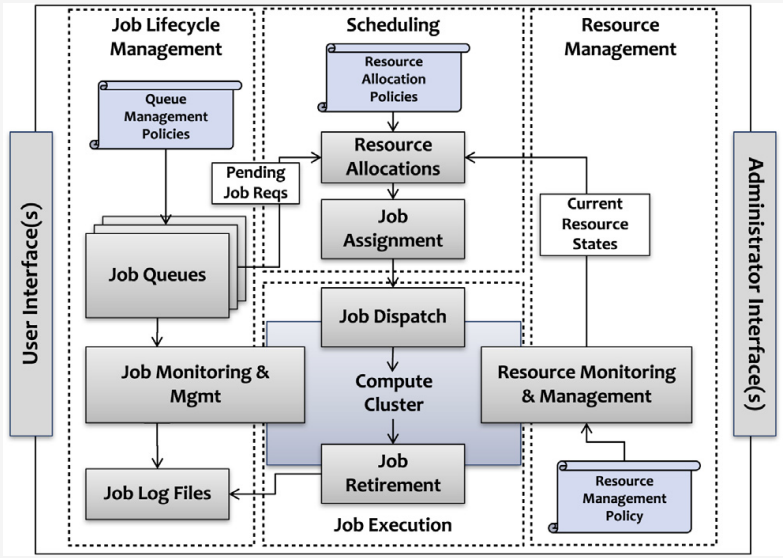
$\Rightarrow$ hard to maintain guarantes

Scheduler/RJMS structure

Let's take a step back, and consider the *whole* system.



(Georgiou 2010)



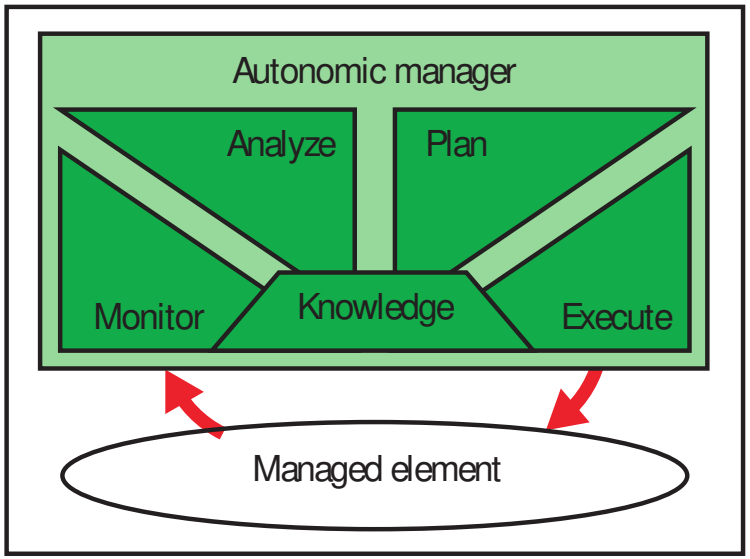
(Reuther et al. 2018)

$\Rightarrow$ open-loop (no feedback) *vs.* closed-loop

Feedback loops (*à la* Control Theory)

Autonomic Computing (Kephart et al. 2003)

1. monitor system state
2. choose/adapt (online) parameters
3. `GOTO 1`



Control Theory

Challenges

- stability, accuracy, explainability
- transient *vs.* steady-state behavior

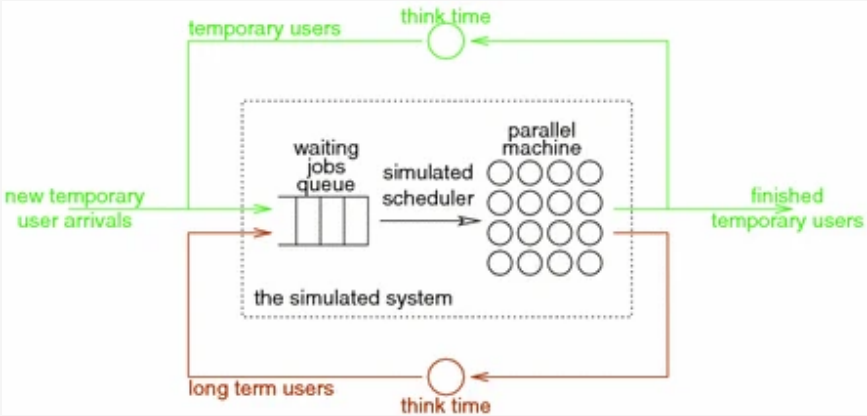
Gains

- simpler models
- adapt to actual behavior

Unexploited loops

Most scheduling approaches rely on an *unrealist* open-loop model.
They struggle/fail to catch for example:

- congestion
- user behavior (Feitelson 2016; Madon et al. 2022)



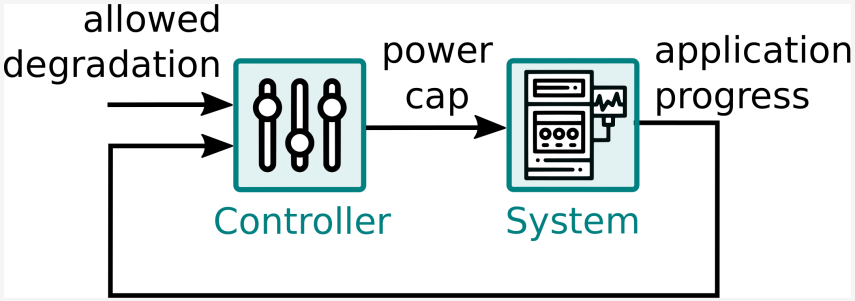
Classic workarounds: "cyclic" scheduling, more variables (increases models' complexity), ...

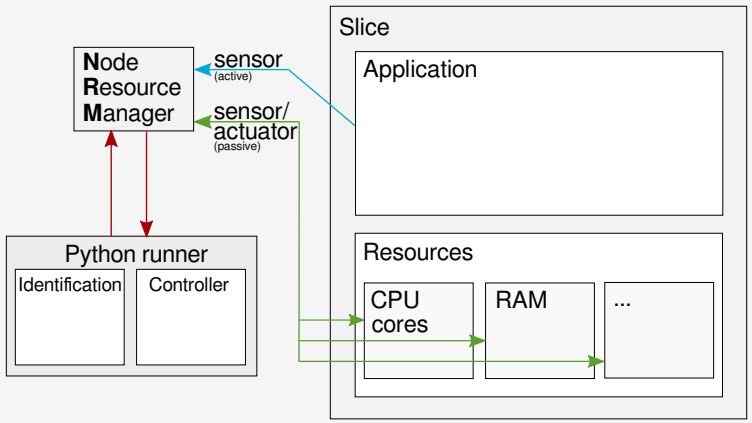
Existing usages/compositions: RAPL×NRM

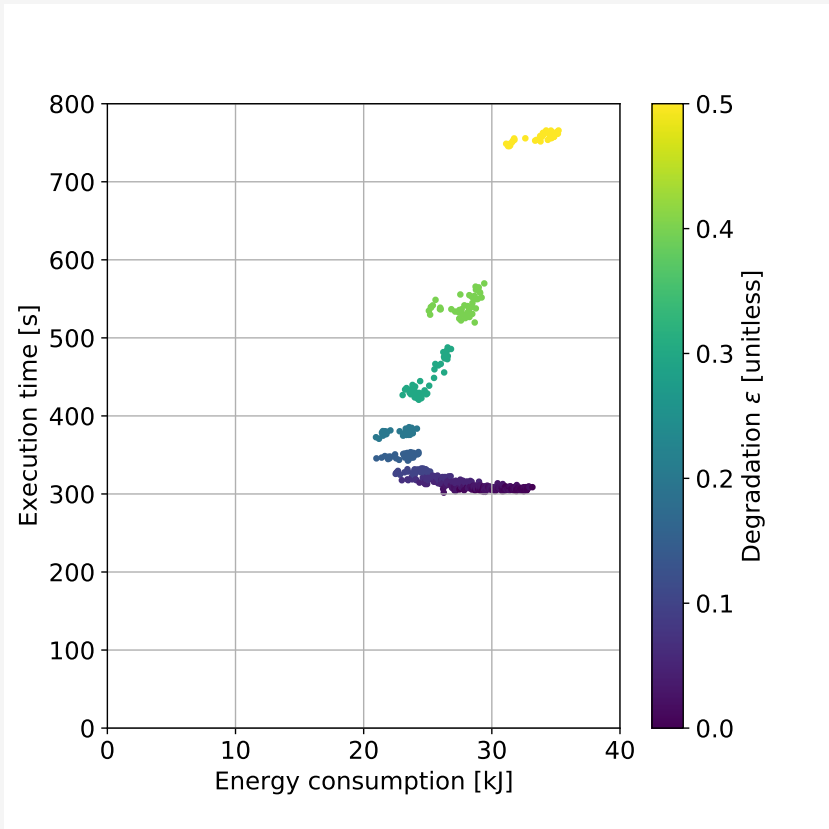
(Cerf et al. 2021; Hawila et al. 2022), ongoing collab. ANL/Inria

Objective Reducing energy consumption while sustaining performance

Approach Dynamic power regulation using Control Theory





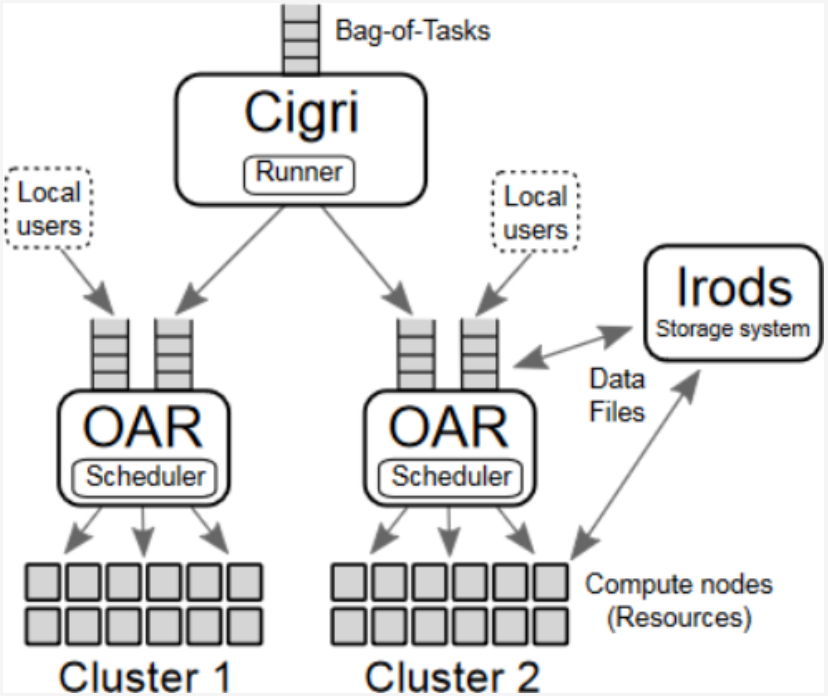


Existing usages/compositions: Cigri

(Guilloteau et al. 2022)

Objective Minimize wasted resources (idle nodes, killed jobs)

Constraint No (low?) impact on local users



best effort jobs

- lowest priority
- killable

- increase scheduling time
- induce load on file system

Existing usages/compositions: Cigri

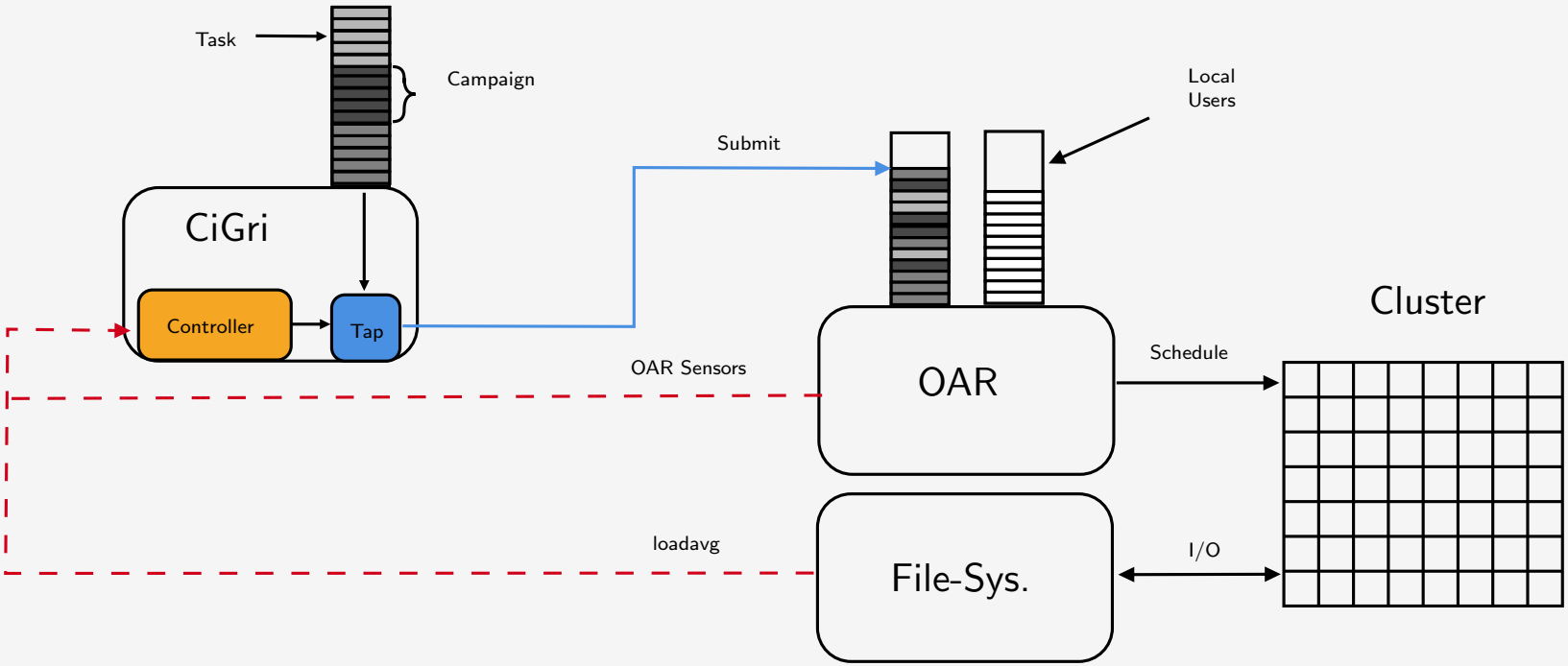
(Guilloteau et al. 2022)

How?

actuator number of best effort jobs "revealed"/sent

sensors queue size, load of the file system

$\Rightarrow$ control law to bind actuator & sensors



Existing usages/compositions: Cigri

(Guilloteau et al. 2022)

Designing the controller (control law) takes three main steps:

1. **system modeling (open loop)**:
   $\text{measure}(k+1) = \sum_{i=0}^{k} a_i \cdot \text{measure}(k-i) + \sum_{i=0}^{k} b_i \cdot \text{action}(k-i)$

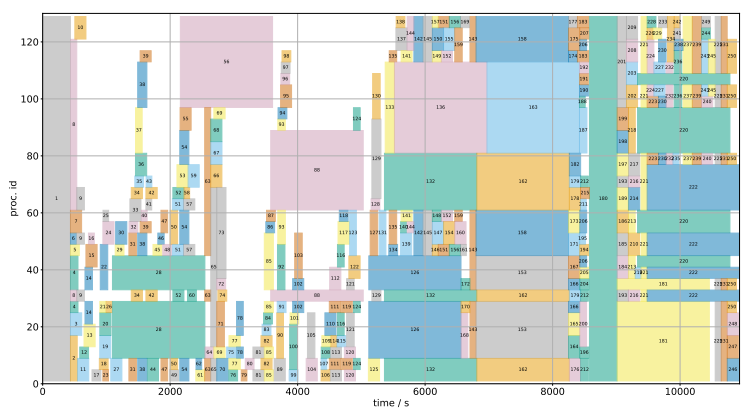
   control law type (closed loop) – e.g., PID:
   $\text{action}(k+1) = K_p\,\text{err}(k) + K_i \sum_{i=0}^{k} \text{err}(i) + K_d\,(\text{err}(k) - \text{err}(k-1))$

2. open-loop experiments (fixed action)

3. fitting of model & choice of controller parameters

Potential combinations

Scheduling × Control Theory



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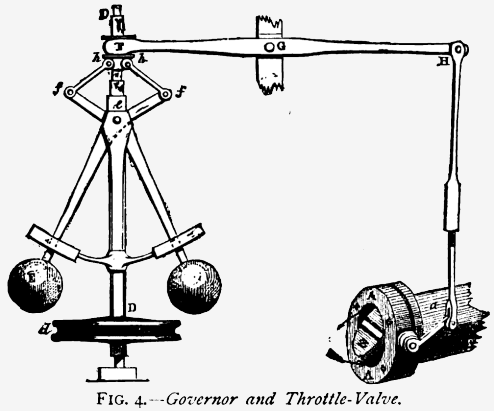
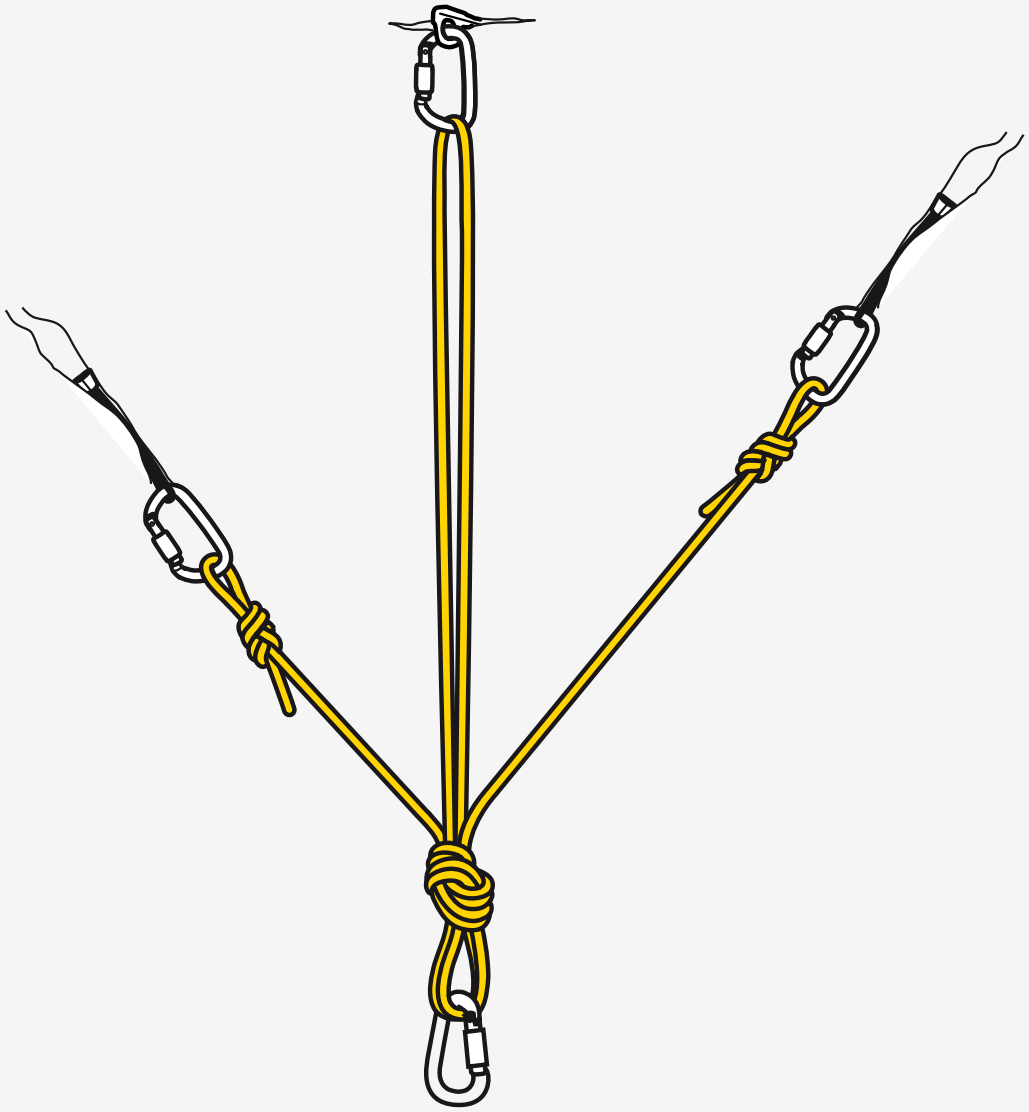


FIG. 4.—*Governor and Throttle-Valve.*

Open questions / Directions to explore

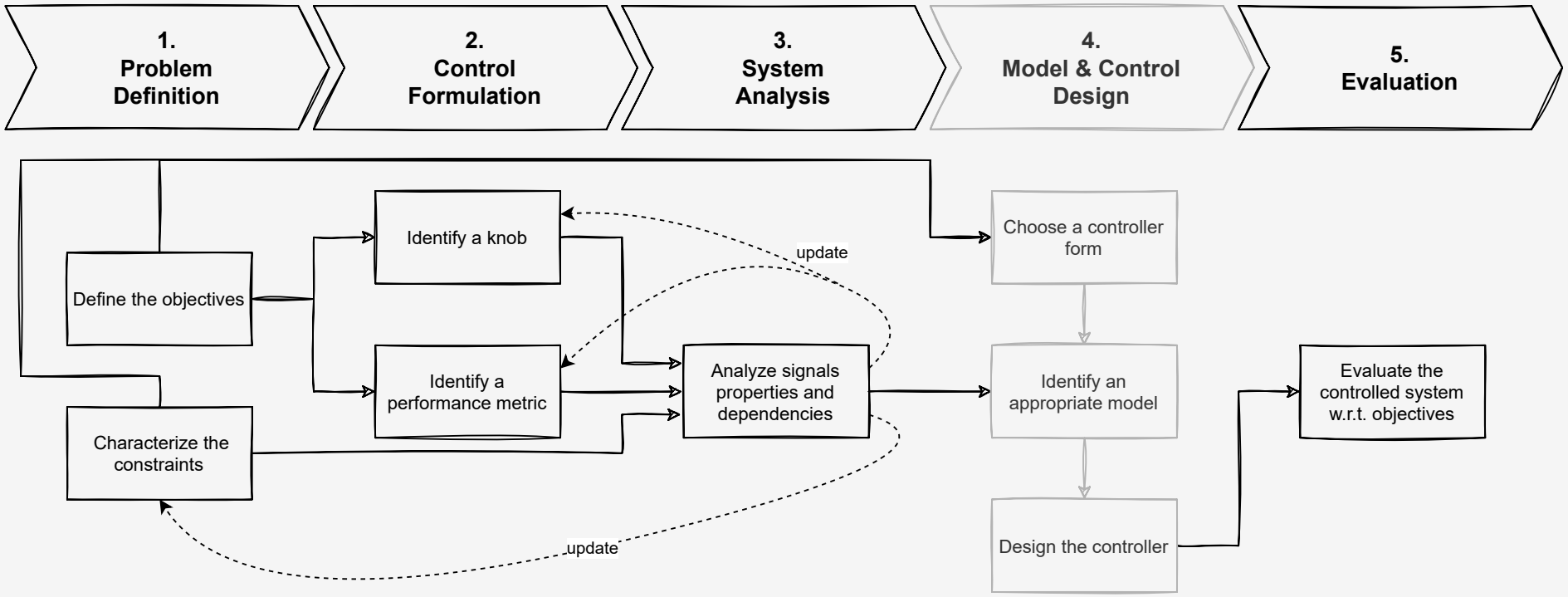
- what are the interesting properties to enforce?
- how to structure the loops?
- what to measure? what to control?
- what is the dynamic at play?

"All models are wrong but some are useful." (Box 1979)



Backup slides

Control Theory Methodology



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