2025-11-01

E011: Configuration & Deployment

config.yaml as Cockpit Control Panel, Pydantic Validation, 3 Deployment Scenarios

Part 2 · Duration: 15-20 minutes

Beginner-Friendly Visual Study Guide

Learning Objective: Understand config.yaml structure (6 sections, 400 lines), Pydantic validation, physics constraints, controller parameters, and 3 deployment environments

The Configuration Problem

Key Concept

Question: How do you prevent users from setting cart mass to -5 kg?
Answer: Validate configuration BEFORE simulation runs (not during, not after)
Principle: Invalid config → Program refuses to start (no silent failures!)

Why Not Hardcode Parameters?

Three Problems with Hardcoding

Problem 1: Reproducibility
Controller gains scattered across 10 Python files → How to reproduce experiment?
Solution: Single config file versioned in Git → Entire simulation reproducible
Problem 2: Validation
Hardcoded values can't be validated before runtime
Solution: Config file parsed, validated, rejected if invalid
Problem 3: Parameter Sweeps
Want to test 100 gain combinations → Must edit code 100 times
Solution: Generate 100 config files, no code changes

config.yaml: The Cockpit Control Panel

Key Concept

Analogy: Like pilot's cockpit with labeled switches for engines, flaps, landing gear
Our Config: 6 main sections (panels) controlling different systems
Size: 400 lines with extensive inline comments

Six Main Sections

1. Physics Panel

- Masses (cart, pendulum 1, pendulum 2)
- Lengths (L1, L2)
- Friction coefficients
- Gravity
- Moments of inertia

2. Controllers Panel

- Gains for each of 7 controllers
- Boundary layers
- Adaptation rates
- Max force limits

3. PSO Optimization Panel

- Particle count (50)
- Iterations (100)
- Inertia weight (0.7)
- Cost function weights

4. Simulation Panel

- Duration (10 seconds)
- Timestep (0.01 s = 100 Hz)
- Initial conditions
- Dynamics model (simplified/full)

5. Hardware-in-the-Loop Panel

- Network settings
- IP addresses
- Timeouts

6. Monitoring Panel

- Latency thresholds
- Deadline detection
- Logging verbosity

Physics Parameters: Defining the System

12 Physical Parameters

Masses: Cart, pendulum 1, pendulum 2
Lengths: L1, L2 (pendulum link lengths)
Centers of Mass: Distance from pivot to center
Moments of Inertia: Rotational resistance
Environment: Gravity (9.81 m/s^2), friction coefficients
Defines: Whether simulating lightweight lab prototype or heavy industrial system

Physics Validation: Preventing Impossible Configurations

Common Pitfall

Example 1: Negative Mass
Config: `cart_mass: -5.0`
Problem: Newton's F=ma with negative mass → Accelerates TOWARD you when pushed away (universe doesn't work this way!)
Pydantic Error: "Field 'cart_mass' expected positive value, received -5.0. Physical masses cannot be negative."
Result: Simulation refuses to start, user fixes config

Common Pitfall

Example 2: Impossible Inertia
Physics Constraint: Inertia $\geq$ mass $\times$ length^2
Config: pendulum1_inertia: 0.0001 (but mass=0.2 kg, length=0.4 m → min inertia=0.008)
Validation Error: "pendulum1_inertia violates physics constraints. You configured 0.0001, but minimum for 0.2 kg at 0.4 m is 0.008."
Prevents: Hours wasted running simulation with meaningless results

Controller Configuration: Seven Variants

Example

Example: Classical SMC Config

```
controllers:
  classical_smc:
    gains: [23.07, 12.85, 5.51, 3.49, 2.23, 0.15]
    max_force: 150.0
    dt: 0.001
    boundary_layer: 0.3
```

Gains Array: 6 values (sliding surface coefficients + switching gains)
Boundary Layer: 0 = perfect but chattering, 0.3 = smooth in 0.3-rad band

Controller-Specific Gain Validation

Schema Enforcement

Pydantic Schema Per Controller:

- ClassicalSMCConfig expects EXACTLY 6 gains
- STASMCConfig expects EXACTLY 6 gains (different interpretation)
- AdaptiveSMCConfig expects EXACTLY 5 gains

Wrong Number? "classical_smc.gains expected 6 elements, received 5"
Prevents: Mismatched gain arrays causing runtime crashes

PSO Configuration: Optimization Parameters

PSO Algorithm Parameters

n_particles: 50 - How many candidate solutions search simultaneously
n_iterations: 100 - How many generations swarm evolves
inertia_weight: 0.7 - Exploration vs exploitation tradeoff
cognitive_coeff: 2.0 - Trust own best position
social_coeff: 2.0 - Trust swarm's best position
cost_weights: Relative importance in cost function

- state_error: 1.0 (minimize tracking error most)
- control_effort: 0.1 (care less about actuator wear)
- settling_time: 0.5 (penalize slow settling moderately)
- overshoot: 0.3 (penalize overshoot somewhat)

Pro Tip

Tuning Cost Weights:
Industrial Robot: control_effort: 0.5 (actuators expensive, wear out)
Academic Benchmark: state_error: 2.0 (maximize tracking accuracy)
No Universal Right Answer - depends on application priorities

Simulation Settings

duration: 10.0 seconds

How long to simulate

dt: 0.01 seconds (100 Hz)

Timestep for numerical integration

initial_state:

`[0.0, 0.05, -0.03, 0.0, 0.0, 0.0]`

Cart at origin, small angle perturbation

use_full_dynamics: false
Simplified (5 µs) vs Full nonlinear (50 µs)
Tradeoff:

- Simplified: PSO in 3 minutes
- Full: PSO in 30 minutes
- Strategy: Develop with simplified, validate with full

Timestep Constraints: Nyquist Stability

Common Pitfall

Physics Limit: Fastest dynamics 5 rad/s (pendulum natural frequency)
Nyquist: Need 10 samples per oscillation → dt 0.1 seconds
Practice: dt=0.01 for 100 Hz (10× safety margin)
Validation: If dt=0.5 → Warning: "Timestep 0.5s exceeds Nyquist limit for system dynamics. Maximum safe: 0.1s"

Pydantic Validation: The Bouncer

Key Concept

Analogy: Pydantic is a nightclub bouncer checking IDs at the door
Checks:

- **1.** Data types correct? (Is cart_mass a number or "heavy"?)
- **2.** Values in acceptable ranges? (Mass positive? Length < 5 m?)

Pass: Simulation starts
Fail: Rejected with specific reason (before wasting time!)

Fail Fast, Fail Clearly

Example

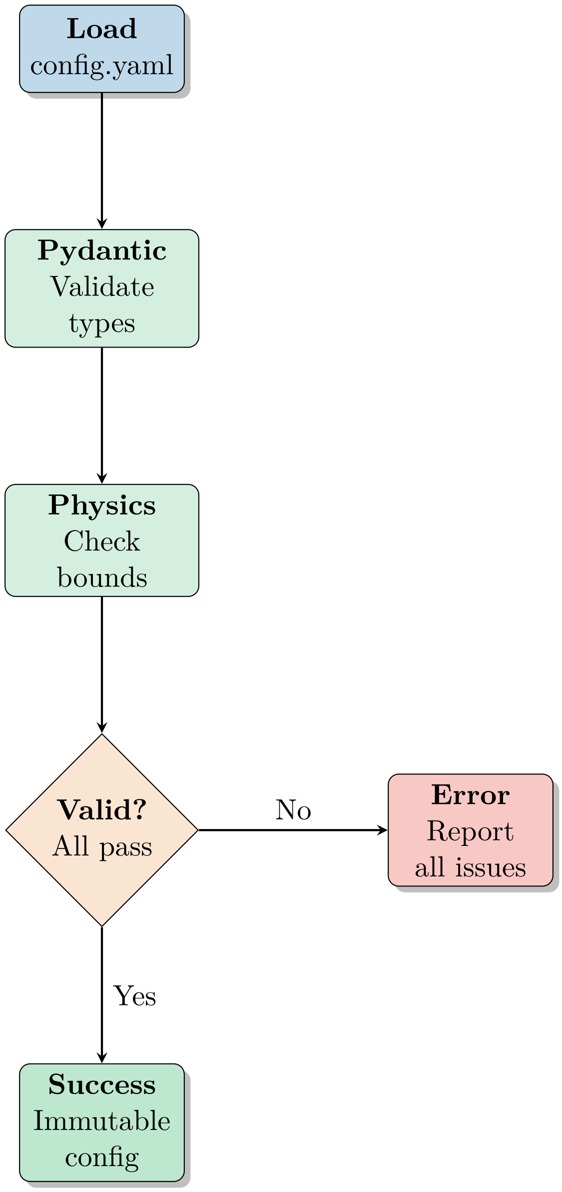
Without Bouncer:

- Start simulation
- Run for 3 minutes
- Crash deep in physics engine: "cannot multiply string by float"
- Debug backwards: what config value was wrong?

With Pydantic Bouncer:

- Try to load config
- Rejected at door immediately: "cart_mass must be float, you provided string"
- Fix config, retry - no time wasted!

Configuration Loading Process



Five-Step Process

Step 1: Read `config.yaml` from disk (PyYAML → nested dictionary)
Step 2: Pass to Pydantic `Config` model (recursively validate all sections)
Step 3: Additional physics validation (inertia bounds, Nyquist criterion)
Step 4: Cross-section validation (if use_full_dynamics=true, check consistency)
Step 5: If all pass → Return immutable config object. If any fail → Collect ALL errors, report together

Pro Tip

Why Collect All Errors?
Bad UX: Fix one error → Re-run → Hit next error → Fix → Hit third error (frustrating!)
Good UX: See all errors at once → "cart_mass negative, pendulum1_inertia violates physics, classical_smc.gains wrong length (5 expected 6)" → Fix all in batch

Deployment: Three Environments

Deployment Scenarios

Environment 1: Local Development

- Clone repo, create venv, `pip install -r requirements.txt`
- Run `python simulate.py`
- Everything on one machine, default config, immediate feedback

Environment 2: Batch Computation

- Research cluster or cloud instance
- Parameter sweeps, Monte Carlo simulations, PSO optimization
- Headless execution (no GUI), results saved to files

Environment 3: Hardware-in-the-Loop (HIL)

- Plant server on one machine (PLC or industrial PC with real hardware)
- Controller client on another machine
- Communicate over network using ZeroMQ

Key Takeaways

Quick Summary

config.yaml: 400 lines, 6 sections (physics, controllers, PSO, simulation, HIL, monitoring)
Cockpit Control Panel: Every parameter has inline comment explaining purpose, units, citations
Physics Validation: Prevents negative mass, impossible inertia, violates Nyquist limits
Controller Gains: Schema per controller (Classical=6, STA=6, Adaptive=5 gains)
Boundary Layer: 0 = perfect/chattering, 0.3 = smooth (chattering mitigation)
PSO Parameters: 50 particles, 100 iterations, cost weights tunable per application
Simulation: dt=0.01 (100 Hz), duration=10s, simplified vs full dynamics tradeoff
Pydantic Bouncer: Validates types + ranges BEFORE simulation (fail fast, fail clearly)
Loading Process: Read YAML → Pydantic validate → Physics check → Cross-section → Immutable config or detailed errors
Three Environments: Local dev (one machine), Batch compute (headless), HIL (networked plant + controller)
Configuration as Code: Version in Git for reproducibility, generate variants for parameter sweeps

Quick Reference: Config Usage

Load and Validate Config

```
lstnumberLoad with validation config = load_config("config.yaml")
lstnumberStrict mode (fail on unknown keys) config = load_config("config.yaml", allow_unknown = False)
lstnumberAccess nested values
cart_mass = config.physics.cart_massgains = config.controllers.classical_smc.gains
```

What's Next?

Key Concept

E012: Hardware-in-the-Loop System
Plant server, controller client, network communication, real-time constraints, latency measurement
Remember: Configuration is a first-class artifact, not an afterthought!