Acaysia Control: Predictive, Safety Aware Control for High Value Industrial Reactors

Abstract

Acaysia Control is a real-time control and decision platform for complex chemical reactors. It replaces reactive tuning with predictive, safety-aware control that explicitly reasons over future trajectories under hard operational constraints. By combining gray-box modeling, sampling-based optimal control, and a proprietary GPU-accelerated reactor engine (AcaysiaRT), the system enables industrial plants to safely operate closer to optimal conditions. In high-throughput and energy-intensive processes, even small percentage improvements can translate into disproportionate economic impact.

Why This Matters (Economic Reality)

In large-scale chemical plants, margins are often driven by small differences:

- A 1-2% increase in yield reduces downstream separation and recycle costs
- A few percent reduction in energy intensity compounds across 24/7 operation
- Avoiding rare but severe constraint violations preserves uptime and asset life

In many real processes, these effects combine such that a **single-digit percent improvement in control performance** can translate into **double-digit percentage margin improvement**, particularly in:

- Exothermic reactors
- Batch and semi-batch operations (pharmaceuticals)
- Energy- and emissions-constrained facilities

Despite this leverage, most reactors are still controlled using methods that cannot reason about the future.

Why PID (and Friends) Hit a Wall

PID control remains dominant because it is simple, robust, and well understood. But it is fundamentally *reactive*.

This limitation becomes acute in **batch and other reactors**:

- Optimal operation follows a *trajectory*, not a fixed setpoint
- Reaction rates, heat release, and constraints evolve over time (through fouling, drift etc)
- The cost of overshoot is asymmetric (violations are expensive or unsafe)

PID controllers:

- Correct errors *after* they occur
- Cannot optimize multi-step tradeoffs (yield vs energy vs risk)
- Require frequent retuning as regimes change (expensive and static)

Even nonlinear MPC struggles in practice due to solver latency, model mismatch, and brittle convergence under tight constraints.

The result: plants operate conservatively, leaving value on the table.

Acaysia Control: What Is Different

Acaysia Control does **not replace** reactive correction but supplements it with **predictive decision making**.

At each control step, the system:

1. Simulates many possible future trajectories over a short horizon
2. Scores each trajectory on performance, energy, and safety (according to custom plant needs)
3. Applies the best safe action (setpoints), with smoothing for actuator realism

Predict futures → Enforce safety → Optimize outcomes

This approach allows the controller to anticipate constraint violations and tradeoffs *before* they occur. While being no rip nor modifying the **SIL**.

A Concrete Look at the Math (MPPI)

We consider discrete-time dynamics:

$$x_{t+1} = g(x_t, u_t), \quad x_t \in \mathcal{X},\ u_t \in \mathcal{U}. \tag{1}$$

The objective is to minimize a finite-horizon cost:

$$J(U) = \Phi(x_H) + \sum_{t=0}^{H-1} \ell(x_t, u_t), \tag{2}$$

where ℓ captures yield, energy usage, and control smoothness, and $\mathcal{X}$,$\mathcal{U}$ encode hard safety limits.

Model Predictive Path Integral (MPPI) control approximates this problem via sampling:

$$U^{(k)} = \bar{U} + \varepsilon^{(k)}, \quad \varepsilon^{(k)} \sim \mathcal{N}(0, \Sigma), \tag{3}$$

with K candidate sequences evaluated via forward simulation.

Classical MPPI computes importance weights:

$$w_k = \frac{\exp(-J^{(k)}/\lambda)}{\sum_j \exp(-J^{(j)}/\lambda)}, \tag{4}$$

while many industrial implementations operate in a low-temperature regime:

$$k^\star = \arg\min_k J^{(k)}, \quad u_0 = u_0^{(k^\star)}, \tag{5}$$

followed by smoothing and rate limiting.

This yields a controller that is:

- Nonlinear
- Constraint-aware
- Free of fragile gradient-based solvers
- Highly adjustable by operators or advisory AI (operators can agentically focus on daily priorities based on world models)

Safety Is Enforced, Not Penalized

A critical distinction: safety constraints are enforced during trajectory evaluation.

Any candidate rollout that violates temperature or pressure limits is rejected outright. This avoids the failure mode of "soft penalties," where unsafe actions can still be chosen if the optimizer misjudges weights.

This is essential for real plants.

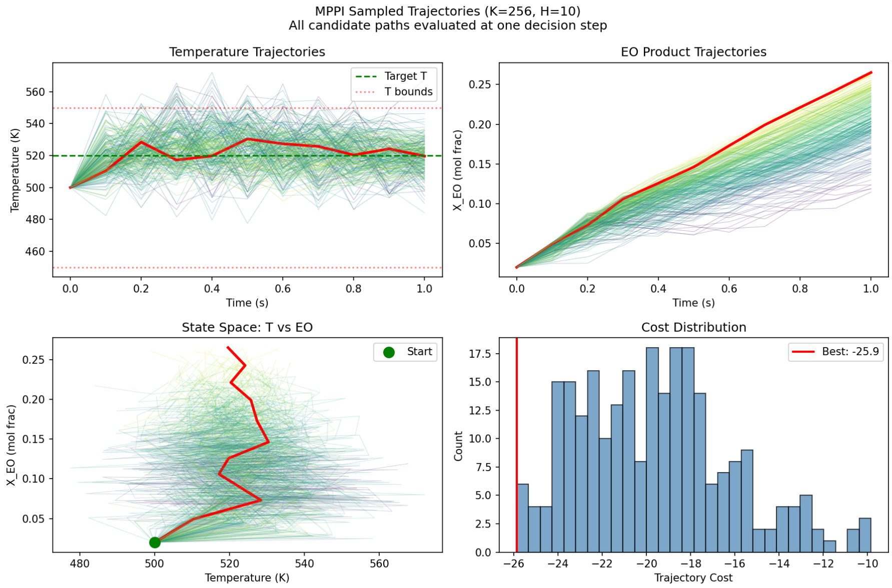

Figure 1: Parallel future rollouts evaluated by Acaysia Control at a single decision step. Hundreds of candidate trajectories are simulated over a short horizon using a gray-box dynamics model. Trajectories that violate safety constraints (temperature bounds) are rejected early. The controller selects a smooth, high-performing action (bold red) from the remaining safe futures. This forward-looking evaluation enables operation closer to optimal limits than reactive controllers.

Why This Is Finally Practical: AcaysiaRT + ML

Predictive control at this scale is only possible if simulation is fast.

AcaysiaRT is Acaysia's proprietary, GPU-native reactor engine that enables high-throughput rollout evaluation. It provides the computational backbone that makes gray-box predictive control viable on edge hardware.

Representative performance (edge GPU):

Workload	Observed Throughput
Single-step simulation ($N = 10{,}000$)	$\sim$2B reactor-steps/sec
Rollout simulation ($N = 10{,}000$, $H = 100$)	$\sim$3B reactor-steps/sec
$10{,}000 \times 100$ rollout batch	$\sim$0.35 ms

This throughput enables:

- Thousands of candidate futures per control decision
- Meaningful lookahead horizons
- Scaling performance with hardware rather than tuning effort
- Keeps accuracy max error 0.003ph compared to industry standards like PHREEQC

AcaysiaRT is not the main product, it is the engine that makes Acaysia Control possible.

Where the ML Lives (Gray-Box Dynamics)

A common misconception is that machine learning replaces physics in Acaysia Control. In reality, the system is explicitly **gray-box by design**.

The role of machine learning is not to decide actions, but to make high-quality predictive control environmentally accurate in real time. With a focus on mitigating hard problems like drift and fouling that currently plague conventional systems

Learned Local Dynamics

Within each MPPI rollout (Figure 1), state transitions are evaluated using a learned surrogate model that approximates short-horizon reactor behavior by tuning AcaysiaRT:

$$x_{t+1} \approx \tilde{g}_\theta(x_t, u_t).$$

This model is trained on physics or plant data and constrained by known structure (e.g. conservation laws, valid state ranges). Its purpose is not perfect global accuracy, but reliable local prediction of traditionally hard to capture effects like fouling.

This allows Acaysia Control to evaluate thousands of candidate futures per decision cycle, something that is computationally infeasible with classical solvers alone.

Anti-Drift and Model Reliability

Model drift is a critical failure mode in industrial ML systems. Acaysia Control explicitly addresses this risk.

During operation, the controller continuously monitors prediction consistency and operating regimes. When the system detects that current conditions are outside the model's trusted envelope:

- planning can fall back to more conservative dynamics,
- uncertainty margins are widened,
- or higher-fidelity simulation is invoked selectively.

This prevents silent degradation and ensures that learning *never* compromises safety.

Why This Matters

This gray-box architecture creates a powerful separation of concerns:

- **MPPI** decides *what* to do,
- **ML surrogates** make planning adaptive (even to specific reactors in the same plant),
- **Physics and constraints** define what is allowable.

The result is a system that improves with data while remaining stable, auditable, and safe — a combination that purely data-driven or purely physics-based approaches struggle to achieve.

Where This Creates Value

Acaysia Control is designed for:

- Batch, semi-batch, and continuous reactors
- Exothermic and safety-constrained processes
- High-throughput, high-value chemical production

It supports:

- Real-time control on edge hardware
- Offline optimization, tuning, and digital twin workflows

This is especially powerful where small control improvements unlock large economic gains.

Conclusion

Acaysia Control brings predictive, safety-aware intelligence to one of the most valuable and difficult classes of industrial systems. By combining sampling-based optimal control with GPU-scale simulation, it enables plants to move beyond reactive tuning and operate closer to their true optimal limits — safely.

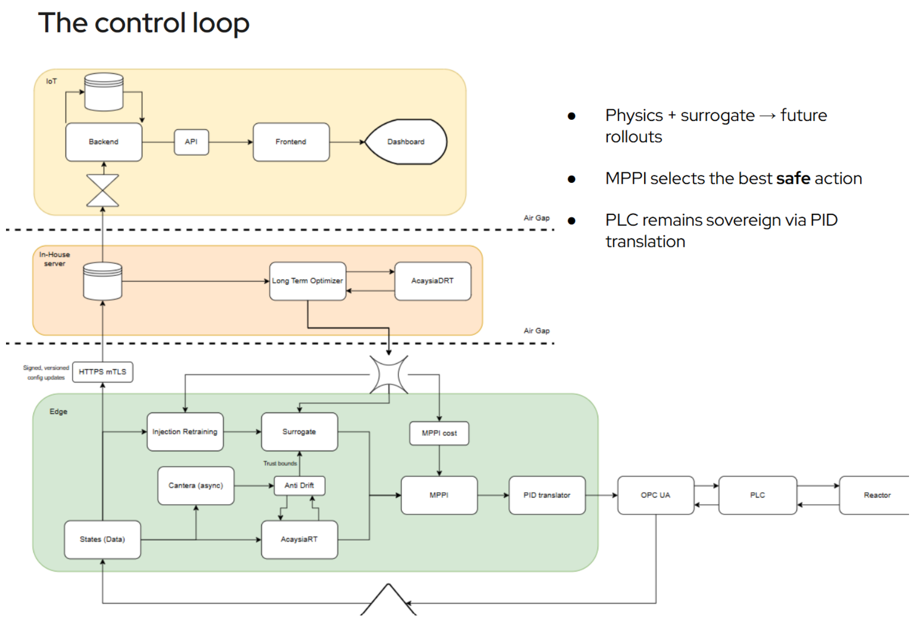

Figure 2: Reference control loop architecture along with hybrid-edge architecture that solves the 2 big problems in our space, cybersecurity and safety. It is double defense in depth system with both an air gap and private network. While also providing **immediate fallback** due to our proprietary Rosetta PID setpoint translation layer. System is currently HIL.

Acaysia: Predictive control for high-value physical systems