TOWARDS BRIDGING THE GAP BETWEEN NONLINEAR CONTROL THEORY AND PROCESS CONTROL PRACTICE

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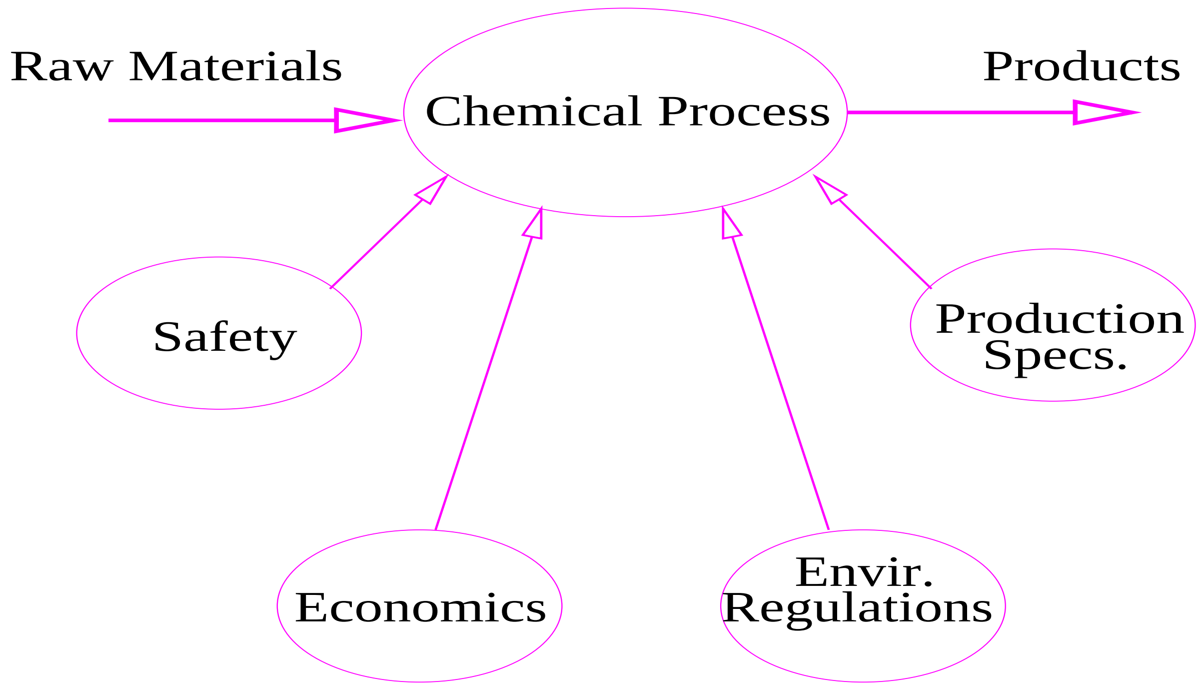
INTRODUCTION

- Incentives for chemical process control.

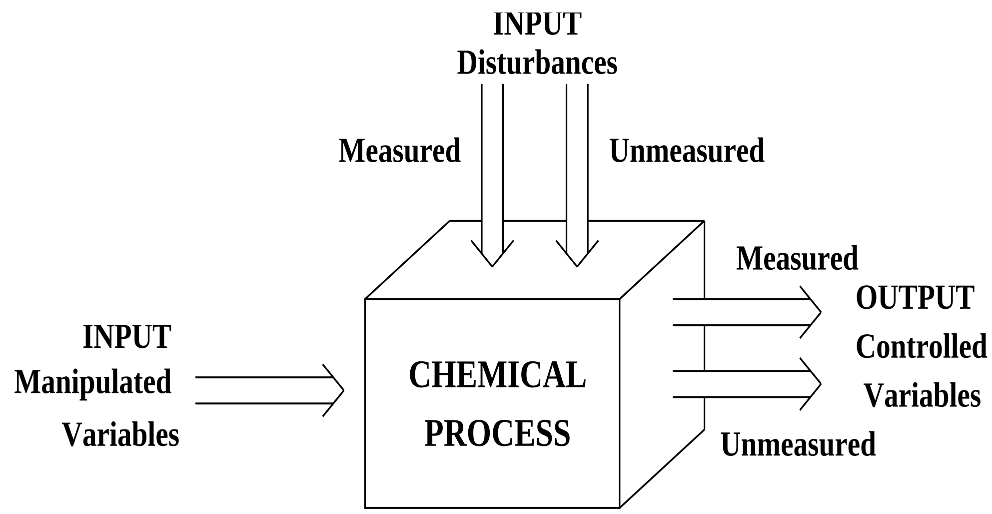


  ◇ Need for continuous monitoring and external intervention (control).

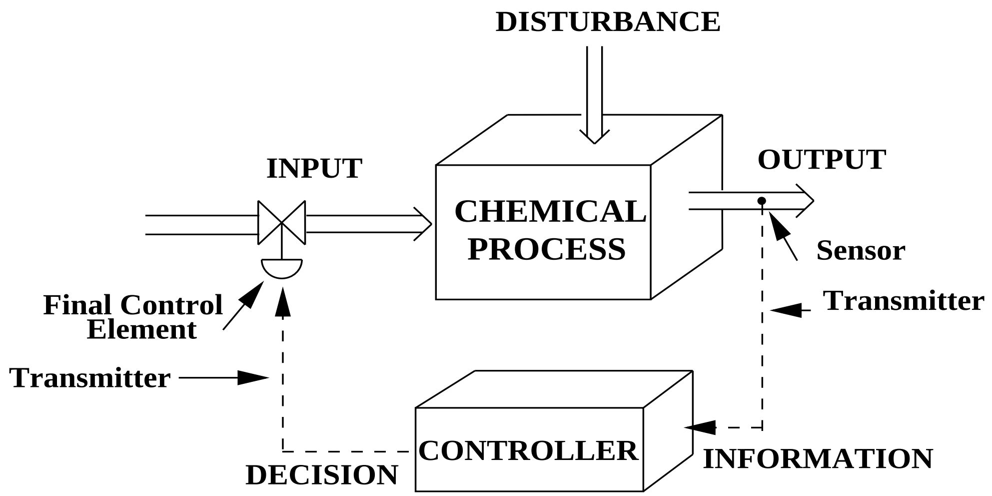
- Objectives of a process control system.
  ◇ Ensuring stability of the process.
  ◇ Suppressing the influence of external disturbances.
  ◇ Optimizing process performance.

BASIC CONCEPTS IN PROCESS CONTROL

- Process variables.

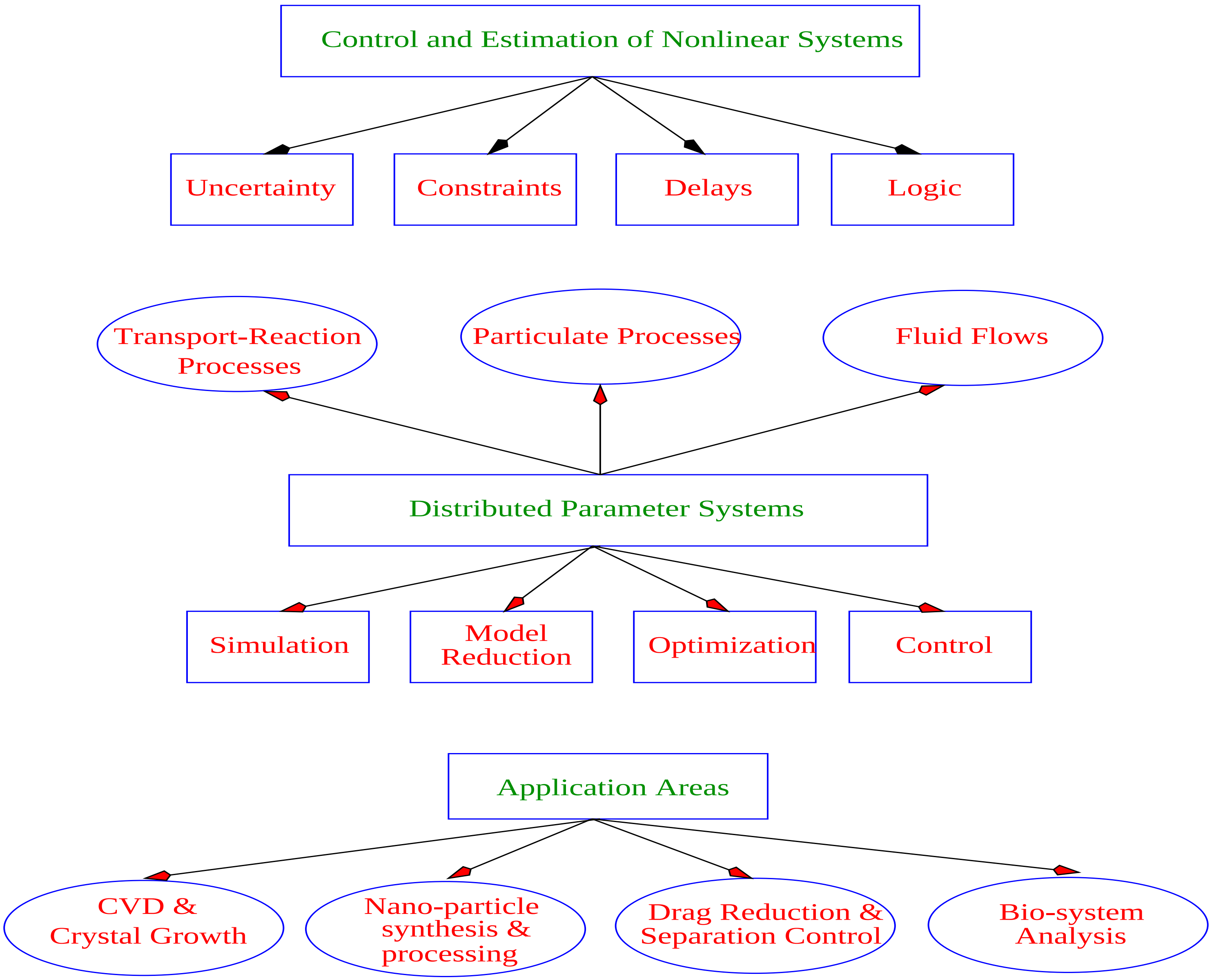


- Feedback control loop.



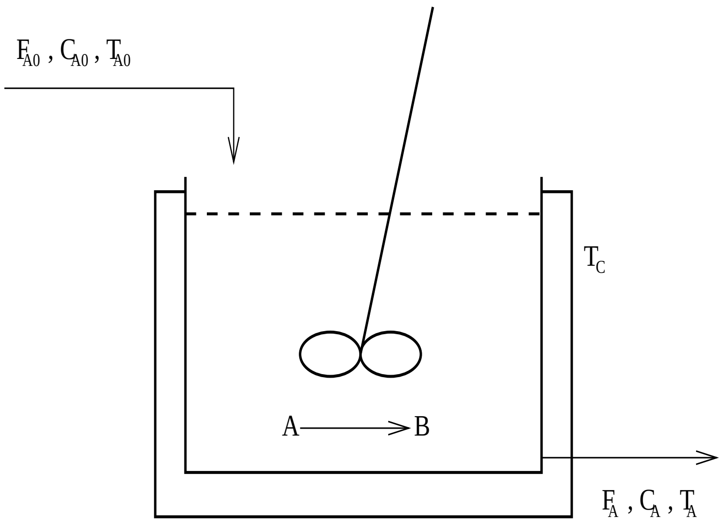
◇ Controller synthesis based on a fundamental process model.

PROCESS CONTROL RESEARCH IN OUR GROUP



ISSUES IN CHEMICAL PROCESS CONTROL

- ◇ Nonlinear behavior:
  - ▷ Arrhenius dependence of reaction rates on temperature.
  - ▷ Complex reaction mechanisms.
- ◇ Model uncertainties:
  - ▷ Unknown process parameters.
  - ▷ Exogenous disturbances.



Continuous-stirred tank reactor

- ◇ Input and state constraints:
  - ▷ Limited capacity of control actuators.
  - ▷ Operating ranges for process variables (environmental, safety, quality reasons).

NONLINEAR CONTROL THEORY VS. PROCESS CONTROL PRACTICE

- Nonlinear control theory and tools:
  - ◇ Requires a nonlinear process model.
  - ◇ Geometric control, Lyapunov-based control, etc.
  - ◇ Allow rigorous analysis of closed–loop stability and performance properties.
- Process control practice:
  - ◇ Proportional-Integral-Derivative (PID) control.
    Linear Model Predictive Control (MPC).
  - ◇ Do not account for the complex dynamics of the process.
- Nonlinear control implementation requires **redesign** of control hardware:

Use nonlinear control theory to aid process control practice

FOCUS OF THE PRESENT TALK

- Integrating Lyapunov-based control & predictive control algorithms:
  - ◇ Design of a hybrid predictive control structure.
  - ◇ Applications to linear systems under state and output feedback.
  - ◇ Application to nonlinear systems.
- Development of “nonlinear” tuning guidelines for PID controllers:
  - ◇ Optimization-based approach to make the PID controller response emulate that of a nonlinear controller.

LINEAR SYSTEMS WITH CONSTRAINTS

- **State-space description:**

$$\begin{aligned} \dot{x}(t) &= Ax(t) + Bu(t) \\ u(t) &\in \mathcal{U} \end{aligned}$$

◇ $x(t) \in \mathbb{R}^n$, vector of process variables: concentrations, temperatures, etc.

◇ $u(t) \in \mathcal{U} \subset \mathbb{R}^m$, control input: flow rates, heat input etc.

◇ $u = 0 \in$ interior of $\mathcal{U}$, nominal operating point.

◇ $\mathcal{U} \subset \mathbb{R}^m$, compact & convex: limited flow rates, heat duties etc.

◇ (A, B) : controllable pair ◇ $A \in \mathbb{R}^{n\times n}, B \in \mathbb{R}^{n\times m}$

- **Stabilization of origin under constraints.**

MODEL PREDICTIVE CONTROL

(Rawlings, IEEE CSM, 2000)

- **Control problem formulation**

  ⋆ Finite-horizon optimal control:

$$P(x,t) \quad : \quad \min\{J(x,t,u(\cdot))|\ u(\cdot) \in U_\Delta\}$$

  ⋆ Performance index:

$$J(x,t,u(\cdot)) \quad = \quad F(x(t+T)) + \int_t^{t+T} \left[\|x^u(s;x,t)\|_Q^2 + \|u(s)\|_R^2\right] ds$$

  ◇ $\|\cdot\|_Q$: weighted norm

  ◇ T : horizon length

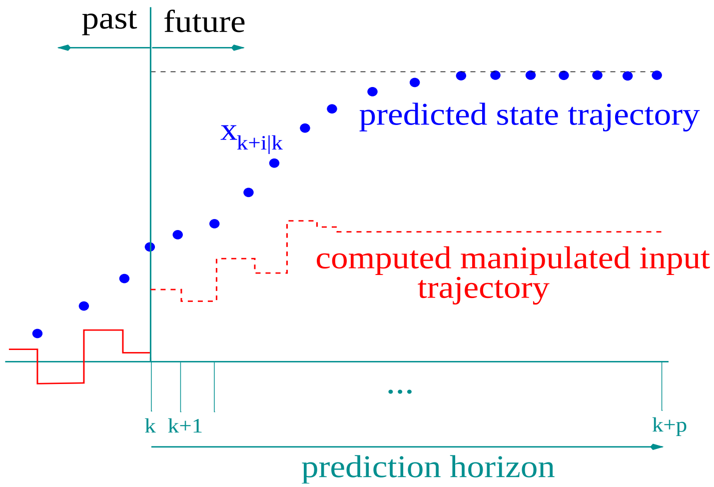
  ◇ $Q,\ R > 0$: penalty weights

  ◇ $F(\cdot)$: terminal penalty

  ⋆ Implicit feedback law

$$M(x) \quad = \quad u^0(t;x,t)$$

"repeated on-line optimization"



MODEL PREDICTIVE CONTROL

- **Formulations for closed-loop stability:**

  (Mayne et al, Automatica, 2000)

  ◇ Adjusting horizon length, terminal penalty, weights, etc.

  ◇ Imposing stability constraints on optimization:

  ▷ Terminal equality constraints: $\boxed{x(t+T) \;=\; 0}$

  ▷ Terminal inequality constraints: $\boxed{x(t+T) \;\in\; W}$

  ▷ Control Lyapunov functions: $\boxed{V(x(t+T)) \;<\; V(x(t))}$

- **Issues of practical implementation:**

  ◇ Lack of explicit characterization of stability region:

  ▷ Extensive closed-loop simulations.

  ▷ Restrict implementation to small neighborhoods.

BOUNDED LYAPUNOV-BASED CONTROL

- **Explicit bounded nonlinear control law:**

$$u = -k(x, u_{max})(L_G V)^T$$

  - ◇ An example gain: (Lin & Sontag, 1991)

$$k(x, u_{max}) = \left(\frac{L_f V + \sqrt{(L_f V)^2 + (u_{max} \|(L_G V)^T\|)^4}}{\|(L_G V)^T\|^2 \left[1 + \sqrt{1 + (u_{max} \|(L_G V)^T\|)^2}\right]} \right)$$

$$\begin{aligned} V &= x^T P x, \quad A^T P + PA - PBB^T P < 0 \\ L_f V &= x^T (A^T P + PA) x, \quad L_G V = 2x^T PB \end{aligned}$$

  - ◇ Nonlinear gain-shaping procedure:
    - ⋆ Accounts explicity for constraints & closed-loop stability.

- **Constrained closed-loop properties:**
  - ◇ Asymptotic stability.
  - ◇ Inverse optimality.

CHARACTERIZATION OF STABILITY PROPERTIES

(El-Farra & Christofides, Chem. Eng. Sci., 2001, 2003)

$$D(u_{max}) \quad = \quad \{x \in \mathbb{R}^n : L_f V < u_{max}|(L_G V)^T|\}$$

- **Properties of inequality:**
  - ◇ Describes open unbounded region where:
    - ▷ $|u| \leq u_{max} \;\; \forall \; x \in D$
    - ▷ $\dot{V} < 0 \;\; \forall \;\; 0 \neq x \in D$
  - ◇ Captures constraint-dependence of stability region.
  - ◇ D not necessarily invariant.
- **Region of guaranteed closed-loop stability:**

$$\Omega(u_{max}) \quad = \quad \{x \in \mathbb{R}^n : V(x) \leq c_{max}\}$$

  - ◇ Region of invariance: $x(0) \in \Omega \Longrightarrow x(t) \in \Omega \subset D \; \forall \; t \geq 0$.
  - ◇ Provides larger estimate than saturated linear/nonlinear controllers.

UNITING BOUNDED CONTROL AND MPC

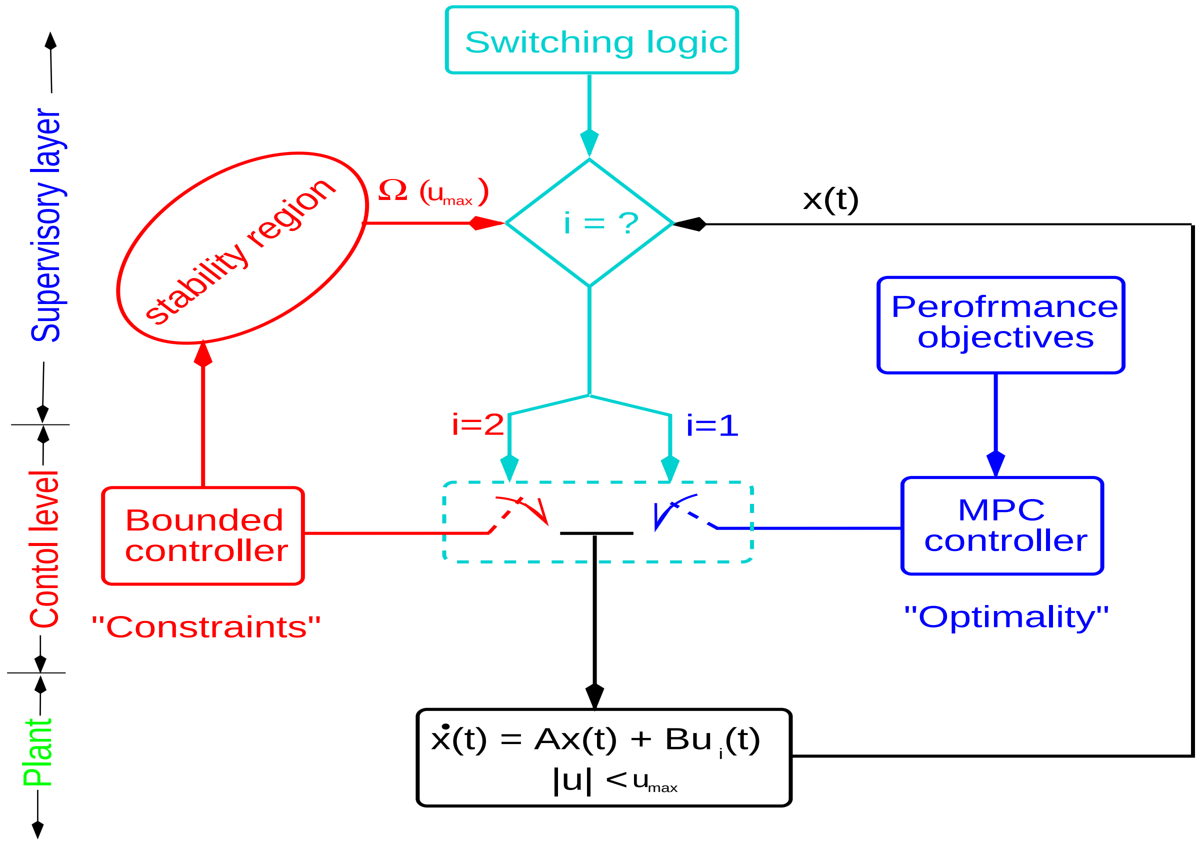
(El-Farra, Mhaskar & Christofides, Automatica, to appear)

- **Objectives:**
  - ◇ Development of a framework for merging the two approaches:
    - ▷ Reconcile tradeoffs in stability and optimality properties
      - ⋆ Explicit characterization of constrained stability region.
      - ⋆ Efficient implementation of MPC.
      - ⋆ Possibility of improved performance.
- **Central idea:**

  Decoupling "optimality" & "constrained stabilizability"

  - ◇ Stability region provided by bounded controller.
  - ◇ Optimal performance provided by MPC.
- **Approach:**
  - ◇ Switching between MPC & bounded controller.

HYBRID PREDICTIVE CONTROL STRUCTURE



- Hierarchical control structure
  - ◇ Plant level ◇ Control level ◇ Supervisory level
- Overall structure **independent** of specific MPC algorithm used:
  - ◇ Switching rules may vary.
- Numerous variants of switching scheme possible.

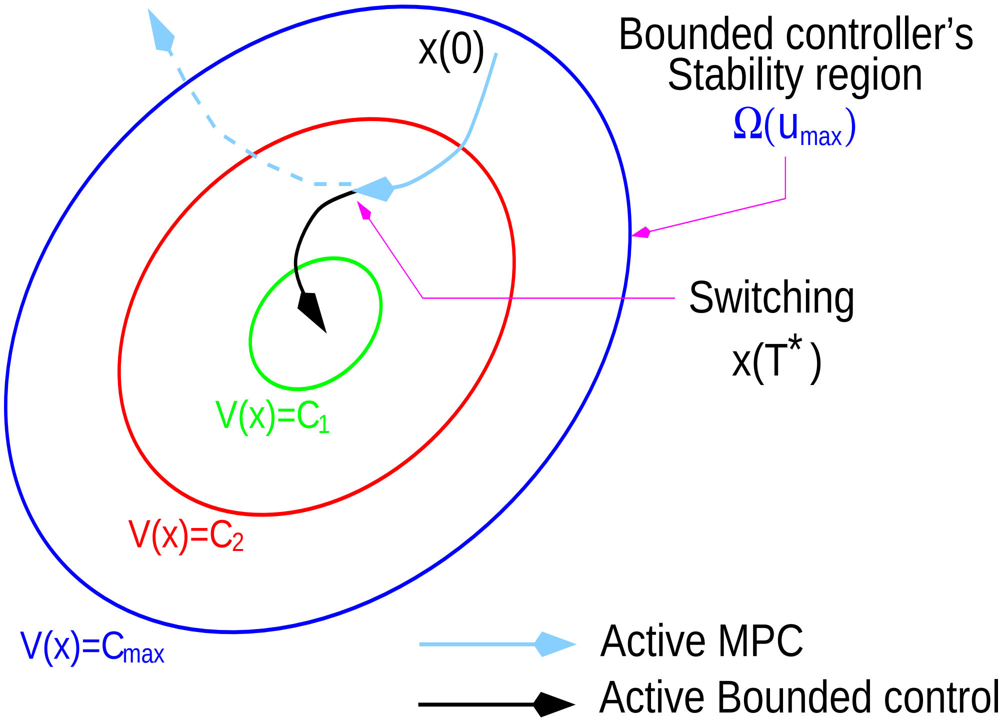
STABILITY-BASED CONTROLLER SWITCHING

- **Switching logic:**

$$u_\sigma(x(t)) = \left\{ \begin{array}{ll} M(x(t)), & 0 \le t < T^* \\ b(x(t)), & t \ge T^* \end{array} \right\}$$

$$T^* = \inf\{T^* \ge 0 : -\|x^M(T^*)\|_{\bar{Q}}^2 + \|B^T P x^M(T^*)\|^2 + 2x^{M^T}(T^*)PBu(T^*) \ \ge \ 0\}$$

- ◇ Initially implement MPC, $x(0) \in \Omega(u_{max})$.
- ◇ Monitor temporal evolution of $V(x^M(t)) = x^T(t)Px(t)$.
- ◇ Switch to bounded controller only if $V(x^M(t))$ starts to increase.



STABILITY-BASED CONTROLLER SWITCHING

- **Implications of switching scheme:**
  - ◇ Switched closed-loop inherits bounded controller's stability region:
    - ▷ A priori guarantees for all $x(0) \in \Omega(u_{max})$.
  - ◇ Lyapunov stability condition checked & enforced by "supervisor":
    - ▷ Reduce computational complexity of optimization.
    - ▷ Scheme does not require stability of MPC within $\Omega(u_{max})$.
    - ▷ Provides a safe mechanism for implementing MPC.
    - ▷ Stability independent of horizon length.
- **Conceptual differences from other schemes:**
  - ◇ Switching does not occur locally.
  - ◇ Provides stability region explicitly.
  - ◇ No switching occurs if $V(x^M(t))$ decays continuously:
    - ▷ Only MPC is implemented $\Longrightarrow$ optimal performance recovered.

ENHANCING CLOSED-LOOP PERFORMANCE

- **Relaxing switching rules:**

$$u_\sigma(x(t)) = \left\{ \begin{array}{ll} M(x(t)), & 0 \le t < \min\{T^*, T_N\} \\ b(x(t)), & t \ge \min\{T^*, T_N\} \end{array} \right\}$$

$$T^* = \inf\{T^* \ge 0 : V(x^M(T^*)) = c_{max}\}$$

$$T_N = \sup\{T_i \ge 0 : \dot{V}(x^M(T_i)) = 0, \; i = 1, \cdots, N < \infty\}$$

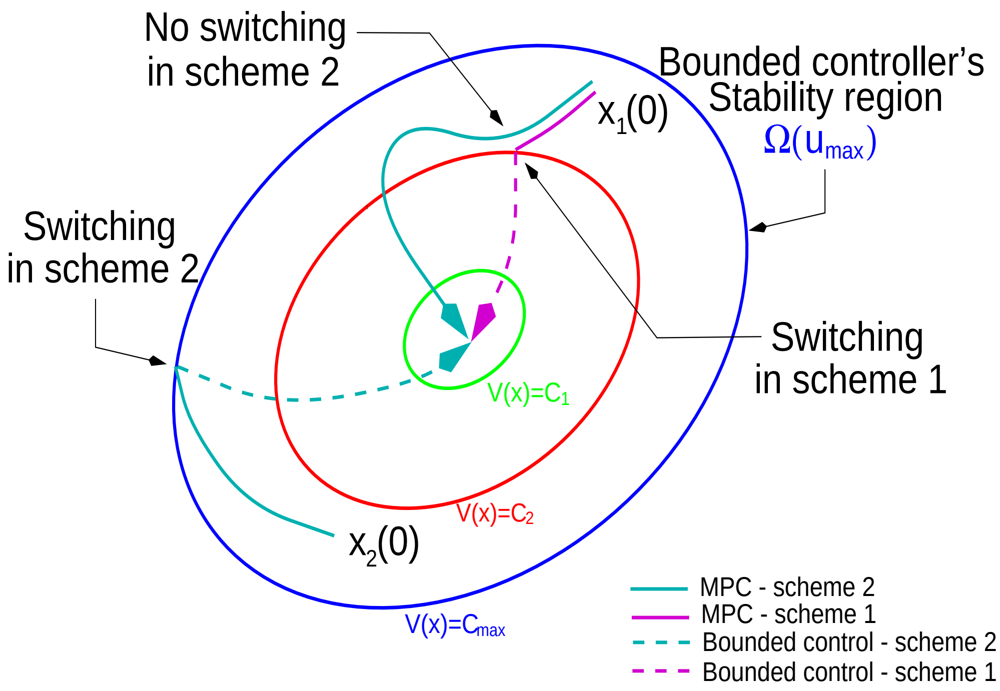
◇ Allow increases in $V(x^M(t))$.

◇ Stability safeguards: switch if

▷ Trajectory hits $\partial\Omega(u_{max})$, or

▷ $\dot{V}(x(t))$ changes sign N times.

◇ Greater flexibility for MPC implementation.



SWITCHING WITH "STABLE" MPC FORMULATIONS

- **MPC with stability constraints:**

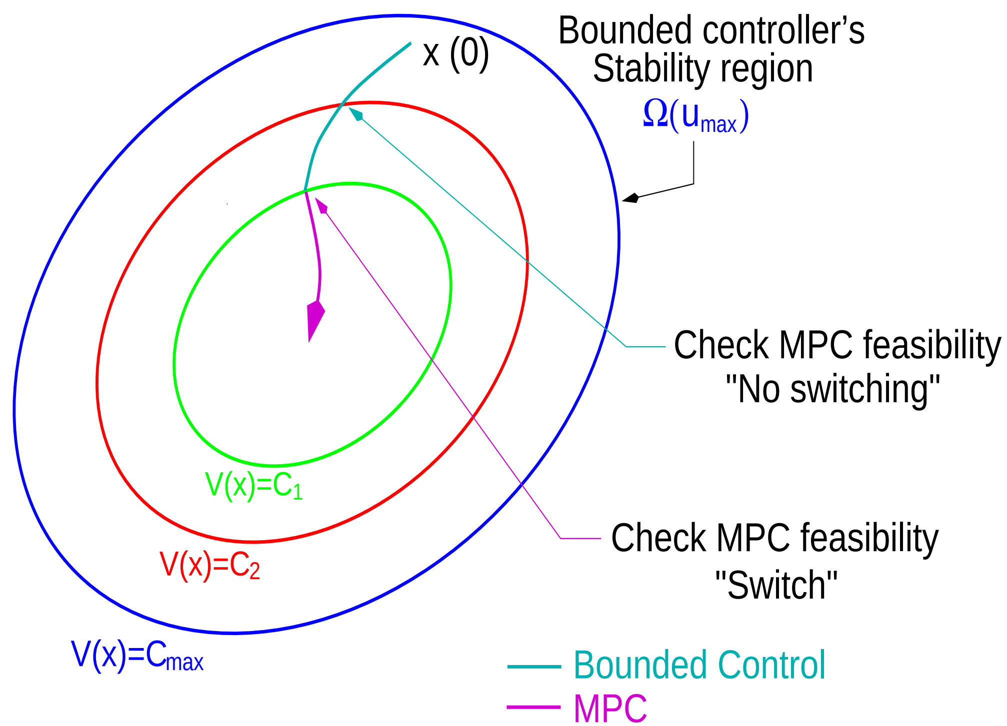
$$
\begin{array}{llcl}
 & \min\limits_{u(\cdot)} & \displaystyle\int_t^{t+T} & (x^T(s)Qx(s) + u^T(s)Ru(s))ds \\
s.t. & \dot{x}(t) & = & Ax(t) + Bu(t), \;\; x(0) = x_0 \\
 & u(\cdot) & \in & U_\Delta \\
 & x(T) & \in & \Omega_{Terminal}
\end{array}
$$

- **Feasibility-based switching:**

$$
u_\sigma(x(t)) = \left\{ \begin{array}{r} b(x(t)), \; 0 \le t < T^* \\ M(x(t)), \;\; t \ge T^* \end{array} \right\}
$$

◇ T^* : earliest time for which MPC yields feasible solution.

◇ Frequent off-line supervisory "checks" of MPC feasibility.



NUMERICAL EXAMPLE

- State space description:

$$\dot{x} = \begin{bmatrix} 0.5 & 0.25 \\ 0.5 & 1 \end{bmatrix} x + \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} u$$

  - ◇ Origin unstable (two real positive eigenvalues).
  - ◇ Input constraints: $u_i \in [-5, 5], \quad i = 1, 2.$

- Bounded controller:
  - ◇ Lyapunov function: $V = x^T P x, \quad P = \begin{bmatrix} 1.03 & 0.306 \\ 0.306 & 1.18 \end{bmatrix}$
  - ◇ Stability region: $x^T (A^T P + PA) x \ < \ 10 \|B^T P x\|$

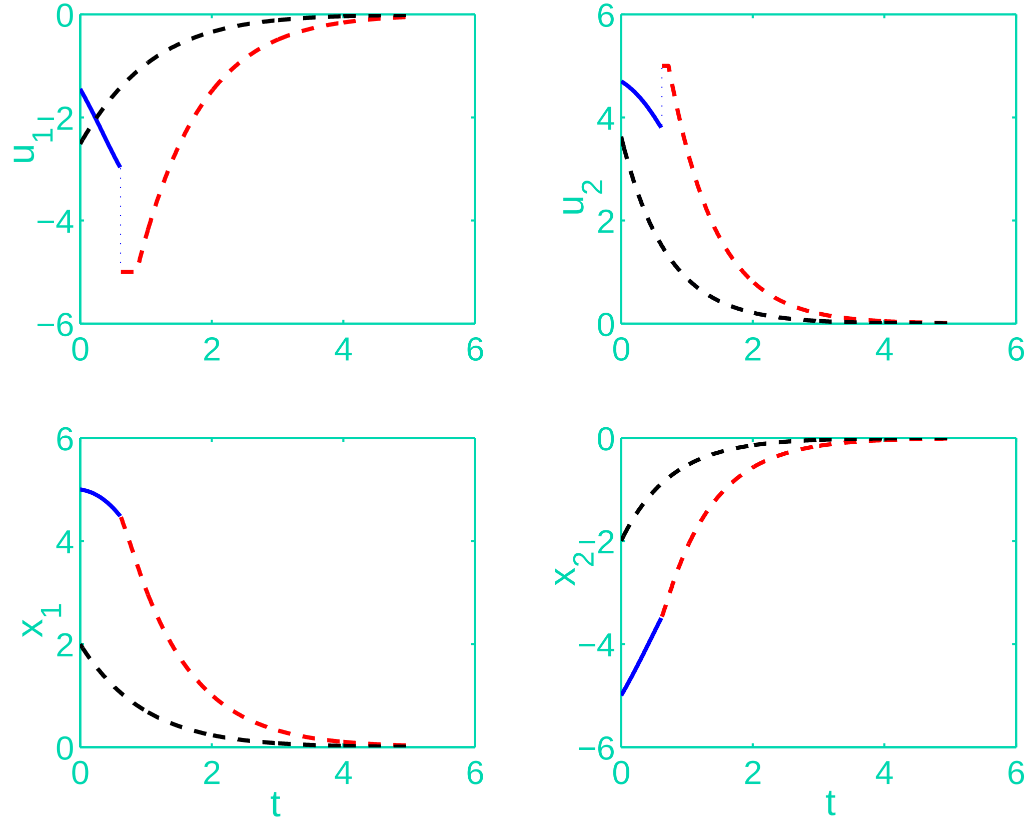
- Model predictive controller:
  - ◇ Performance index:

$$J = \int_t^{t+T} \left[\|x(\tau)\|_Q^2 + \|u(\tau)\|_R^2 + \|\dot{u}(\tau)\|_S^2 \right] d\tau$$

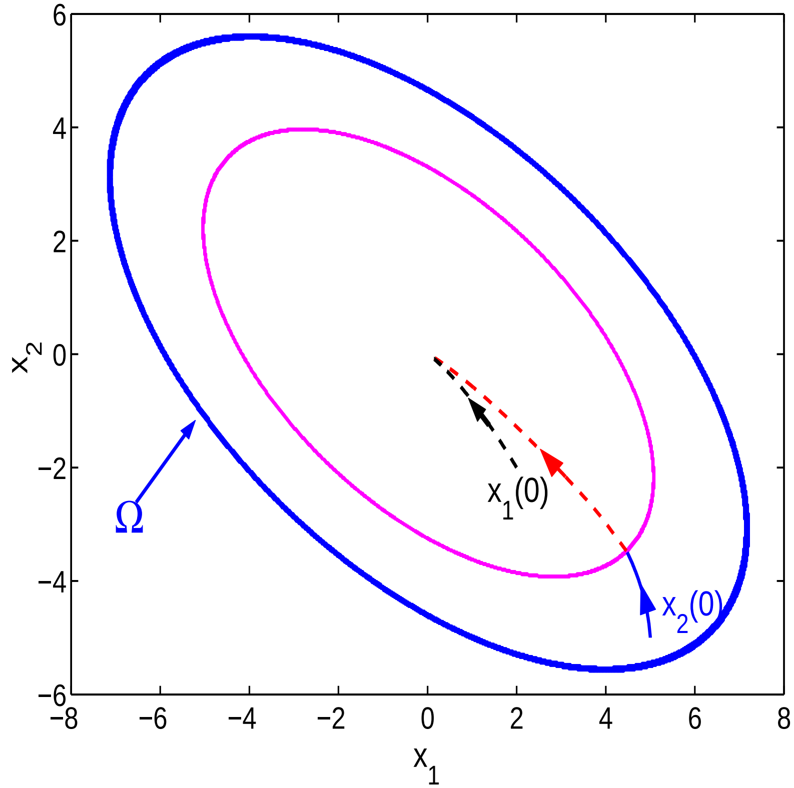
$$Q = qI > 0, \ R = rI > 0, \ S = sI > 0$$

CLOSED-LOOP SIMULATION RESULTS

"Feasibility-based switching"



⋆ Input & state profiles



⋆ Closed-loop trajectories

◇ $x_1(0) = [2 \quad -2]^T \in \Omega \implies$ MPC ($q = 1;\ r = 4;\ T = 1$) feasible

◇ $x_2(0) = [5 \quad -5]^T \in \Omega \implies$ MPC ($q = 1;\ r = 4;\ T = 1$) NOT feasible

⋆ Use bounded controller ⋆ Switch to MPC at $t = 0.6$

STATE ESTIMATION & OUTPUT FEEDBACK CONTROL

- **Lack of full state measurements:**
  - ◇ Inaccessibility of some process variables for measurement.
  - ◇ Estimation of states from measured outputs necessary.
- **Main objectives for output feedback controller design:**
  - ◇ To establish guaranteed stability from an explicitly characterized set of initial conditions:
    - ▷ Design technique for the state estimator.
    - ▷ Devise switching rules, based on available state measurements.
  - ◇ Controlled rate of convergence of state estimation error.
- **Approach for output feedback controller design:**
  - ◇ Relies on separation principle: combination of
    - ▷ State feedback controllers.
    - ▷ State observers.

DESIGN OF STATE OBSERVER

- **State space description of estimator:**

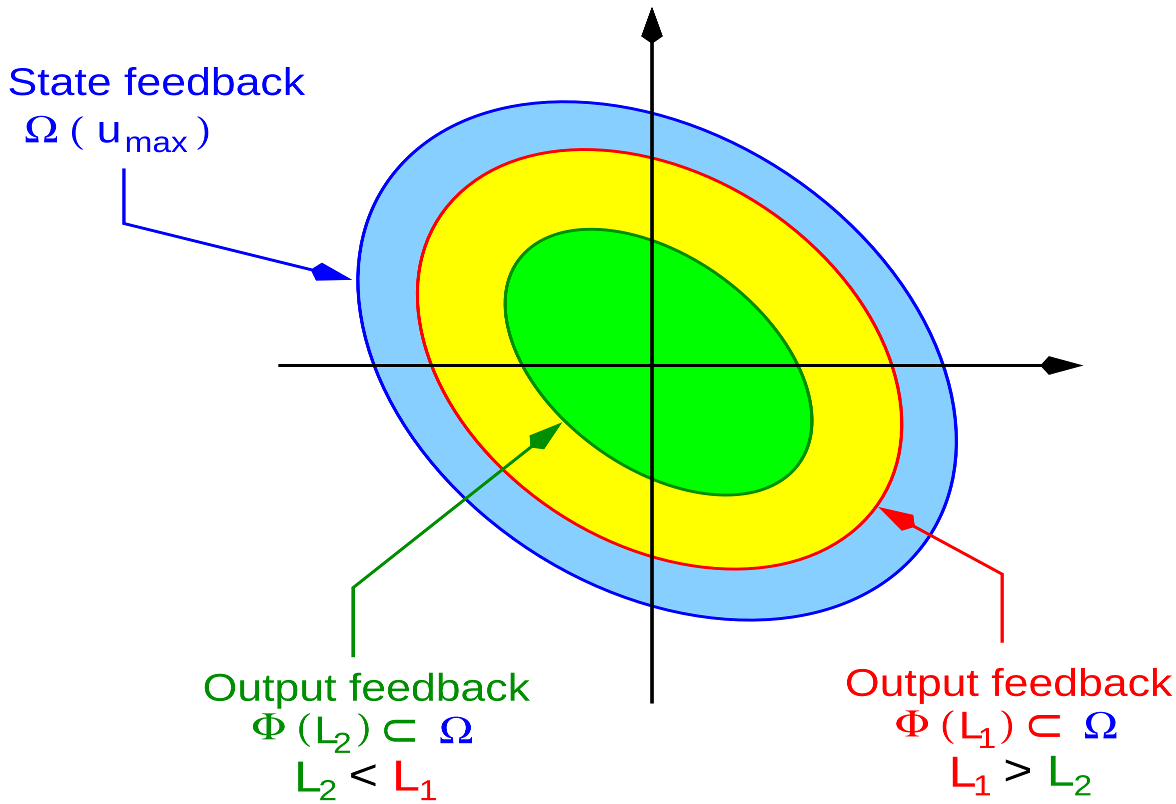
$$\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + L(y - C\hat{x})$$

  - ◇ $\hat{x}$: state estimate.
  - ◇ L: Observer gain matrix.

- **Structural features:**
  - ◇ Observer pole placement:
    - ▷ Enforce desired decay of estimation error
  - ◇ Effect of observer peaking eliminated through:
    - ▷ Input saturation (indirect).
    - ▷ Estimate-saturation (direct)(e.g., El-Farra & Christofides, IJC, 2001).

- **Closed-loop analysis:**
  - ◇ Fall back (bounded controller) robust to a certain allowable error.
  - ◇ For a given choice of initial conditions:
    - ▷ State estimator designed to force error under the allowable error.
    - ▷ Switching laws, based on the state estimates, for "safe" MPC implementation.

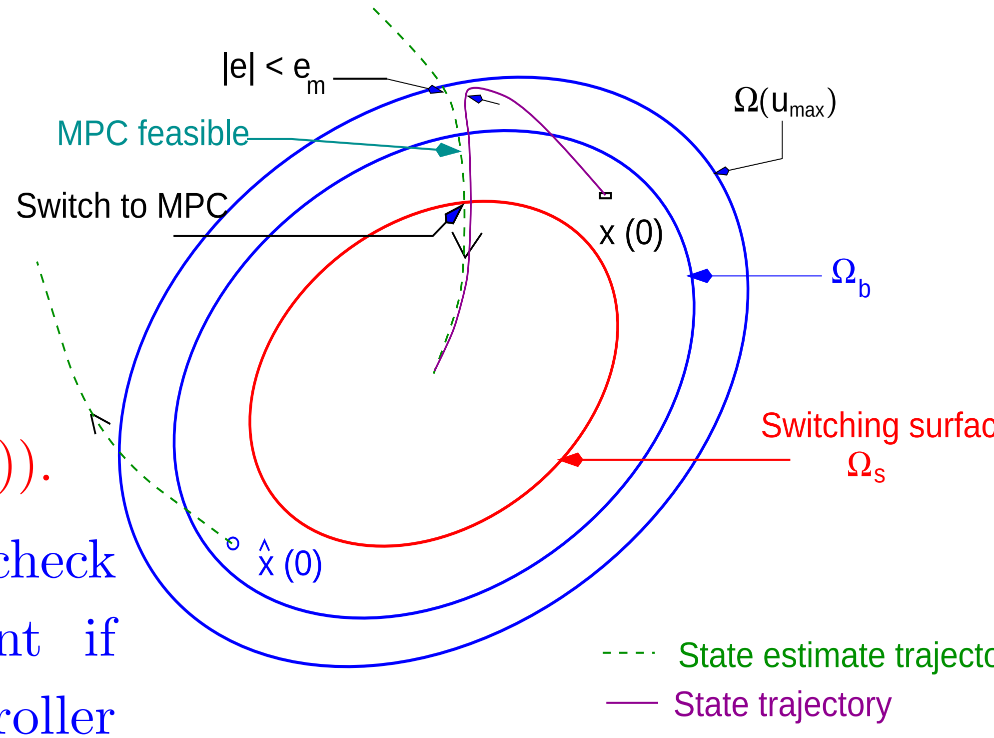
- **Practical implications:**
  - ◇ Any other estimation scheme, such as Moving Horizon Estimation (MHE), can be used.
  - ◇ Requires a transparent relationship between error decay and estimator parameters.
  - ◇ MPC implemented in a region where the fall back controller can step in any time to rescue stability.



OUTPUT FEEDBACK IMPLEMENTATION OF SWITCHING

(Mhaskar, El-Farra & Christofides, AIChE J., to appear)

- Bounded controller design
  ($u = -k(x)L_gV$, $\Omega(u_{max})$).
- State observer design
  (given $\Omega_b \subset \Omega$, compute L).
- Estimate 'safe' region
  (given $\hat{x} \in \Omega_s \Rightarrow x \in \Omega$).
- Initialize: $\hat{x}(0) \in \Omega_b$, $u(0) = b(\hat{x}(0))$.
- After $\hat{x}$ enters 'safe' region, Ω_s, check feasibility of MPC & implement if $\dot{V}(\hat{x}) < 0$ else keep bounded controller active.



NONLINEAR SYSTEMS WITH INPUT CONSTRAINTS

- **State–space description:**

$$
\begin{aligned}
\dot{x}(t) &= f(x(t)) + g(x)u(t) \\
u(t) &\in \mathcal{U}
\end{aligned}
$$

◇ $x(t) \in \mathbb{R}^n$: state vector

◇ $u(t) \in \mathcal{U} \subset \mathbb{R}^m$: control input

◇ $\mathcal{U} \subset \mathbb{R}^m$: compact & convex

◇ $u = 0 \in$ interior of $\mathcal{U}$

◇ $(0,\ 0)$ an equilibrium point

- **Stabilization of origin under constraints**

NONLINEAR MPC: IMPLEMENTATION ISSUES

- Optimization problem non-convex:
  - ◇ Does not reduce to a Quadratic Program.
  - ◇ Possibility of multiple, local optima.
  - ◇ Optimization problem hard to solve (e.g., algorithm failure).
  - ◇ Stability requirements harder to implement.
  - ◇ Difficult to obtain solution within "reasonable" time.
- Lack of explicit characterization of stability region:
  - ◇ Extensive closed-loop simulations.
  - ◇ Restrict implementation to small neighborhoods.

BOUNDED LYAPUNOV-BASED CONTROL

- **Explicit bounded nonlinear control law:**

$$u = -k(x, u_{max})(L_G V)^T$$

- **Region of guaranteed closed-loop stability:**

$$\Omega(u_{max}) = \{x \in \mathbb{R}^n : V(x) \leq c_{max}\}$$

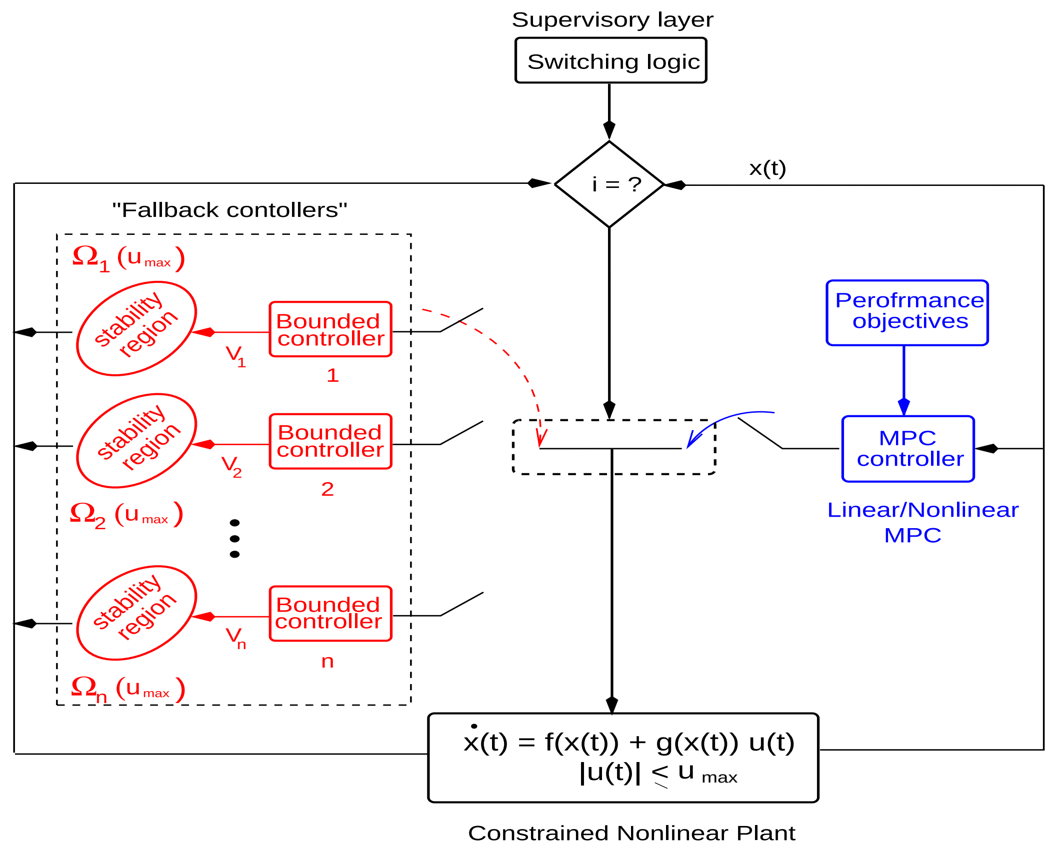
◇ Region of invariance:$x(0) \in \Omega \Longrightarrow x(t) \in \Omega \subset D \; \forall \; t \geq 0$.

◇ Larger estimates using a combination of several Lyapunov functions.

◇ Other Lyapunov–based bounded control designs can be used.

HYBRID PREDICTIVE CONTROL STRUCTURE

(El-Farra, Mhaskar & Christofides, IJRNC, to appear)



- **Hierarchical control structure**
  - ◇ Plant level ◇ Control level ◇ Supervisory level
- Overall structure **independent** of specific MPC algorithm used:
  - ◇ Could use linear/nonlinear MPC with or without stability constraints.

STABILITY-BASED CONTROLLER SWITCHING

- **Switching logic:**

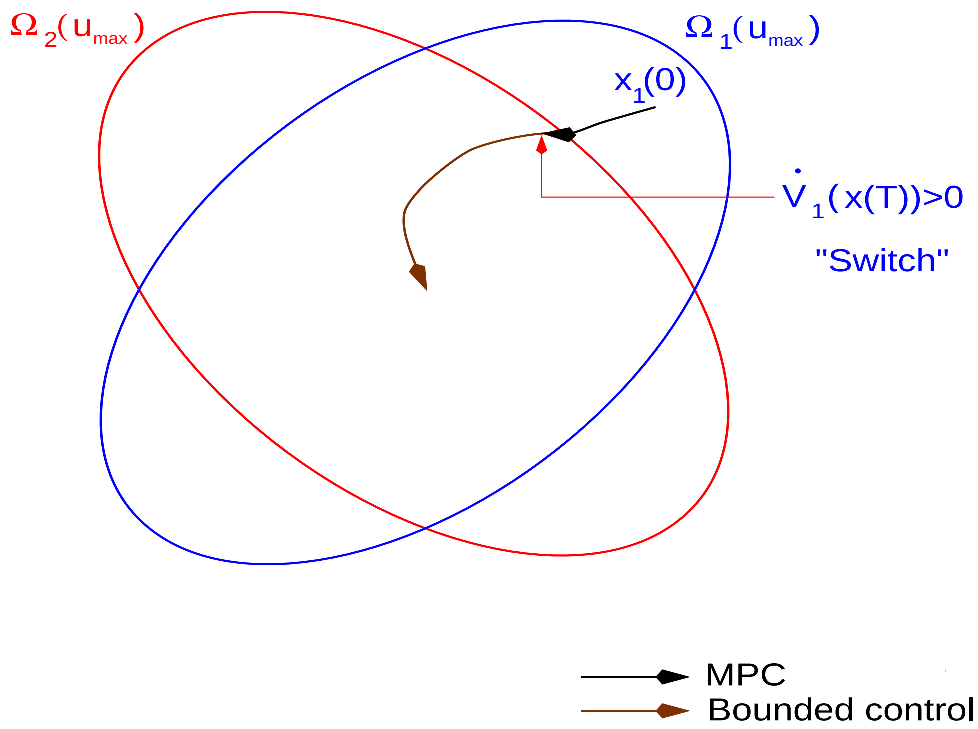
$$u_\sigma(x(t)) = \left\{ \begin{array}{ll} M(x(t)), & 0 \leq t < T^* \\ b(x(t)), & t \geq T^* \end{array} \right\}$$

$$L_f V_k(x) + L_g V_k(x) M(x(T^*)) \geq 0$$

◇ Initially implement MPC, $x(0) \in \Omega_k(u_{max})$.

◇ Monitor temporal evolution of $V_k(x^M(t))$.

◇ Switch to bounded controller only if $V_k(x^M(t))$ starts to increase.



PRACTICAL IMPLEMENTATION

- A "typical" predictive control design:
  - ◇ Nonlinear process model:

$$\dot{x} = f(x) + g(x)u$$
$$u^i_{min} \leq u_i \leq u^i_{max}$$

  - ◇ Linear representation:

$$\dot{x} = Ax + Bu$$
$$u^i_{min} \leq u_i \leq u^i_{max}$$

    - ▷ Linearization (around desired steady-state)
    - ▷ Model identification (e.g., through step tests)
  - ◇ Use of computationally efficient linear MPC (QP) algorithms.
  - ◇ No closed-loop stability guarantees for nonlinear system.
- Practical value of the hybrid control structure:
  - ◇ Provides stability guarantees through fall-back controllers.
  - ◇ Entails no modifications in existing predictive controller design.

APPLICATION TO A CHEMICAL REACTOR

- **Process dynamic model:**

$$
\begin{aligned}
\dot{C}_A &= \frac{F}{V}(C_{A0} - C_A) - k_0 e^{\frac{-E}{RT_R}} C_A \\
\dot{T}_R &= \frac{F}{V}(T_{A0} - T_R) + \frac{(-\Delta H)}{\rho c_p} k_0 e^{\frac{-E}{RT_R}} C_A + \frac{UA}{\rho V c_p}(T_c - T_R)
\end{aligned}
$$

◇ Multiple steady–states.

◇ Control objective:

▷ Stabilization at open–loop unstable equilibrium point, $(C_{As},\ T_s) = (0.52\ mol/L,\ 398\ K)$.

◇ Manipulated input: $u = T_c \in [275,\ 370]$.

CONTROLLER DESIGN

- **Model predictive controller:**
  - ◇ Performance index:

$$J = \int_t^{t+T} \left[\|x(\tau)\|_Q^2 + \|u(\tau)\|_R^2 + \|\dot{u}(\tau)\|_S^2 \right] d\tau$$

$$Q = qI > 0, \; R = rI > 0, \; S = sI > 0$$

  - ◇ Prediction model:

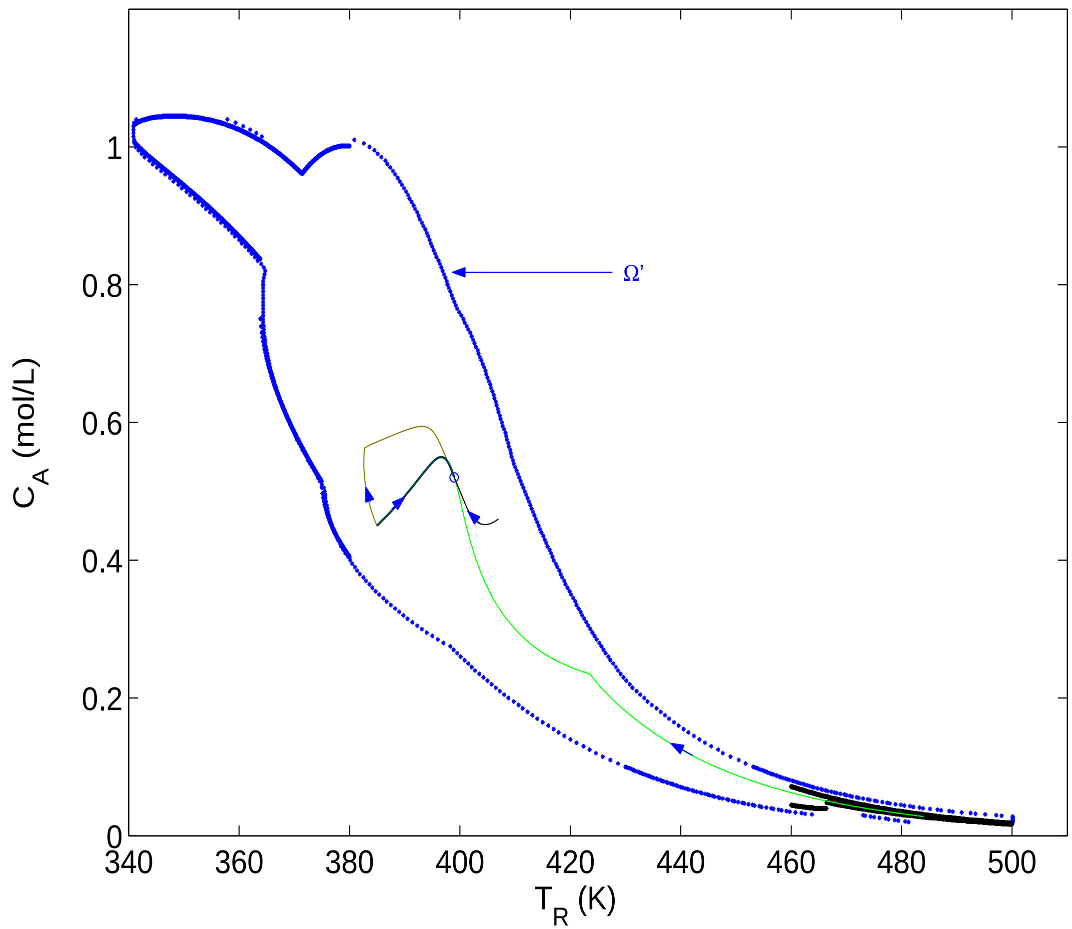
$$\dot{x} = Ax + Bu$$

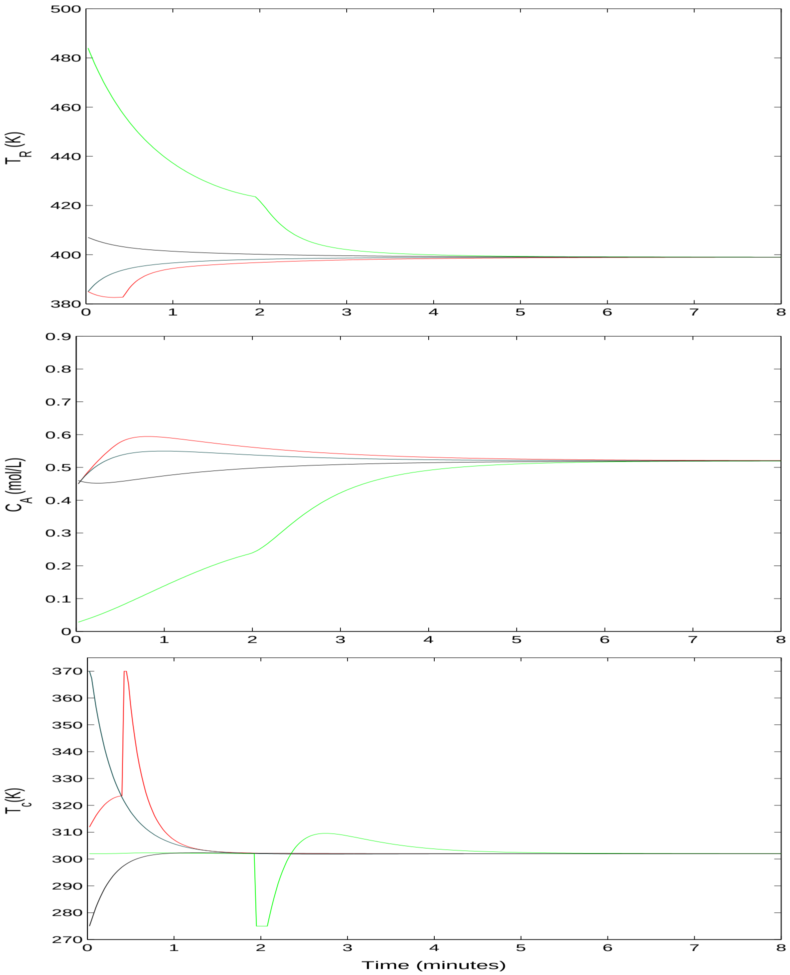
    - ▷ (A, B) from linearizing the nonlinear model around $(C_{As}, \; T_s)$.
  - ◇ Terminal equality constraint: $x(t+T) = 0$.

- **Family of bounded controllers:**
  - ◇ Designed using a normal form representation.
  - ◇ Several Lyapunov functions: $V_k = \xi^T P_k \xi, \;\; k = 1, 2, 3, 4.$
  - ◇ Stability region: $\Omega = \bigcup_{k=1}^{4} \Omega_k$

CLOSED-LOOP SIMULATION RESULTS

"Stability-based switching"





- ◇ MPC with $T = 0.25$; MPC/BC(4) switching ($t = 0.4$).
- ◇ MPC with $T = 0.5$; MPC/BC(3) switching ($t = 1.9$).

APPLICATION TO A CONTINUOUS CRYSTALLIZER

- **Crystallizer moments model:**

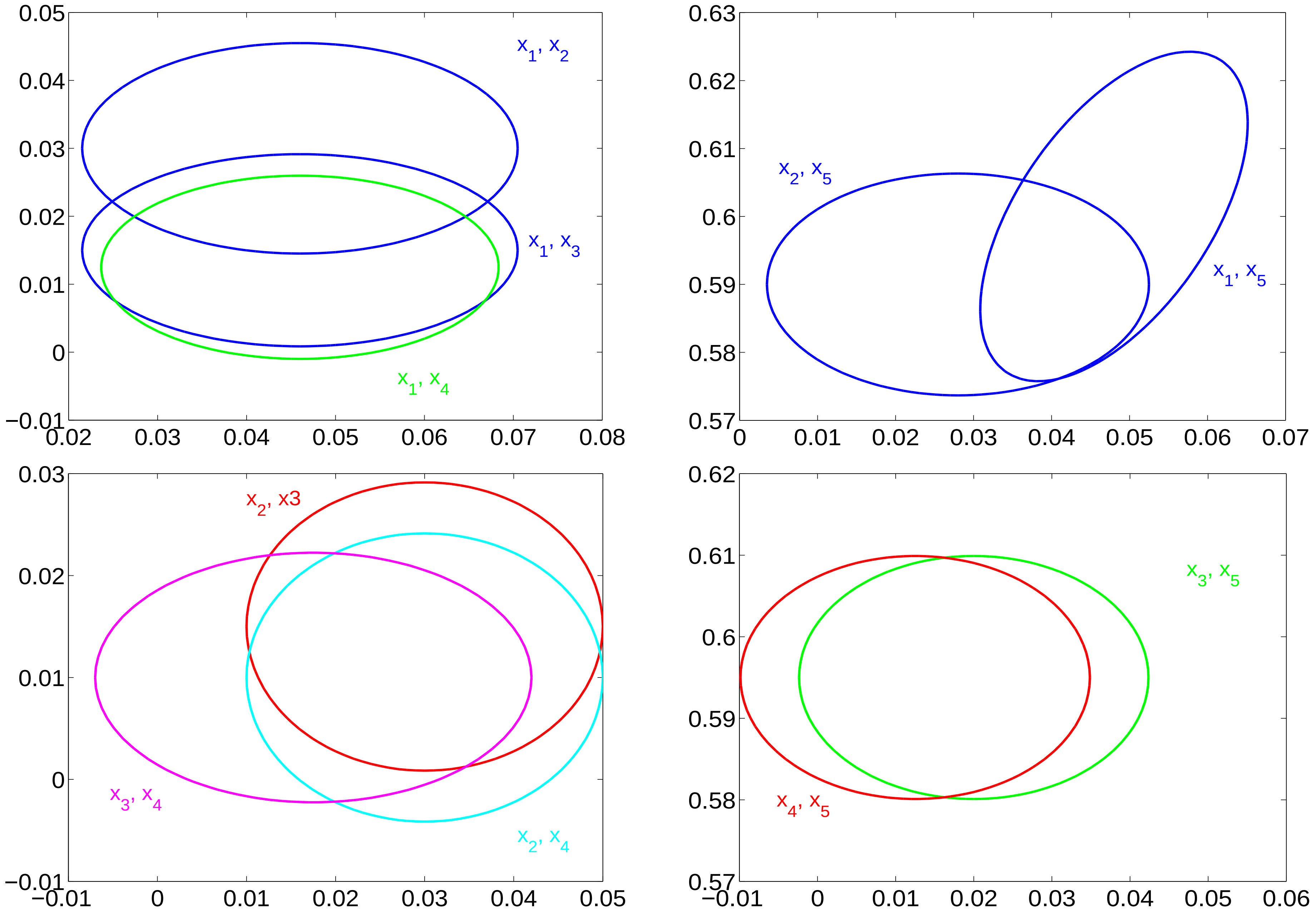
$$\begin{aligned}
\dot{x}_0 &= -x_0 + (1 - x_3) Da \exp\left(\frac{-F}{y^2}\right) \\
\dot{x}_1 &= -x_1 + y x_0 \\
\dot{x}_2 &= -x_2 + y x_1 \\
\dot{x}_3 &= -x_3 + y x_2 \\
\dot{y} &= \frac{1 - y - (\alpha - y) y x_2}{1 - x_3} + \frac{u}{1 - x_3}
\end{aligned}$$

  - ◇ Unstable equilibrium point surrounded by stable limit cycle.
  - ◇ Control objective:
    - ▷ Stabilization at unstable equilibrium point.
    - ▷ Input constraints: $u \in [-1, 1]$.

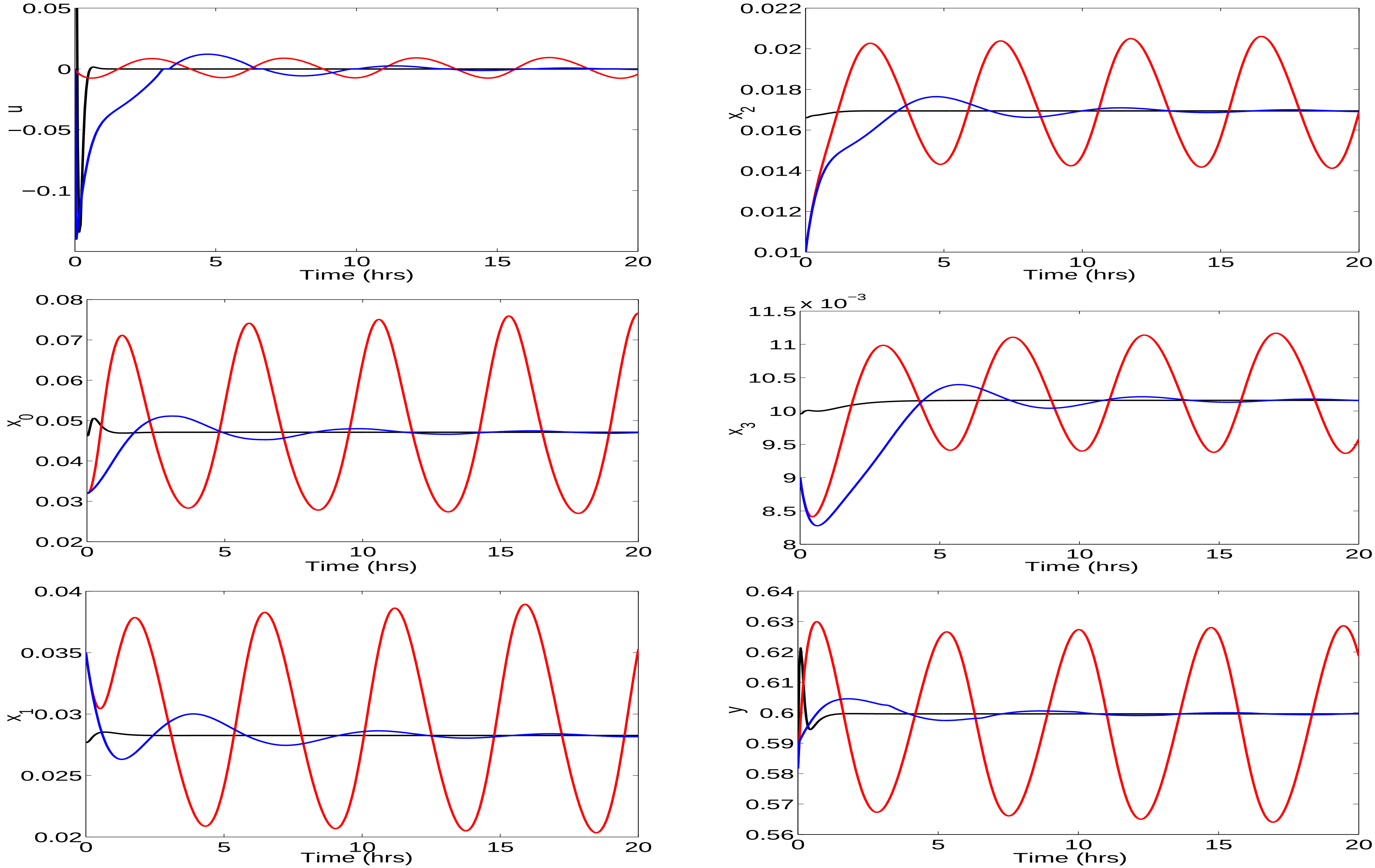
- Bounded controller: designed using normal form.

- Predictive controller: linear prediction model with stability constraints.

PROJECTIONS OF STABILITY REGION



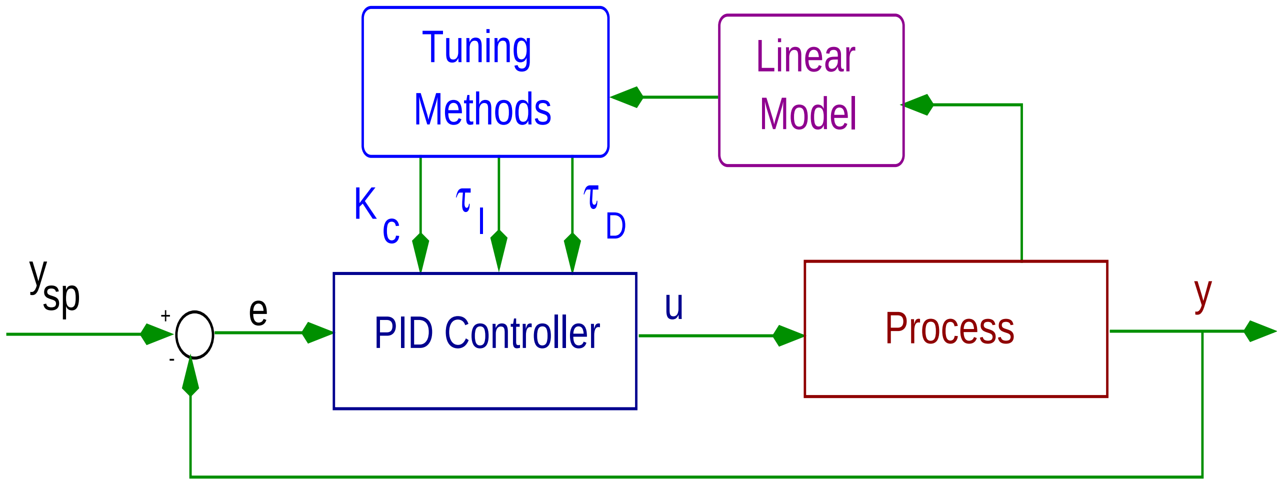
CLOSED-LOOP SIMULATION RESULTS



- $x_1(0)$: MPC with $T = 0.25$ feasible
- $x_2(0)$: MPC with $T = 0.25$ (no terminal constraints)
- $x_2(0)$: switching to bounded controller

TUNING CLASSICAL CONTROLLERS USING NONLINEAR CONTROL THEORY

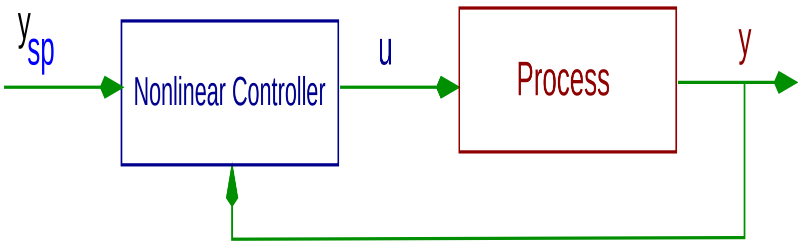
- Proportional-Integral-Derivative (PID) control:



- "Easy" to use and implement:
  - ◇ Tuning rules based on linear process models.
- Do not account for
  - ◇ Process nonlinearities, uncertainties, constraints etc.
- Extensive re-tuning / poor performance.

TUNING CLASSICAL CONTROLLERS USING NONLINEAR CONTROL THEORY

- Nonlinear controllers:



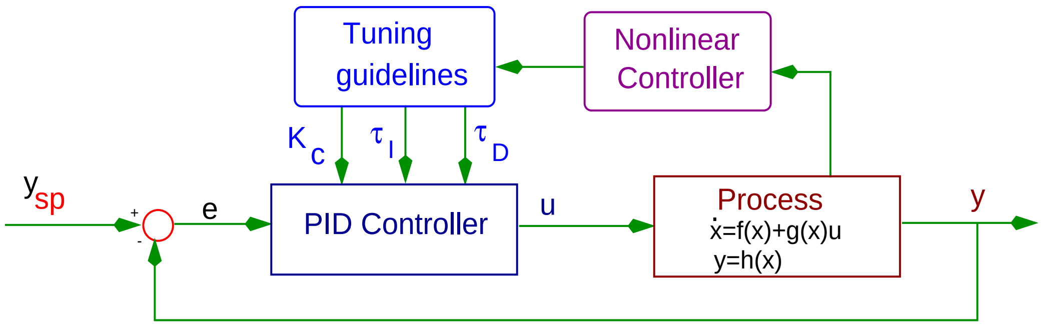
  - ◇ Handle process uncertainties/time delays/state estimation/...
  - ◇ Provide rigorous results and analysis.
  - ◇ Require better understanding of the process (nonlinear models).
  - ◇ Implementation requires redesign of existing control hardware.

- Gap between
  - ▷ Nonlinear control theory tools.
  - ▷ Process control practice (K_c, τ_i, τ_d).

Use/develop nonlinear control tools for PID controller tuning

TUNING METHOD

- Tuning method:



  ◇ Design a nonlinear controller that accounts for the complex process dynamics.

  ◇ Compute, but not implement, the control action as prescribed by the nonlinear controller.

  ◇ Set up and solve an optimization problem:

    ▷ The objective function 'measures' the difference between the control action of the PID and the nonlinear controller.

    ▷ The decision variables are the PID controller parameters.

APPLICATION TO A NONLINEAR PROCESS MODEL

- Process description:

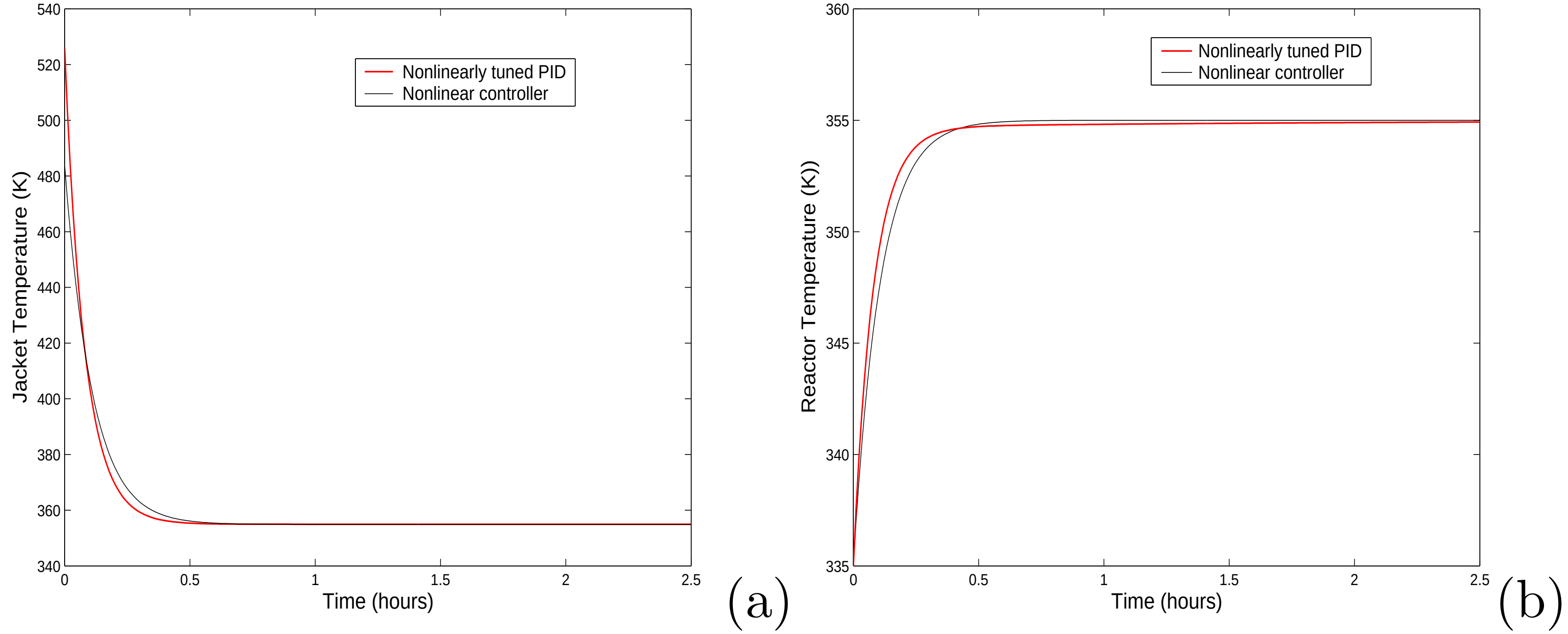
$$\frac{dT}{dt} = \frac{F}{V}(T_{A0} - T) + \sum_{i=1}^{3} \frac{(-\Delta H_i)}{\rho c_p} k_{i0} e^{\frac{-E_i}{RT}} C_A + \frac{Q}{\rho c_p V}$$

$$\frac{dC_A}{dt} = \frac{F}{V}(C_{A0} - C_A) - \sum_{i=1}^{3} k_{i0} e^{\frac{-E_i}{RT}} C_A$$

  - ◇ Three steady-states (two locally asymptotically stable and one unstable).
  - ◇ Stabilize the reactor at the open–loop unstable steady–state using the jacket temperature as the manipulated input.

CLOSED-LOOP SIMULATION RESULTS

"Nonlinear-control based PID tuning"



- ◇ (a) Input & (b) state profiles.
- ◇ The nonlinear controller is only designed, **not** implemented.
- ◇ PID controller designed to 'emulate' the action of the nonlinear controller.

CONCLUSIONS

- Issues in Process Control:
  - Nonlinearities, uncertainties, constraints and state estimation.
- Integrate tools from nonlinear control theory with existing process control practice.
  - Safety–net for predictive control implementation.
  - Improved tuning of classical controllers.
- Practical implementation:
  - Software: Direct incorporation into existing MPC packages.
  - Hardware: Does not require redesigning existing classical control hardware.

ACKNOWLEDGEMENT

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