Perfect Tracking for Non-minimum Phase Systems:

with Applications to Biofuels from Microalgae

Mike Buehner

Ph. D. Final Defense

Monday July 12th, 2010

Colorado State University

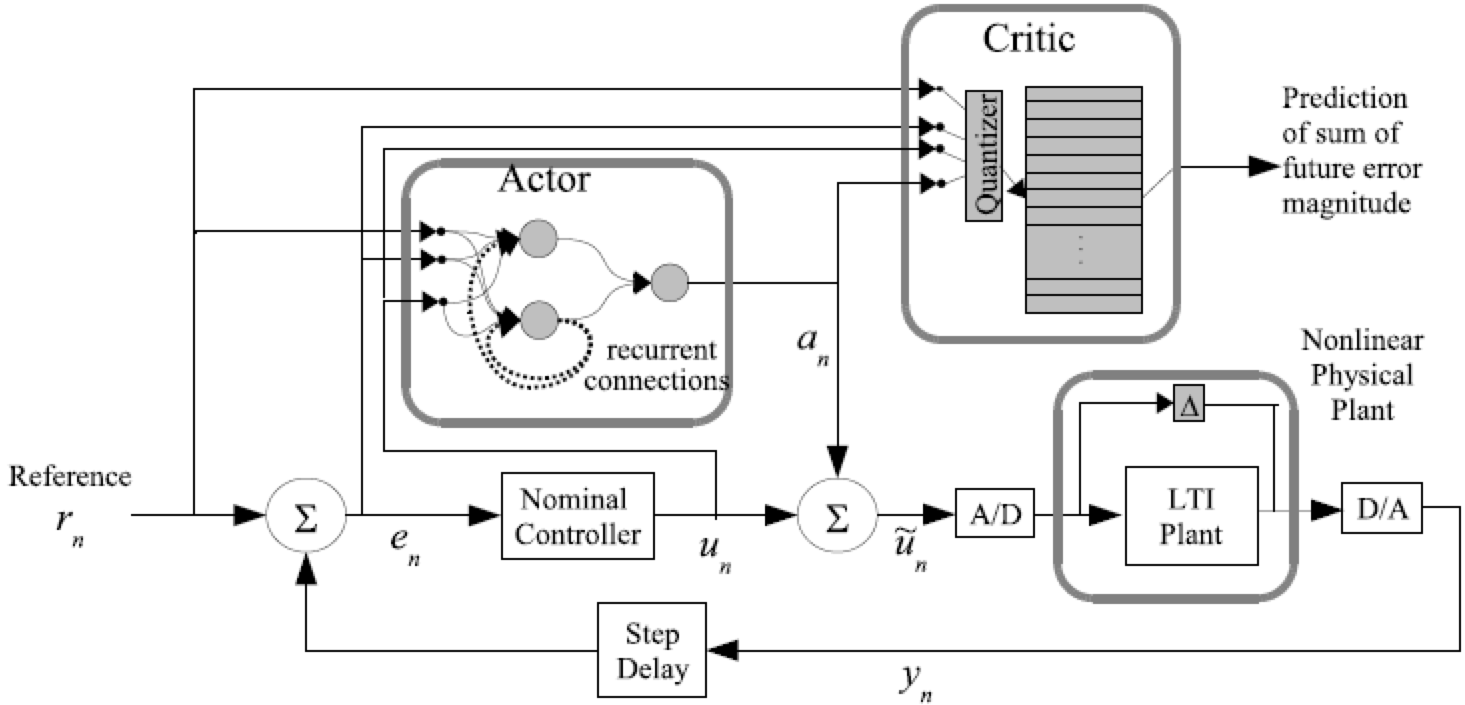
Overview of Presentation

- History of project / Motivation
- Perfect tracking control of non-minimum phase systems
- Biofuels from microalgae
- Conclusions / Future Directions

Commercial HVAC

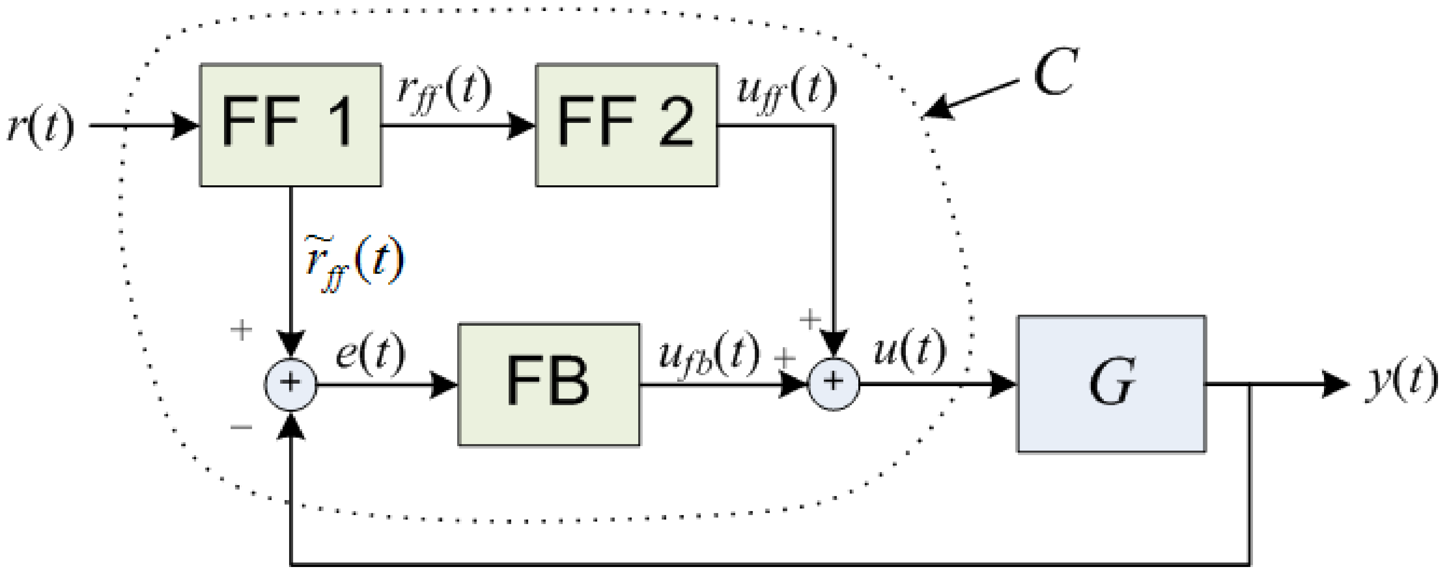
- Difficult to model a whole building
- Knowledge of “disturbances”
- Reinforcement learning control
- Adaption (done inside the feedback loop)

Robust Reinforcement Learning Control



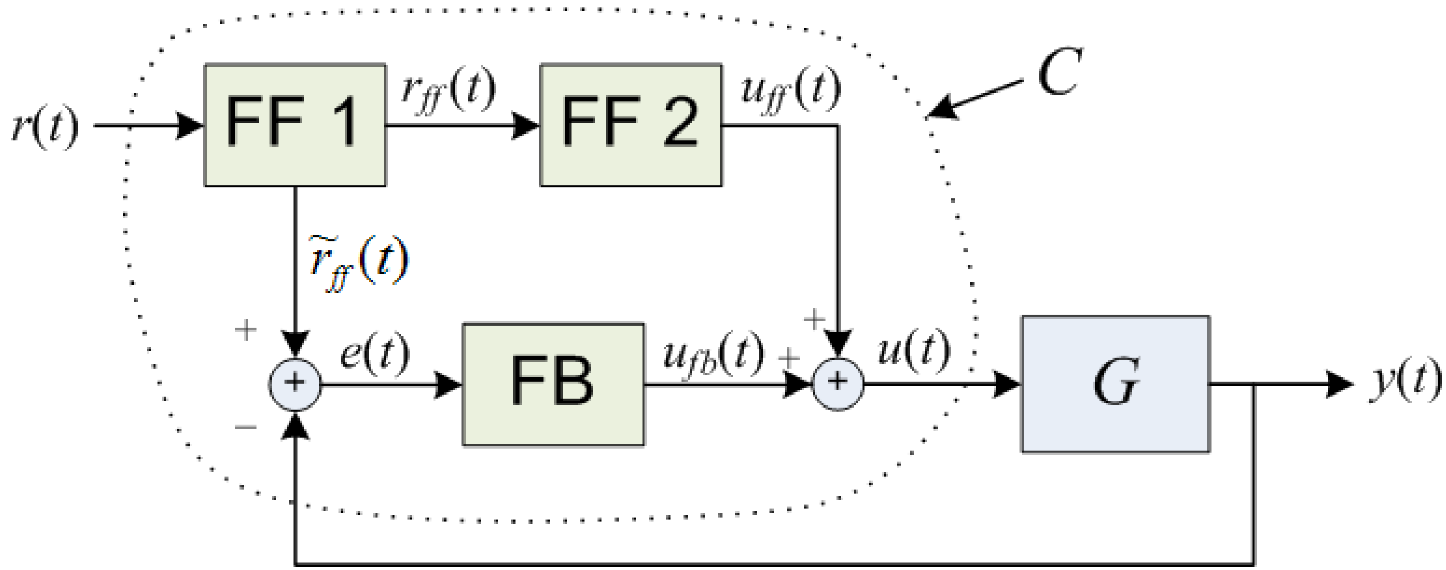
- Guaranteeing stability ~ Computationally intensive
- Based on IQCs (Integral Quadratic Constraints)
- Can adapt to both reference and disturbance inputs

Reduce Stability Complexity



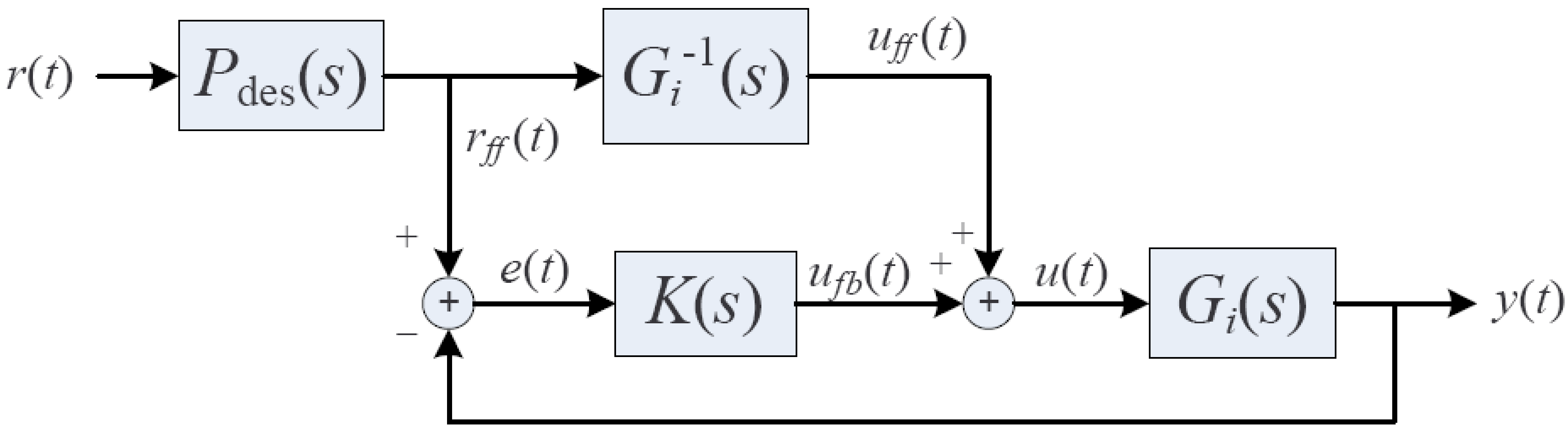
- Fix the feedback (FB) controller
- Adapt the feedforward (FF) controllers
- Closed-loop stability ~ Provide by FB
- FF adaptation ~ Anything (provided bounded)

Neuromuscular Actuation Systems



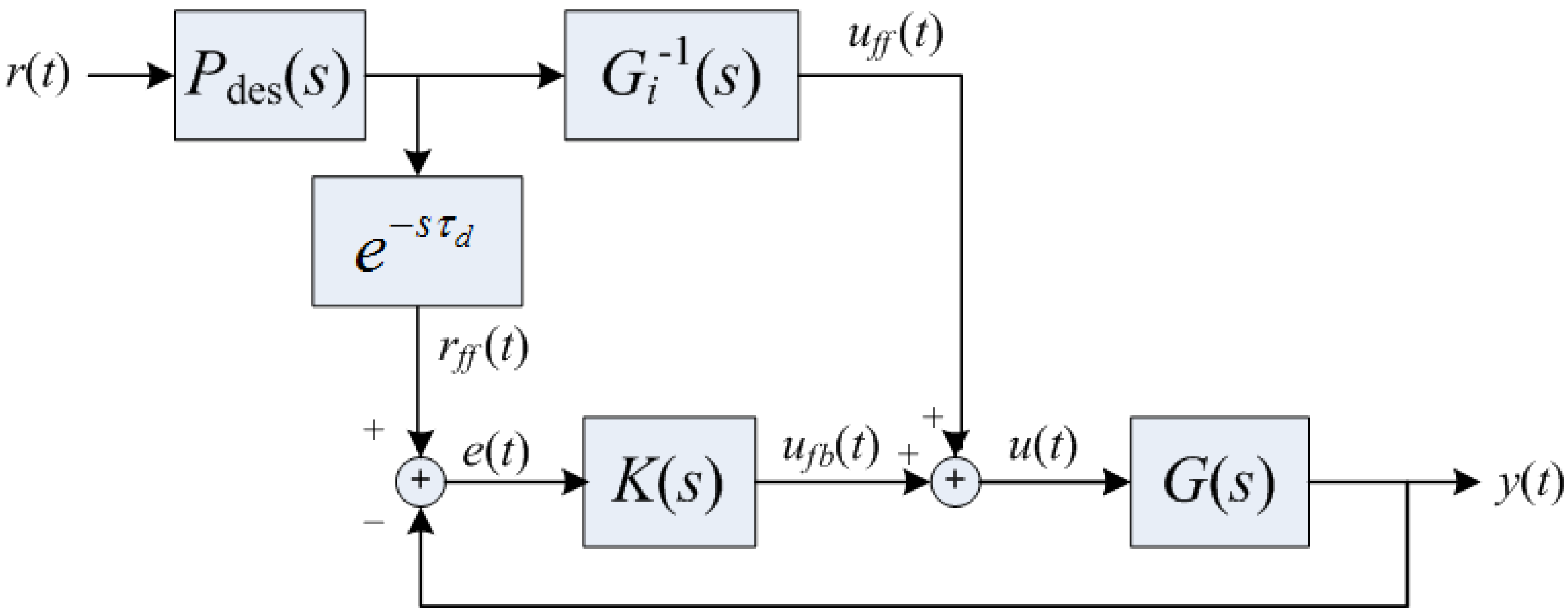
- Calculate desired path (FF calculation)
- Ballistic response (FF Control)
- Dynamic corrections to ballistic response (FB control on small error signals)

Standard Architecture



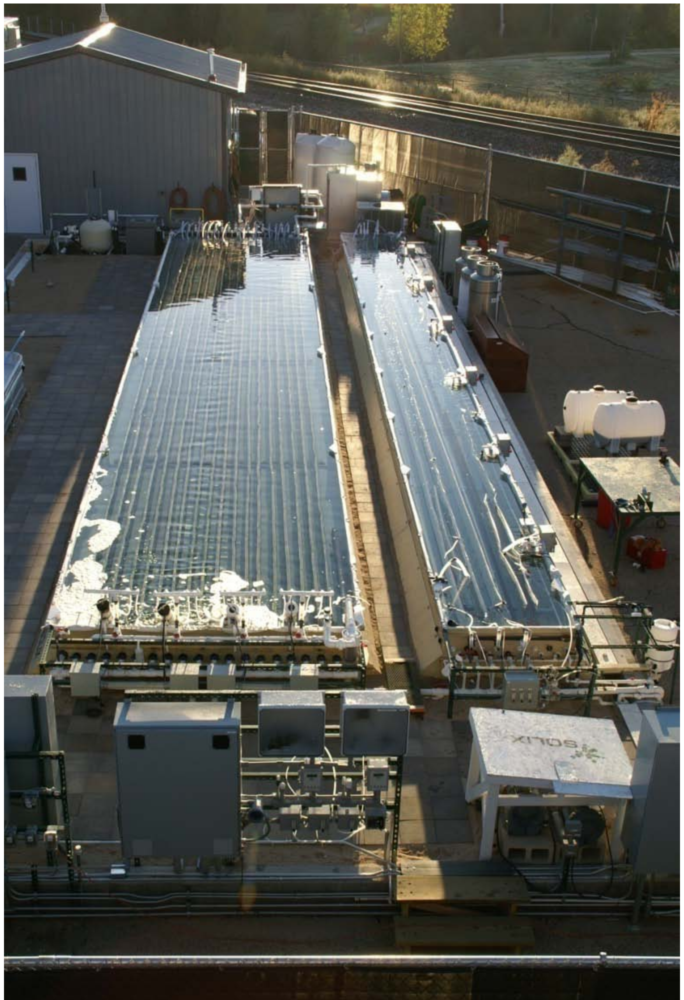
- Can provide perfect tracking for minimum-phase systems
- Unstable plants allowed
- Cannot (stably and causally) handle time delays and right-half plane zeros

Extension to Time Delays



- Delay reference input
- Later – extension to (RHP zeros)
- Previously not presented in literature

Motivation: Growing Microalgae



- Application: Biofuels from microalgae
- Utilize externally supplied CO_2 to produce more microalgae.
- CO_2 source and microalgae physically separated (transport delays)
- Sensors are expensive and unreliable (FF control desirable)

Perfect Tracking Control of Non-minimum Phase Systems

Perfect Tracking

- What trajectory can the plant actually follow?
- What control signal will drive the plant along this trajectory?
- Characterize the class of signals that may be tracked in the nominal case (i.e., when the plant model is perfect) with no external disturbances.
- Extensions to non-minimum phase systems.

Contributions

- Two controller architectures that provide perfect tracking for a larger class of systems (particularly, systems with time delays)
  - Dual Feedforward Predictive Control (DFFPC)
  - Dual Feedforward Smith Predictor (DFFPC)
    - Clarify limitations of Smith predictor
- Robustness tools
- Feedforward controller design methodologies
- Adaptation techniques

Plant Factorization

$$G(s) = \frac{K_{\mathrm{DC}} N_{nmp}(s) N_{mp}(s)}{D_s(s) D_u(s)} e^{-s\tau_d}$$

- Minimum-phase and stable: Re(s) < 0
- Non-minimum phase and unstable Re(s) ≥ 0
- Non-minimum phase includes RHP zeros and time delays
- Normalize via K_{DC} such that:
  - $N_{nmp}(0) = N_{mp}(0) = D_s(0) = D_u(0) = 1$
- Could extend to integrators (include in $D_u(s)$)

Plant Decomposition

$$G(s) = G_{noi}(s)G_i(s)$$

Split plant into non-invertible and invertible part

$$\begin{aligned} G_{noi}(s) &= N_{nmp}(s)e^{-s\tau_d} \\ G_i(s) &= \frac{K_{\mathrm{DC}}N_{mp}(s)}{D_s(s)D_u(s)} \end{aligned}$$

Non-invertible part contains non-minimum phase components

Invertible part contains minimum- phase components

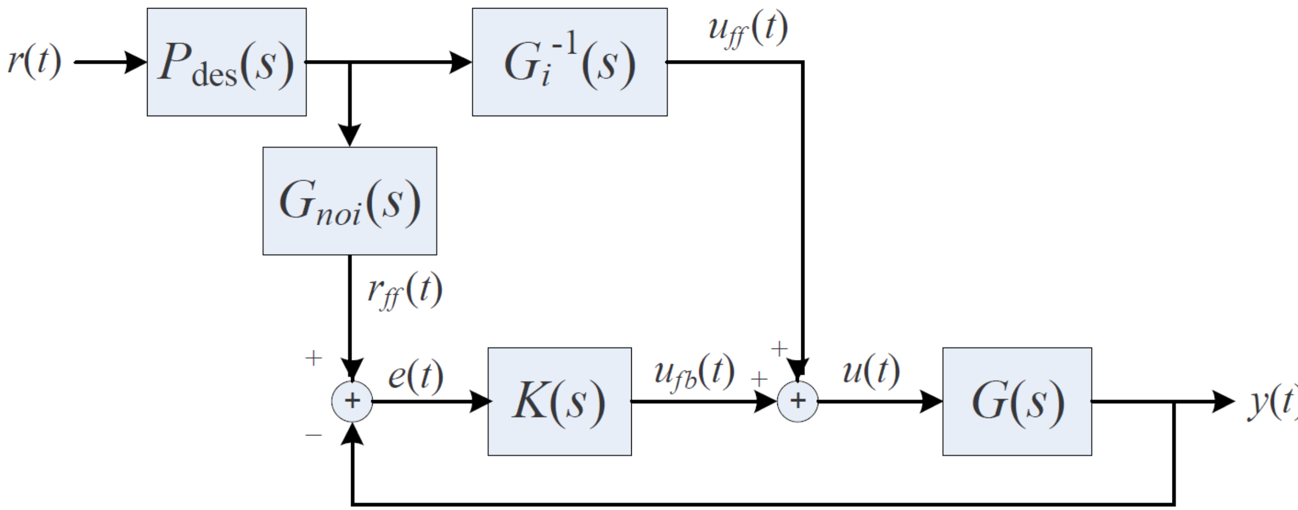
$$G_i^{-1}(s) = \frac{D_s(s)D_u(s)}{K_{\mathrm{DC}}N_{mp}(s)}$$

NB: In general, $G_{noi}(s)$ and $G_i^{-1}(s)$ are *not* proper transfer functions

DFFPC Overview

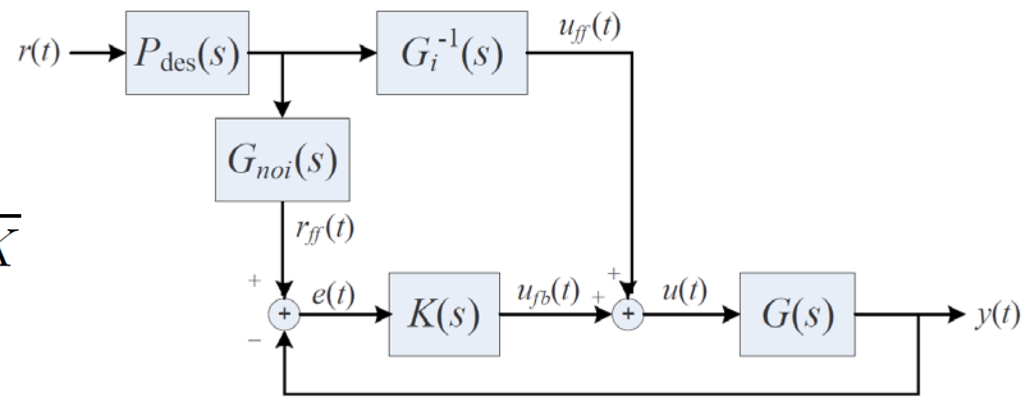
- Restricted to causal SISO systems (i.e., no prior knowledge of the reference input).
- Define a class of signals that can be perfectly tracked by non-minimum phase LTI systems.
  - Perfect tracking of a filtered reference input in the nominal case with no external disturbances
- Robustness tools for evaluating robust performance on a physical system.
- Stable adaptation techniques to improve performance. (Addressed Later)
- Can handle unstable systems

Dual Feedforward Predictive Control



- At steady-state, $r_{ff}(t) = r(t)$ or $P_{\text{des}}(0)G_{noi}(0) = 1$
- The feedforward transfer functions must be proper: $P_{\text{des}}(s)G_{noi}(s)$ and $P_{\text{des}}(s)G_i^{-1}(s)$

Nominal Case



$$S = \frac{1}{1+GK} \quad \text{and} \quad T = \frac{GK}{1+GK}$$

$$\begin{aligned} S_{\text{DFFPC}} &= P_{\text{des}} G_{noi} S - P_{\text{des}} G_i^{-1} G S \\ &= P_{\text{des}} G_{noi} S - P_{\text{des}} G_{noi} S \\ &= 0. \end{aligned}$$

- Perfect Tracking

$$\begin{aligned} M_{\text{DFFPC}} &= \frac{P_{\text{des}} G_{noi} G K}{1+GK} + \frac{P_{\text{des}} G_i^{-1} G}{1+GK} \\ &= P_{\text{des}} G_{noi} \frac{1+GK}{1+GK} \\ &= P_{\text{des}} G_{noi} \end{aligned}$$

- Desired closed-loop response contains non-minimum phase dynamics

Example: Perfect Tracking of a NMP System

$$G(s) = 75\frac{-s+2}{(s+5)(s+10)} = 3\frac{\frac{-s}{2}+1}{(\frac{s}{5}+1)(\frac{s}{10}+1)}$$

$$G_{noi}(s) = \frac{-s}{2}+1, \quad G_i^{-1}(s) = \frac{1}{3}(\frac{s}{5}+1)(\frac{s}{10}+1)$$

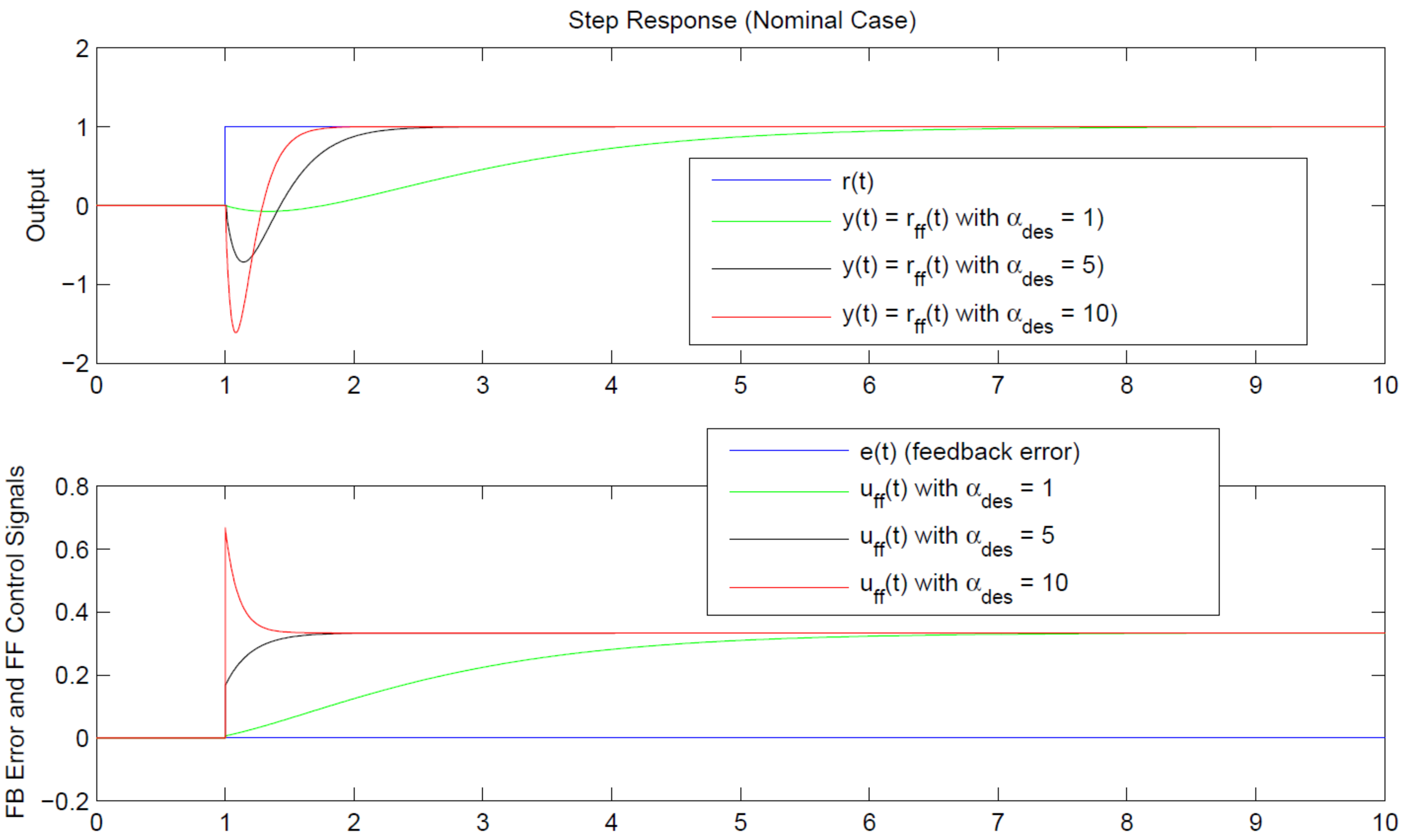
$$P_{\text{des}}(s) = \frac{1}{(\frac{s}{\alpha_{\text{des}}}+1)^2}$$

Picked a $P_{\text{des}}(s)$ that will make the two feedfoward controllers (below) proper

$$FF1(s) = P_{\text{des}}(s)G_{noi}(s) = \frac{\frac{-s}{2}+1}{(\frac{s}{\alpha_{\text{des}}}+1)^2}$$

$$FF2(s) = P_{\text{des}}(s)G_i^{-1}(s) = \frac{1}{3}\frac{(\frac{s}{5}+1)(\frac{s}{10}+1)}{(\frac{s}{\alpha_{\text{des}}}+1)^2}$$

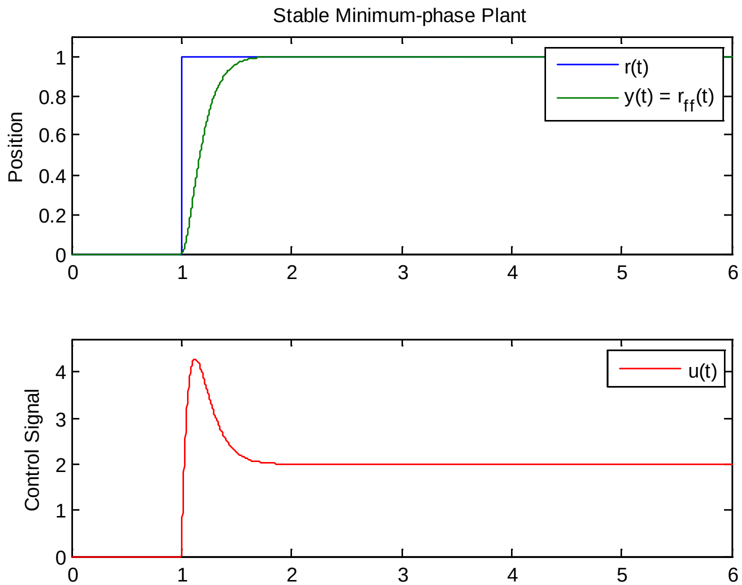
Simulation Results



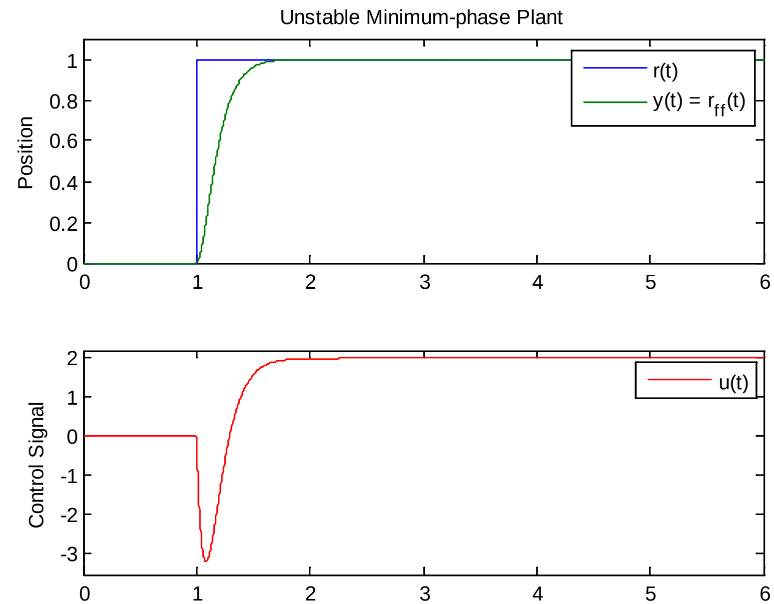
Plant Implications

Min Phase

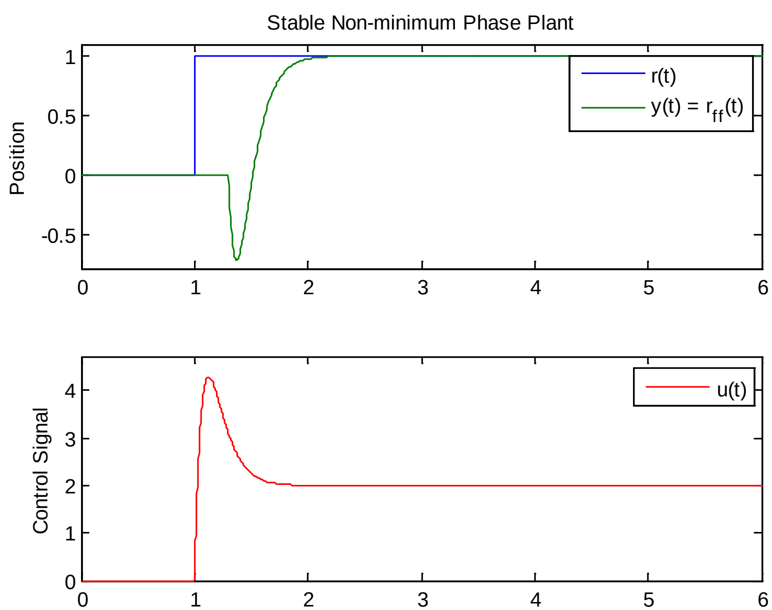
Stable

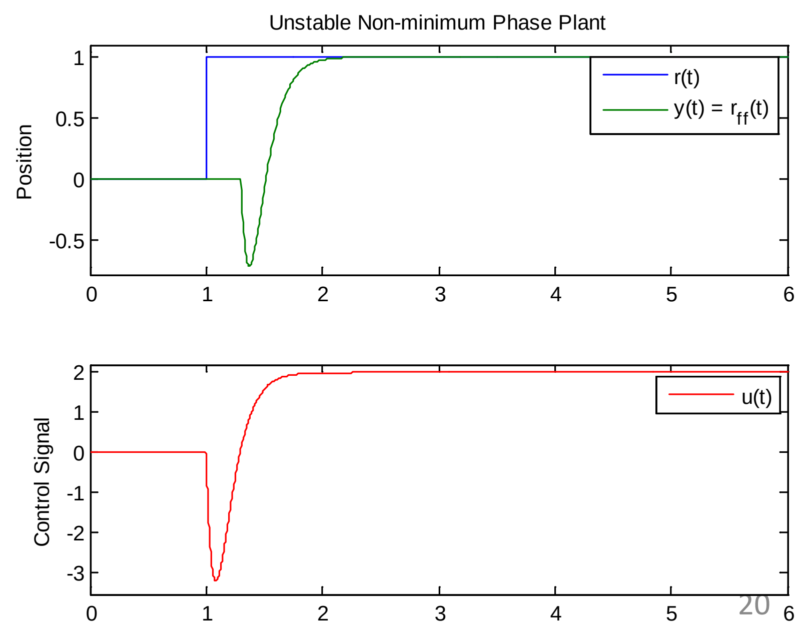


Unstable



NMP

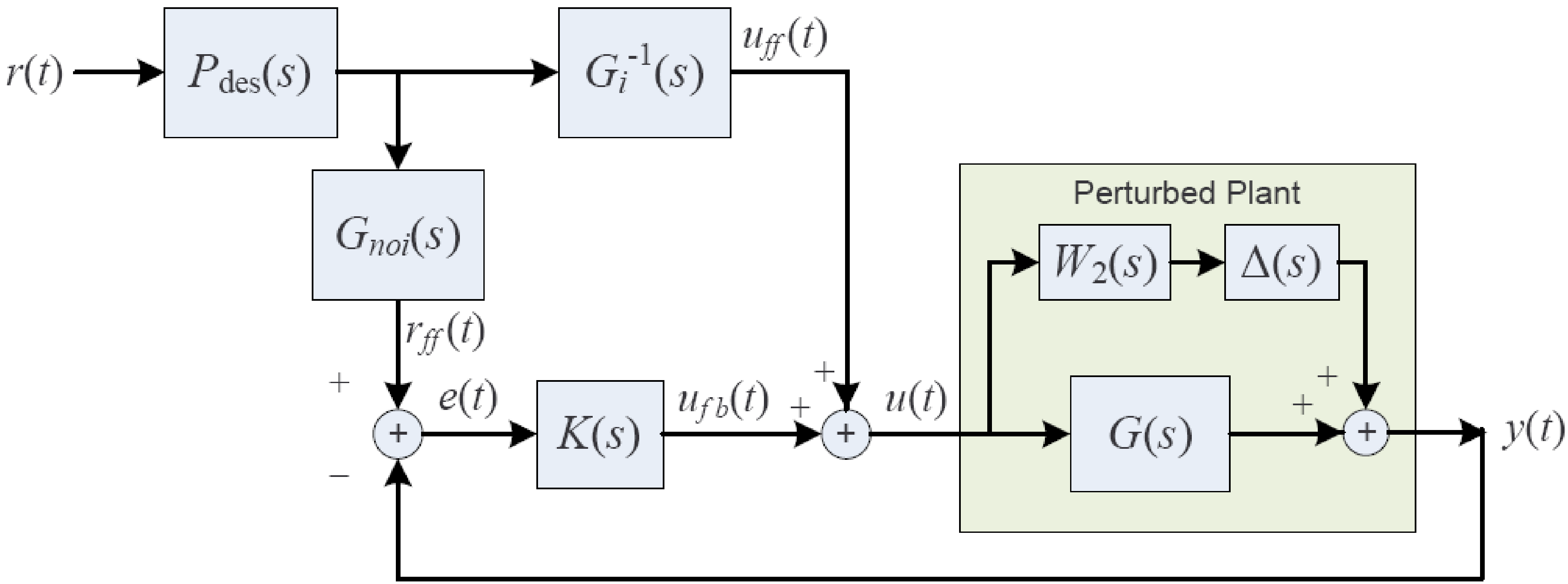




Robustness Analysis:

Additive Uncertainty

$$\tilde{G} = G + W_2\Delta$$



Robustness Analysis:

Additive Uncertainty

$$\tilde{G} = G + W_2\Delta$$

$$\begin{aligned}
\tilde{S}_{\text{DFFPC}} &= \frac{P_{\text{des}}G_{noi}}{1+(G+\Delta W_2)K} - \frac{P_{\text{des}}G_i^{-1}(G+\Delta W_2)}{1+(G+\Delta W_2)K} \\
&= \frac{P_{\text{des}}G_{noi} - P_{\text{des}}G_{noi} - P_{\text{des}}G_i^{-1}\Delta W_2}{1+(G+\Delta W_2)K} \\
&= -\frac{P_{\text{des}}G_i^{-1}\Delta W_2/(1+GK)}{(1+GK+\Delta W_2 K)/(1+GK)} \\
&= -\frac{P_{\text{des}}G_i^{-1}\Delta W_2 S}{1+\Delta W_2 K S}
\end{aligned}$$

Robustness Analysis Cont’

$$\tilde{S}_{\text{DFFPC}} = -\frac{P_{\text{des}} G_i^{-1} \Delta W_2 S}{1 + \Delta W_2 K S}$$

Assuming that $\|\Delta\|_\infty \leq 1$, robust stability requires that

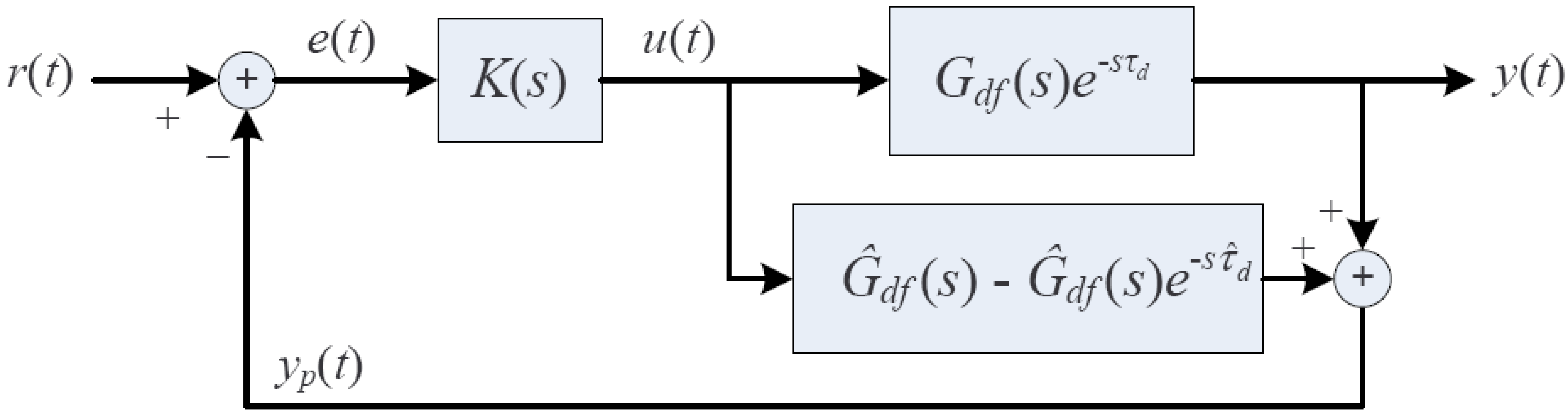
$$\|W_2 K S\|_\infty < 1.$$

- Necessary and sufficient condition for robust performance with additive uncertainty is:

$$\| |W_1 P_{\text{des}} G_i^{-1} W_2 S| + |W_2 K S| \|_\infty < 1$$

- Similar result for multiplicative uncertainty.

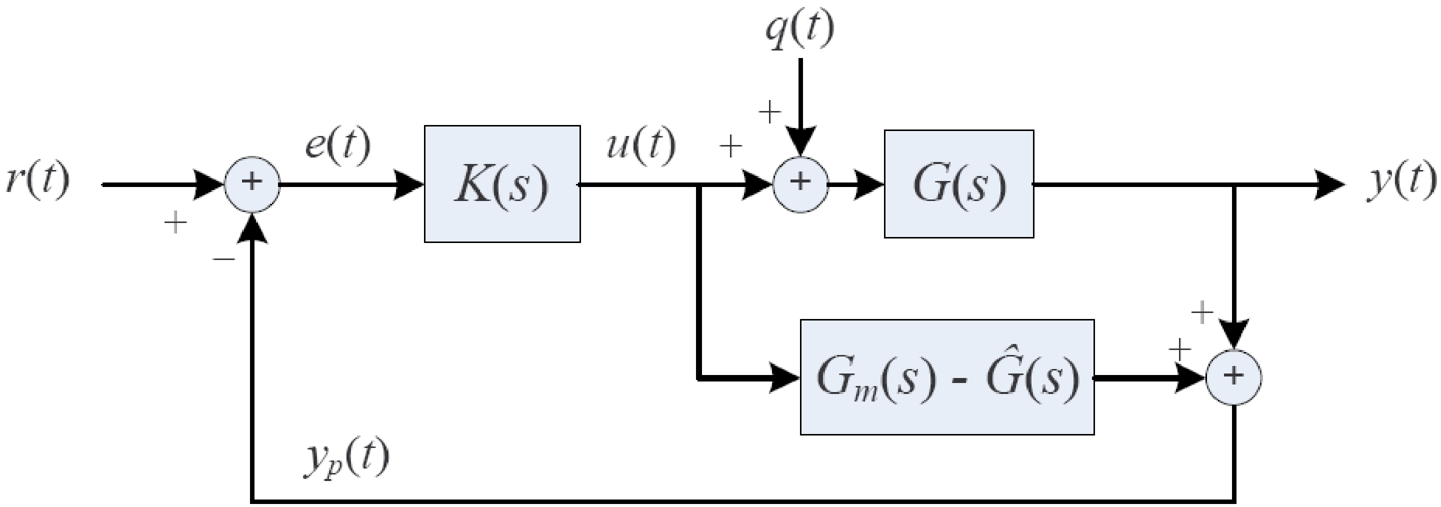
Original Smith Predictor



$$M(s) = \frac{G(s)K(s)}{1 + K(s)(G(s) + G_{df}(s) - G(s))} = \frac{G(s)K(s)}{1 + G_{df}(s)K(s)}$$

- Eliminate time delay from feedback loop (better nominal tracking performance)

Modified Smith Predictor



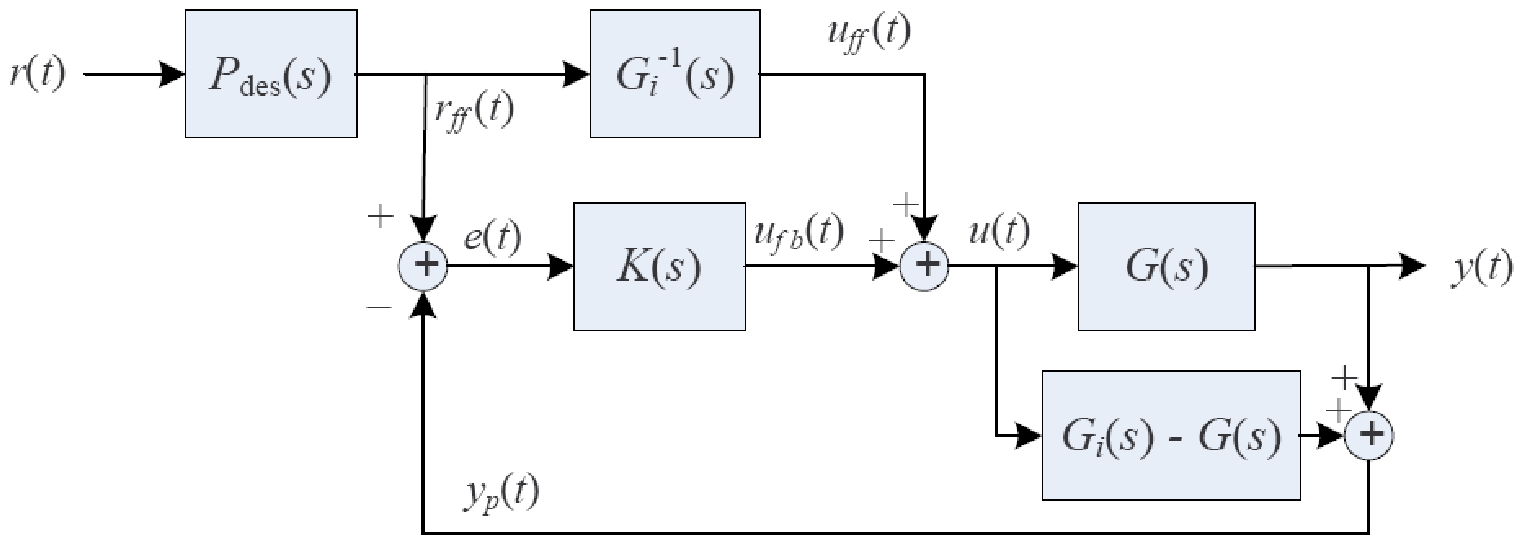
$$
\begin{aligned}
\frac{Y(s)}{Q(s)} &= \frac{G(s)(1+G_m(s)K(s)-G(s)K(s))}{1+G_m(s)K(s)} \\
&= G(s)\left(1-\frac{G(s)K(s)}{1+G_m(s)K(s)}\right) \\
&= \frac{N_G(s)}{D_G(s)}\left(\frac{D_G(s)D_m(s)D_K(s)+N_m(s)N_K(s)D_G(s)+N_G(s)N_K(s)D_m(s)}{D_G(s)D_m(s)D_K(s)+N_m(s)N_K(s)}\right)
\end{aligned}
$$

- Improved disturbance rejection
- Not suitable for unstable systems

DFFSP Overview

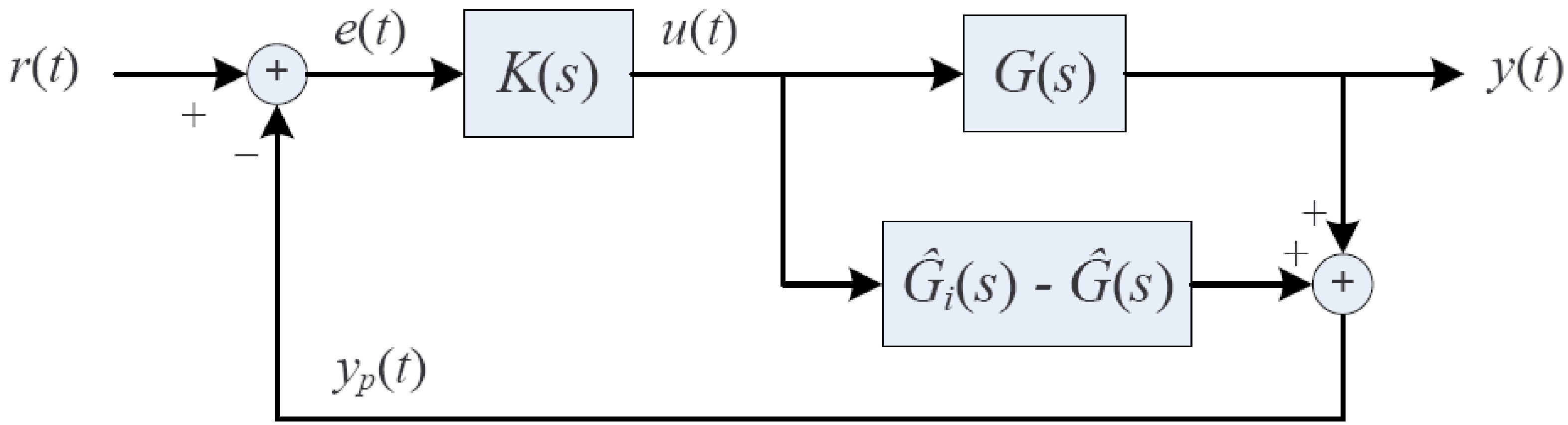
- Restricted to causal SISO systems (i.e., no prior knowledge of the reference input).
- Define a class of signals that can be perfectly tracked by stable non-minimum phase LTI systems.
  - Perfect tracking of a filtered reference input in the nominal case with no external disturbances
- Robustness tools for evaluating robust performance on a physical system.
- Stable adaptation techniques to improve performance. (Addressed Later)
- *<u>Cannot</u>* handle unstable systems

Dual Feedforward Smith Predictor



- At steady-state, $r_{ff}(t) = r(t)$ or $P_{\text{des}}(0) = 1$
- The feedforward transfer functions must be proper: $P_{\text{des}}(s)$ and $P_{\text{des}}(s)G_i^{-1}(s)$
- $G_{noi}(s)$ handled in feedback loop

(Nominal) Smith Predictor

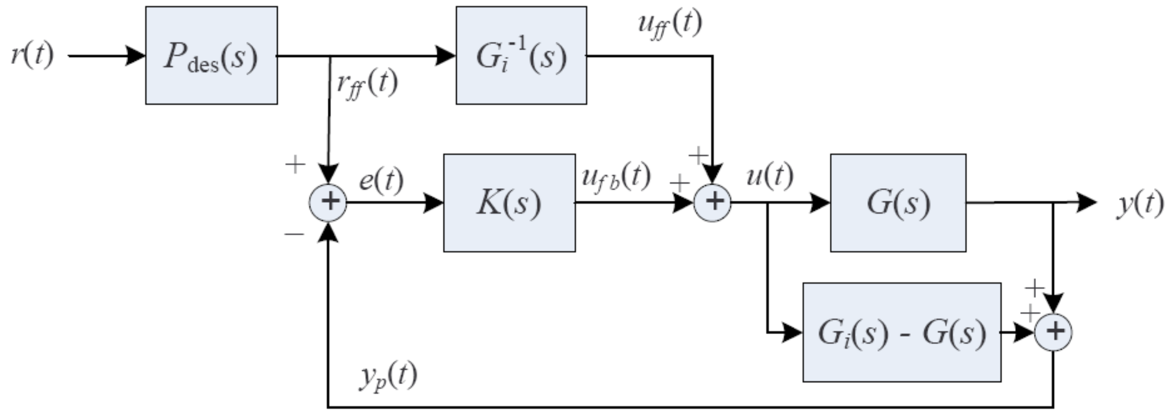


$$S_i(s) = \frac{E(s)}{R(s)} = \frac{1}{1 + G_i(s)K(s)}$$

$$T_i(s) = 1 - S_i(s) = \frac{G_i(s)K(s)}{1 + G_i(s)K(s)} = \frac{Y_p(s)}{R(s)}$$

$$M_i(s) = \frac{Y(s)}{R(s)} = \frac{G(s)K(s)}{1 + G_i(s)K(s)} = T_i(s)G_{noi}(s)$$

Nominal DFFSP



$$
\begin{aligned}
S_{\text{DFFSP}}(s) &= P_{\text{des}}(s)S_i(s) - P_{\text{des}}(s)G_i^{-1}(s)G_i(s)S_i(s) \\
&= P_{\text{des}}(s)S_i(s) - P_{\text{des}}(s)S_i(s) \\
&= 0,
\end{aligned}
$$

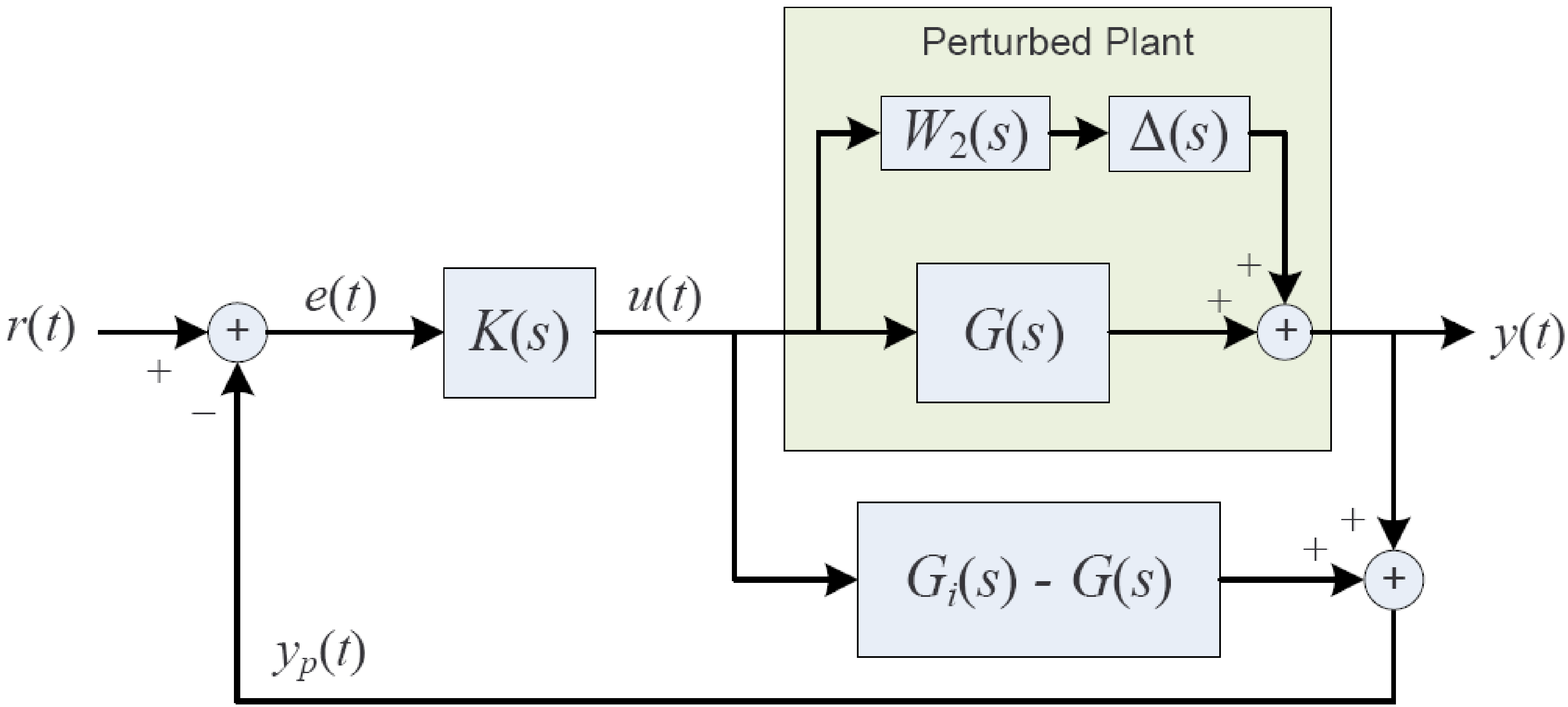
- Perfect Tracking

$$
\begin{aligned}
M_{\text{DFFSP}}(s) &= \frac{P_{\text{des}}(s)G(s)K(s)}{1+G_i(s)K(s)} + \frac{P_{\text{des}}(s)G_i^{-1}(s)G(s)}{1+G_i(s)K(s)} \\
&= \frac{P_{\text{des}}(s)G_{noi}(s)G_i(s)K(s) + P_{\text{des}}(s)G_{noi}(s)}{1+G_i(s)K(s)} \\
&= P_{\text{des}}(s)G_{noi}(s)\frac{1+G_i(s)K(s)}{1+G_i(s)K(s)} \\
&= P_{\text{des}}(s)G_{noi}(s),
\end{aligned}
$$

- Desired closed-loop response contains non-minimum phase dynamics

Robustness Analysis:
Additive Uncertainty

$$\tilde{G} = G + W_2\Delta$$



Robustness Analysis:

Additive Uncertainty

$$\tilde{G} = G + W_2\Delta$$

$$\begin{aligned}
\tilde{S}_{\mathrm{DFFSP}} &= \frac{P_{\mathrm{des}}}{1+(G_i+\Delta W_2)K} - \frac{P_{\mathrm{des}}G_i^{-1}(G_i+\Delta W_2)}{1+(G_i+\Delta W_2)K} \\
&= \frac{P_{\mathrm{des}} - P_{\mathrm{des}} - P_{\mathrm{des}}G_i^{-1}\Delta W_2}{1+(G_i+\Delta W_2)K} \\
&= -\frac{P_{\mathrm{des}}G_i^{-1}\Delta W_2/(1+G_iK)}{(1+G_iK+\Delta W_2 K)/(1+G_iK)} \\
&= -\frac{P_{\mathrm{des}}G_i^{-1}\Delta W_2 S_i}{1+\Delta W_2 K S_i}
\end{aligned}$$

Robustness Analysis Cont'

$$\tilde{S}_{\mathrm{DFFSP}} = -\frac{P_{\mathrm{des}} G_i^{-1} \Delta W_2 S_i}{1 + \Delta W_2 K S_i}$$

$$\text{robust stability requires } \|\Delta W_2 K S_i\|_\infty < 1 \text{ for all } \|\Delta\|_\infty \le 1$$

- Necessary and sufficient condition for robust performance additive uncertainty is:

$$\| |W_1 P_{\mathrm{des}} G_i^{-1} W_2 S_i| + |W_2 K S_i| \|_\infty < 1$$

- Similar result for multiplicative uncertainty

DFFPC vs. DFFSP

- DFFPC can handle unstable systems, DFFSP cannot
- DFFSP will result in a higher order controller due to ($G_i(s)$-$G(s)$)
- Smith predictor improved disturbance rejection properties are not applicable here ($G_m(s) = G_i(s)$)
- Adapting the DFFSP architecture is less straightforward than the DFFPC architecture

Comments on Methods

- Valid for both continuous-time and discrete-time implementations
- Perfect control for a wide class of systems
  - Minimum-phase and non-minimum phase
  - Stable and Unstable*
  - Biproper and strictly proper systems
  - Systems with or without time delays
- Robustness tools
- Design Methodologies (Next)
- Adaptation (Later)

* (for DFFPC only)

Feedforward 2 ($FF2(s)$) Design

- $P_{\mathrm{des}}(s)$ (and $FF2(s)$)common to feedforward plus feedback architectures presented here

- Direct design

- Robust and optimal design

Direct Design

- Design for specific closed-loop characteristics
  - e.g., specific rise time with no overshoot

$P_{\text{des}}(s)$ **Design Constraints:**

- Relative degree of $P_{\text{des}}(s) \geq$ Relative degree of $G_i(s)$ (assuming $G(s)$ is proper)

- $P_{\text{des}}(0) = 1$ (assuming that $G_{noi}(0) = 1$ from the problem formulation).

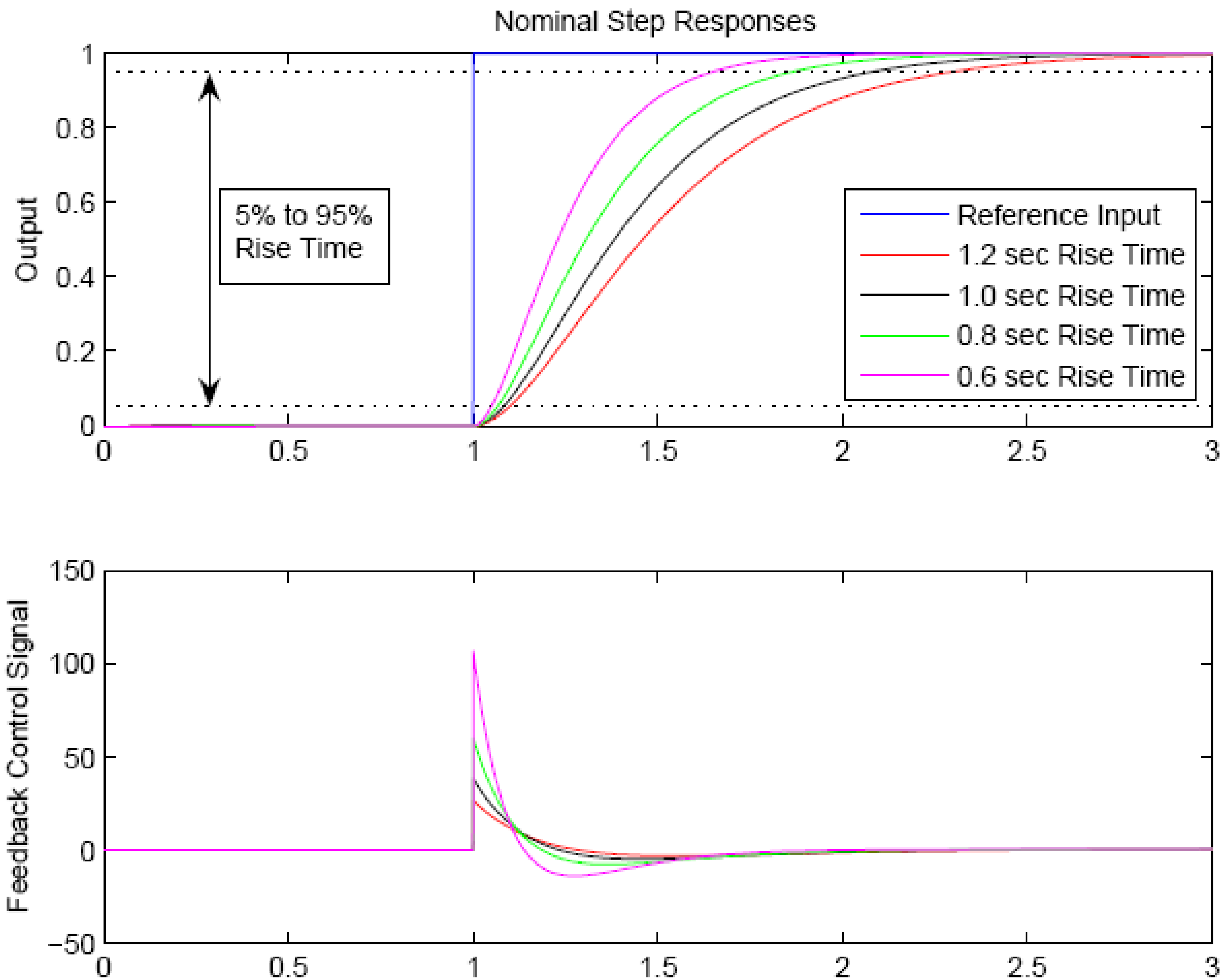
Direct Design Example

- Minimum-phase Plant
- Closed-loop is $P_{\text{des}}(s)$
- Example: $P_{\text{des}}(s) = \dfrac{1}{(\tau s + 1)^2}$
- Design for rise time (with no overshoot):

$$\tau = \frac{t_{r(\text{des})}}{4.3885}$$

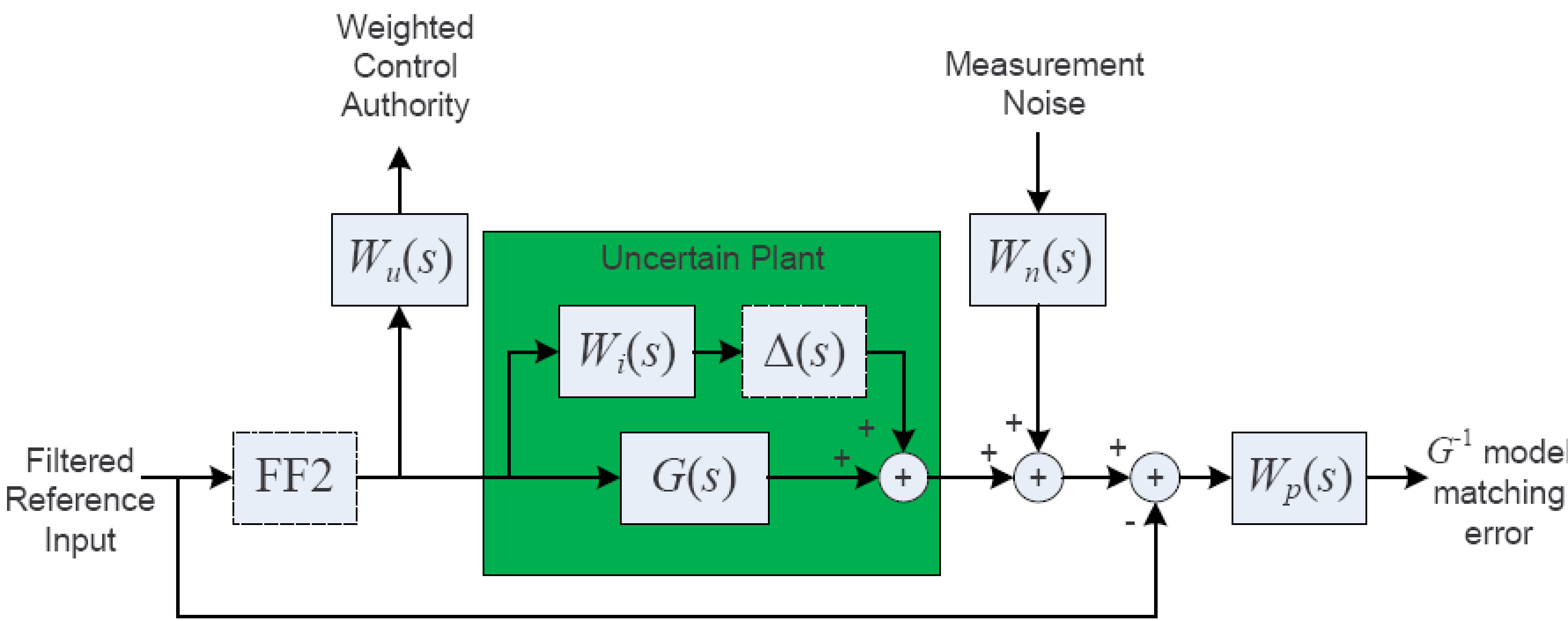
- NB: Numerical solution to above equation.

Nominal Step Responses



Robust and Optimal FF Design

- Optimal control – minimize gain from exogenous inputs to exogenous outputs
- Robust control – optimal control in the presence of uncertainty



Design Method

NB: $FF2(s) = P_{des}(s)\, G_i^{-1}(s)$

1. Design a robust/optimal $FF2(s)$.
2. Define $Z(s) = \frac{1}{K_\mu} FF2(s) G_i(s)$ (where K_μ is selected to make $Z(0) = 1$).
3. Use a minimum realization and model reduction techniques to reduce the order of $Z(s)$.
4. Define $P_{\text{des}}(s) = Z(s)F(s)$, where $F(s)$ is a stable and proper transfer function with $F(0) = 1$. NB: $F(s) = 1$ is a valid (and common) choice here.

FF Design Summary

- Based on an existing example (Faanes 2003)
- Provided more investigation into the resulting feedforward controller structure
  - Cancellations and near misses (lower order $P_{\mathrm{des}}(s)$ designs)
- Extensions may be made to unstable plants
- Option to design on either $G(s)$ or $G_i(s)$

Numerical Example

- Plant definition:

$$G(s) = 25\frac{-s+6}{(s+5)(s+10)}e^{-0.7s}$$

$$= 3\frac{\frac{-s}{6}+1}{(\frac{s}{5}+1)(\frac{s}{10}+1)}e^{-0.7s}.$$

$$K_{\mathrm{DC}} = 3$$

$$N_{nmp}(s) = (\tfrac{-s}{6}+1),\ N_{mp}(s) = 1$$

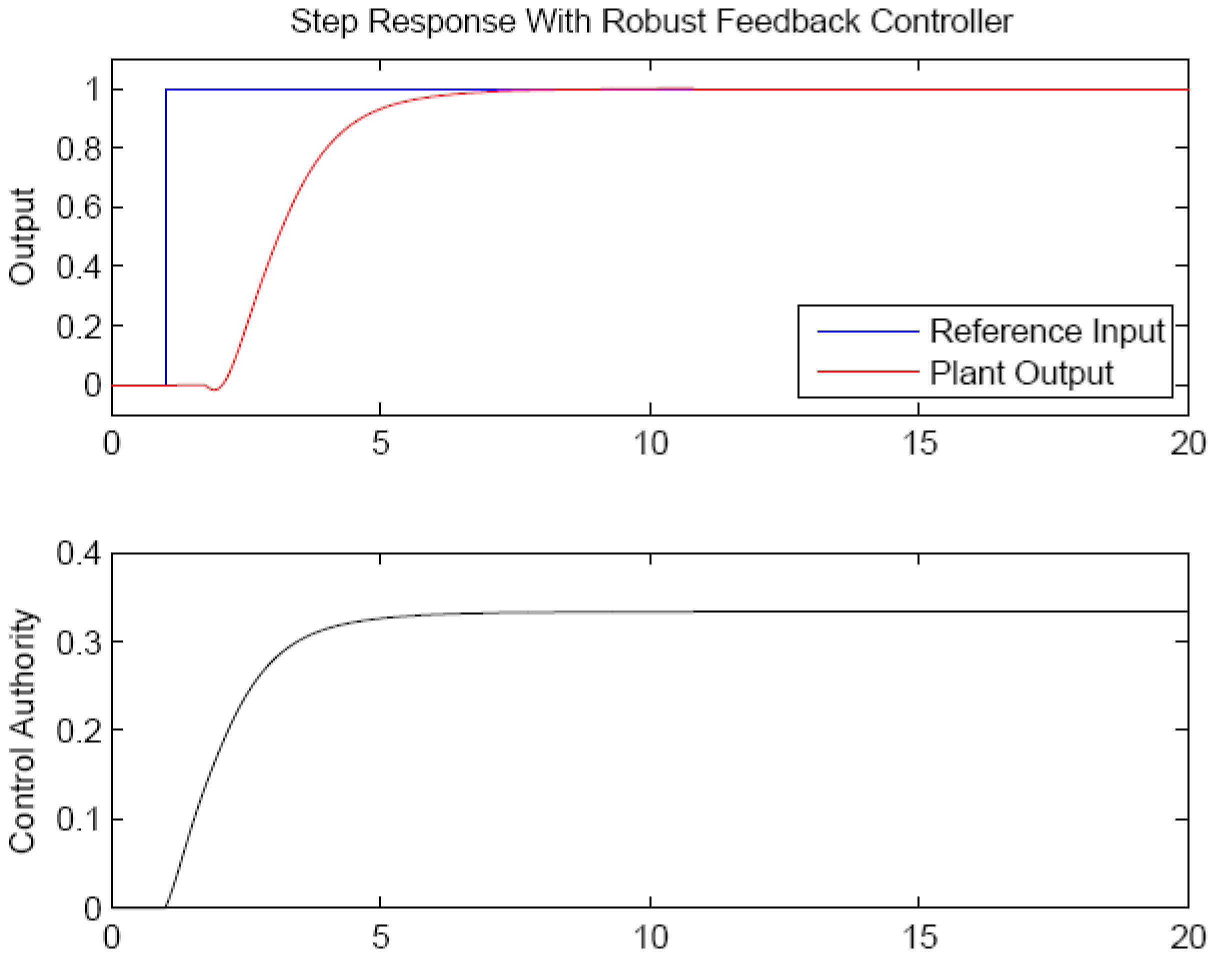
$$D(s) = (\tfrac{s}{5}+1)(\tfrac{s}{10}+1)$$

$$G_{noi}(s) = (\frac{-s}{6}+1)e^{-0.7s}$$

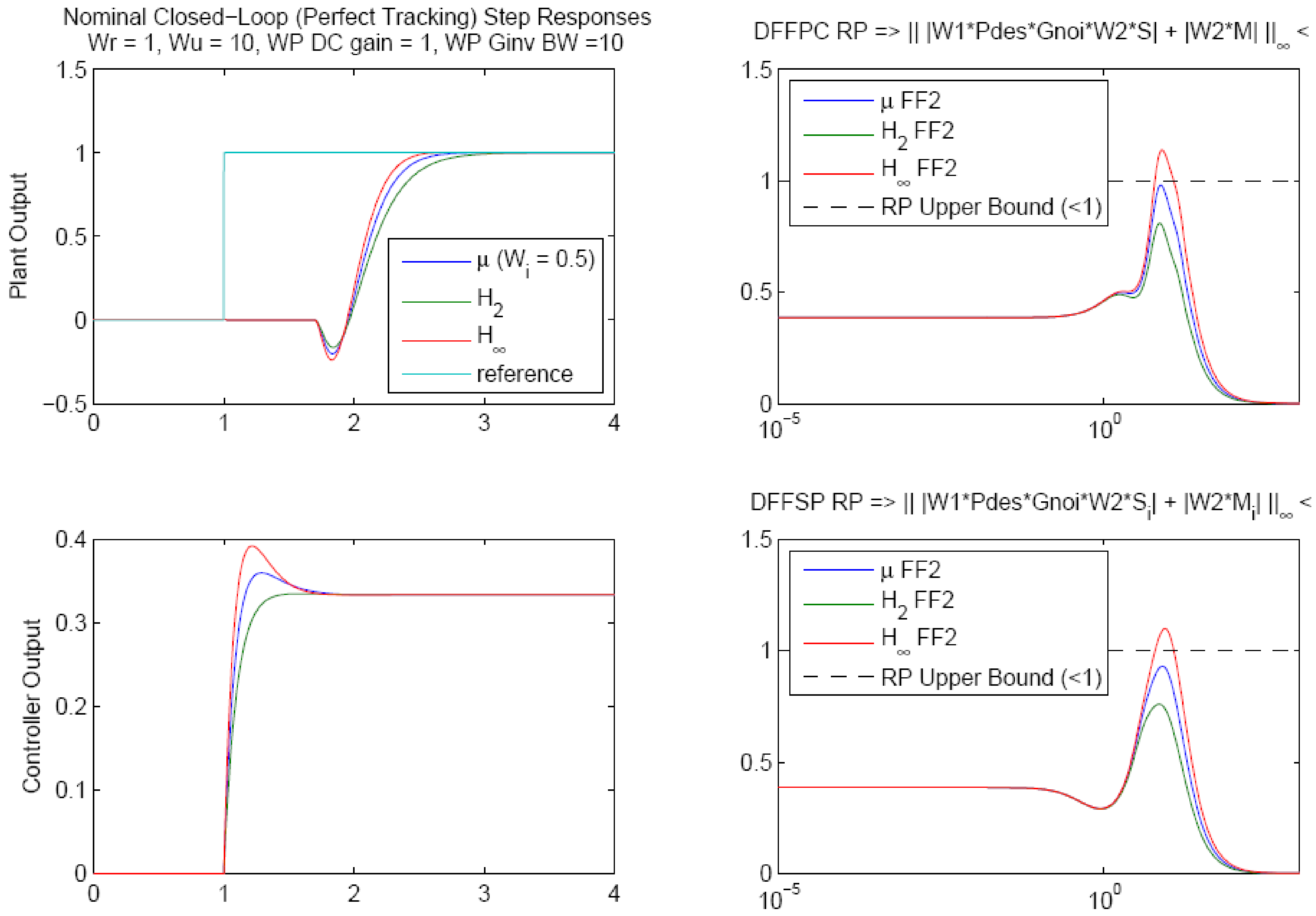
$$G_i^{-1}(s) = \frac{1}{3}(\frac{s}{5}+1)(\frac{s}{10}+1)$$

Robust Feedback Controller Design

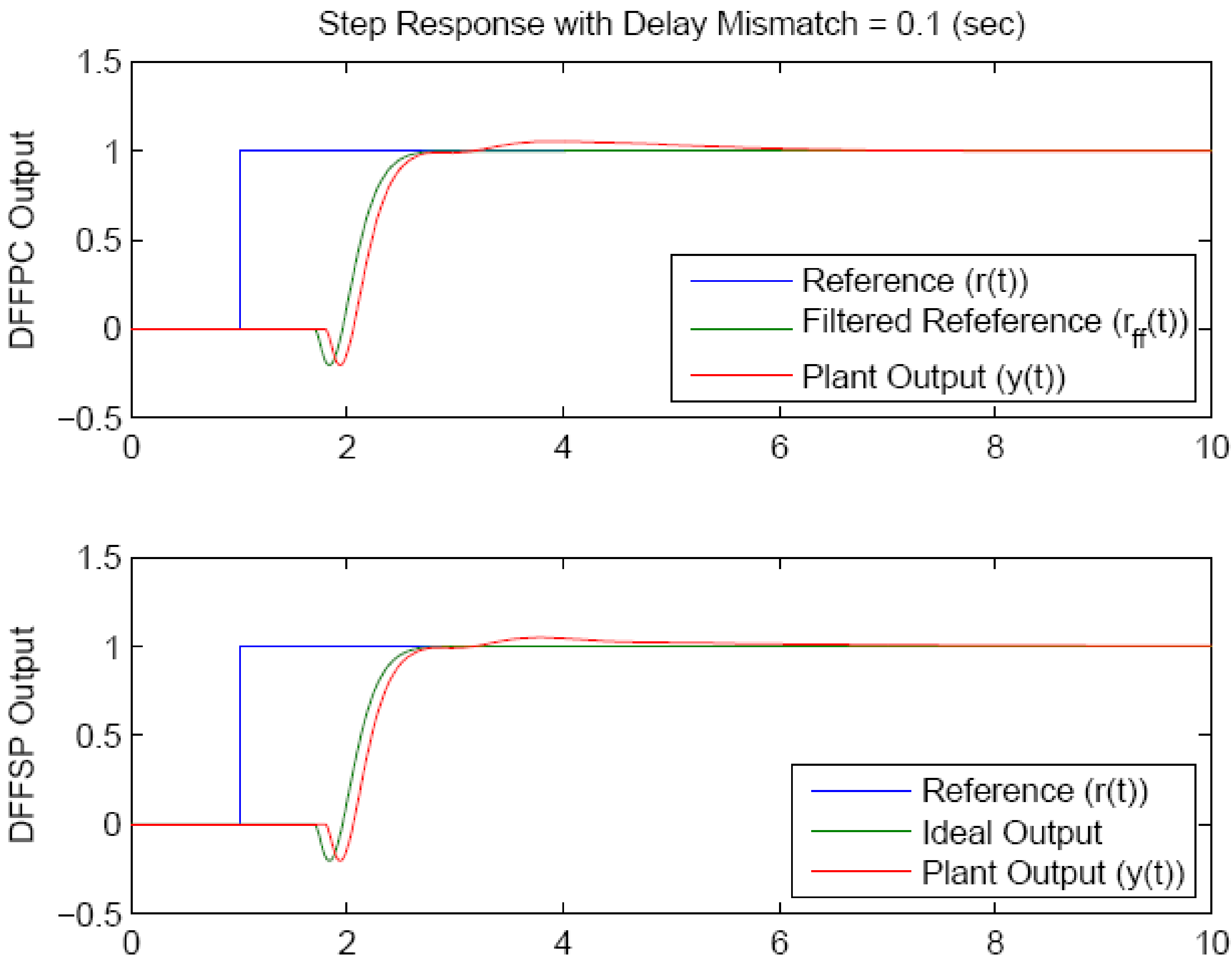
$$K(s) = \frac{0.13089(s+8)(s+10)(s+5)(s+2.857)(s+1.061)}{s(s+10.61)(s+6.804)(s+1.058)(s^2+4.579s+14.65)}$$



Feedforward Design



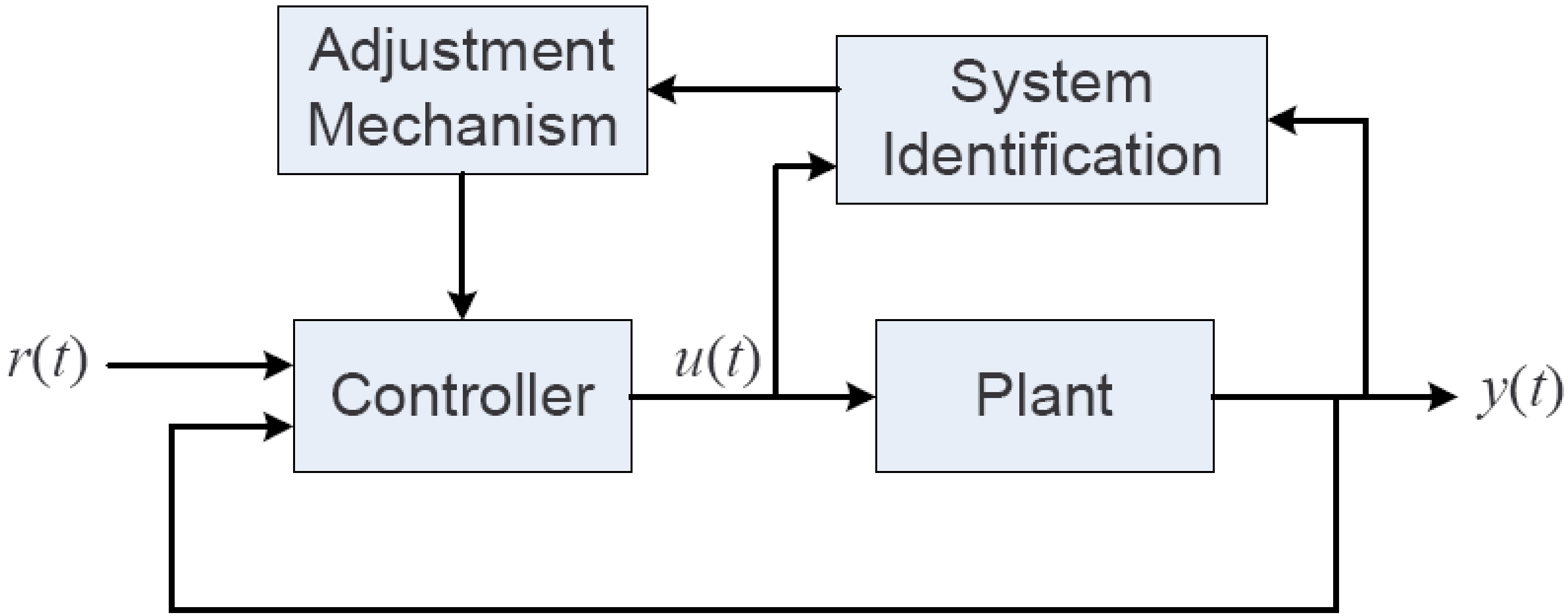
Example Robust Performance



Adaptation

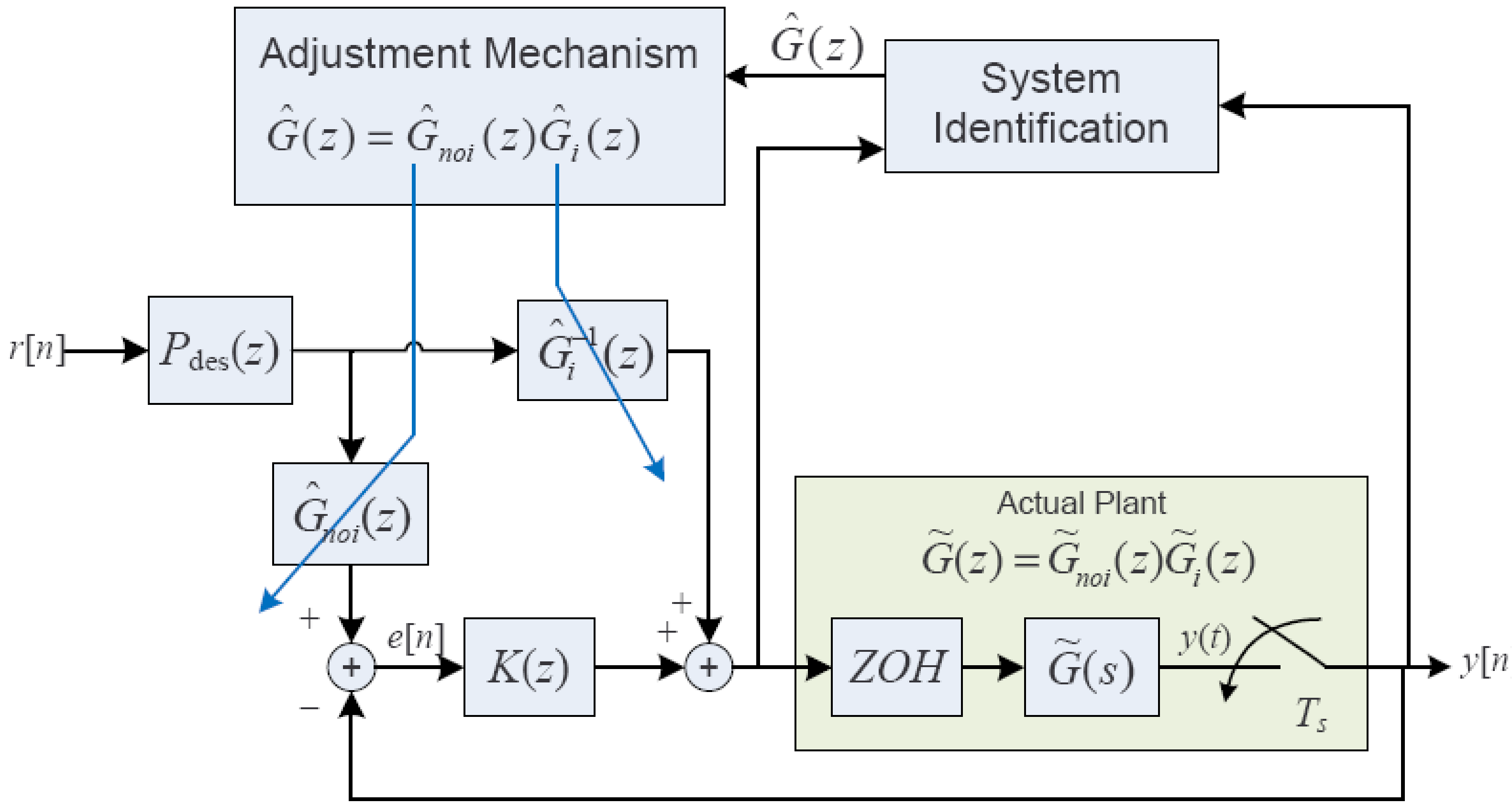
- Stability provided by only adapting FF pieces
- Model identification adaptive control
  - Identify LTI plant models
  - Update feedforward controller blocks directly
- Reinforcement learning control
  - Original motivation
  - Echo state networks

Model Identification Adaptive Control



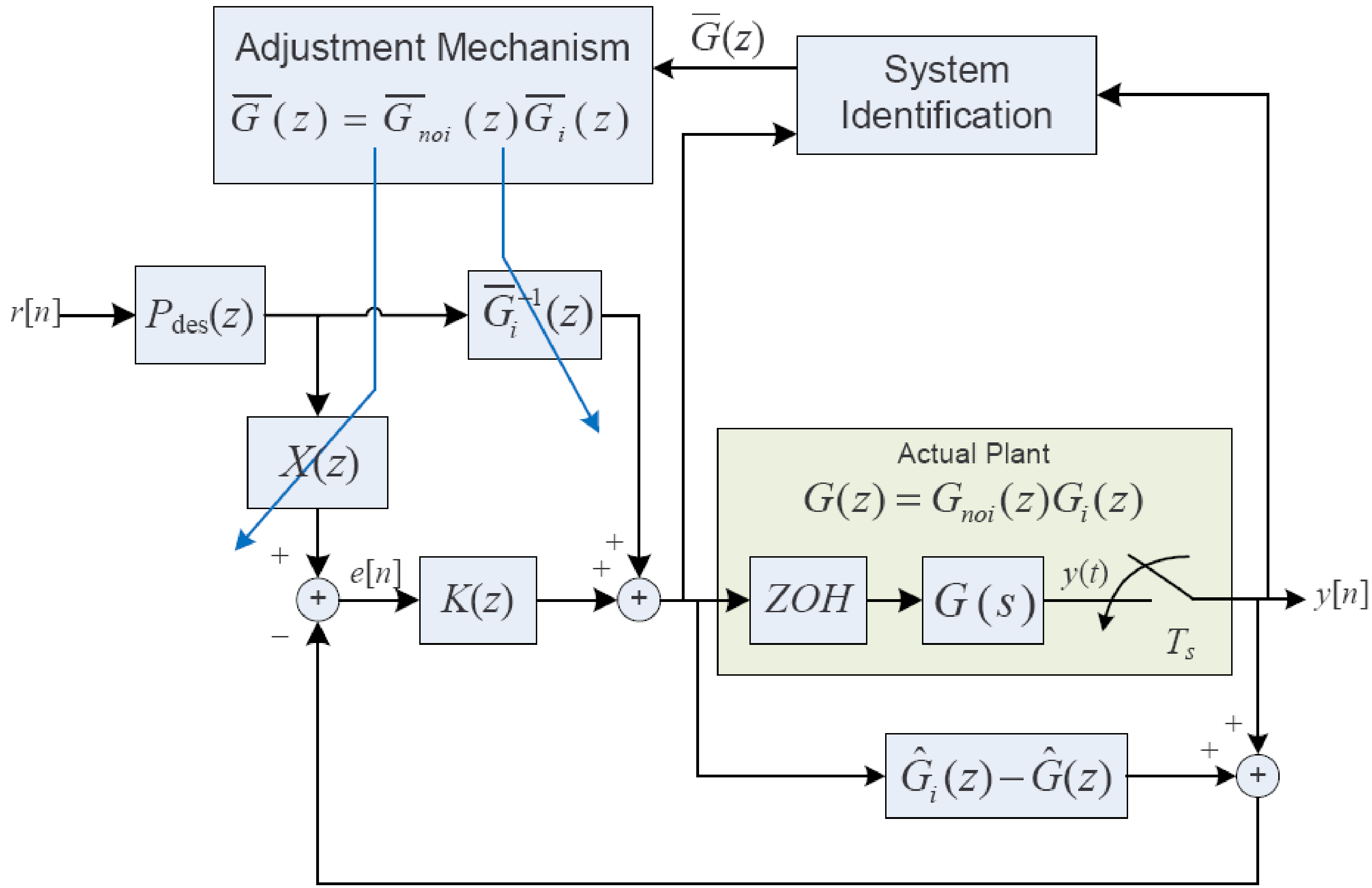
- For stability, only adapt feedforward controllers
- Architectures provide a unique and straightforward way to update feedforward controllers

MIAC DFFPC



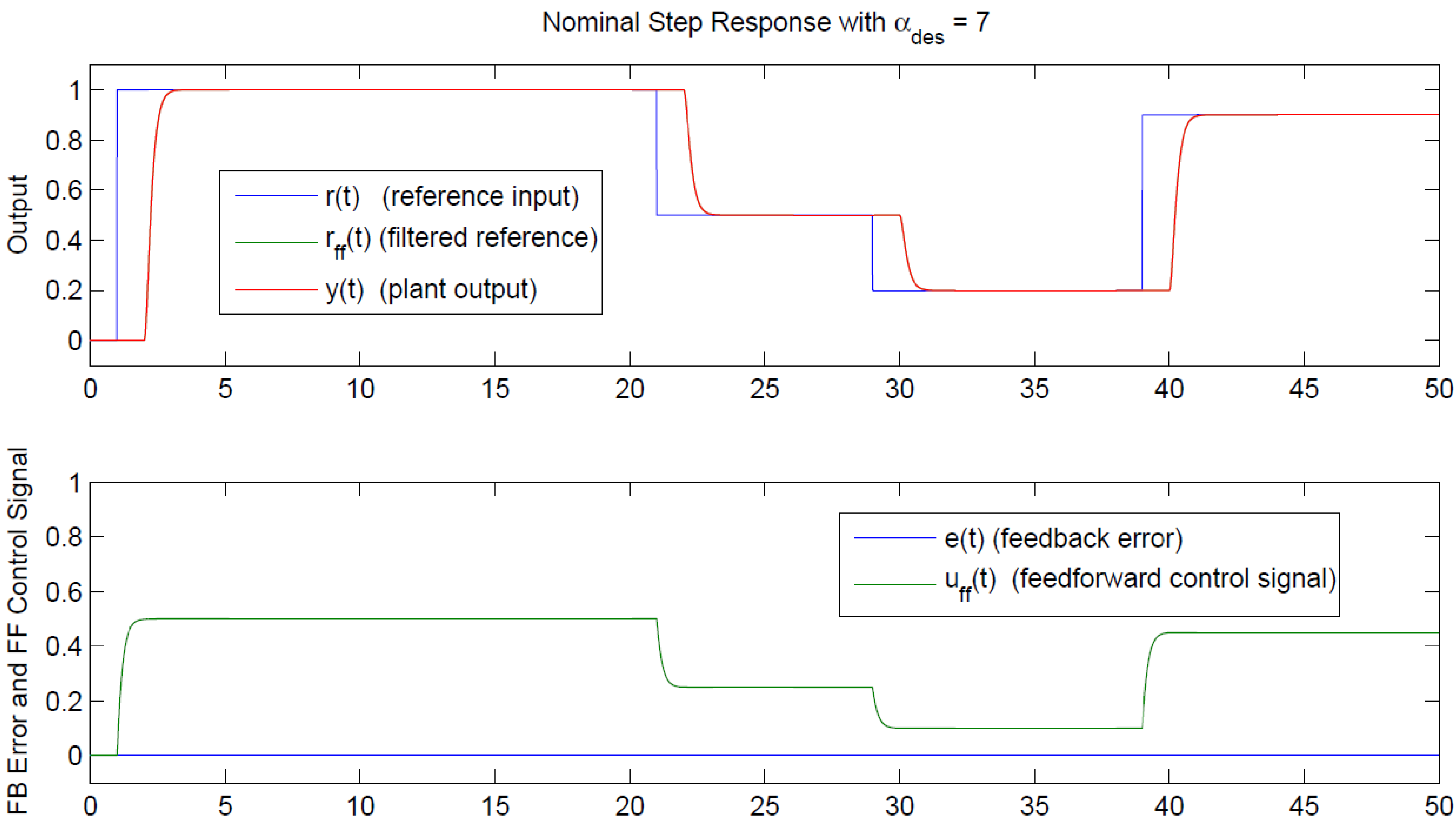
- Natural split of identified plant to FF controllers
- Stability guaranteed (even if plant is unstable)

MIAC DFFSP

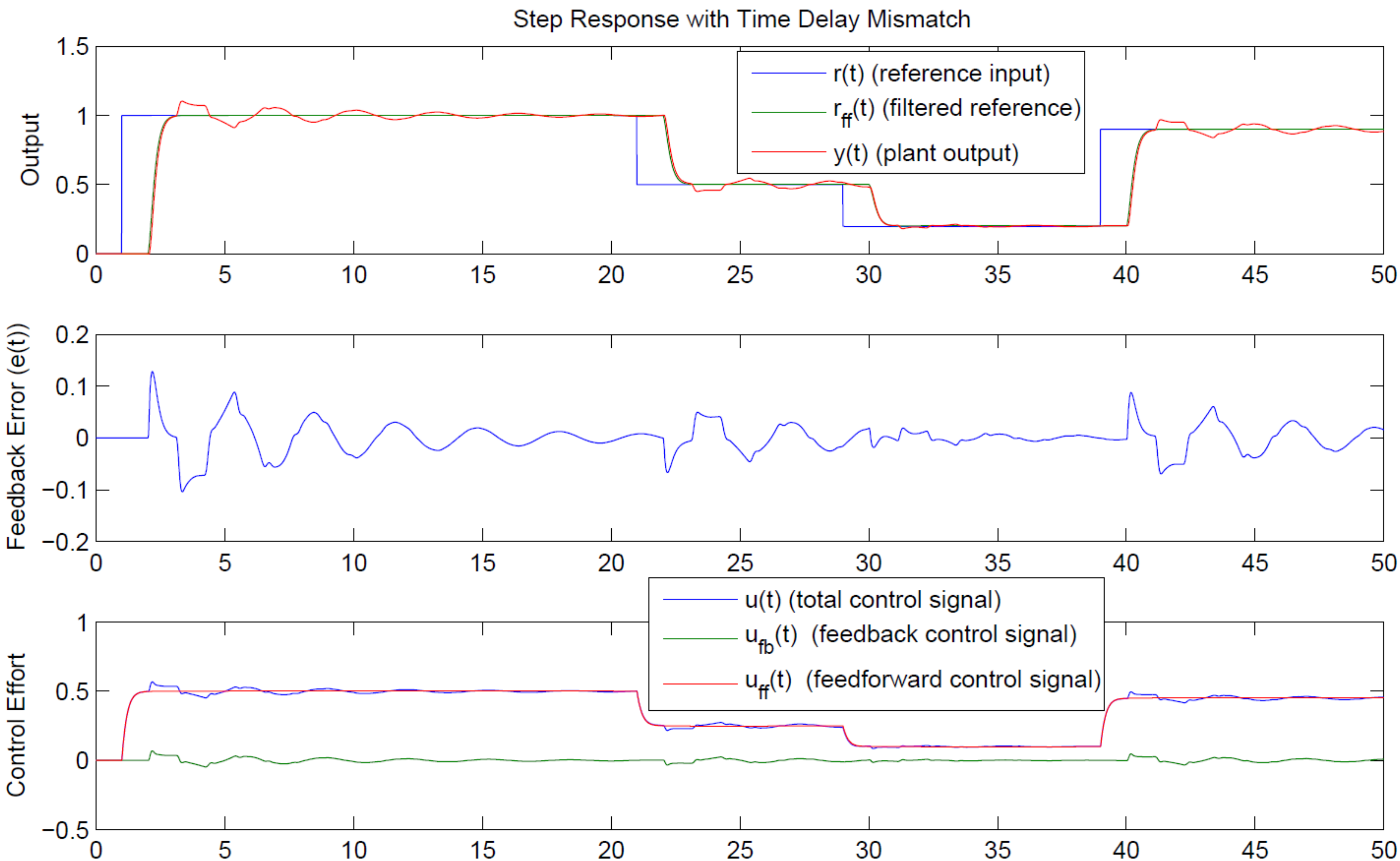


- Augmentation required to restore perfect tracking
- Smith predictor still requires a stable plant

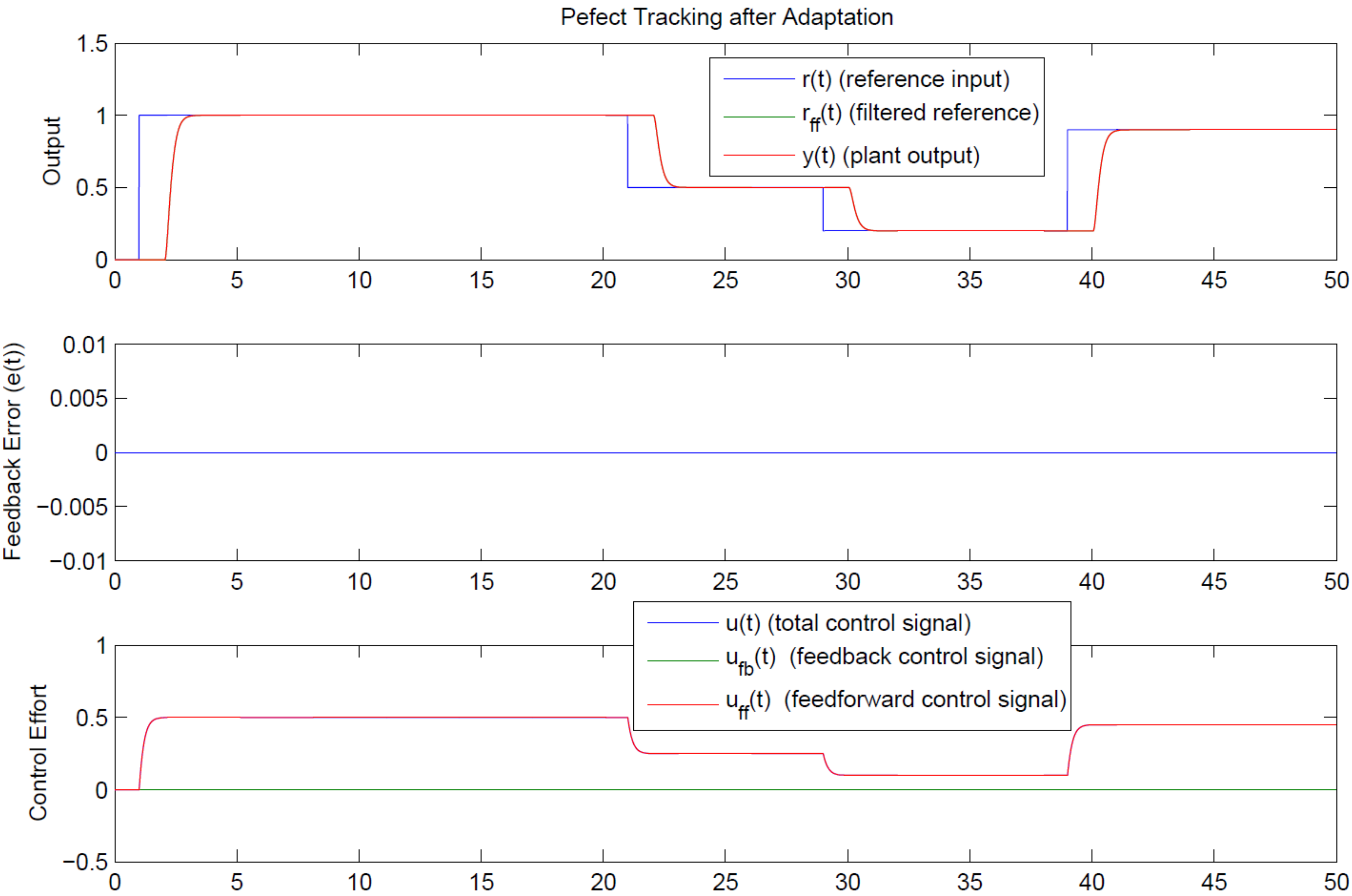
Adaptation Example: Nominal Simulation



Perturbed Simulation (Time Delay Mismatch of 0.05 seconds)



Perfect Tracking Restored after Adaptation



Reinforcement Learning Control

- Augment (or replace) existing feedforward structure
- Echo state networks
  - Ability to guaranteed stability of recurrent connections
  - Allows for larger networks (one-time stability analysis)

Microalgae Modeling and Control

Microalgae Overview

- Algae can convert excess carbon from human activity into biofuels
- Produce an estimated 7000-15000 gallons per acre per year[1]
- Supply 50% of the US fuel needs while using only 1.1% to 2.5% of the existing cropping land[2]
  - Much of the land around existing power plants is open and would be suitable for algae farms
  - Does not compete with agricultural land

[1] NREL (1998)

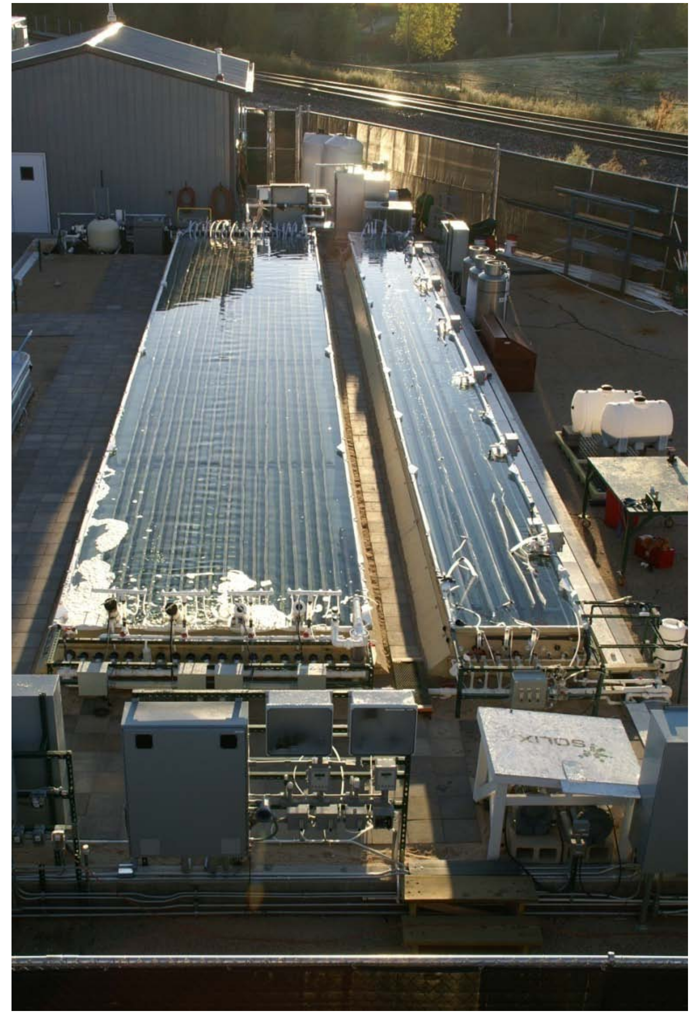
[2] Chisti (2007)

Research Challenges

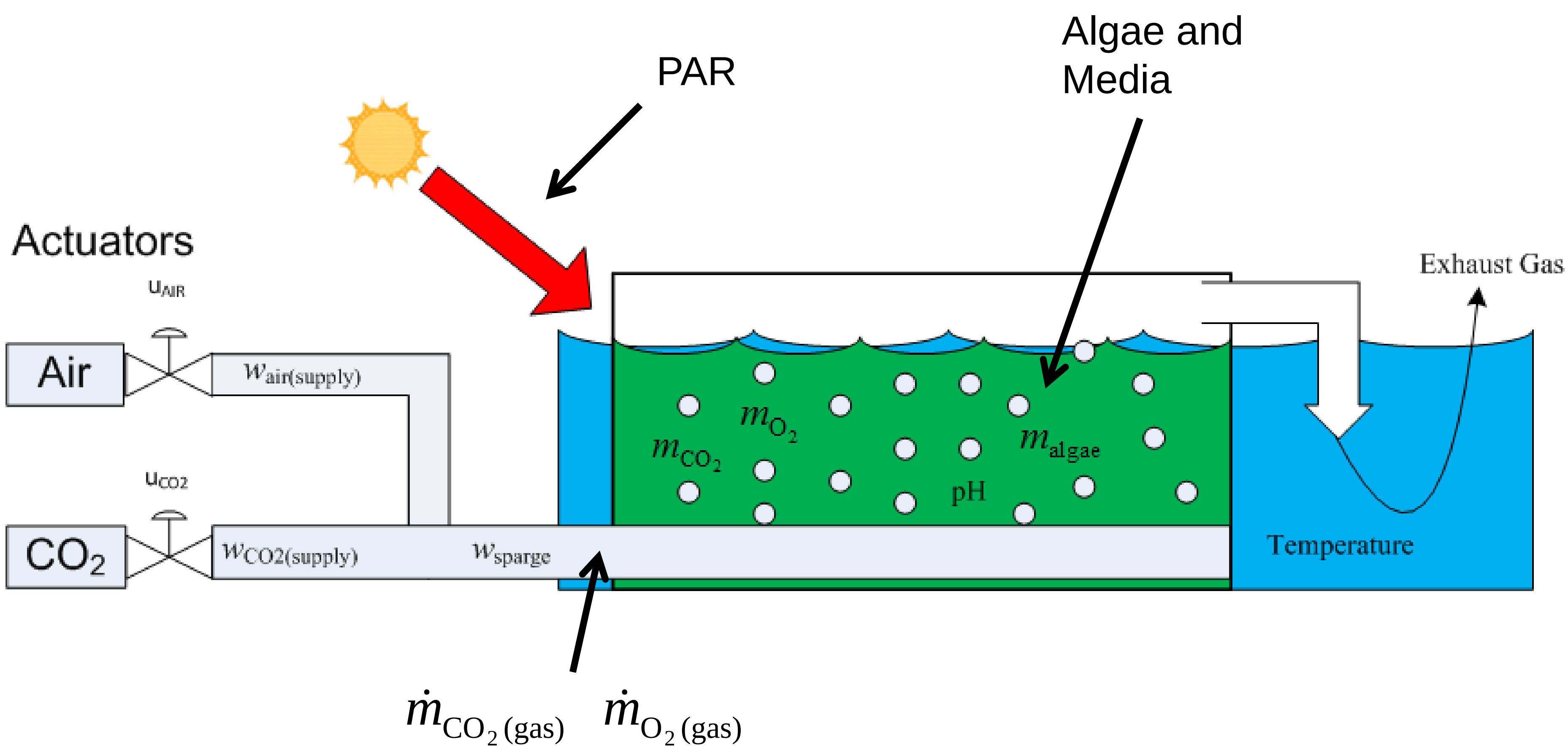
- Design and operate PBRs at a large scale
  - Problems with dissolved oxygen (DO) removal
  - Problems with efficient CO_2 delivery (i.e., achieving mass transfer)
  - Efficient utilization of all available light (PAR)
  - Requires a mechanical, biological, chemical, electrical, and controls solution
- Developing models and controllers based on the physics of the reactor that scale to commercial size reactors

Reactor Test Bed

- Extended surface flat panel reactor provides efficient sun utilization
- CO_2 rich gas bubbled through the flat panels to deliver CO_2 and remove produced dissolved O_2



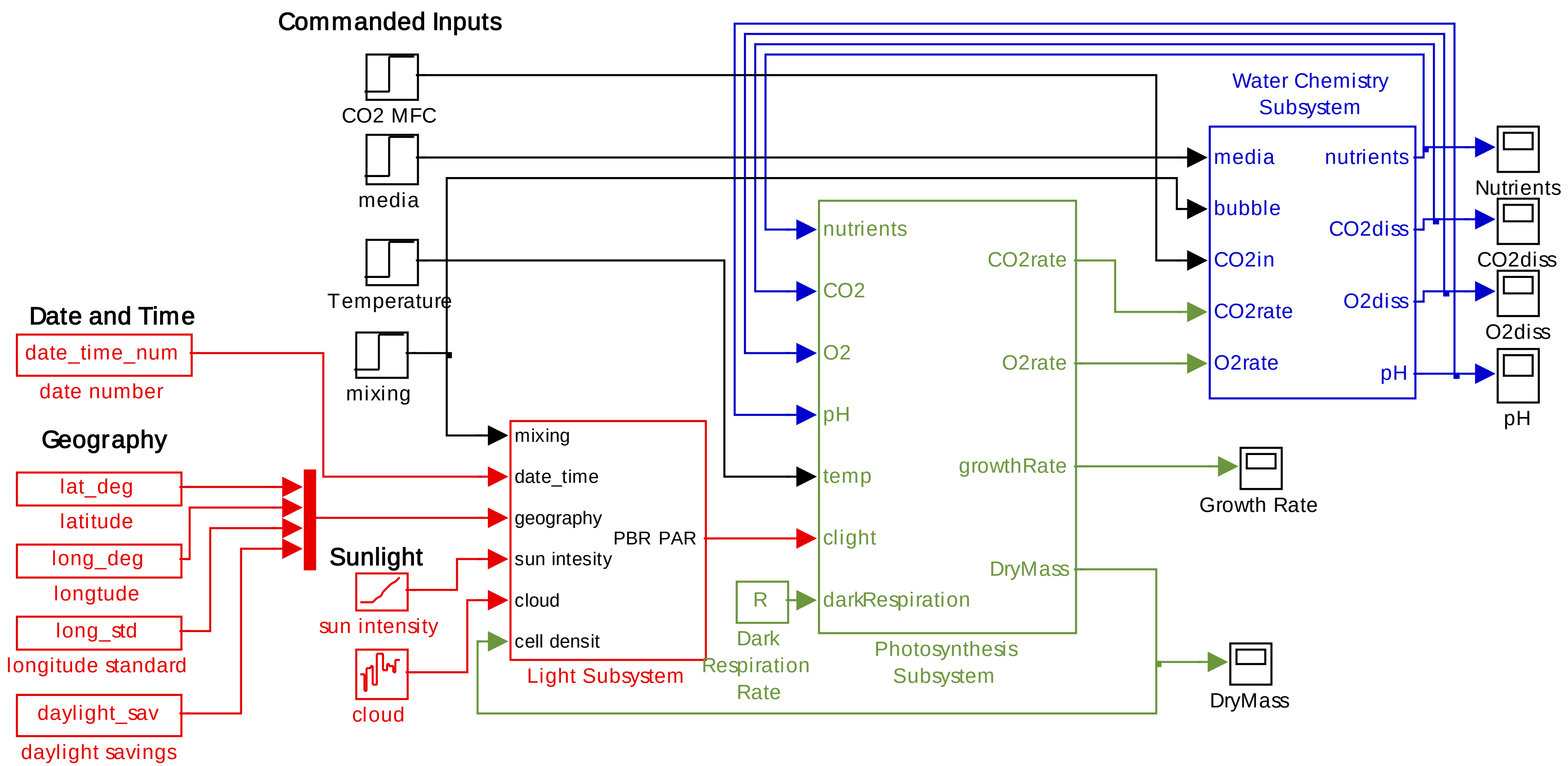
Reactor Setup



Modeling and Control Overview

- Develop a component based model that isolates the three components
  - Light subsystem (algebraic model)
  - Photosynthesis subsystem (algae dynamics)
  - Water chemistry subsystem (media dynamics)
- Use model to provide feedforward CO_2 delivery to maintain pH.

Model Block Diagram



Light Subsystem

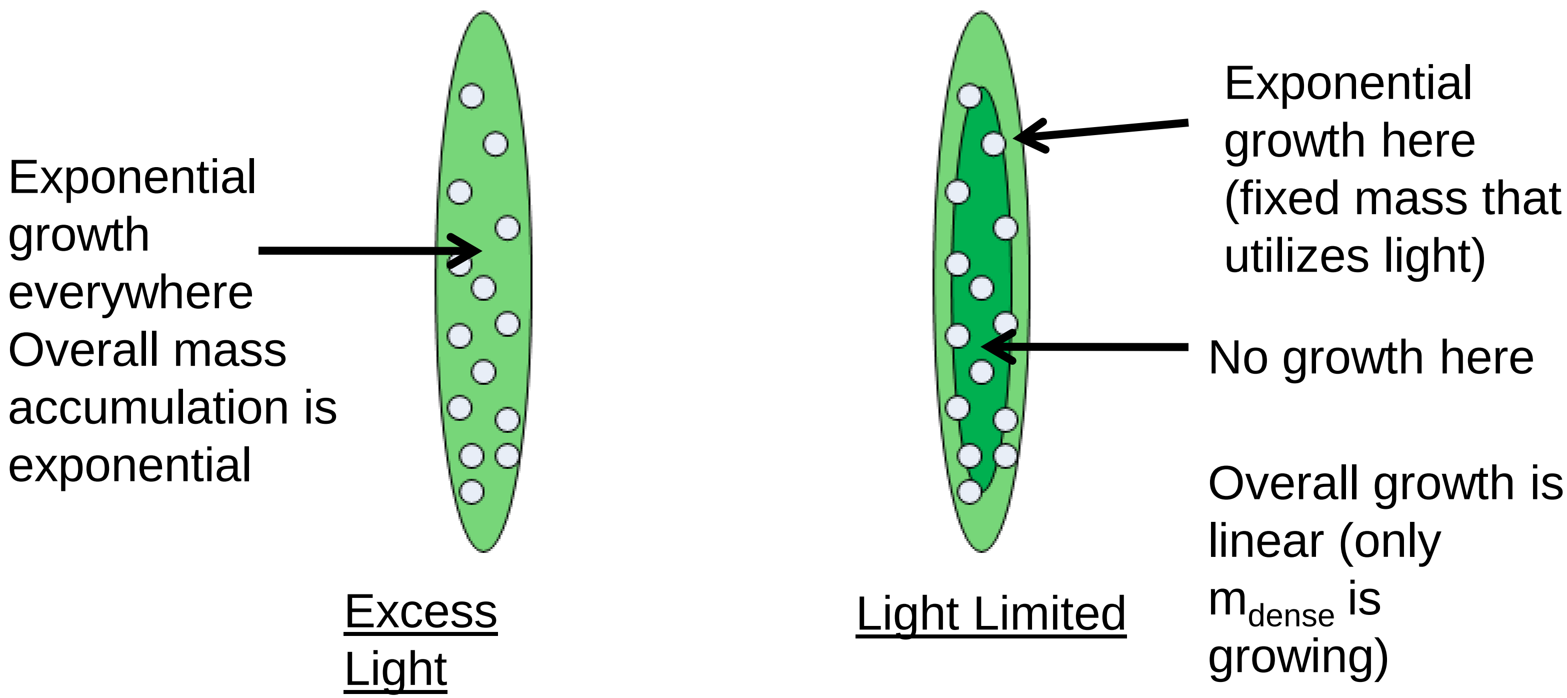
- About 45% of the full spectrum of light is photosynthetically active radiation (PAR)
- A fraction of the direct light will enter the bath and the rest will reflect
- Amount of light that reaches the algae is function of direct light and reactor orientation
- Mixing affects the amount of light the algae can utilize

Photosynthesis Subsystem

- Models growth as a function of incident PAR
- Growth measures
  - Biomass produced
  - CO_2 consumed
  - O_2 produced
- Based on densities
  - Allows for reactor comparison independent of scale

Growth Model Description

- Growth – driven by photosynthesis
  - Exponential when excess light
  - Linear above critical density (m_{dense})
  - Exponential Respiration (during both light and dark)



Growth Model Equations

$$\dot{m}_{\text{algae}} = K_{\text{PAR}} I_{\text{PAR}} \overline{m}_{\text{algae}} - R m_{\text{algae}}$$

$$\overline{m}_{\text{algae}} = \min(m_{\text{algae}}, m_{\text{dense}})$$

$$m_{\text{dense}} = f(m_{\text{algae}}, \text{mixing, geometry})$$

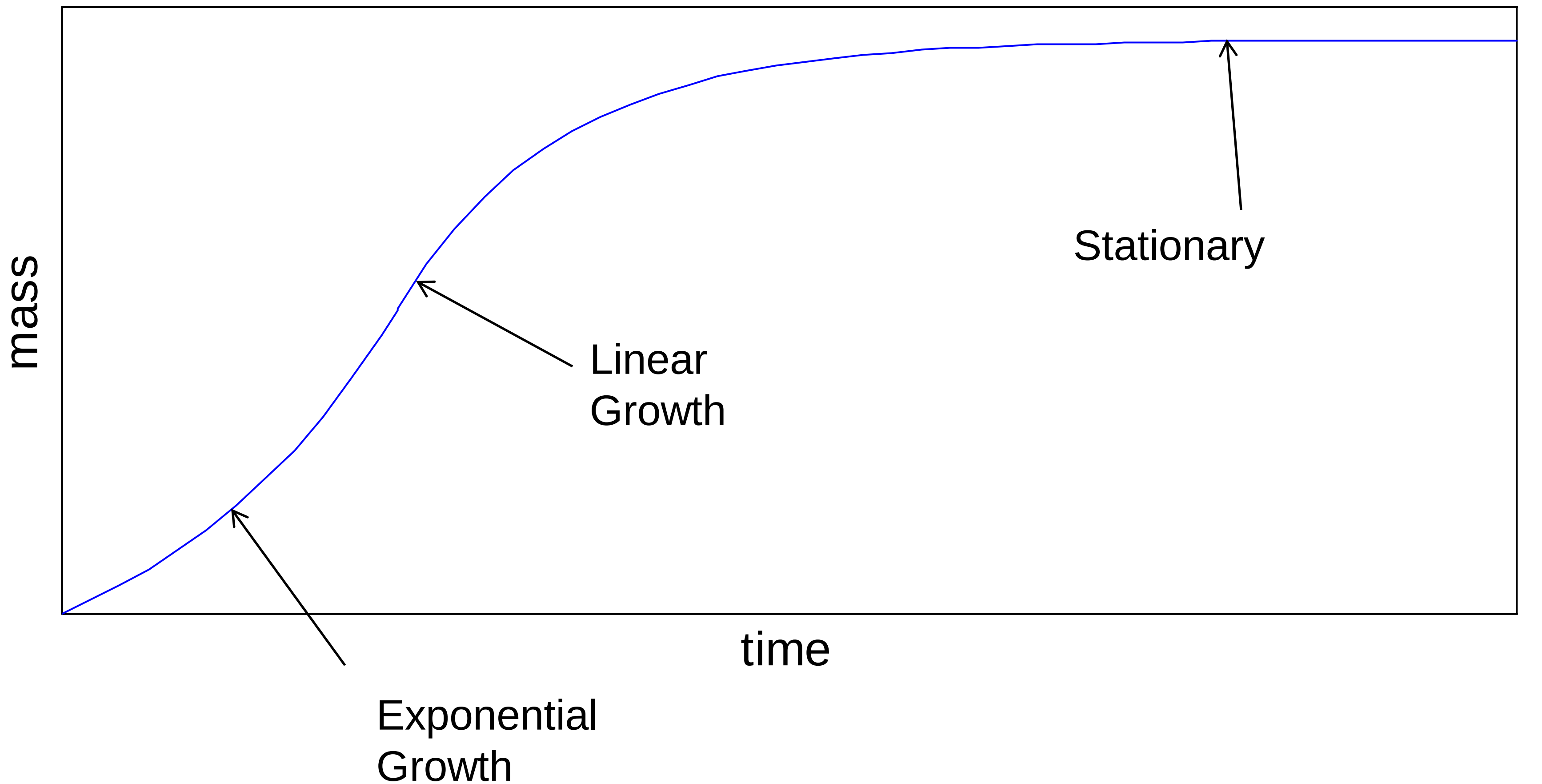
I_{PAR} : PAR reading from the light subsystem
K_{PAR} : Sun Utilization Parameter
R : Rate of respiration in the dark
m_{algae} : The density of algae (g/L or OD units/L)

Gas Consumption/Production Measures

$\dot{m}_{CO_2} = K_{CO_2} \dot{m}_{\text{algae}}$ CO_2 Consumption (used later for pH regulation)

$\dot{m}_{O_2} = K_{O_2} \dot{m}_{\text{algae}}$ O_2 Production

Growth Phases



Water Chemistry Subsystem

- Models the dissolved gases (CO_2 and O_2) in the media
- Interactions with algae
  - CO_2 consumed / O_2 produced during photosynthesis, vise versa during respiration
- Interactions with sparged gas
  - Dissolved O_2 and dissolved CO_2 seek equilibrium between bubbles and media
  - First order plus dead time models
- pH used to infer CO_2 concentration
  - Takes a few seconds for pH to equilibrate from dissolved CO_2

Water Chemistry Models

$$\dot{m}_{\mathrm{O_2\,(media)}}(t) = \frac{w_{\mathrm{sparge}}}{\tau_{\mathrm{O_2}}}\left(m_{\mathrm{O_2\,(gas)}}(t-\tau_{\mathrm{d,gas}}) - m_{\mathrm{O_2\,(media)}}(t)\right) + \dot{m}_{\mathrm{O_2\,(algae)}}(t)$$

$$\dot{m}_{\mathrm{CO_2\,(media)}}(t) = \frac{w_{\mathrm{sparge}}}{\tau_{\mathrm{CO_2}}}\left(m_{\mathrm{CO_2\,(gas)}}(t-\tau_{\mathrm{d,gas}}) - m_{\mathrm{CO_2\,(media)}}(t)\right) - \dot{m}_{\mathrm{CO_2\,(algae)}}(t)$$

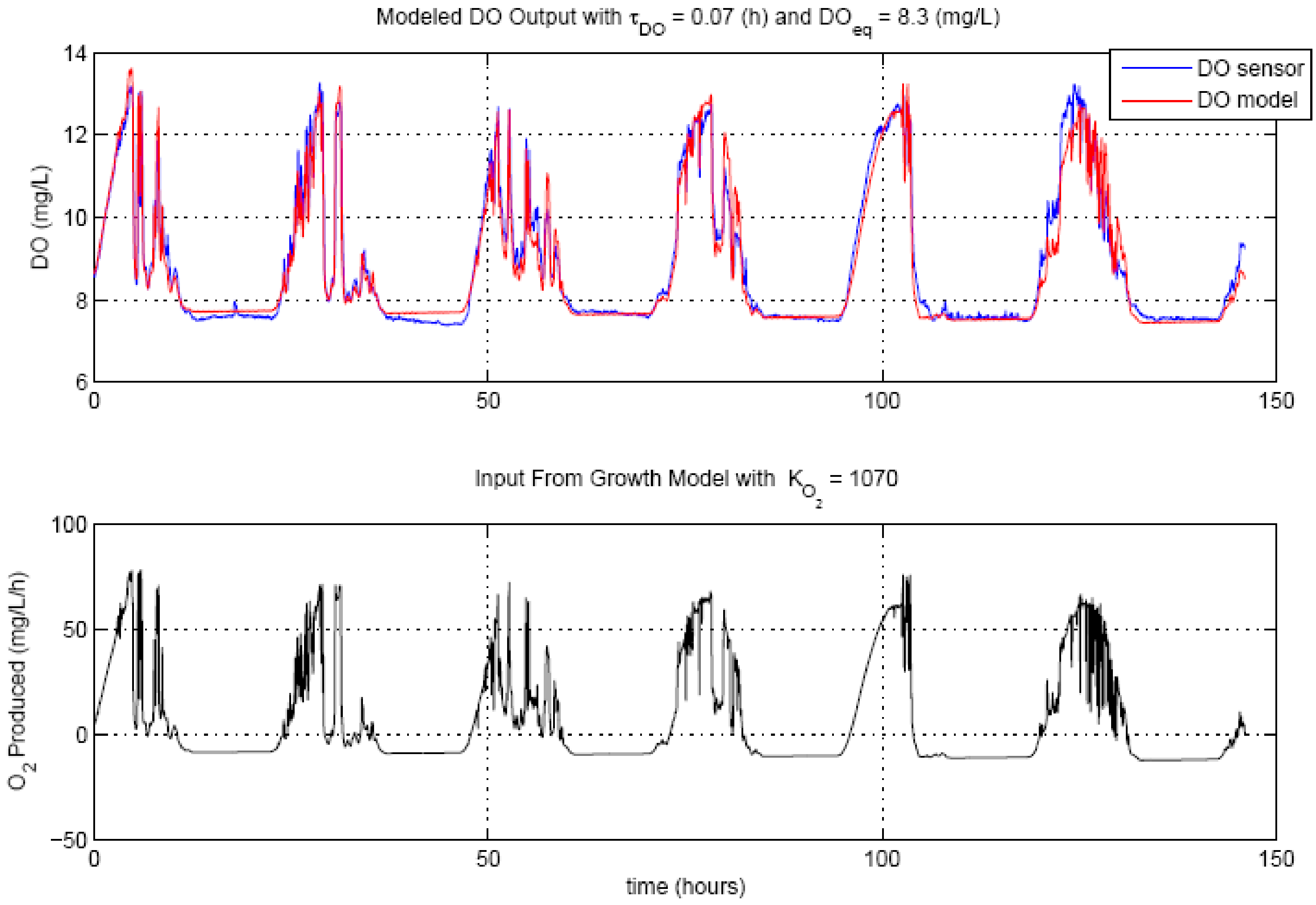
$$\mathrm{p\dot{H}} = \frac{1}{\tau_{\mathrm{pH}}}\left(K_{\mathrm{pH}} m_{\mathrm{CO_2\,(media)}}(t) - \mathrm{pH}(t)\right)$$

w_{sparge} : flow rate of sparge gas (~ number of bubbles)

$\tau_{\mathrm{O_2}}, \tau_{\mathrm{CO_2}}$: time constant for gas transfer between bubbles and media

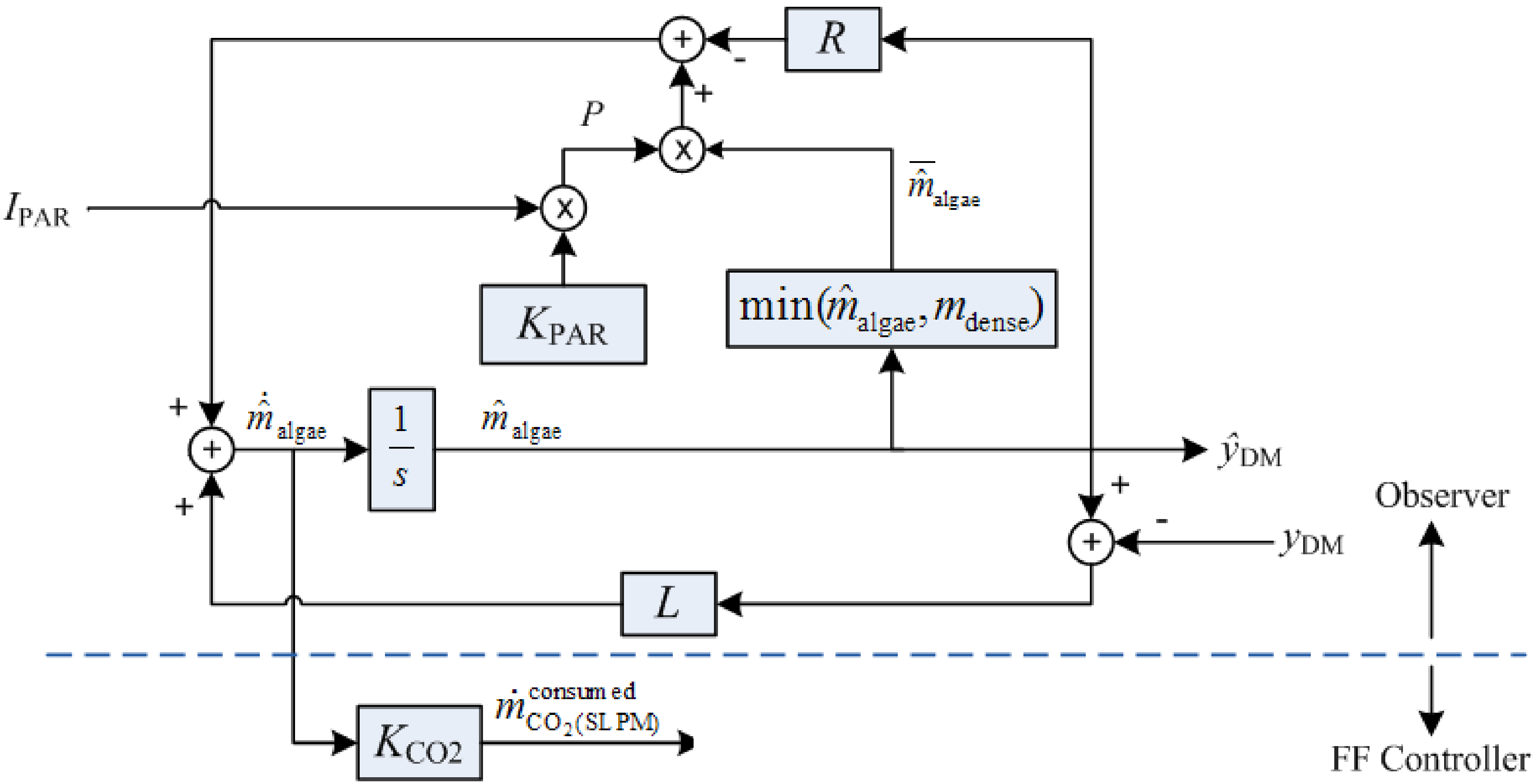
τ_{pH} : time constant for pH to settle

Dissolved Oxygen Model

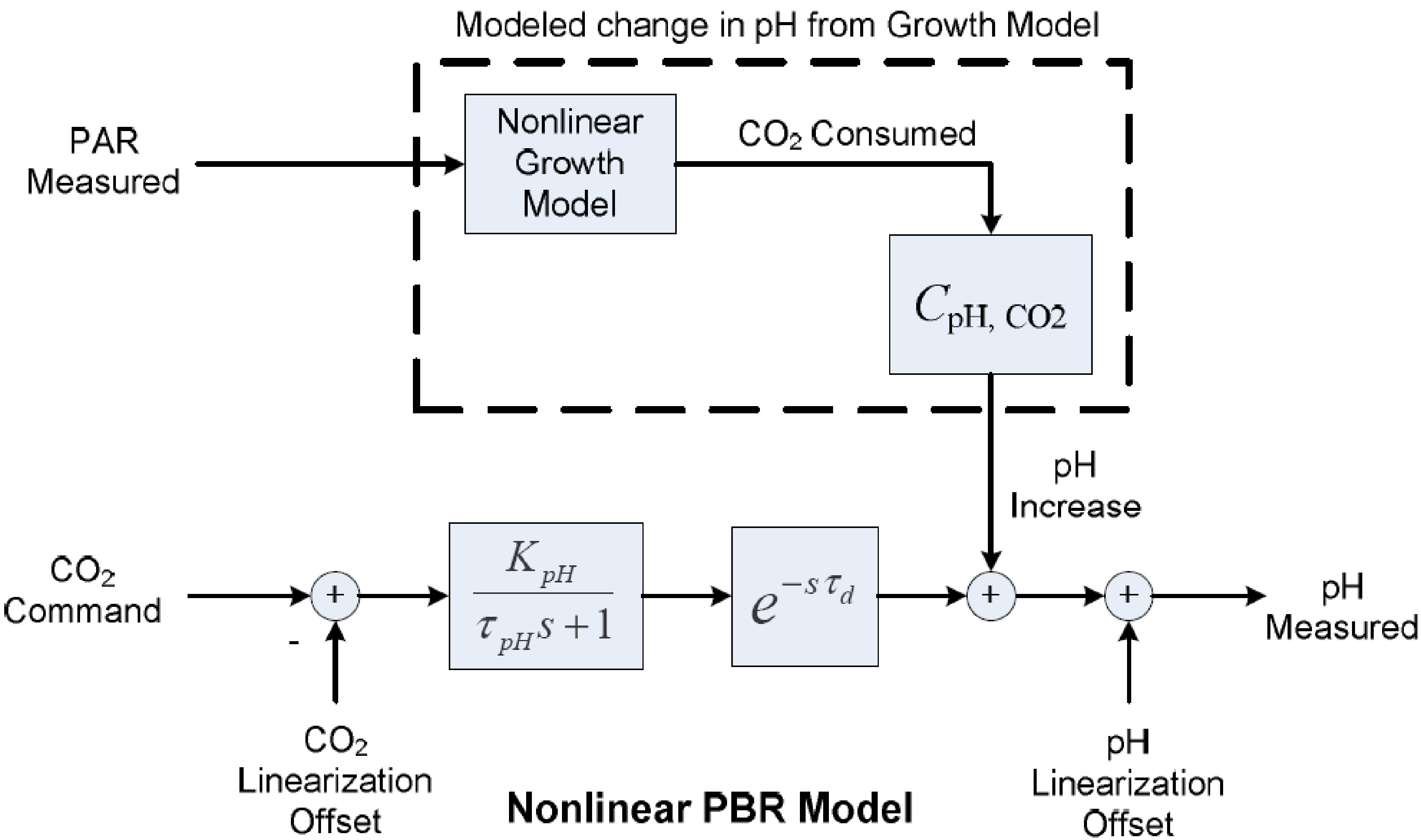


$$K_{O_2 (mg O_2 / g \text{ algae})} = 1.07_{(g O_2 / g \text{ algae})} \times 1000 \frac{mg}{g} = 1070.$$

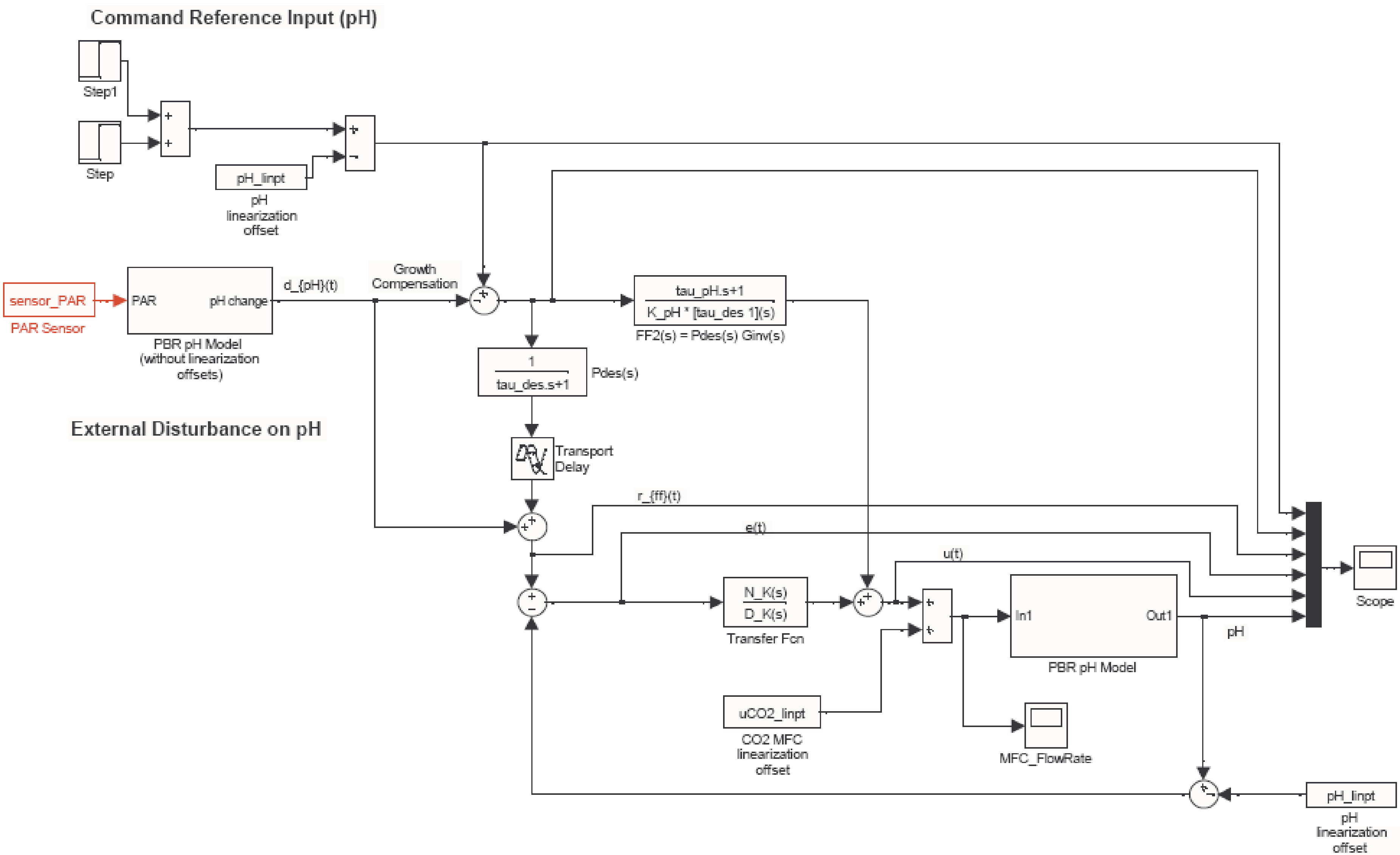
Observer-Based FF Control



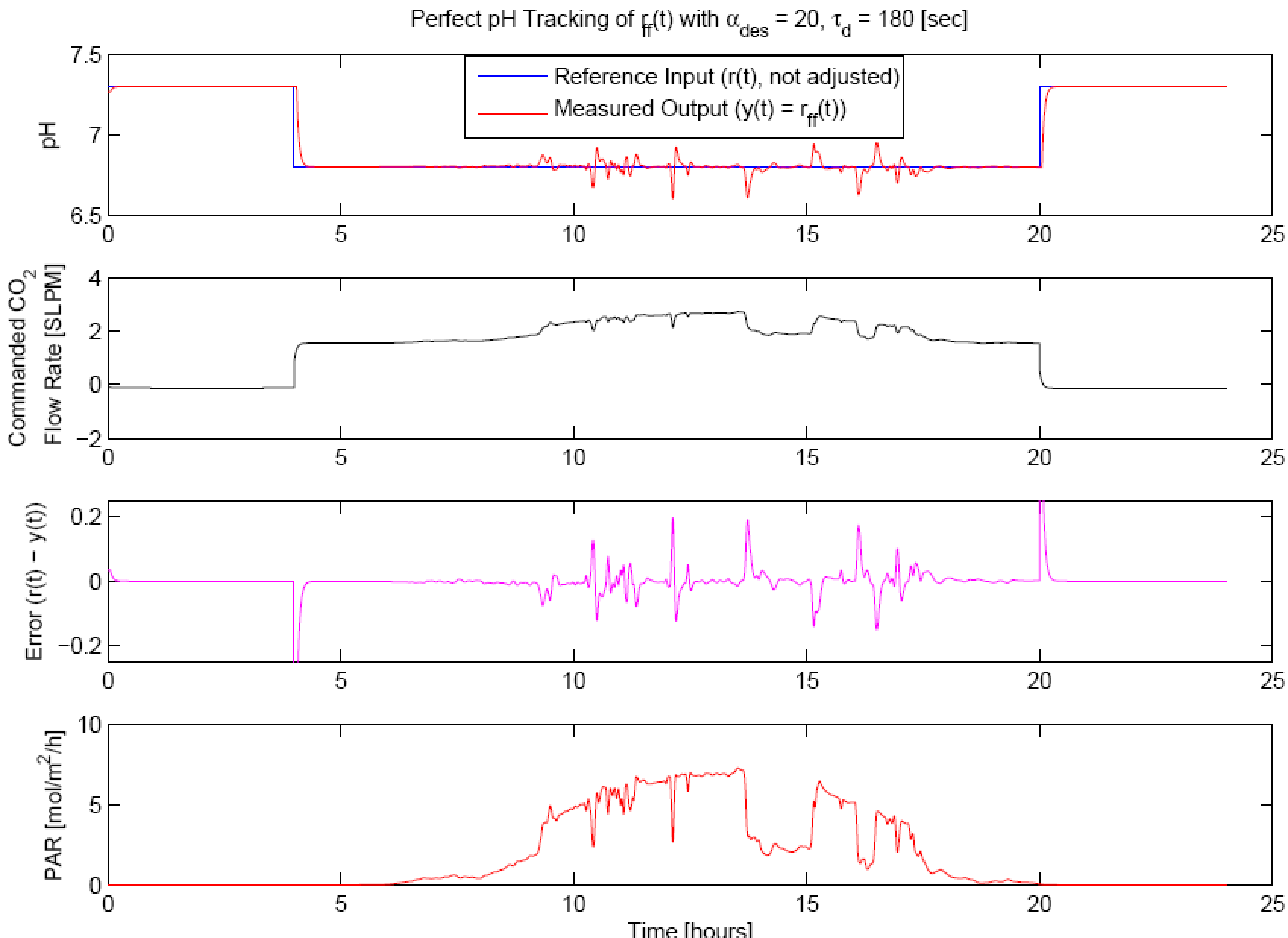
pH Model (with Growth Dynamics)



Modified DFFPC pH Regulation



Achievable pH Regulation



Conclusions

- Perfect tracking for a larger class of systems
  - Characterize achievable performance
- Robustness tools to analyze performance in the presence of model uncertainty
- Adaption methods for the LTI and NL Feedforward controller(s)
- Physics-based algae model
- Verified algae model on experimental data
- Characterized achievable pH control

Future Directions

- Feedforward design
  - Design for $e(t) = y(t) - r(t)$
  - Design perfect tracking of $r(t)$
- Adaptation
- MIMO systems
- Microalgae modeling and control
  - Lipid model
  - System level optimization
- Control-Structure Interactions

Conference Publications

- **Buehner, M.R.** and P.M Young. 2010. “Perfect Tracking for Non-minimum Phase Systems”. In: *Proceedings of the 2010 American Control Conference*, Baltimore, Maryland, July, 2010.
- **Buehner, M.R.**, P.M Young, B.D. Willson, D. Rausen, R. Schoonover, G. Babbitt, and S. Bunch. 2009. “Microalgae Growth Modeling and Control for a Vertical Flat Panel Photobioreactor”. In: *Proceedings of the 2009 American Control Conference*, St. Louis, Missouri, pp. 2301-2306, June, 2009.
- **Buehner M.R.**, C.W. Anderson, P.M. Young, K.A. Bush, and D.C. Hittle. 2007. “Improving Performance using Robust Recurrent Reinforcement Learning Control”. In: *Proceedings of the European Control Conference 2007*, Kos, Greece, pp. 1676-1681, July, 2007.

Journal Publications

- Anderson M.L., **M.R. Buehner**, P.M. Young, D.C. Hittle, C.W. Anderson, J. Tu, and D. Hodgson. 2008. "MIMO Robust Control for Heating, Ventilating, and Air Conditioning (HVAC) Systems". *IEEE Transactions on Control Systems Technology*, 16(3):475-483.

- Anderson M.L., **M.R. Buehner**, P.M. Young, D.C. Hittle, C.W. Anderson, J. Tu, and D. Hodgson.2007. "An Experimental System for Advanced Heating, Ventilating, and Air Conditioning (HVAC) Control". *Energy and Buildings* 39(2):136-147.

- Anderson C.W., P.M. Young, **M.R. Buehner**, J.N. Knight, K.A. Bush, and D.C. Hittle. 2007. "Robust Reinforcement Learning Control using Integral Quadratic Constraints for Recurrent Neural Networks", *IEEE Transactions on Neural Networks: Special Issue on Neural Networks for Feedback Control Systems* 18(4):993-1002.

- **Buehner M.R**. and P.M.Young. 2006. "A Tighter Bound for the Echo State Property". *IEEE Transactions on Neural Networks* 17(3):820-824.

Questions