Overview of a Nonlinear Model Predictive Optimal Control Technology

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Outline

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- Provide a brief overview of model predictive control evolution in the chemical industry
  - Honeywell's business in APC/Optimization/Modeling
  - Model predictive control (MPC) history
- Nonlinear Model Predictive Control Overview
  - Motivation for nonlinear model predictive control
  - Honeywell's Profit NLC technology
  - History of development
  - Combining nonlinear MPC and dynamic real time optimization (NMPOC)
  - Mathematical Problem formulation
  - Technology components
  - Implementation issues
  - NMPOC application results
- Future challenges and trends in Honeywell's application domains
  - Business and technical challenges
  - Future trends

Honeywell Overview

Honeywell

- Automation and Control Solutions (ACS)
  - Honeywell Process Solutions
  - Honeywell Building Solutions
- Transportation Systems (TS)
  - Turbochargers
- Aerospace (AERO)
  - Aircraft systems and engines
  - Flight management systems
  - Avionics
- Specialty Materials (SM)
  - Fluorocarbons, films, advanced fibers
  - UOP – refining technology

Honeywell Overview

Honeywell

- Honeywell Technology Solutions
  - Shanghai
  - Bangalore
  - Prague
  - Minneapolis
- Honeywell has 446 locations in over 100 countries
- Honeywell 2009 sales – $31 billion
- Automation and Control Solutions
  - 2009 sales - $13 billion

Honeywell Process Solutions

Honeywell

- Advanced Solutions Business
  - Advanced Process Control & Optimization
    - Profit Suite
    - Miscellaneous specialized control packages
    - Model predictive control software
  - Simulation
    - Unisim Design
    - Unisim Operations
  - Manufacturing Execution Systems
    - Planning and Scheduling
    - Business applications
- Control and Safety Systems
  - Experion PKS

Model Predictive Control

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- A control algorithm that embeds a predictive model
  - Usually a linear dynamic model
  - Step or impulse response form (discrete)
- Use of MPC is considered advanced process control (APC)
  - As opposed to lower level regulatory control
  - MPC normally sends setpoints to lower level controllers, but can move valves directly
  - 5000-10000 applications, Est benefits: $1-2 billion/yr (Badgwell 2010)
- MPC controllers contain different variable types
  - CVs: Controlled Variables; MVs: Manipulated Variables; DVs: Disturbance Variables
- Compute optimal solution for MVs over a future time horizon
- Usually employs a linear or quadratic programming component to solve the control problem
  - Allows proper constraint handling
- May have a separate calculation for economic optimization
  - Computes steady state targets
- Main difference between linear MPC and nonlinear MPC is choice of linear or nonlinear model
  - Solver may be nonlinear for NMPC

Model Predictive Control

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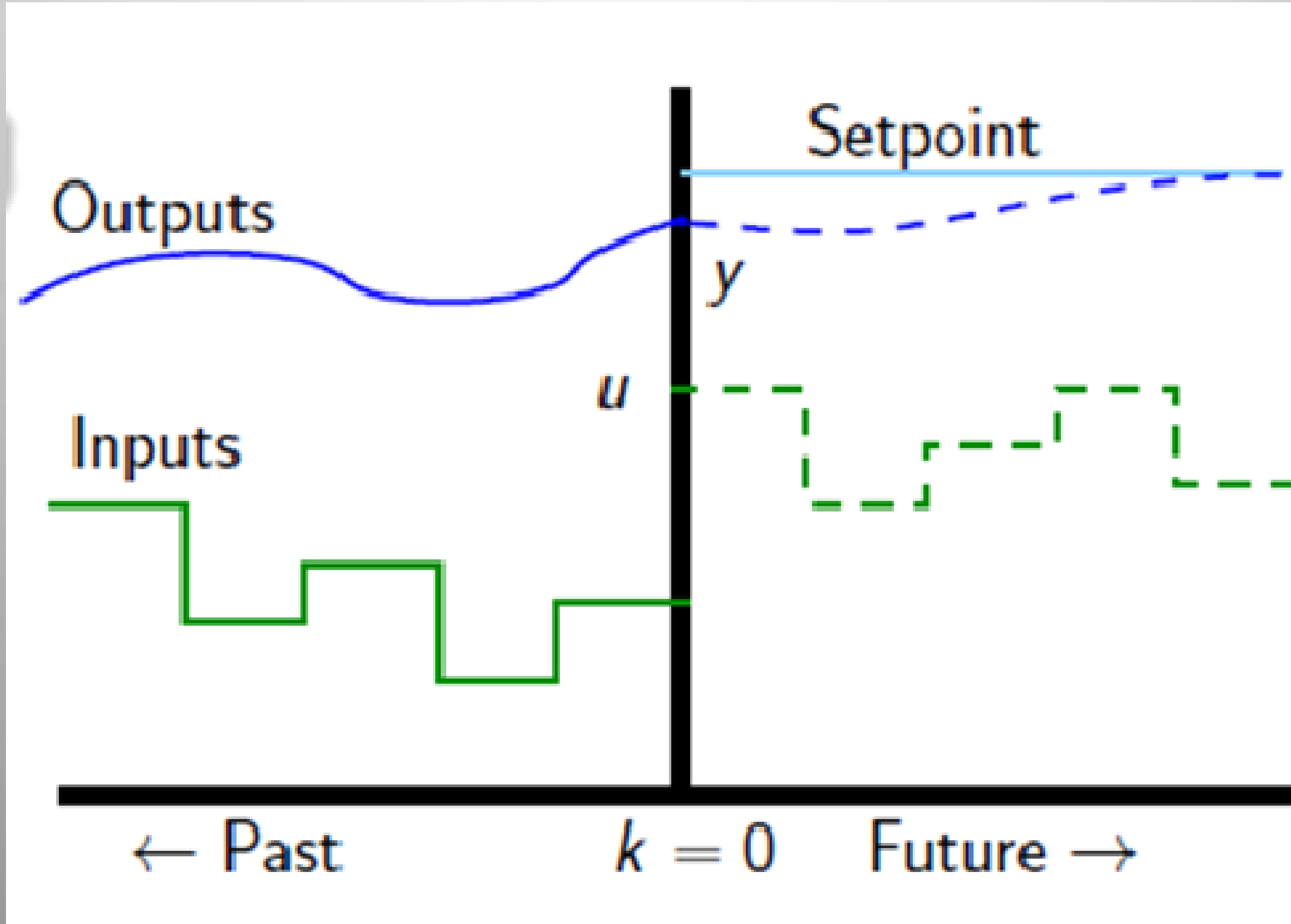

Rawlings, AIChE, 2010

Nonlinear Model Predictive Control Motivation

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- Linear MPC performed poor for certain applications
- Polymer process control problems were the initial motivation
  - Frequent product grade changes
    - Regulatory control performance varies from grade to grade
    - Product specifications change drastically from grade to grade
  - Typically a need to minimize loss during grade transitions
    - Reprocessing costs are high (energy intensive)
    - Need to minimize waste material
  - On-grade control can be problematic with large disturbances
    - Dramatic lead/lag effect in reactors
  - Linear dynamic models are inadequate
- Process gains changing significantly over operating region
  - Gain changes for transitions: Typical - 10x to 20x Possible – 100x
- Process dynamics changing significantly over operating region
  - Production rate changes and different catalyst affect dynamics
- Growing market interest in non-polymer applications where grade changes and/or highly nonlinear system

Example of Process Nonlinearity

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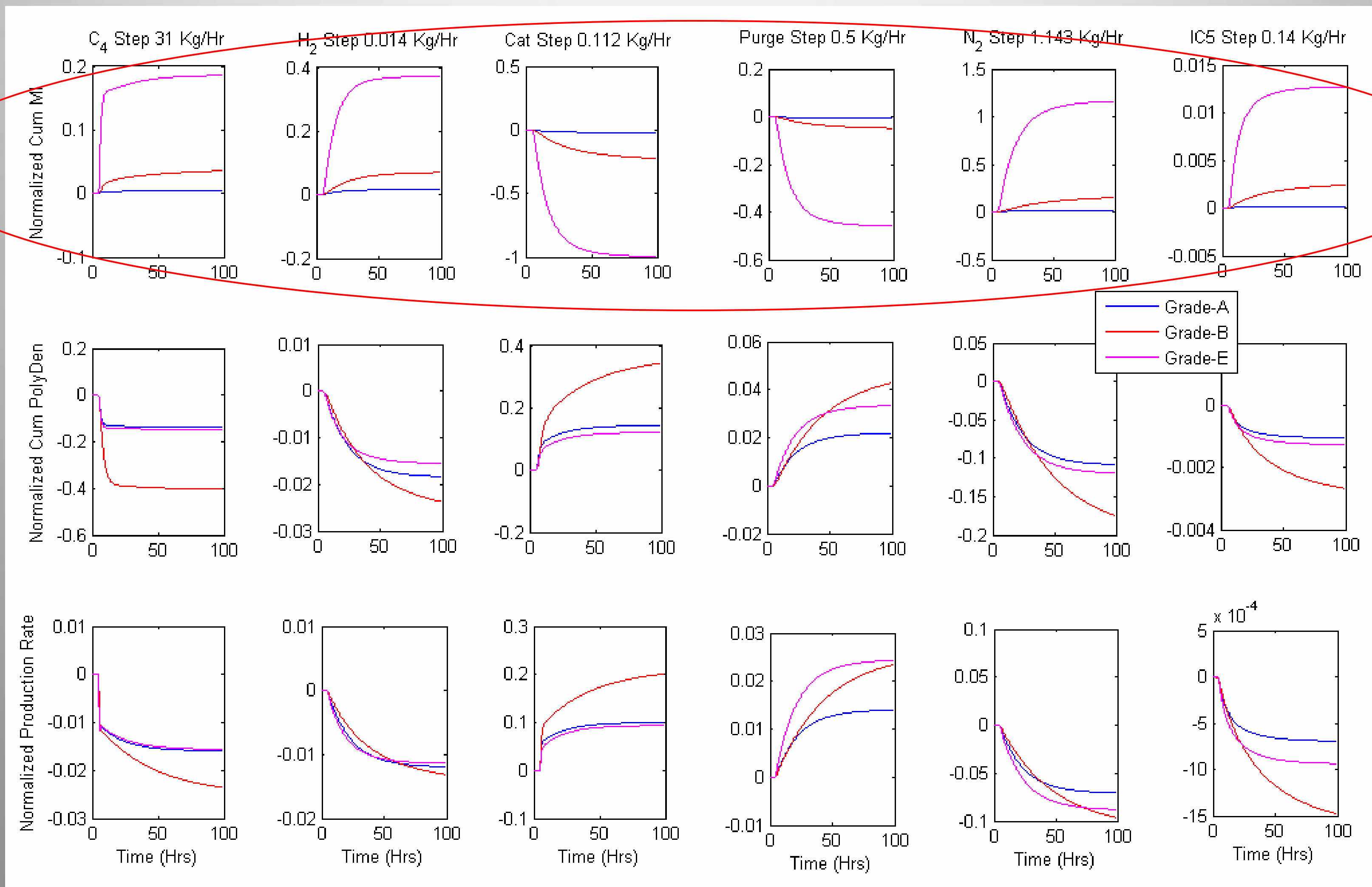
Step responses at three operating points for a polymer process



Proposed Methods for Nonlinear Control

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- Linear Control
  - Detune to obtain robustness – poor performance
  - Use transformations of variables
- Linear Control with Gain Updating
  - Maintenance issues – Process upset if changed abruptly
- Linear Control with Model Updating
  - Linearization of offline nonlinear model
  - Better regulatory performance
  - Poor transition performance due to poor future predictions
- Offline dynamic optimization with online linear control
  - Still have poor transition performance because gains don't change over the prediction horizon
- Nonlinear control with empirical model
  - Performance good for model validity region
- Nonlinear control with rigorous models
  - Performance good but application more complex

Nonlinear Dynamic Models

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- Empirical Black Box
  - Fixed model structure
  - Solution constrained by various techniques to manage extrapolation problems
  - Normally requires excitation data for suitable models
- Empirical Grey Box
  - Model form can be defined using engineering knowledge
  - Known parameters can be fixed
  - Regressed to provide complete solution
  - Lower data requirements – hybrid of historical and excitation data
- Rigorous, First Principles
  - Dynamic and steady-state elements
  - Reactor kinetics and equipment operating parameters
  - Usually only historical data and process config info

Model Predictive Control Genealogy

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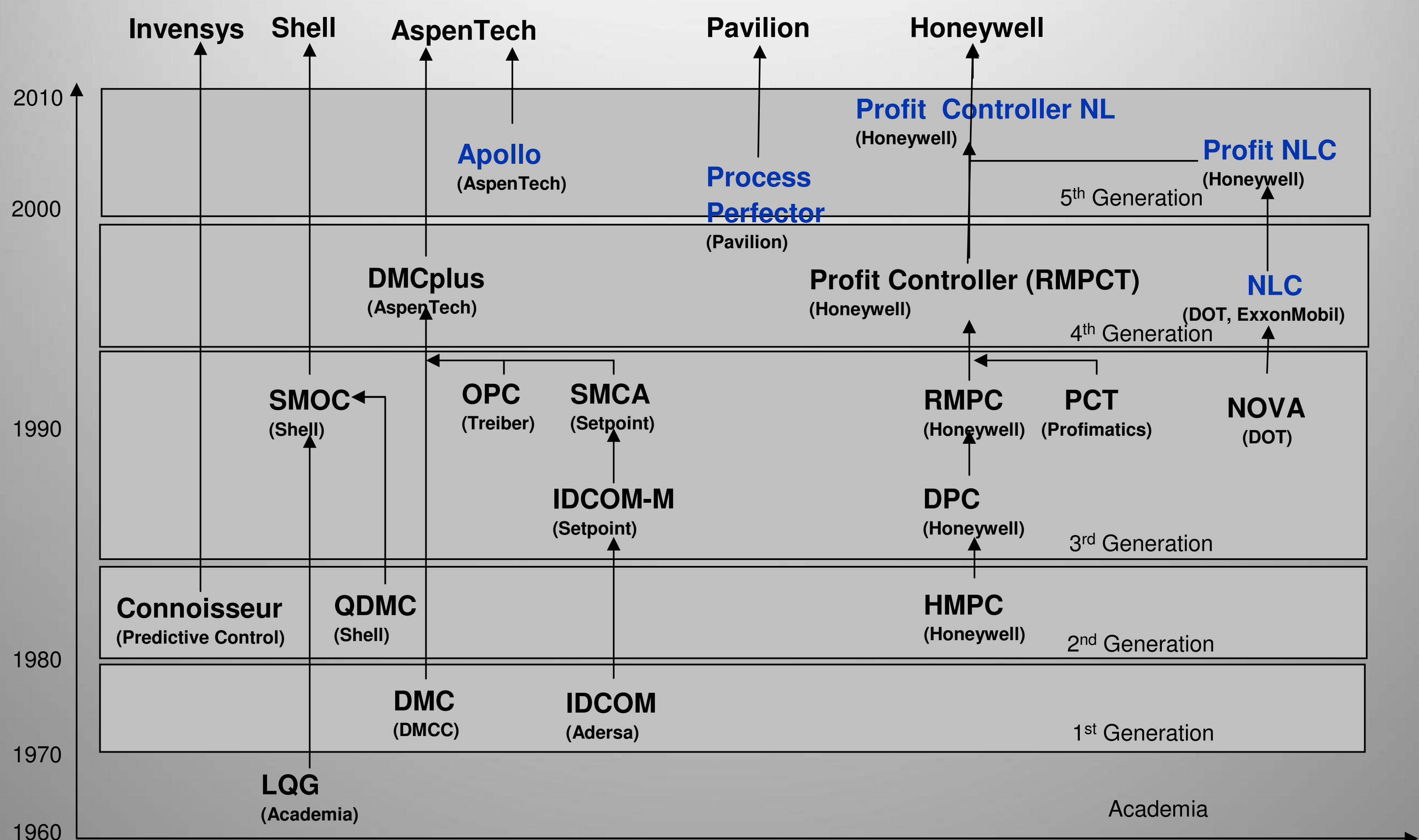


Adapted (and modified) from the following literature source:

Qin, Joe S. , Badgwell, Thomas A.,

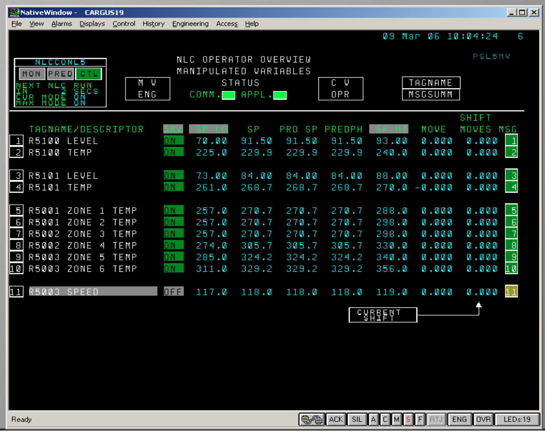
"A Survey of Industrial Model Predictive Control Technology "

Profit NLC Overview

Profit NLC ®

Honeywell

- A product for nonlinear optimal control applications in Honeywell's Profit Suite
- Developed in conjunction with ExxonMobil Chemical APC Group to address advanced control problems where performance expectations could not be met by linear model predictive control
  - ExxonMobil development began in early 1990s
  - Bartusiak, Fontaine – U.S. Patent 5,682,309 (1997)
  - Renfro , Lu – U.S. Patent Pending (2008)
  - Applied to polymer process control problems
  - In service for 15 years; proven technology
- Embeds a nonlinear dynamic model into the application
- Ability to handle multiple objectives of prioritized control and economic optimization
- Equation based solution of dynamic models enables dynamic optimization problems to be solved very fast compared with integration based sequential strategies



MPC Control Error Formulations*

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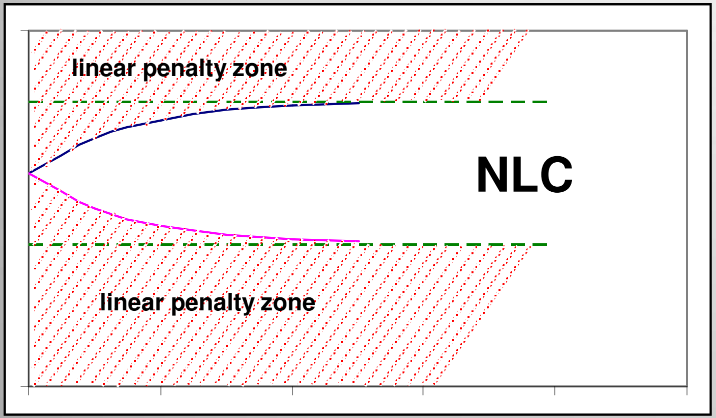

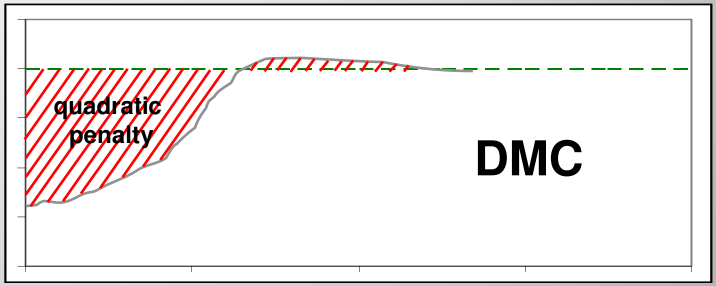

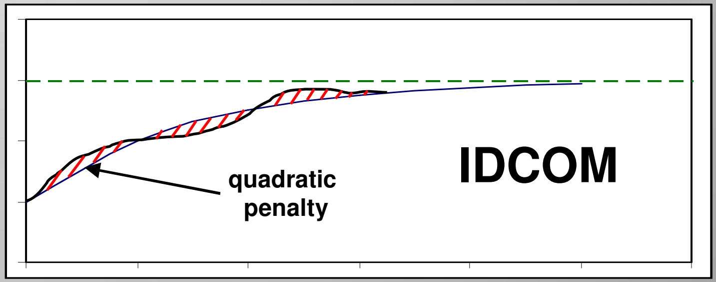

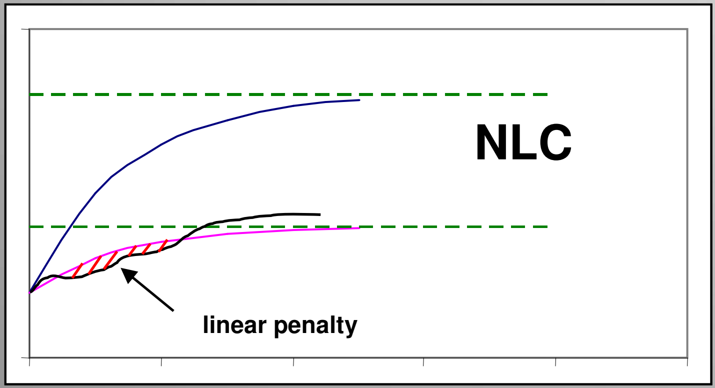

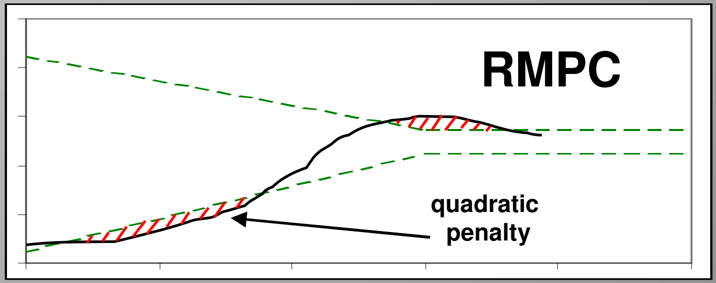

* Courtesy Bartusiak

RMPC funnel: 1^{st} Order ODE Form

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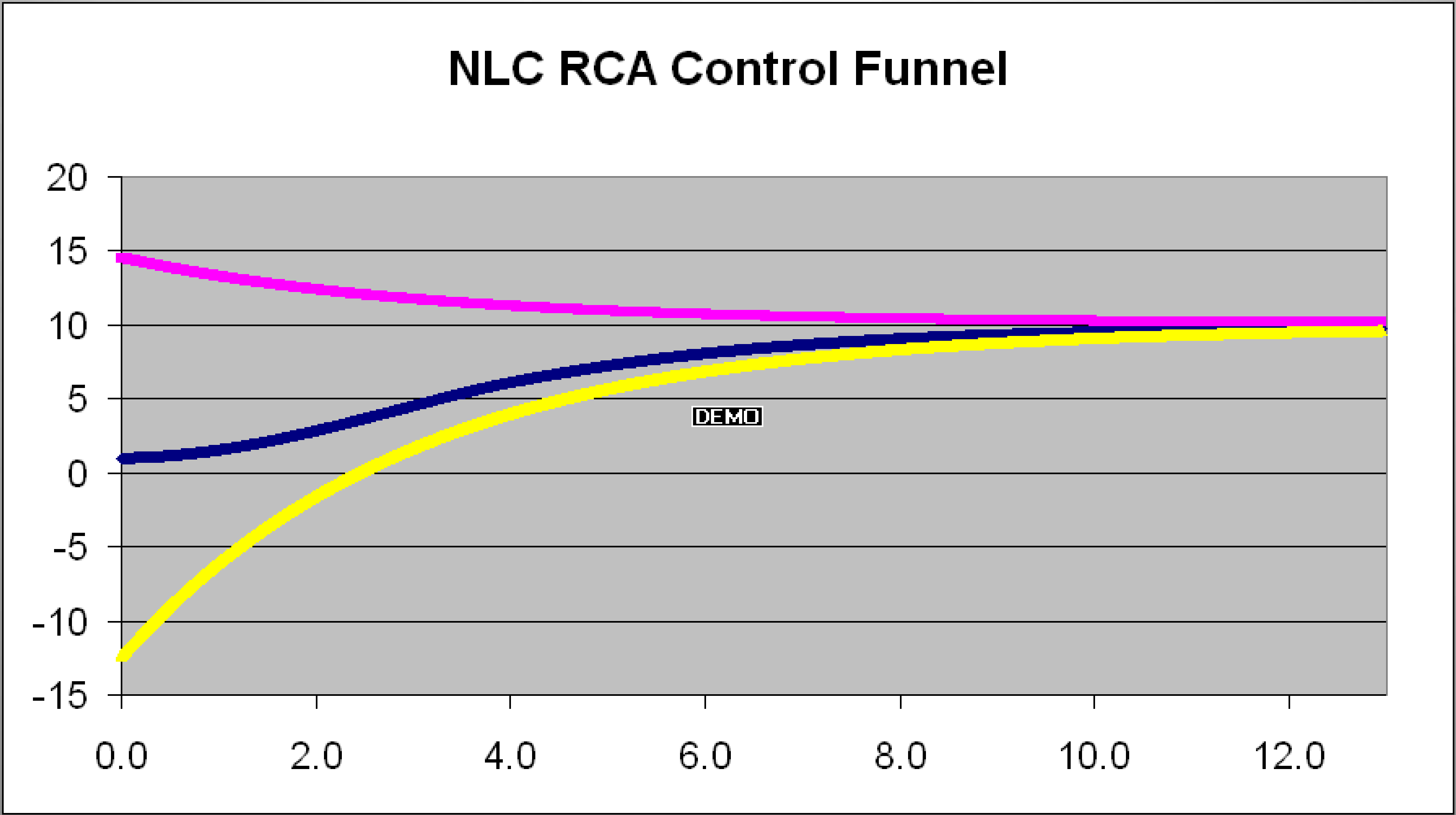

Simultaneous Optimization and Control

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- MPC is often combined with steady state real-time optimization (RTO)
- Honeywell combines its linear MPC (Profit Controller) with dynamic optimization (Profit Optimizer)
- Profit NLC is a formulation that actually combines nonlinear MPC with dynamic optimization in the same application
- This combined control and optimization formulation is called Nonlinear Model Predictive Optimal Control (NMPOC)
- The NMPOC formulation is actually a multi-level optimization problem
  - Resolve prioritized control error in order
  - Solve dynamic optimization problem subject to previously computed error constraints
- The NMPOC problem can also be solved by composite objective function with proper weighting

Profit NLC NMPOC Problem

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$$\min \Psi = \mu_1 F_1(\mathbf{e},\mathbf{w}) + \mu_2 F_2(\mathbf{y},\mathbf{u},\mathbf{d},\mathbf{c}) + \mu_3 F_3(\Delta\mathbf{u},\mathbf{c})$$

$$\mathbf{h}(\dot{\mathbf{x}}(t), \mathbf{x}(t), \mathbf{u}(t), \mathbf{d}, \mathbf{v}, t) = \mathbf{0}$$

$$\mathbf{x}(t_0)) = \mathbf{x}_{\mathbf{0}}$$

$$\mathbf{g}(\mathbf{y}(t), \mathbf{x}(t), \mathbf{u}(t)) = \mathbf{0}$$

$$\mathbf{r}^{sphi}(\ddot{\mathbf{y}}, \dot{\mathbf{y}}, \mathbf{y}, \tau, \xi, \mathbf{y}^{sphi}, \mathbf{e}^{sphi}, \mathbf{s}^{sphi}) = \mathbf{0}$$

$$\mathbf{r}^{splo}(\ddot{\mathbf{y}}, \dot{\mathbf{y}}, \mathbf{y}, \tau, \xi, \mathbf{y}^{splo}, \mathbf{e}^{splo}, \mathbf{s}^{splo}) = \mathbf{0}$$

$$\mathbf{f}(\mathbf{y}(t_0), \mathbf{y}^{meas}(t_0), \mathbf{e}_f, \tau_f, \mathbf{v}) = \mathbf{0}$$

$$\mathbf{u}(t) - \mathbf{u}(t_0) - \sum_{j=1}^{n_p} H(t - j\Delta t)\Delta\mathbf{u}_j = \mathbf{0}$$

$$\mathbf{y}_{\min} \le \mathbf{y} \le \mathbf{y}_{\max} \quad \mathbf{u}_{\min} \le \mathbf{u} \le \mathbf{u}_{\max} \quad \Delta\mathbf{u}_{\min} \le \Delta\mathbf{u} \le \Delta\mathbf{u}_{\max}$$

$$\mathbf{e}^{sphi}, \mathbf{e}^{splo}, \mathbf{s}^{sphi}, \mathbf{s}^{splo} \ge 0$$

Profit NLC DAE Model

Honeywell

$$\mathbf{h}(\dot{\mathbf{x}}(t), \mathbf{x}(t), \mathbf{u}(t), \mathbf{d}, \mathbf{v}, t) = \mathbf{0}$$

$$\mathbf{x}(t_0) = \mathbf{x}_0$$

where:

$\mathbf{x} = \textit{state variables}$

$\mathbf{u} = \textit{manipulated variables}$

$\mathbf{d} = \textit{measured disturbance variables}$

$\mathbf{v} = \textit{estimated disturbance variables}$

$t = \textit{time}$

Profit NLC Objective Function

Honeywell

Controller Error Term	Economic Term	Minimum MV Movement Term

$$\Psi = \mu_1 F_1(\mathbf{e},\mathbf{w}) + \mu_2 F_2(\mathbf{y},\mathbf{u},\mathbf{d},\mathbf{c}) + \mu_3 F_3(\Delta\mathbf{u},\mathbf{c})$$

$$F_1(\mathbf{e},\mathbf{w}) = \frac{1}{t_f - t_0}\int_{t_0}^{t_f} (\mathbf{w}^{sphi^T}\mathbf{e}^{sphi}(t) + \mathbf{w}^{splo^T}\mathbf{e}^{splo}(t))\Omega(t)\,dt$$

$$F_2(\mathbf{y},\mathbf{u},\mathbf{d},\mathbf{c}) = \frac{1}{t_f - t_0}\int_{t_0}^{t_f} (\mathbf{c}_y^T\mathbf{y}(t) + \mathbf{c}_u^T\mathbf{u}(t) + \mathbf{c}_d^T\mathbf{d}(t))\Omega(t)\,dt$$

$$F_3(\mathbf{u},\mathbf{c}) = \frac{1}{t_f - t_0}\int_{t_0}^{t_f} \mathbf{c}_{\Delta u}^T\left(\frac{d\mathbf{u}^*}{dt}\right)\Omega(t)\,dt$$

Profit NLC Objective Function

Honeywell

Controller Error Term

Economic Term

Minimum MV Movement Term

$$\Psi = \mu_1 F_1(\mathbf{e}, \mathbf{w}) + \mu_2 F_2(\mathbf{y}, \mathbf{u}, \mathbf{d}, \mathbf{c}) + \mu_3 F_3(\mathbf{u}, \mathbf{c})$$

$$F_1(\mathbf{e}, \mathbf{w}) = \frac{1}{t_f - t_0} \sum_{j=1}^{n_p} (\mathbf{w}^{sphi^T} \mathbf{e}^{sphi}(t_j) + \mathbf{w}^{splo^T} \mathbf{e}^{splo}(t_j))\Delta t_j$$

$$F_2(\mathbf{y}, \mathbf{u}, \mathbf{d}, \mathbf{c}) = \frac{1}{t_f - t_0} \sum_{j=1}^{n_p} (\mathbf{c}_y^T \mathbf{y}(t_j) + \mathbf{c}_u^T \mathbf{u}(t_j) + \mathbf{c}_d^T \mathbf{d}(t_j))\Delta t_j$$

$$F_3(\Delta\mathbf{u}, \mathbf{c}) = \frac{1}{t_f - t_0} \mathbf{c}_{\Delta u}^T \Delta\mathbf{u}^* \qquad \Delta u_i^* = \sum_{j=1}^{n_p} \left|\Delta u_{ij}\right|$$

Profit NLC Multilevel Optimization Problem

Honeywell

Choose $\mu_1, \mu_2, \mu_3, \mathbf{w}_{sphi}, \mathbf{w}_{splo}$ to implicitly solve

- Minimize Priority 1 CV errors
- Minimize Priority 2 CV errors
- …
- Minimize Priority N_p CV errors
- Optimize Economic Objectives with minimum movement

Profit NLC NMPOC Problem

Honeywell

$$\min \Psi = \mu_1 F_1(\mathbf{e},\mathbf{w}) + \mu_2 F_2(\mathbf{y},\mathbf{u},\mathbf{d},\mathbf{c}) + \mu_3 F_3(\Delta\mathbf{u})$$

$$\mathbf{h}(\dot{\mathbf{x}}(t), \mathbf{x}(t), \mathbf{u}(t), \mathbf{d}, \mathbf{v}, t) = \mathbf{0}$$

$$\mathbf{x}(t_0)) = \mathbf{x_0}$$

$$\mathbf{g}(\mathbf{y}(t), \mathbf{x}(t), \mathbf{u}(t)) = \mathbf{0}$$

$$\boxed{\begin{aligned} \mathbf{r}^{sphi}(\ddot{\mathbf{y}}, \dot{\mathbf{y}}, \mathbf{y}, \tau, \xi, \mathbf{y}^{sphi}, \mathbf{e}^{sphi}, \mathbf{s}^{sphi}) &= \mathbf{0} \\ \mathbf{r}^{splo}(\ddot{\mathbf{y}}, \dot{\mathbf{y}}, \mathbf{y}, \tau, \xi, \mathbf{y}^{splo}, \mathbf{e}^{splo}, \mathbf{s}^{splo}) &= \mathbf{0} \end{aligned}}$$

$$\mathbf{f}(\mathbf{e}_f, \tau_f, \mathbf{v}) = \mathbf{0}$$

$$\mathbf{u}(t) - \mathbf{u}(t_0) - \sum_{j=1}^{n_p} H(t - j\Delta t)\Delta\mathbf{u}_j = \mathbf{0}$$

$$\mathbf{y}_{\min} \le \mathbf{y} \le \mathbf{y}_{\max} \qquad \mathbf{u}_{\min} \le \mathbf{u} \le \mathbf{u}_{\max} \qquad \Delta\mathbf{u}_{\min} \le \Delta\mathbf{u} \le \Delta\mathbf{u}_{\max}$$

$$\mathbf{e}^{sphi}, \mathbf{e}^{splo}, \mathbf{s}^{sphi}, \mathbf{s}^{splo} \ge 0$$

Profit NLC 2nd Order Reference Trajectory

Honeywell

$$r_i^{sphi} = \frac{\tau_i}{4\xi_i^2}\frac{d^2 y_i}{dt^2} + \frac{dy_i}{dt} + \frac{1}{\tau_i}(y_i - y_i^{sphi}) - e_i^{sphi} + s_i^{sphi} = 0$$

$$r_i^{splo} = \frac{\tau_i}{4\xi_i^2}\frac{d^2 y_i}{dt^2} + \frac{dy_i}{dt} + \frac{1}{\tau_i}(y_i - y_i^{splo}) + e_i^{splo} - s_i^{splo} = 0$$

$$e_i^{sphi}, e_i^{splo}, s_i^{sphi}, s_i^{splo} \geq 0$$

SISO 1st Order ODE Model (RCA vs. RT)

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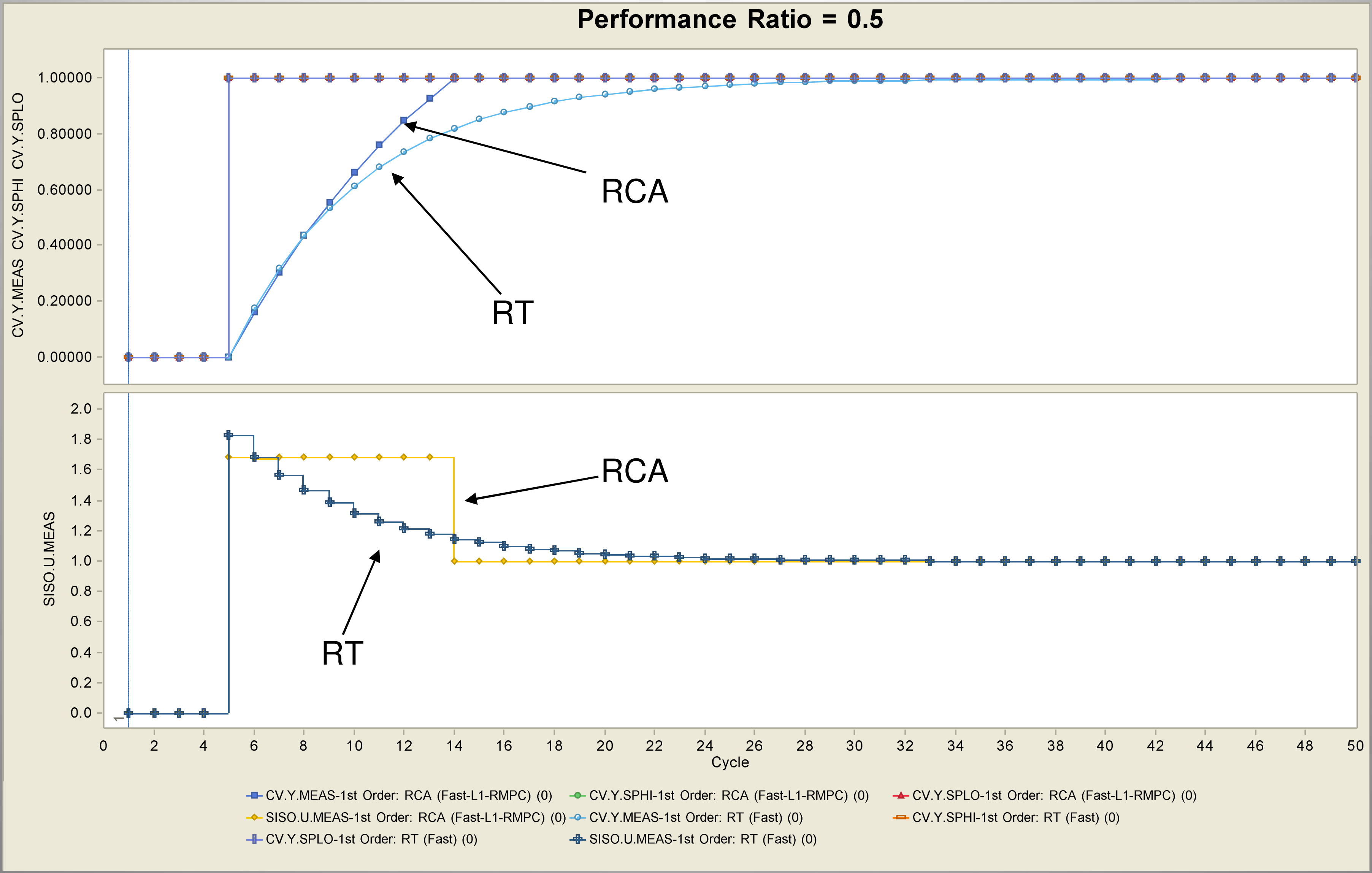

Feedback Technology

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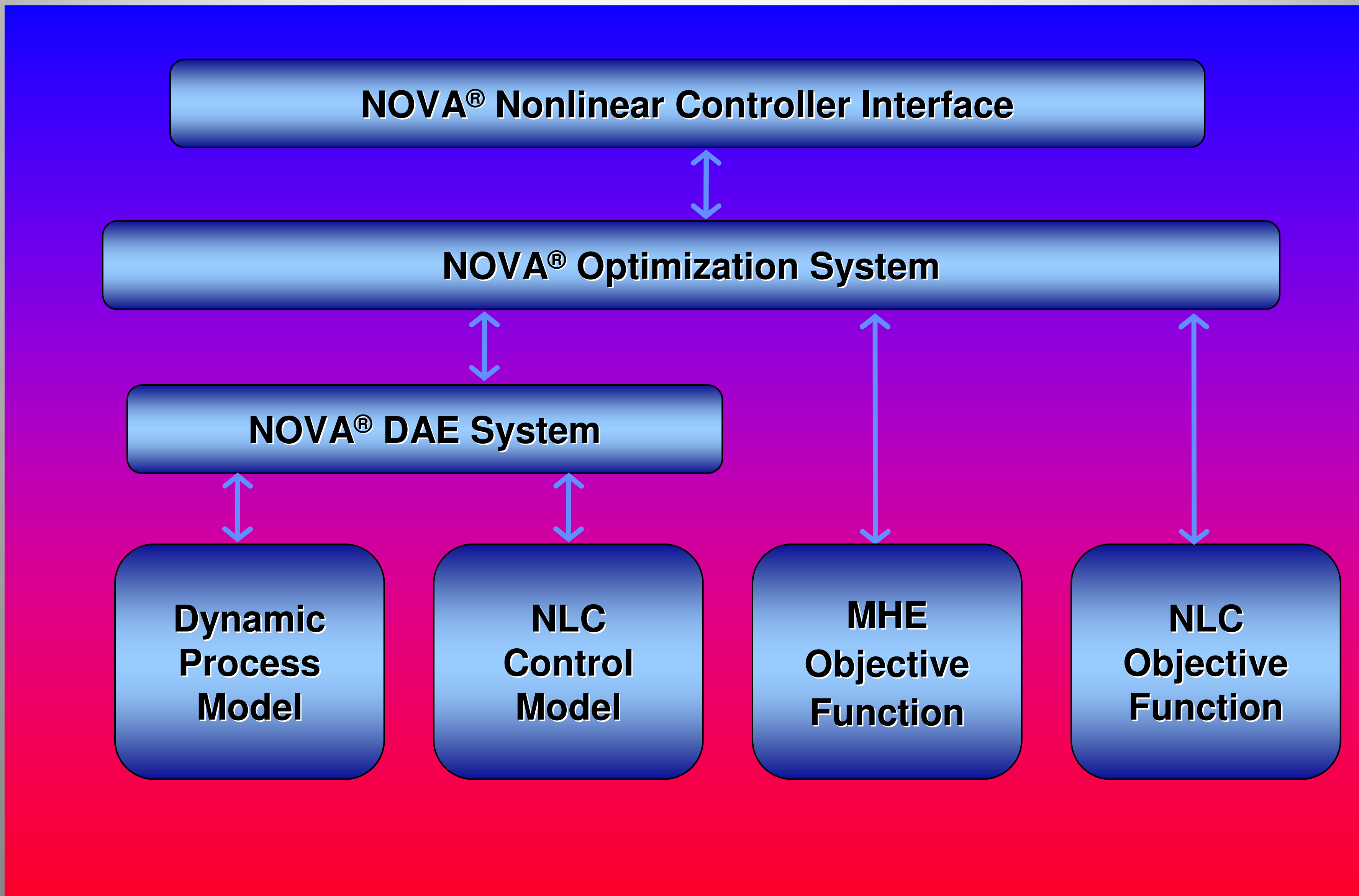
- Simple filtered bias approach
  - Use for years in many linear MPC packages
  - Use in initial NLC prototypes
- Implicit Dynamic Feedback (IDF®)
  - Use in most applications for NLC
  - Generalization of steady state feedback (calibration) approaches used in real-time optimization for dynamic models
  - Similar to a multivariable PID with automatic decoupling
- State Estimation
  - Extended Kalman Filtering
    - Clipped and constrained formulations
    - Not practical for general model forms or large scale systems
  - Moving Horizon Estimation (method used for for NLC)
    - Natural optimization based formulation
    - Better constraint handling
    - More general model forms (PDAEs)
    - Addresses issues for large scale dynamic models

Nonlinear Model Predictive Optimal Control Problem Solution Technology

Profit NLC Internal Architecture



NOVA Optimization Technology

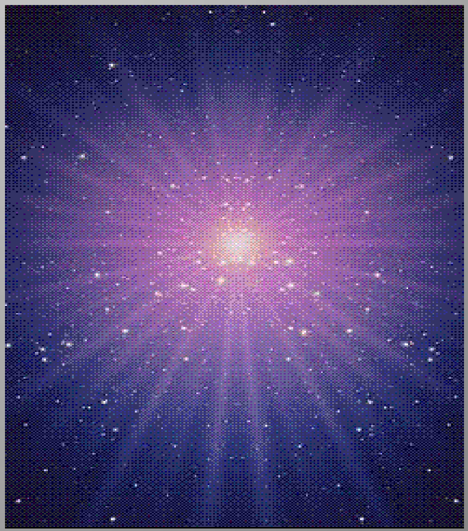
Honeywell

N*onlinear*

O*ptimization* **for**

V*ersatile*

A*pplications*



$$\min p(\mathbf{x})$$

$$\mathbf{f}_{\min} \le \mathbf{f}(\mathbf{x}) \le \mathbf{f}_{\max}$$

$$\mathbf{x}_{\min} \le \mathbf{x} \le \mathbf{x}_{\max}$$

NOVA Optimization System

Honeywell

- General Purpose Optimization System
- Equation-Based Design
- Application Building Environment
  - Ability to incorporate custom models
- Flowsheeting System
  - Configure and solve complex process modeling problems
- SQP Optimization Solver
- Used in real time optimization applications in the 1990s

NOVA Solver Technology

Honeywell

- Large Scale active set optimization solver
- State-of-the-art sparse generalized successive quadratic programming (SQP) algorithm
- Unique, highly efficient and robust algorithm for local and actual infeasible problems
- Employs numerical stability procedures established over 20 years of solving real online applications for maximum reliability
- Large degrees of freedom capability (>1000)
- Handles nonlinear complementarity problems (certain logic based constraints where logic is solved for simultaneously)
- Currently the NLP solver in a number of Honeywell Advanced Solutions products

NOVA DAE System

Honeywell

- Differential/Algebraic Equation (DAE) Interface
- Equation-Based design
  - Allows simultaneous integration and optimization
  - Also known as direct transcription method
- Integration structure is configurable
- Based on orthogonal collocation on finite elements
- Converts DAE models into an equivalent set of algebraic equations
- Provides basis for the solution of all dynamic models

$$\mathbf{h}(\dot{\mathbf{x}}(t), \mathbf{x}(t), \mathbf{u}(t), \mathbf{d}, \mathbf{v}, \mathbf{p}, t) = \mathbf{0}$$

$$\mathbf{x}(t_0) = \mathbf{x}_0$$

Nonlinear MPOC Application Implementation Issues

NMPOC Computation Time

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- NLP solution times can vary
- Needs to solve in less than 50% of cycle time
- Typical cycle times 2-5 minutes
  - Linear MPC times down to 15 sec cycles
- Limited on what can be controlled by cycle time
- Most cycles solve fast during periods of slow change in operations
- Hot starts important – active set methods still best for this real time domain
- Simultaneous solution and optimization is the only feasible way
- Feasibility Mode enables limiting iterations
  - Suboptimal solution is acceptable

NMPOC Solution Reliability

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- Many NLP solves
  - 2 minute cycle running continuously means about 262,800 solves per year
  - Most cases just like previous solve – things don't change continuously
- Solver Robustness
  - Solver contains many robustness techniques
  - Several layer anti-cycling strategies
  - Rigorous handling of local infeasibilities
  - Extensive line search heuristics
  - Virtually "crash proof"
  - Handles degeneracy well

NMPOC Solution Reliability

Honeywell

- Can tolerate 1-2 failures per month
  - Need to recover automatically
  - Can add logic to help
- Need to use engineering knowledge for models to bound in a reasonable solution domain
  - Process operation domain is known
  - Flows, temp, pres, compositions positive
  - Iteration step bounding used (manual trust region)
  - Avoids most problems caused by nonconvexity issues

NMPOC Solution Reliability

Honeywell

- Control Problem posed to always be feasible
- All decision variables bounded so solution should never be unbounded
- Solver must return with a valid status
- Watchdog application monitors all components of the application
  - If application got stuck in a cycle or due to a bug
- Extensive Input / Output Validation
  - Input Validation
  - Output Validation
  - Scripting for special circumstances and safety
    - Stop catalyst moves up if cooling water valve is constrained
    - Monitoring estimated variables for abnormal values

NMPOC Solution Failure Types

Honeywell

- **Maximum iterations**
  - Tries to get feasible, suboptimal solution
  - Can occur when huge operation changes occur
  - Controller initialization can also be difficult
  - Can filter input changes in to help solve if required
- **Infeasible**
  - Usually only if there are input problems for the hard limits and this means validation logic was not complete
  - Can occur if hard model validity limits are active; this failure is by design – something is wrong if this limit is active; model needs attention

Nonlinear MPOC Application Description and Results

UNIPOL™ PE: Process Overview

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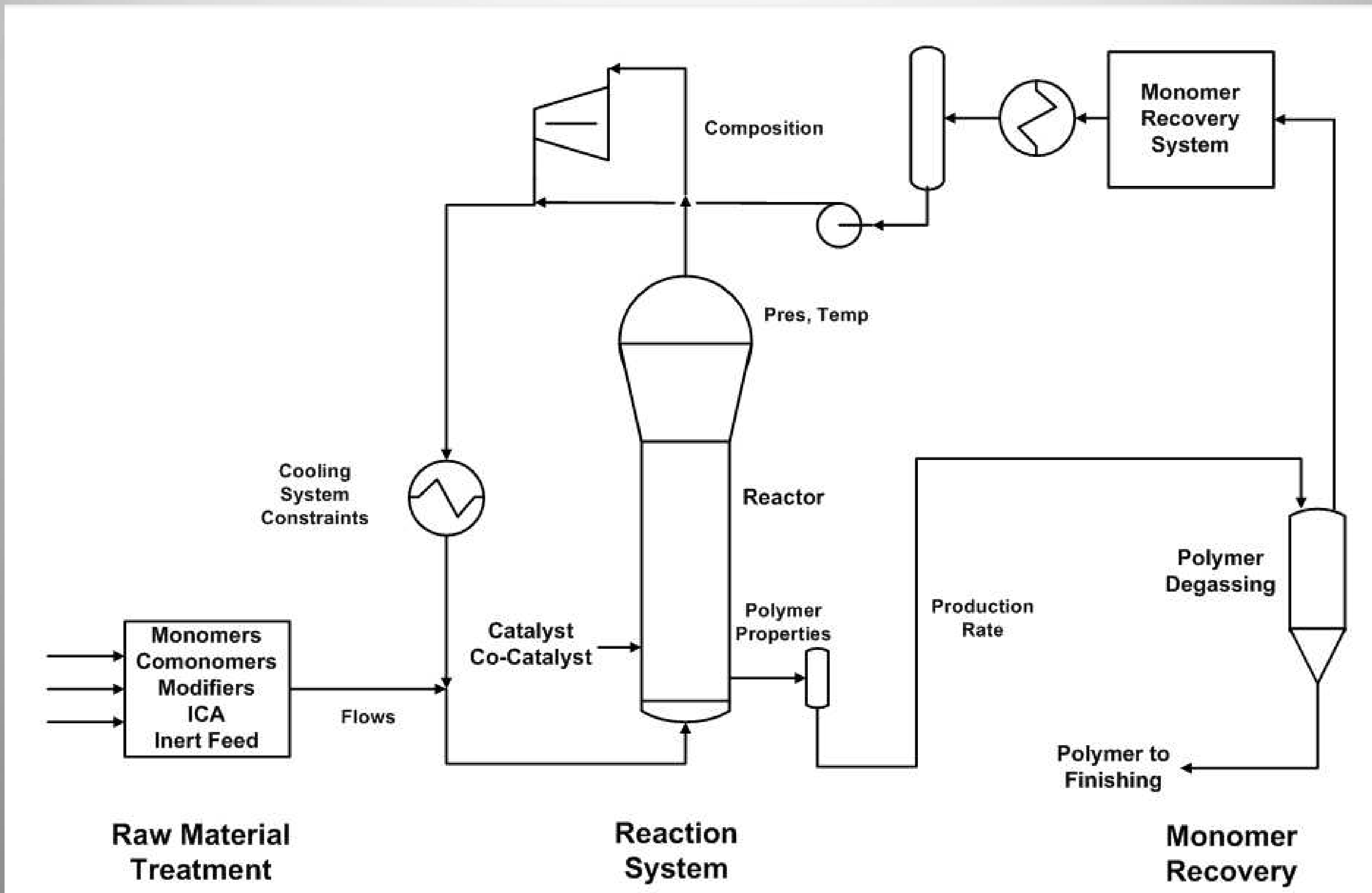
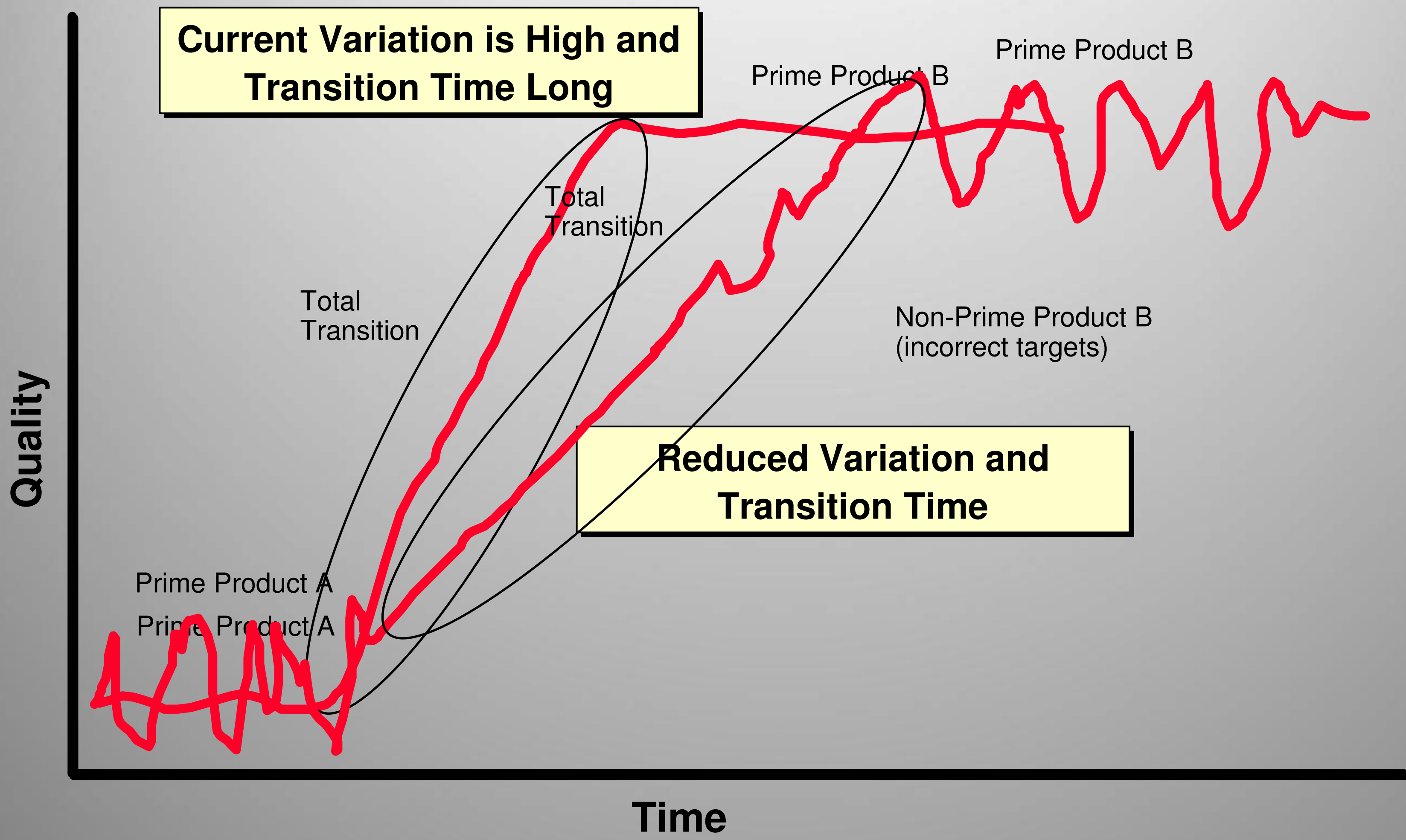


Present Operation
Desired Operation



Profit NLC Controller Design: SASOL PE

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- 15 Controlled Variables
  - Density, melt index, production rate, compositions,
  - Cooling constraints, pressure
- 9 Manipulated Variables
  - Chain transfer agent flow, Comonomer flow, monomer flow, Catalyst flow, co-catalyst flow
- 16 Measured State Variables
- 26 Measured Disturbance Variables
- 21 Estimated Disturbance Variables
- Cycle time: 5 minutes

Profit NLC NLP Problem: SASOL PE

Honeywell

- **NLP Problem Attributes**
  - 90792 variables
  - 90474 equations
  - 318 degrees of freedom
  - 410976 nonzeros
- **Typical Solve Time: 10-30 secs**

Profit NLC SASOL Application Performance

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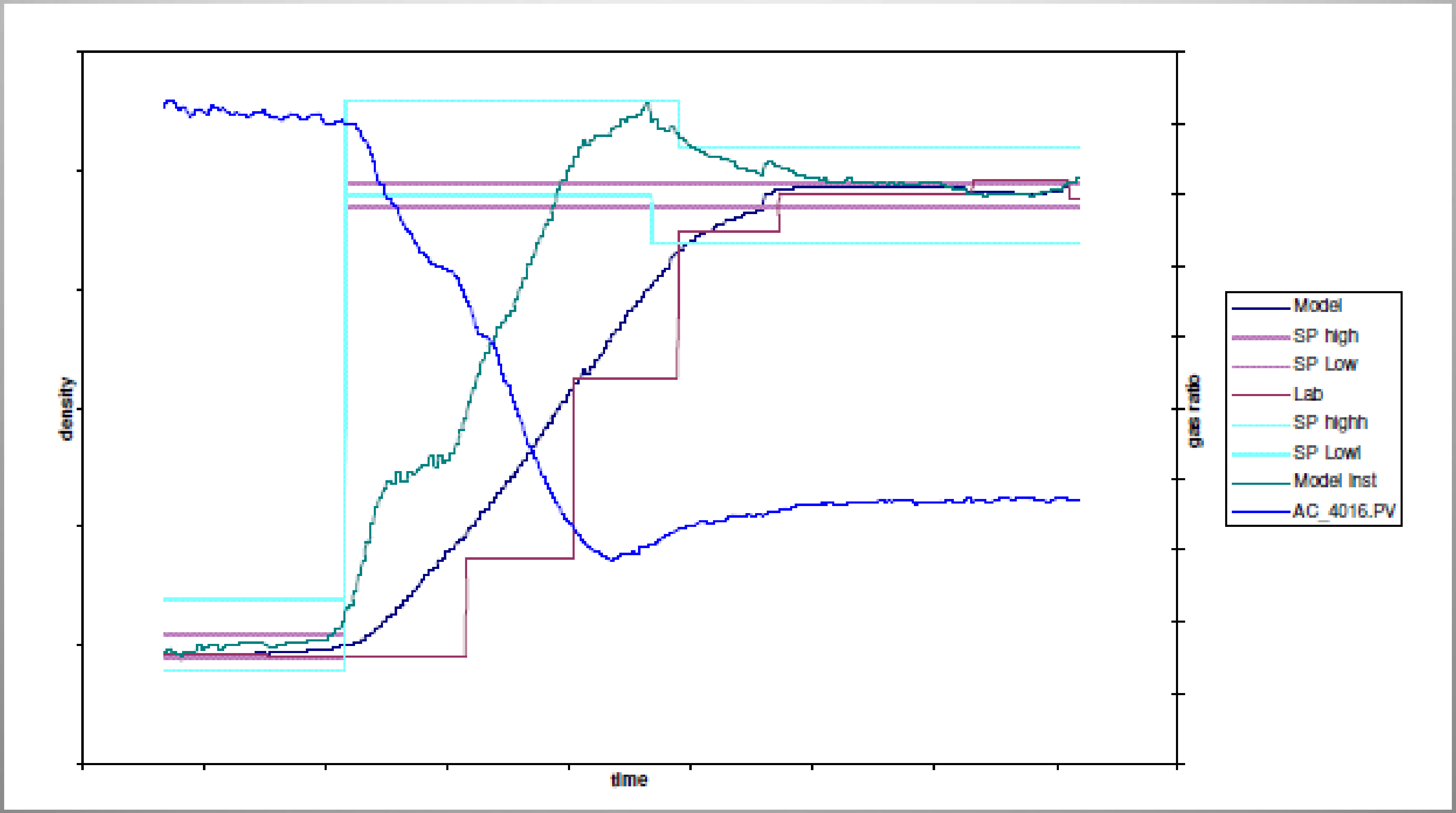
Polymer Density Control



Profit NLC SASOL Application Benefits

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- Six month performance evaluation after commissioning
- 29% reduction in transition time
- 59% reduction in off-specification product
- Confidence to increase production rate change by 260%
- Use of estimated disturbance parameters to identify abnormal operations
- Better insight into unmeasured compositions

* Allsford, Goodman, Ramlal, Beigley, “Nonlinear Multivariable Control and Optimization of a Polyethylene Process Based on Embedded Dynamic Chemical Engineering Model”, AIChE Meeting 2008, ADCONIP 2008

Nonlinear Model Predictive Optimal Control Challenges

NMPOC Business Challenges

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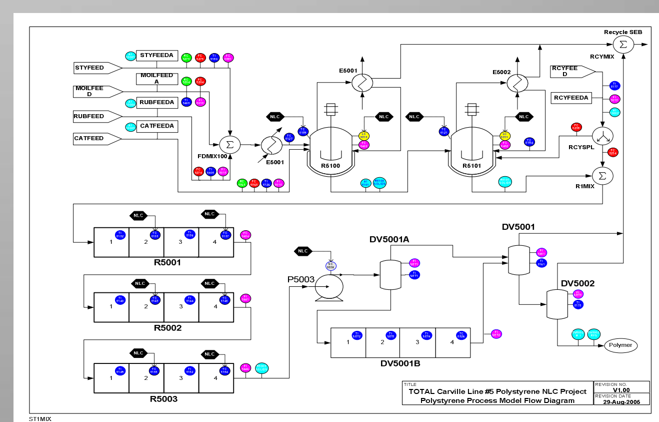
- Low Cost Advanced Solutions
  - Deliver simpler low cost solutions meeting performance expectations
  - Meet cost requirements in emerging markets
  - Some processes have low benefits but on a %basis can still use optimization and control
  - Challenge is to make complex technology easy to configure, deliver and sustain
  - Model development can be large component of project man-hours
    - Need simpler approaches that capture nonlinearity
- Maintenance Issues
  - Model configuration changes
  - Site expertise for diagnosis
- New Processes
  - Need domain expertise
  - Project estimation uncertain - risks

NMPOC Modeling Challenges

Honeywell

- Nonlinear Empirical Models
  - Tools to support black, grey box models
  - Incorporation of different model types in same flowsheet model
  - Need to match first principles models with simpler forms
- Life cycle modeling
  - Modeling requirements are different for different domains
  - Spread model development costs between different groups that use the model
  - Computational requirements in some domains limit general usage



NMPOC Optimization Challenges

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- Large Scale Optimization
  - Large degrees of freedom
  - Active set methods still fastest for online problems
  - Prediction horizon design limited by computation time
  - Interior point methods OK but have weaknesses in some scenarios important to online applications
    - Warm starts
    - Degeneracy
- Mixed Integer Dynamic Optimization/Control
  - Extending nonlinear control to startup, shutdown and abnormal situations
  - Regulatory controller mode changes
  - Discrete event modeling

NMPOC Technology Path Forward

Honeywell

- Simplify
- Refine the work process to achieve predictability
- Offer a variety of dynamic modeling approaches all compatible with the controller
- Standardize on Moving Horizon Estimation
- Always looking to improve optimization technology for better performance and reliability.