Plant-wide Dynamic Economic Optimization: Key Challenges & New Opportunities
Outline

• Plant-wide Dynamic Economic Optimization Problem in Refineries & Chemical Plants
  • Layered Approach
    • Integrated RTO systems
    • Optimal Synergy of RTO and MPC systems
    • Adaptive Modeling for MPC systems
• New Business Opportunities & Novel Approaches
Achieving Plant Performance Improvement

Refinery & Chemical Plants’ Profitability Levers

- Improve product yields
- Lower raw material costs
- Reduce operating costs
- Extend life of equipment/Catalyst

Methods

- Scale / integration
- Operating discipline - Reliability (Availability)
- Technology (Improve Utilization, Operate at Optimum constraints)

  - i.e. Process Control Applications, Automation & Optimization
Typical Refinery/Chemicals of Today
Plant-Wide Optimization Systems

**Offline**
Multi-refinery and Chemical Plants Optimization
Planning & Scheduling

**Online**

- Crude Distillation
- CFHT
- FCC
- VDU
- CHD
- HDC
- HDS
- CCR
- ALKY
- ISOM
- Unsaturated Gas Plant
- Crude Distillation
- Sat. Gas Plant
- L-MPC / econ-RTO’s
- Multi-period Optimization
- Polymers NL-MPC

**Molecular Representation of Crude Assays**

**Raw Material Acquisition**

**Raw Material Costs**

**Operating Costs**

**Product Values**

- Gasoline
- Jet Fuel
- Diesel
- Lubricants

**ExxonMobil**
The Plant-Wide “Dynamic” Economic Optimization: Challenges

• A typical plant is an integrated set of sections (operating areas)
  • Each section has multiple feeds & products, reactors, columns, & many trade-offs within
  • Different sections of a plant have different process characteristics (time-scale) and operating strategies (i.e. continuous, semi-batch, multi-period) – Different reliability/Availability
  • Complex set of optimization variables among the sections - multiple economic trade-offs
Layered Approach

- Build **economic steady-state** section RTOs
  - Use rigorous fundamental-principles process models, real time data, and an economic objective function to optimize the current operation of each section typically every 1-2 hours
  - Many refineries and chemical sites have installed RTOs for one or more sections (Crude, FCCU, Reformers, Olefins, Aromatics, etc.)

- Combine section RTOs into an **integrated RTO** (i-RTO) to achieve the **plant-wide economic optimum**

- The economic optimum is implemented as an **economic strategy** (not only “traditional” targets) via MPC

- Extend applicability of MPC over **wide nonlinear** operating window (“**adaptive**” MPC)

Other Potential Approaches: Full scale dynamic model, Multi-period RTOs, etc.
# Understanding the Difference

## MPC vs Economic (steady-state) RTO

### MPC

- *Mainly manipulates flows & bulk properties*
- Usually implements an “operational” strategy or a “perceived” economic optimization (priority of constraints)
  - Usually simplified economics are used to determine the LP costs before controller commissioning. Infrequently updated
  - No feed characterization
- **Multiple controllers per area/section**
- Simple linear dynamic models
  - Benefits or costs increase or decrease at the same rate throughout a variable range
- **No automatic model update**
- “Constraint pusher”. Pushes always to high or low limit
- Limited to on-line use only

### RTO

- *Mainly manipulates molecules (compositions)*
- True economic optimization.
  - *Guarantees closure of mass & energy balance*
  - Feed, product, and utilities economics are updated whenever they change. Usually every week. Uses componential prices
  - Detailed feed characterization
- **Encompasses entire area/section**
- Rigorous steady-state models
  - Benefits or costs change at different rates throughout a variable range
- **Model updated to current oper. region**
  - “Constraint reliever”. Pushes to the economic point between limits
- Off-line use-what-if cases/scenarios
  - Wider range of accuracy
The Plant-Wide “Dynamic” Economic Optimization: Technology Challenges

- Challenge (1): How to Integrate local (steady-state) economic RTOs towards a plant-wide online economic optimization (i-RTO)

- Challenge (2): How to integrate local RTOs with local MPCs towards dynamic economic optimization
  - MPC should have consistent & satisfactory dynamic performance within the space of the nonlinear optimization space

- Challenge (3): How to extend applicability of linear MPC models over wide non-linear operating window
Plant-Wide Dynamic Economic Optimization Challenge (1):

How to integrate of multiple local economic RTOs towards a plant wide online economic optimization (i-RTO) (1), (2)

(1)
“Integrated Real-Time Optimization Technology”

A. Georgiou (Presenter), M. Andrei
P. Hanratty, J. D. Terry

Invensys OpsManage ’10 North America
October 18-22, 2010

(2)
(Patent Application No: 2011/0098,862
“Multi-Stage Processes and Control Thereof”
2006-EE-032

(Real-Time Intermediate Stream Pricing for Integration of Multiple RTO Applications)

Apostolos Georgiou, Marco Andrei
Towards a Plant-wide RTO

Instead of many section RTOs why not a single plant-wide RTO that

- Eliminates the need for intermediate stream pricing
- “Upstream RTOs” are fully aware of compositional effects and active constraints in “Downstream RTOs” and finished product blending
- Economic drivers are set entirely by commercial terms for feed stocks and finished products
  - Purchase and sales prices
  - Product quality specs. (bounds)

For smaller, more “compact” manufacturing sites a single RTO might be “feasible”

- Facilitated by “once-through” processing and off-the-unit, in-line product blending
- Still the issue of the time to steady state of the different “complexes” needs to be addressed

For large and complex sites this is quite impractical & not feasible

- “Sections” have different time to steady-state. What is the steady state of “single” RTO?
- Plant scheduling/logistics
- The “equipment” reliability varies from complex to complex
- Effect of inventory tanks,
- Many other reasons (i.e. model maintenance)

Solution: Make it distributed, independent, but coordinated.
Plant Wide Economic RTO: i-RTO Integration Approaches

- **Simplest form – “Leader Follower”**
  - “Leader” RTO feeds into “Follower” RTO
  - “Follower” RTO performs its optimization taking into account info from “Leader”
  - Downside – “Leader” has no way to receive feedback on limits and constraints from “Follower” RTO.

- **Two-Way Feed forward-feedback communications**
  - Upstream RTO passes intermediate stream volumes and compositions to downstream RTO
  - Downstream RTO optimizes using this info and passes back “Coordination” variables’ shadow values to upstream RTO
  - When upstream RTO optimizes, it uses Shadow values from downstream RTO to price its products

- **More accurate methodologies developed if downstream constraints and prices dominate the upstream solutions**
  - Upstream RTO passes knowledge of volumes/compositions but also knowledge of its constraint set and how downstream moves affect it

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Distributed, independent, but coordinated
Example of “Coordination” Variables:
Quality-Barrel Shadow Value Additions

- **“Downstream” RTO modifications**
  - A fixed term is added to the blending equation for each intermediate stream that will generate Shadow Values for the flow rate and quality-barrel effects
  - The Profit function is modified to include intermediate stream flows and Planner-supplied price as a feed stock debit

- **“Upstream” RTO modifications**
  - Intermediate stream price calculations are added to modify the Planner-supplied prices using Shadow Values for flow and quality-barrel
  - The Profit function is adapted to include the Shadow-Value modified Planner prices for each intermediate stream

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**“Downstream” Product Blending Equation:**

\[
\sum_{i=1}^{I} F(i) \cdot q(i,j) \cdot \phi(i,j) + \sum_{k=1}^{M} \left[F(k) \cdot q(k,j) + A q b(k,j)\right] \cdot \phi(k,j) = Q(j) \left[\sum_{i=1}^{N} F(i) \cdot \phi(i,j) + \sum_{k=1}^{M} F(k) \cdot \phi(k,j)\right]
\]

**“Downstream” RTO Profit Function:**

\[
\text{Profit} = \sum_{i=1}^{I} \left[ F_{p}(i) \cdot P_{p}(i) \right]_{\text{prod}} - \sum_{j=1}^{J} \left[ F_{j}(j) \cdot P_{j}(j) \right]_{\text{feeds}} - \sum_{m=1}^{M} \left[ F_{u}(m) \cdot P_{u}(m) \right]_{\text{unit}} - \sum_{k=1}^{K} [F_k] \cdot P_{Ref(k)}
\]

**“Upstream” RTO Intermediate Price Equation:**

\[
P_{p}(k) = P_{Ref(k)} + \Delta P_{SP}^{F}(k) + \sum_{j=1}^{J} \phi(k,j) \cdot \left[ q_1(k,j) - Q_{Ref(k,j)} \right] \cdot \Delta P_{SP}^{Q}(k,j)
\]

**“Upstream” RTO Profit Function:**

\[
\text{Profit} = \sum_{i=1}^{I} \left[ F_{p}(k) \cdot P_{p}(k) \right]_{\text{products}} - \sum_{j=1}^{J} \left[ F_{j}(j) \cdot P_{j}(j) \right]_{\text{feeds}} - \sum_{m=1}^{M} \left[ F_{u}(m) \cdot P_{u}(m) \right]_{\text{utilities}}
\]
Plant-Wide Dynamic Economic Optimization Challenge (2):

How to integrate MPC with RTO towards a dynamic economic optimization

The MPC-RTO “Synergizer” (algorithm) Technology (1),(2)


MPC-RTO Integration

The “Synergizer” Technology:

• A new technology developed to improve the RTO-MPC Implementation for Non-linear Economic Optimum away from the constraints (30-40% cases)

• The Synergizer implements the RTO economic strategy instead of just the “absolute” economic targets (ET)

Implement Economic (steady-state) Targets Only (ET)  
From RTO MPC to RTO MPC  
Implement Economic Strategy
Synergizer Technology Overview

Traditional Technology

- MPCs typically use LP and empirically determined cost coefficients to push the process against constraints.
- 10-30% RTO independents are typically unconstrained.
- RTO provides a **fixed set** of External (Economic) steady-state targets (ETs) as additional constraints to MPC LP to force MPC to implement RTO solution.

Synergizer Technology

- **Dynamic MPC cost coefficients** are based on RTO computed shadow values and MPC model (MPC frequency).
  - Surrogate variables used for active RTO constraints not represented in MPC.
- **Dynamic selection of ETs** based on the RTO determined economically optimal direction (MPC frequency).

US patent: 8,620,705 B2
Synergizer calculates MPC costs based on RTO shadow values

- MPC Costs are set to drive the LP to the same constraint set as the RTO

\[ c_i = -\lambda_i^{MV} - \sum_j K_{ij} \lambda_j^{CV} \]

- Shadow Value of Manipulated Variable (MV) \( \lambda_i^{MV} \)
- Shadow Value of Controlled Variable (CV) \( \lambda_j^{CV} \)
- MPC gain of Manipulated Variable \( i \) to Controlled Variable \( j \) \( K_{ij} \)
- Manipulated Variable cost \( c_i \)

- The costs depend solely on the MV & CV shadow values from RTO and the gains from the MPC
  - accuracy of MPC gains become more important in this approach (requires robust control)

- The LP costs change dynamically (at every MPC Run)
Use surrogates if variables are not in the scope of the MPC

- Some constrained variables in the RTO may be outside the scope of the underlying MPC

- Find a surrogate variable that is almost parallel to the constrained variable

\[
\cos \theta = \frac{a \cdot b}{\|a\| \|b\|}
\]

where \( a \) and \( b \) are vectors of gains of the constrained and surrogate variables

- \( \cos \theta = 1 \) or \( \cos \theta = -1 \) if the variables are very similar

- Check that the surrogate is sufficiently independent of the other constrained variables prior to accepting it
Use External Targets (ETs) to square up control problem

- ETs are selected dynamically (at each MPC run)
- Pre-populate a list of CVs that provide economic benefit if targeted, i.e. high priority optimal values which are typically not constrained
- Ultimately ETs are used to help the LP reach a consistent solution by squaring up the problem

N-dimensional LP requires N active constraints
Need as many active constraints as there are MVs
Plant-Wide Dynamic Economic Optimization Challenge (3):

How to extend applicability of linear MPC models over wider operating window
Adaptive MPC

The controller should be capable to perform satisfactory at different operating (optimum) regions/points defined by the Non-Linear Fundamental Compositional RTO

- Controller model is a linear approximation of truly nonlinear process at an operating point
- Identified model is fit-for-control in a small region around the operating point at the time of plant test

Current approaches are semi-automated:
- Automated Gain Scheduling
- Adaptive modeling concepts are used to calibrate the online model in a more frequent fashion compared to the past
New Business Opportunities & Novel Approaches
New Business Opportunities for Simple Cyclic / Semi-Continuous Processes – How to Achieve Dynamic Performance (Quality control and/or scheduling)

Empirical MPC vs Fundamental model based Non-linear Control (1)

- Examples: Polymer properties control during grade transition

- Polymers Grade Transitions → Reduce lower margin/waste material produced during in-grade and grade transitions modes of operation

Optimization of Cyclic Processes

- Examples: Heat Exchange fouling/cleaning, Reactor catalyst deactivation/reactivation

Examples
• Coker (1)
• Lubes (i.e. Extraction)
• Other (i.e. batch blending)

A Non-steady-state (cyclic) Process
Dynamic Economic Optimization

Semi-batch Reactor system (drum switch from A to B)

Event Detection vs Steady-State detection “concepts”

Integration with New Technologies (i.e. Big Data & analytics) Opens the Window of Benefits

**Virtual Organizational Support**

- New Sensors
- Soft Sensors
  - Big data - Analytics

**Equipment/Abnormal Events Technologies**

- Online Analyzers
- Inferential Models (data analytics & Adv. Kalman Filters)

**RTOs & MPCs**

**Continuous Step-Change in Economic Performance**

New Larger Economic Optimization Windows During non-typical operations

**Dynamic Optimization Operating Window**

Controlling & Optimizing During Abnormal Situations (i.e. < 50% capacity)

- Big Data Analytics
- Self Learning Machines

*ExxonMobil*
Questions?

Energy lives here
Creating Opportunities to Conceptualize Problems in New Ways and Maximize Value of Assets

Asset Performance Improvement Through Automation & Optimization Technology Evolution

Global Integration
Integration of IT & OT

1990
ExxonMobil

2000
2010

Enterprise-Scale
- Integrated Real Time Optimization Systems
- Dynamic Economic Control
- Multi-period / Multi-plant Optimization
- Data Analytics - Advanced Forecasting
- Big Data - Self-learning Machines; Advanced Operator Tools
- Large-Scale Database – Data Visualization
- Virtual Teams

Integrated
- Composition-Specific Apps / RTO
- Multivariable Predictive Control (MPC)
- Abnormal Event Monitoring / Prediction
- Automated Data Interpretation
- Plant Data Analysis

Local
- Planning / Scheduling
- Basic / Constraint Control
- Equipment Advisory Systems
- Plant Data Historians

Creating Opportunities to Conceptualize Problems in New Ways and Maximize Value of Assets

Asset Performance Improvement Through Automation & Optimization Technology Evolution