The 5th IFAC Workshop on Mining, Mineral and Metal Processing

Complex chemical process optimization and its industrial applications

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Content

Introduction

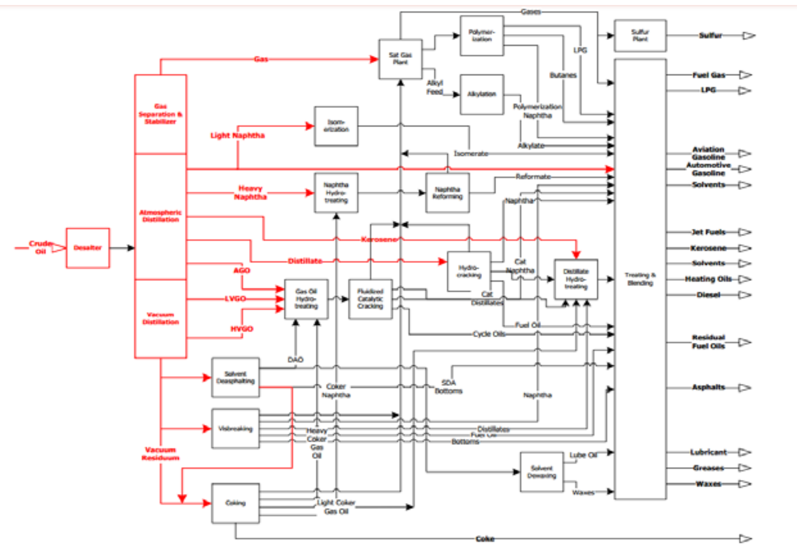
Complexity of chemical process and product

- Interconnected, interactive multiscale structure (complexity in structure)
- Diverse performance or property (complexity in behavior)
- System behavior cannot be deduced directly from analyzing the behavior of individual components

Approaches to complex chemical process system

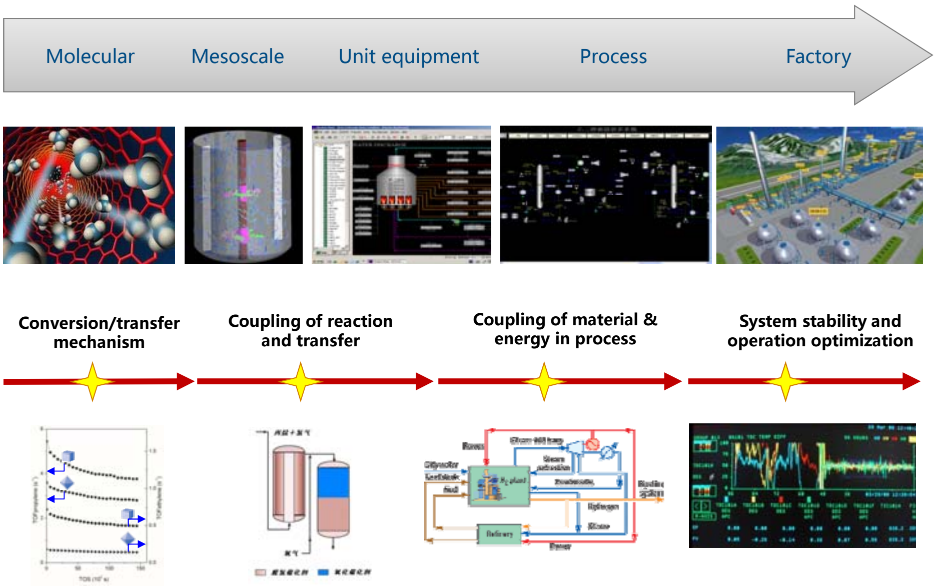
- Creating proper degree of complexity, avoiding unnecessary or "redundant" complexity
- Concentrating on dominant level(s), ignoring undesired details

Introduction



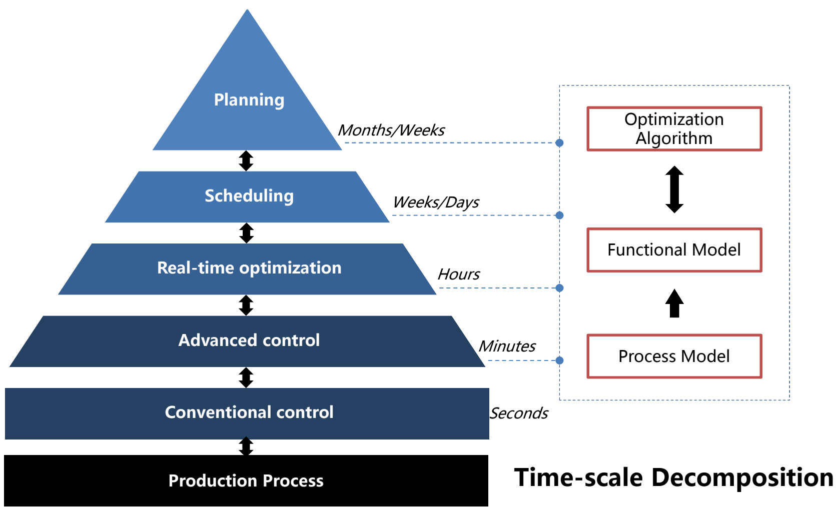
Flowsheet of Refinery Plant

Introduction



Introduction

Automation Hierarchy



Introduction

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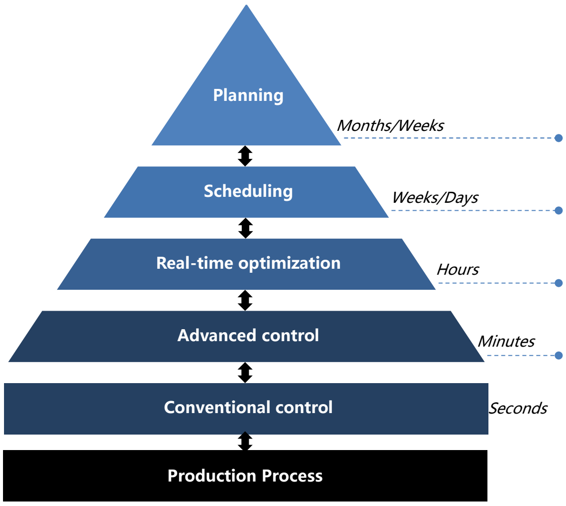
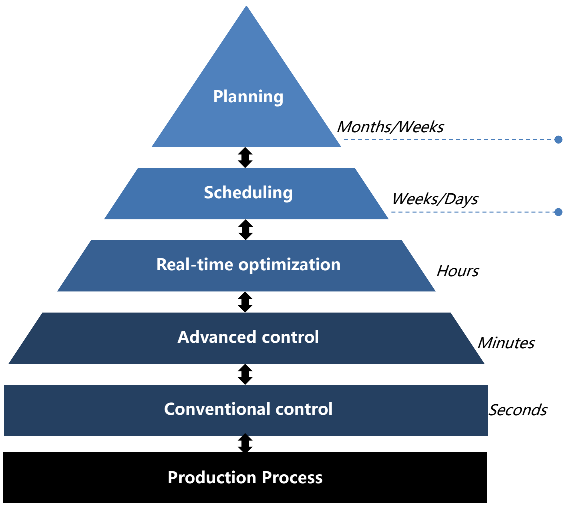


Commercial Software

- **PIMS/RPMS**
- **Aspen ORION**
- **Profit Optimizer**
- **DMC/RMPCT**

Introduction

Automation Hierarchy

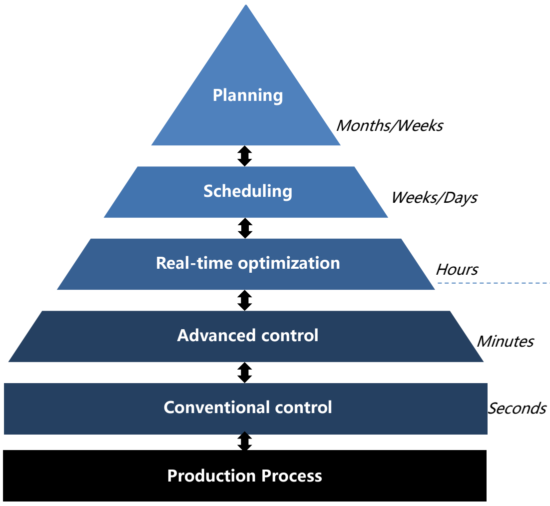


PIMS/ORION
- What products to make
- When to make them
- What equipment to use

Raw Material Acquisition / Run Plan Optimization/Scheduling scheme
- Plant-wide optimization
- Based on simplified models, considering balance of material and tanks
- Linear Programing is used

Introduction

Automation Hierarchy



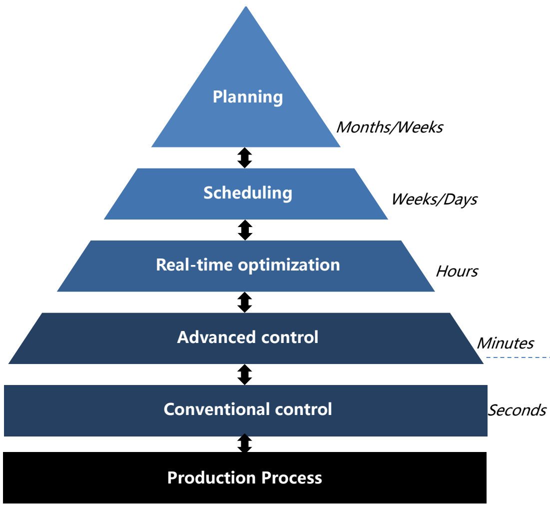
Current - Real Time - Operations Optimization

- Unit-scale optimization
- Based on rigorous models, considering balance of material and tanks
- Maximizing profits, considering current states, production constraints and constraints from scheduler - hours

Profit Optimizer/GAMS

Introduction

Automation Hierarchy



Advanced Control Systems

- Unit-scale control
- Based on identified linear dynamic model
- Multi-variable, constrained control
- Predefined constraints with different priorities

RMPCT/DMC

Introduction

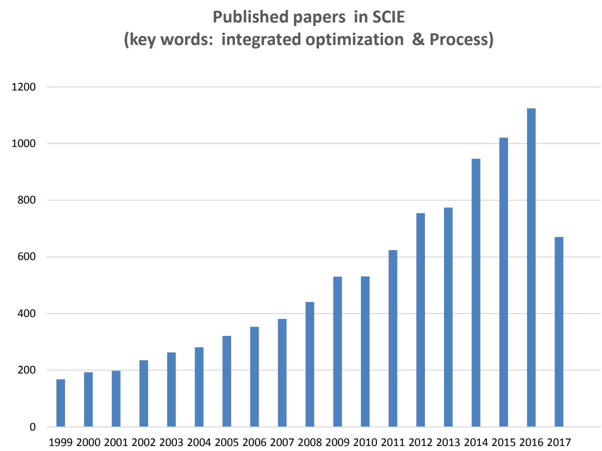
Complexity of Chemical Process ⟶ / ⇠ ? Hierarchical Automation Structure

Problems in practical application:

- Process design: how to integrated the factors as safety, controllability and flexibility? e.g. Energy coupled process integration VS inadequate freedom
- Process optimization: open loop, model mismatch with MPC etc. ...
- Process scheduling: only for material balance, lack optimization
- Process Planning: fixed DB parameters, hard to match actual situation

Introduction

Growing trend for integrated optimization



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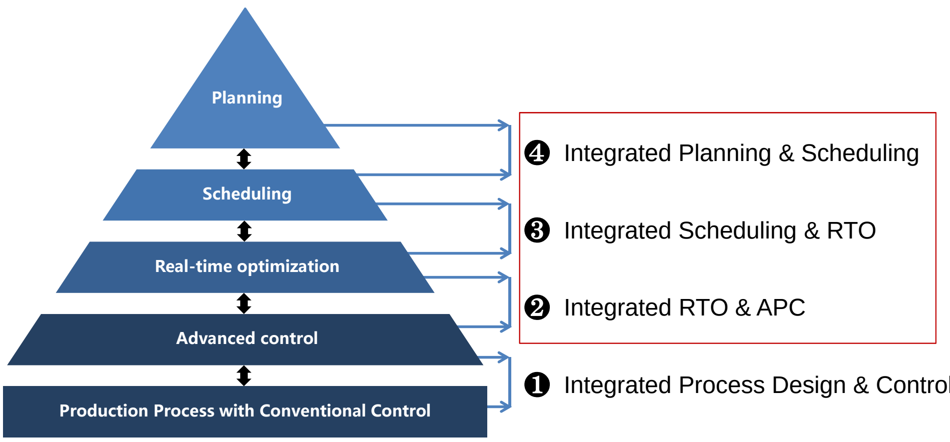
Integrated Optimization of Process Automation

Integrated Optimization of Process Automation



Integrated Optimization of Process Automation

- Integration of RTO and MPC in Styrene Plant
- Dynamic Scheduling and Optimization in Olefin Plant
- Integration of Planning and Scheduling in Gasoline Blending

Integration of RTO & APC

Major Problem

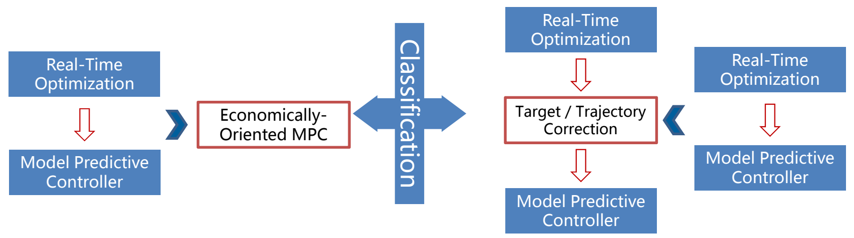
- Different execution frequencies
- Different models

→

- Conflicts in decisions
- Infeasible for MPC
- Non-optimal conditions

One-layered Approach

Two-layered Approach



Lynn Würth, Ralf Hannemann, Wolfgang Marquardt . A two-layer architecture for economically optimal process control and operation. Journal of Process Control. 2011, 21(3): 311-321

Integration of RTO & APC

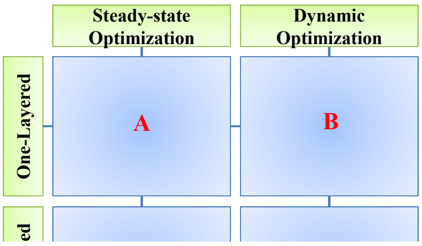
Methodologies

A: LEMPC

Integrate nonlinear steady-state optimization into linear MPC.

- Economic functions added as additional term of the controller
- Nonlinear steady- state model included as additional constraints

(Zanin, 2002), (Glauce, 2010), (Teodoro, 2014)



B:NEMPC

Incorporate a general cost function or performance index in NMPC, EMPC

- Used for feedback control directly
- Respond to changes in the operating conditions faster

(Ellis, 2014), (Tran, 2014), (Biegler, 2015)

C:

Insert Steady-State Target Optimization(SSTO) layer between RTO and MPC

- Calculate best admissible target for the MPC using SSTO
- SSTO predicts based on steady-state version of linear model in MPC

(Rao, 1999), (Marchetti, 2014)

$$\min_{u(k+i|k);i=0,\dots,m-1} \sum_{j=1}^{p} \left\| W_1(y(k+j|k)-r) \right\|_2^2$$

A

$$+\sum_{j=0}^{m-1} \left\| W_2 \Delta u(k+j|k) \right\|_2^2 + W_3 f_{eco}\left(u(k+m|k), y(k+\infty|k)\right)$$

C、D

$$\min_{\Delta z} \frac{1}{2}\Delta z^{\mathrm{T}} \frac{\partial L^2}{\partial z}\Delta z + \Delta p^{\mathrm{T}} \frac{\partial L^2}{\partial z \partial p}(p_0)\Delta z + \frac{\partial \varphi}{\partial z}(p_0)\Delta z$$

B

$$s.t.\ g(p_0) + \frac{\partial g}{\partial z}(p_0)\Delta z + \frac{\partial g}{\partial p}(p_0)\Delta p \geq 0$$

NLP Sensitivity (QP)

D:

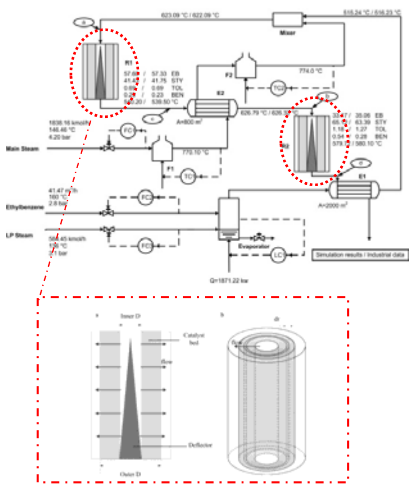
Integrate Dynamic Real-Time Optimization (D-RTO) and Model Predictive Control (MPC)

- Re-optimization trigger strategy
- Fast updates of the trajectories based on NLP sensitivities

(Kadam, 2003), (Wolf, 2014)

Integration of RTO & APC

Ethylbenzene dehydrogenation process



Objective & Challenges

$$\min_{\mathbf{u}^*,\mathbf{y}^*} -(p_1 \times y_3 - ((p_2 + 0.02 \times (u_3 - T_{ref1}) + 0.02 \times (u_4 - T_{ref2})) \times u_1 + p_2 \times u_2)/1000 - \rho \times d_{eb})$$

$$s.t.\quad \mathbf{y} = \mathbf{S}(\mathbf{u}, \boldsymbol{\theta})$$

$$y_1 + \varepsilon_1 \leq T_{\max}, y_2 + \varepsilon_2 \leq T_{\max}, y_3 + \varepsilon_3 \leq F_{\max}$$

$$1.3 \leq (u_1 + u_2)/(\rho \times d_{eb}) \leq 1.8$$

Process description

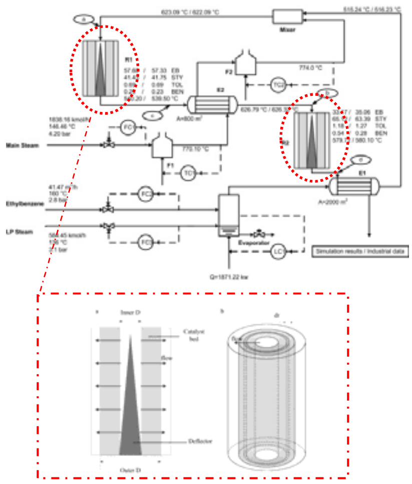
- Radial-flow reactor with strong endothermic reversible reaction
- Reaction Temperature
  - Low Temp.→ Low yields; High Temp. → thermal cracking
- Ratio of steam to ethylbenzene
  - Low Ratio: carbon decomposition; High R.→ energy waste

Control difficulties

- Plant-model mismatch
- dynamic change of Constraints related to catalyst deactivation
- Various and frequent disturbances

Integration of RTO & APC

Ethylbenzene dehydrogenation process



Objective & Challenges

$$\min_{\mathbf{u}^*,\mathbf{y}^*} \ -(p_1 \times y_3 - ((p_2 + 0.02\times(u_3 - T_{ref1}) + 0.02\times(u_4 - T_{ref2}))\times u_1 + p_2 \times u_2)/1000 - \rho \times d_{eb})$$

$$s.t. \quad \mathbf{y} = \mathbf{S}(\mathbf{u}, \boldsymbol{\theta})$$

$$y_1 + \varepsilon_1 \le T_{\max}, y_2 + \varepsilon_2 \le T_{\max}, y_3 + \varepsilon_3 \le F_{\max}$$

$$1.3 \le (u_1 + u_2)/(\rho \times d_{eb}) \le 1.8$$

Process description

- Radial-flow reactor with strong endothermic reversible reaction
- Reaction Temperature
  - L: low yields; H: thermal cracking
- ratio of steam to ethylbenzene
  - L: carbon decomposition; H: energy waste

MPC & RTO:

MV(4):
- u_1: flowrate of main steam FC1
- u_2: flowrate of LP steam FC3
- u_3: temperature of furnace 1 TC1
- u_4: temperature of furnace 2 TC2

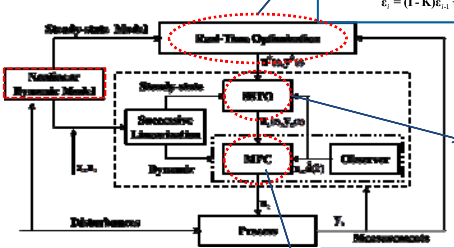
CV(3):
- y1: inlet temperature of R1
- y2: inlet temperature of R2
- y3: outlet flowrate of styrene

Fat system

Integration of RTO & APC

Integration Structure

Motivation:
- Same model origination
- Model adaptation on a lower level (MPC-NSL)



RTO Layer

- Constraint-adaptation strategy

$$\min_{\mathbf{u}^*,\mathbf{y}^*} \ \Phi(\mathbf{u}, \mathbf{y})$$
$$s.t.$$
$$\mathbf{y} = \mathbf{S}(\mathbf{u}, \boldsymbol{\theta})$$
$$\mathbf{y}^L \le \mathbf{y} + \boldsymbol{\varepsilon} \le \mathbf{y}^U$$
$$\mathbf{u}^L \le \mathbf{u} \le \mathbf{u}^U$$
$$\boldsymbol{\varepsilon}_i = (\mathbf{I} - \mathbf{K})\boldsymbol{\varepsilon}_{i-1} + \mathbf{K}(\mathbf{y}_p^i - \mathbf{y}^i)$$

Constraint -adaptation strategy
- Easy for model update
- Better for handling the plant-model mismatch

SSTO Layer

- Approximation of RTO

$$\min_{\mathbf{u}_s,\mathbf{y}_s} \ \frac{\partial \Phi}{\partial \mathbf{u}}(\mathbf{u}_s - \mathbf{u}^*) + \frac{1}{2}\left\|\mathbf{u}_s - \mathbf{u}^*\right\|_{\mathbf{H}}^2$$
$$\text{s.t}$$
$$\mathbf{y}_s = \mathbf{G}_k \mathbf{u}_s + \mathbf{y}_0(k) + \mathbf{d}(k)$$
$$\mathbf{y}^L \le \mathbf{y}_s \le \mathbf{y}^U$$
$$\mathbf{u}^L \le \mathbf{u}_s \le \mathbf{u}^U$$

SSTO (Steady State Target Optimization)
- Approximate RTO
- Based on steady-state version of linear dynamic model

MPC Layer

- MPC with nonlinear successive linearization

$$\mathbf{A}_k^c = \frac{\partial \mathbf{f}}{\partial \mathbf{x}}(\mathbf{x}_k, \mathbf{u}_k, \boldsymbol{\theta}) \quad \mathbf{B}_k^c = \frac{\partial \mathbf{f}}{\partial \mathbf{u}}(\mathbf{x}_k, \mathbf{u}_k, \boldsymbol{\theta})$$
$$\mathbf{C}_k^c = \frac{\partial \mathbf{h}}{\partial \mathbf{x}}(\mathbf{x}_k, \mathbf{u}_k, \boldsymbol{\theta}) \quad \mathbf{D}_k^c = \frac{\partial \mathbf{h}}{\partial \mathbf{u}}(\mathbf{x}_k, \mathbf{u}_k, \boldsymbol{\theta})$$

MPC-NSL
- An approximation/simplification of nonlinear MPC
- Low computational burdens

Integration of RTO & APC

Nonlinear dynamic model

Reaction mechanism

- Highly endothermic reaction

Reaction	Rate
$C_6H_5CH_2CH_3 \leftrightarrow C_6H_5CHCH_2 + H_2$	$R_1 = k_1(P_{EB} - P_{STY}P_{H2}/K_{EB})$
$C_6H_5CH_2CH_3 \rightarrow C_6H_6 + C_2H_4$	$R_2 = k_2(P_{EB})$
$C_6H_5CH_2CH_3 + H_2 \rightarrow C_6H_5CH_3 + CH_4$	$R_3 = k_3(P_{EB}P_{H2})$
$2H_2O + C_2H_4 \rightarrow 2CO + 4H_2$	$R_4 = k_4(P_{H2O}P_{ETH}^{0.5})$
$H_2O + CH_4 \rightarrow CO + 3H_2$	$R_5 = k_5(P_{H2O}P_{MET})$
$H_2O + CO \rightarrow CO_2 + H_2$	$R_6 = k_6(P_{H2O}P_{CO})P/T^3$

»

Reactor model

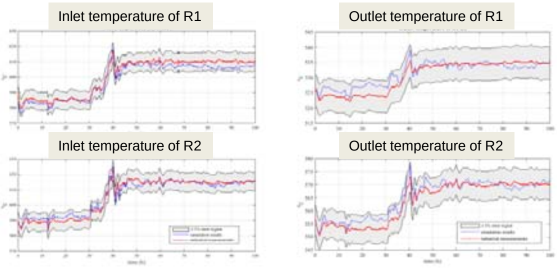
- Radial-flow reactor

$$\varepsilon c_t \frac{\partial y_i}{\partial t} = -\frac{F_t}{A_r}\frac{\partial y_i}{\partial r} + R^i \rho_B$$

$$\bar{c}\frac{\partial T}{\partial t} = -\frac{F_t}{A_r} c_{pt} \frac{\partial T}{\partial r} + \rho_B \sum_{j=1}^{N} R_j(-\Delta H_j)$$

$$\frac{dP}{dr} = -1\times10^5 \frac{(1-\varepsilon)G}{d_p \varepsilon^3 \rho_g}\left[\frac{150(1-\varepsilon)\mu}{d_p} + 1.75G\right]$$

Model validation

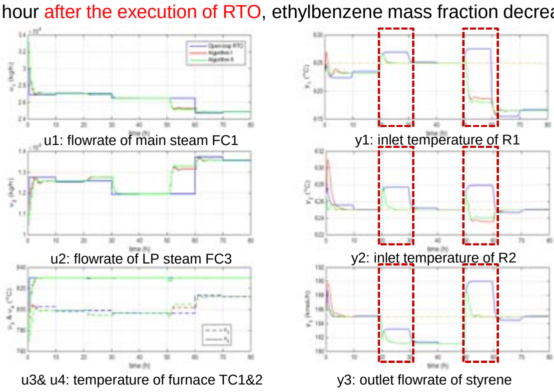


Integration of RTO & APC

Implementation

Disturbances:

- flowrate of ethylbenzene stream
  20th hour after the execution of RTO, decreases by 3%
- composition of ethylbenzene stream
  50th hour after the execution of RTO, ethylbenzene mass fraction decreases by 5%



- Open-loop RTO
- Algorithm I
- Algorithm II: our study

Improved
1) Control performance
2) RTO convergence

Algorithm I: Steady-state target optimization designs for integrating real-time optimization and model predictive control. Journal of Process Control, 2014, 24(1):129-145.

Algorithm II: Real-time optimization and control of an industrial ethylbenzene dehydrogenation process. Chemical Engineering Transaction. 2017 (61) 331-336

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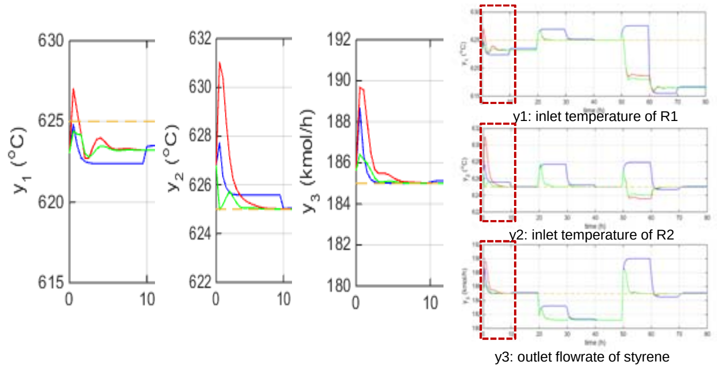

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Integrated Optimization of Process Automation

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Integration of Scheduling & Operation Optimization

Task of Scheduling :

- Keep process operation continuously (with reasonable level, inventory etc.), while need smooth transition among process units.
- Pursue the economic profit with less time or the cost

Problems :

- Simulation driven scheduling policy (NO optimization)
- Difficult to define a general problem or solved by general algorithm, especially for large scale process with uncertainties

Integration of Scheduling & Operation Optimization

Cracking furnaces system in ethylene plant

- Various feedstocks with different yields
  - NAP、LNAP、LPG、HVGO…
- Multiple cracking furnaces with different characteristics
- Thermal cracking reaction & coking inside coils

Goal:

Max. Yields of high added-value products

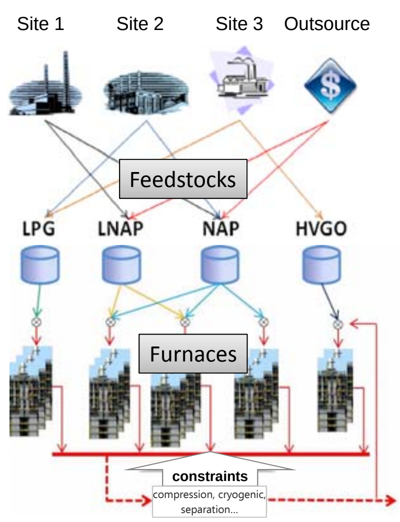
Max. Run-length of furnaces

By

Feedstock selection

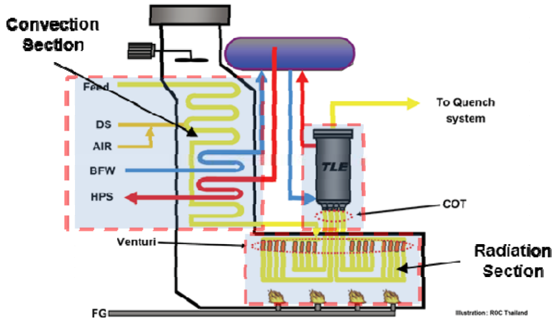
Load dispatching

Operating condition optimization



Integration of Scheduling & Operation Optimization

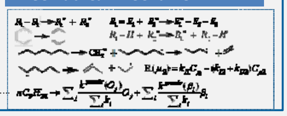
Reaction Kinetics / Reactor Model



Process Conditions

- Feedstock composition
- Reactor & Furnace
- Operating conditions

Free-radical mechanism



1-D reactor model

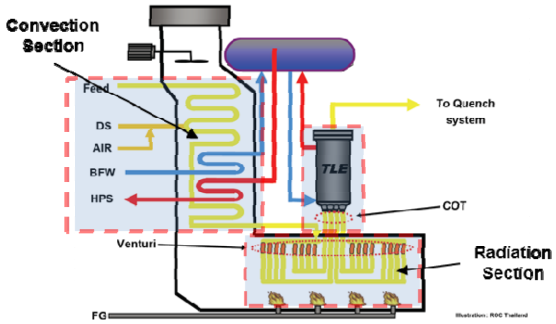
$$\frac{dF_i}{dz} = \left(\sum_{k=1}^{N} \upsilon_{ik} r_k\right)\Omega$$

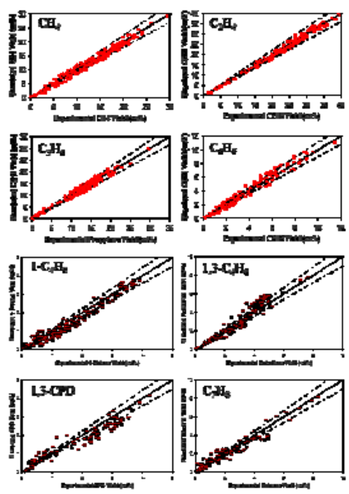
$$\sum_i F_i c_{pi} \frac{dT}{dz} = \omega\, q + \Omega \sum_k r_{v,k}(-\Delta_r H_k)$$

$$-\frac{dp_t}{dz} = \alpha\left(\frac{2f}{d_t} + \frac{\zeta}{\pi r_b}\right)\rho_g u^2 + \alpha\, \rho_g u \frac{du}{dz}$$

Integration of Scheduling & Operation Optimization

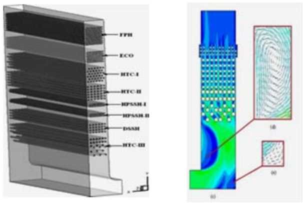
Reaction Kinetics / Reactor Model



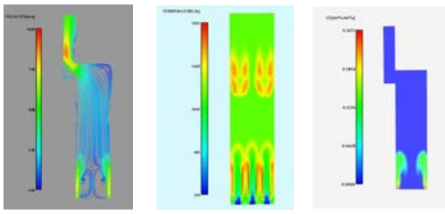


Integration of Scheduling & Operation Optimization

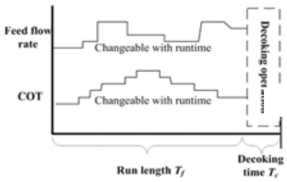
Thermal condition simulation in the furnace



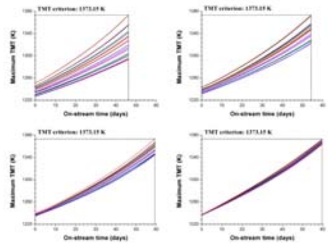
Convection section model



Radiant box model



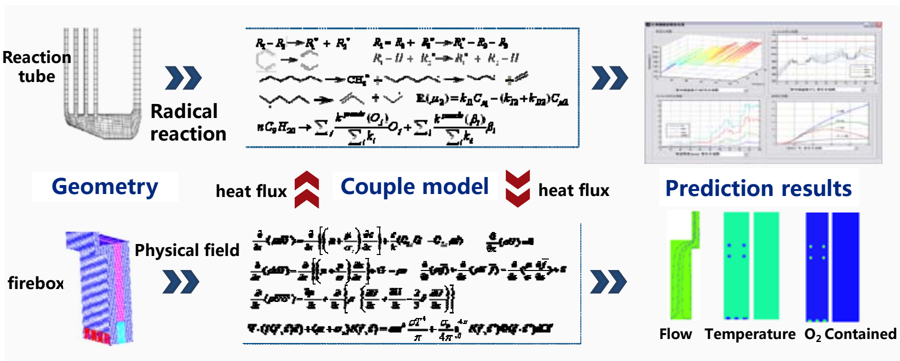
Run length Simulation



Chem. Eng. Sci., 2011, 66(8): 1600-1611; Ind. Eng. Chem. Res. 2013, 52(5): 645-657; AIChE J 2017, 63, (7), 3199-3213

Integration of Scheduling & Operation Optimization

Coupled modeling of furnace and reactor



Coupled simulation of convection section with dual stage steam feed mixing of an industrial ethylene cracking furnace. Chemical Engineering Journal. 2016, 286: 436-446
Impact of flue gas radiative properties and burner geometry in furnace simulations. AIChE Journal 2015, 61, (3), 936-954.
Numerical simulation on flow, combustion and heat transfer of ethylene cracking furnaces. Chemical Engineering Science, 2011, 66(8): 1600-161
Industrial & Engineering Chemistry Research. 2013, 52(2): 645-657 ……

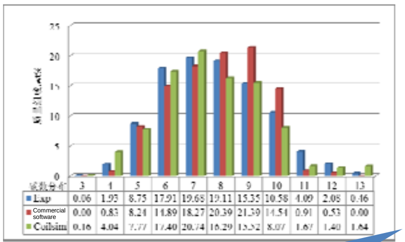
Integration of Scheduling & Operation Optimization

Coupled modeling of furnace and reactor

Sinopec Zhenhai Refining & Chemical Company

BA105 furnace (HCR), BA109 furnace (NAP)

Feedstock molecular reconstruction(NAP)

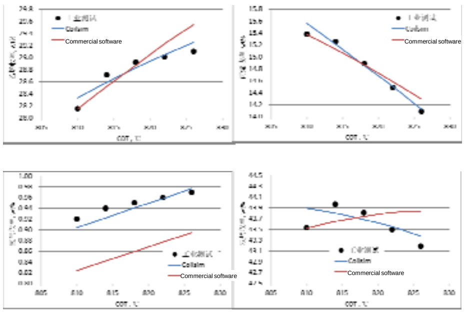


	3	4	5	6	7	8	9	10	11	12	13
Lap	0.06	1.93	8.75	17.91	19.68	19.11	15.35	10.58	4.09	2.08	0.46
Commercial software	0.00	0.83	8.24	14.89	18.27	20.39	21.39	14.54	0.91	0.53	0.00
Coilsim	0.16	4.04	7.77	17.40	20.74	16.29	15.52	8.07	1.67	1.40	1.64

Full composition analysis of industrial data

(Analyzed by Beijing Research Institute of Chemical Industries)

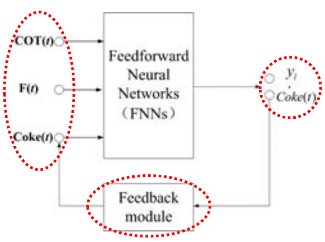
Yields of C_2H_4, H_2, C_3H_6, benzene etc. products (NAP)



Integration of Scheduling & Operation Optimization

Surrogate model of cracking furnace

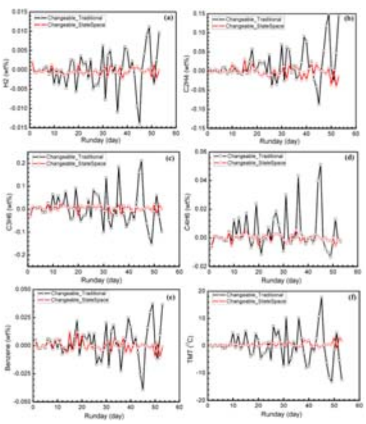
Prediction of change rate of coke thickness



Feedforward Neural Networks– State Space Model(FNN-SSM)

$$
\begin{cases}
\dot{x}_{\mathrm{coke}}(t) = f_{\mathrm{ANN}}(coke(t), COT(t), F(t)) \\
y_i(t) = g_{\mathrm{ANN},i}(coke(t), COT(t), F(t)) \\
x_{\mathrm{coke}}(t+1) = x_{\mathrm{coke}}(t) + \dot{x}_{\mathrm{coke}}(t) \cdot T_s(t) \\
x_{\mathrm{coke}}(1) = x_{\mathrm{coke,ini}}
\end{cases}
$$

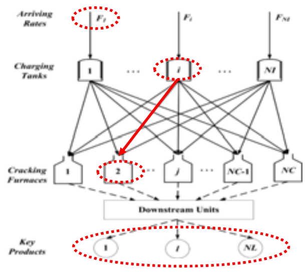
Prediction of product yield and KPI



Comparison with traditional surrogate model

Integration of Scheduling & Operation Optimization

Integration of cyclic scheduling & operation optimization



$$\max obj^{M} = \frac{\sum_{ij}\left\{n_{ij}\cdot\left[\sum_{l}\left(\int_0^{t_{ij}} u_{F\,ij}(t)\cdot y_{ijl}(t)\cdot P_l dt\right) - Cs_{ij}\right]\right\}}{H} - \delta\cdot\sum_i SV_i^2$$

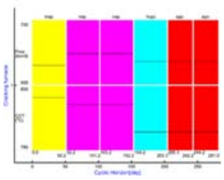
$$\begin{cases} \dot{x}_{\text{coke}\,ij}(t) = f_{ij}(x_{\text{coke}\,ij}(t), u_{\text{COT}\,ij}(t), u_{F\,ij}(t)) \\ y_{ijl}(t) = g_{ijl}(x_{\text{coke}\,ij}(t), u_{\text{COT}\,ij}(t), u_{F\,ij}(t)) \end{cases}$$

- OCFE is used for discretization on time
- MIDO is transformed into MINLP solved by sBB
- Decision variables of scheduling and operation are determined simultaneously

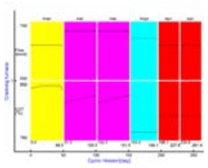
$$T_{ij} = n_{ij}\cdot(\tau_{ij}+t_{ij})\ \ \forall i,j \quad \sum_i T_{ij} \le H\ \ \forall j$$

$$H \ge 0,\ \ t_{ij}\ge 0,\ \ T_{ij}\ge 0,\ \ \varepsilon \le n_{ij} \le NK,\ \ \forall i,j,\ \ w_{ijk}\in\{0,1\}\ \ \forall i,j,k.$$

a



b



a. Traditional cyclic scheduling

b. Cyclic scheduling with operation optimization

Day mean profit increases by 13.5%

Industrial & Engineering Chemistry Research, 2015, 54 (15), 3844-3854 ; *Chemical Engineering & Technology*, 2015, 38 (5), 900-906;
Chinese Journal of Chemical Engineering. 2013 21(5): 537-543 *Knowledge-Based Systems.* 2016, 96(C):156-170

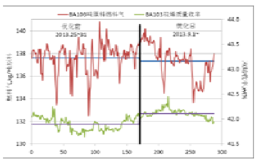
Integration of Scheduling & Operation Optimization

Implementation results

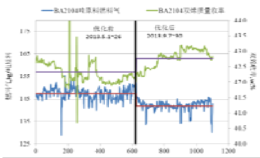
Applied in Shanghai Petrochemical :

- Average yield of ethylene and propylene increased by 0.187% ;
- Fuel consumption reduced by 1.806kg/t(feedstock), i.e. 1.64% under same feedstock load.

Sinopec Shanghai Petrochemical Company Limited



Comparison of yields and fuel gas consumption of BA103 before and after optimization



Comparison of yields and fuel gas consumption of BA2104 before and after optimization

Integrated Optimization of Process Automation

- Integration of RTO and MPC in Styrene Plant
- Dynamic Scheduling and Optimization in Olefin Plant
- Integration of Planning and Scheduling in Gasoline Blending

Integration of Planning & Scheduling

Production Planning ⇄ **Scheduling**

Model mismatch with plant
(e.g. feedstock properties fluctuation, device capabilities ...)

Solved by human experience

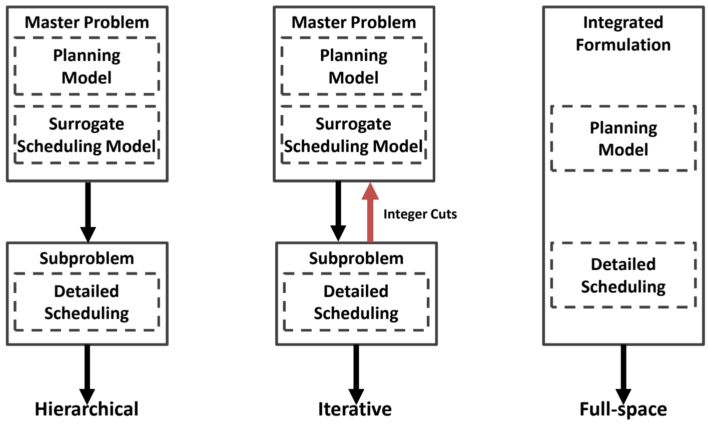
Similar model
Similar optimizer

Production Planning ⇄ **Scheduling** **?**

Short-term Planning
Difficult to get the statistics of the current inventory、product ..., difficult to respond to temporary order

Temporal aggregation model

Integration of Planning & Scheduling

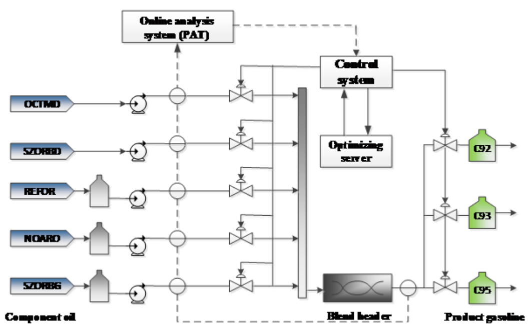


Hierarchical	Iterative	Full-space
McKay, 1995 Lin et al., 2002 Menezes et al., 2016 Vogel et al., 2017	Papageorgiou and Pantelides, 1996 Stefansson and Shah, 2006 Wu and Ierapetritou, 2007	Joly et al., 2002 Neiro and Pinto, 2005 Blanco et al. 2005 Yan and Zhang, 2007

Maravelias C T, Sung C. Integration of production planning and scheduling: Overview, challenges and opportunities[J]. Computers & Chemical Engineering, 2009,

Integration of Planning & Scheduling

Online gasoline blending process



Target

- Demand driven optimal recipe & blending conditions

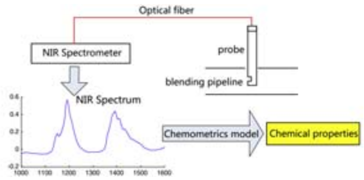
Difficulties

- Online measurement of oil properties
- Blending rules or recipe models
- Functional models for Planning and Scheduling optimization

Integration of Planning & Scheduling

Online measurement of oil properties

Wavelength selection is the basis of NIR system. It is directly related to prediction performance and model complexity.

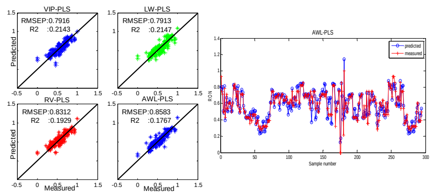


Response to change of operating conditions

- Intermediate component type
- Intermediate component property
- Oil additives

Proposed framework (AWL-PLS)

1. Sample database and data pre-processing
2. Model parameters initialization
3. Selection of local sample sets from database
4. Wavelength structure update of calibration set
5. Local calibration model and property prediction



Model	Rs^2	RMSEP
VIP-PLS	0.7916	0.2143
RV-PLS	0.8312	0.1929
LW-PLS	0.7913	0.2147
AWL-PLS	0.8583	0.1767

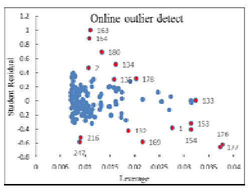
Integration of Planning & Scheduling

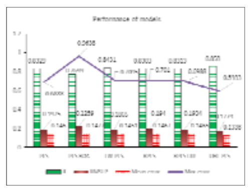
NIR spectral analysis and modeling

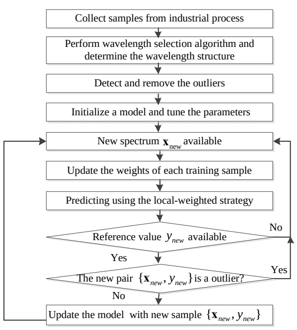
Adaptive algorithm and outlier detection are two key factors for adaptive modeling

Adaptive strategies for online model update (ORL-PLS)

- Outlier detection
- Locally weighted learning
- Improved recursive strategy





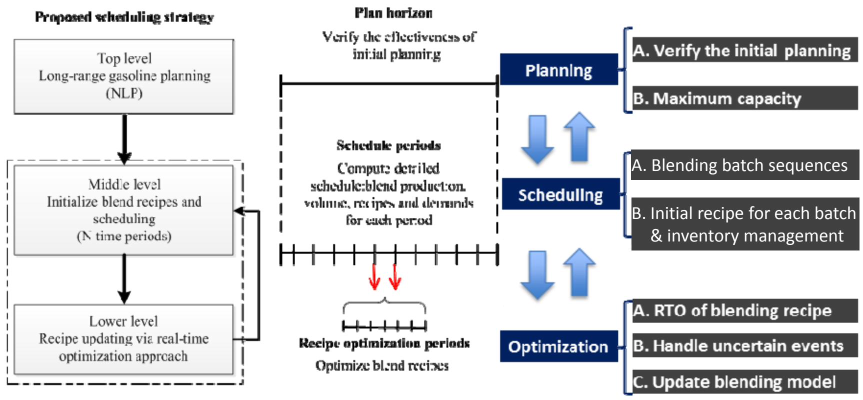


Model	Rs^2	RMSEP	Mean-error	Max-error
PLS	0.8329	0.1925	0.1460	0.6888
PLS-Bias	0.7699	0.2259	0.1477	0.9638
LW-PLS	0.8431	0.1865	0.1451	0.7095
RPLS	0.8303	0.1940	0.1467	0.7010
RPLS-OD	0.8313	0.1934	0.1465	0.6988
ORL-PLS	0.8580	0.1774	0.1338	0.5933

Integration of Planning & Scheduling

Integrated planning and blend recipes optimization

Three-level optimization structure

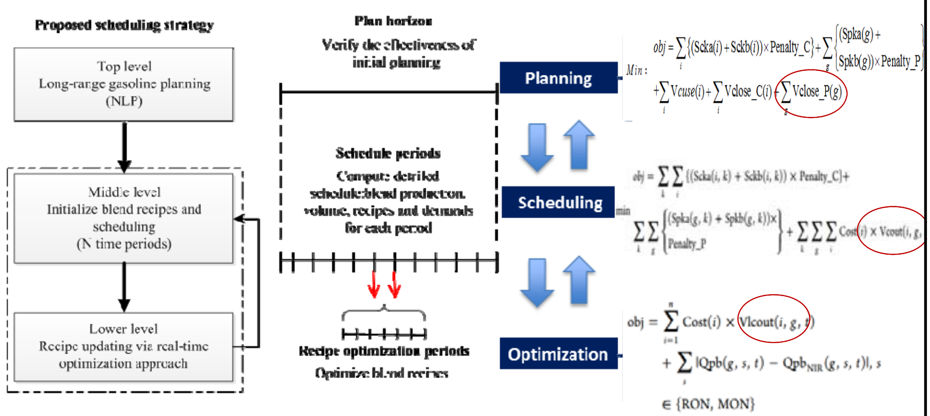


Ind. Eng. Chem. Res, 2016, 55 (16), 4632-4645

Integration of Planning & Scheduling

Integrated planning and blend recipes optimization

Three-level optimization structure



Ind. Eng. Chem. Res, 2016, 55 (16), 4632-4645

Integration of Planning & Scheduling

Integrated planning and blend recipes optimization

The necessity for integration

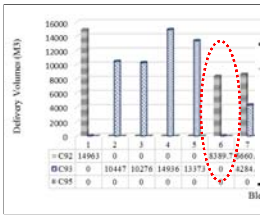
Blend recipe calculated **by scheduling level**

Period	1	2	3	4	5	6	7	
SZORBD	0.152	0.443	0.444	0.445	0.48	0.444	0.14	
OCTMD	9.76E-04	0.364	0.184	0.349	0.375	0.139	0.694	
REFOR	0.349	0.152	0.195	0.157	0.006	0.213	4.34E-04	
NOARO	0.444	0.017	0.175	0.025	0.009	0.2	0.035	
SZORBG	0.053	0.023	0.002	0.024	0.13	0.004	0.13	
Period	8	9	10	11	12	13	14	15
SZORBD	0.444	0.441	0.444	0.223	0.444	0.403	0.44	0.44
OCTMD	0.152	0.363	0.049	0.606	0.147	0.459	0.175	0.173
REFOR	0.208	0.068	0.258	0.04	0.212	0.001	0.199	0.201
NOARO	0.192	0.004	0.248	0.001	0.195	0.008	0.183	0.184
SZORBG	0.003	0.123	0.002	0.13	0.002	0.128	0.003	0.003

blend recipes by **Real-time optimization**

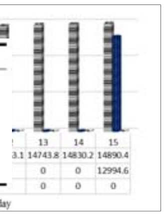
	1	2	3	4	5	6	7	
SZORBD	0.449	0.446	0.45	0.448	0.45	0.449	0.416	
OCTMD	0.276	0.275	0.277	0.276	0.277	0.277	0.358	
REFOR	0.126	0.169	0.124	0.127	0.167	0.167	0.109	
NOARO	0.108	0.068	0.108	0.108	0.065	0.066	0.017	
SZORBG	0.041	0.041	0.041	0.041	0.041	0.041	0.1	
	8	9	10	11	12	13	14	15
SZORBD	0.443	0.456	0.448	0.401	0.45	0.449	0.448	0.448
OCTMD	0.289	0.301	0.276	0.378	0.277	0.277	0.276	0.276
REFOR	0.13	0.119	0.169	0.107	0.124	0.125	0.128	0.127
NOARO	0.038	0.024	0.065	0.015	0.108	0.108	0.107	0.108
SZORBG	0.099	0.1	0.041	0.099	0.041	0.041	0.041	0.041

Response to temporary delivery



Optimized recipe for the temporary delivery

	Recipe	Volumes (M3)
SZORBD	0.324	3404.386
OCTMD	0.381	4000
REFOR	0.145	1518.545
NOARO	0.085	889.946
SZORBG	0.065	687.123

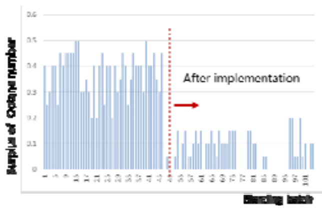


Integration of Planning & Scheduling

Integrated planning and blend recipes optimization

Implementation Results：

- Jinling Pec. (3.6Mt/a Gasoline product) in Nanjing City as validation
  - The cost of the blending is reduced by 95M￥/a;
  - The blending period is reduced by 6-8hour/tank;
  - VOC emission is reduced by 3000t/a;
  - The quality giveaway (Octane Number) is decreased from 0.5 to 0.2。



overquality of octane number reduced

Summary and considerations

Summary

- Traditional hierarchical automation structure
- Cases for integrated optimization method
  - Styrene Plant : RTO & MPC
  - Olefin Plant : Scheduling & RTO
  - Gasoline blending : Planning & Scheduling+RTO

Considerations

Hierarchical solution strategy seems to be currently the only realistic approach to tackle industrial size problems, but needs appropriate cooperative solution.

Embedded AI

»» … »»»

Embedded CI

CPS(Cyber Physical System): ubiquitous perception, interconnection
CAPS(Collaborative Process Automation Systems) : infrastructure, interaction with user/human operator, …
……

Thanks for your attention