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THE STATE UNIVERSITY OF NEW JERSEY

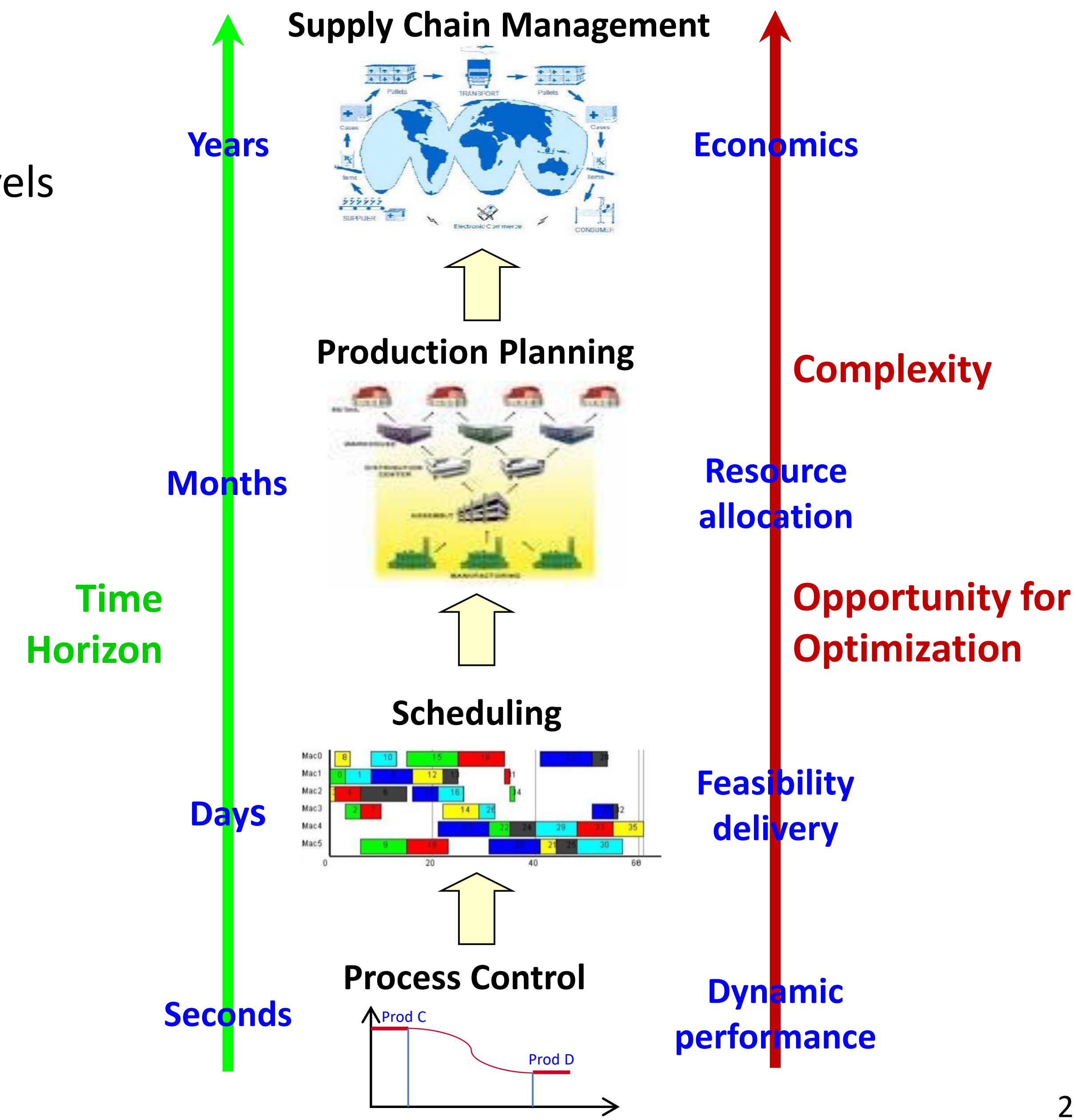
Decision Making Across Different Scales: From Process Control to Supply Chain Management

Marianthi Ierapetritou
Nihar Sahay and Lisia Dias

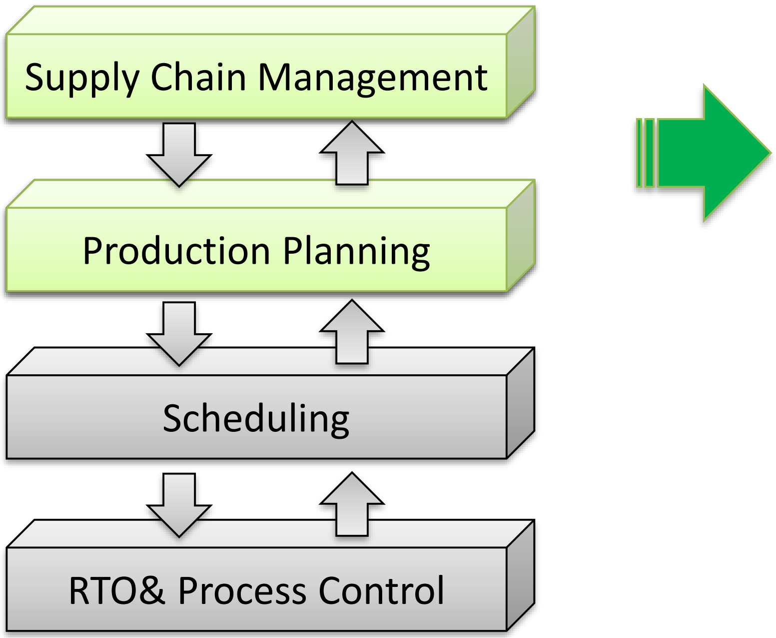
Decision Making Process

Objective

- Identify and reduce bottlenecks at different levels
- Integration of the whole decision-making process



Integrated Decision Making



Determine best supply chain network, production and distribution targets

Integrated decisions making

- Ensure accuracy and consistency across decision processes
- Aim to obtain feasible and optimal solution for overall supply and production network

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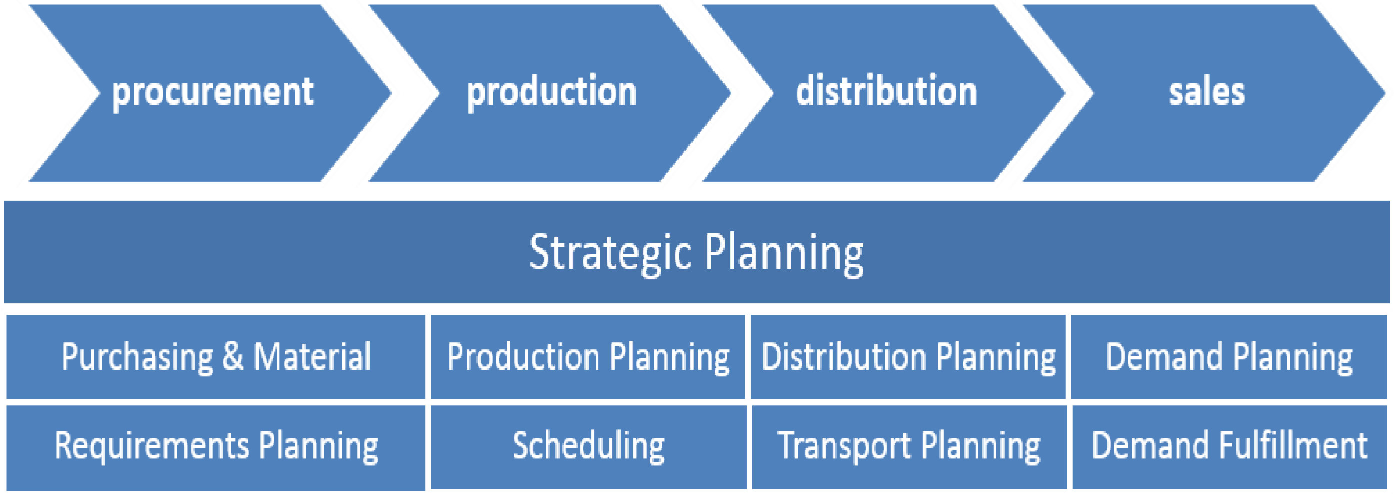
Production Planning

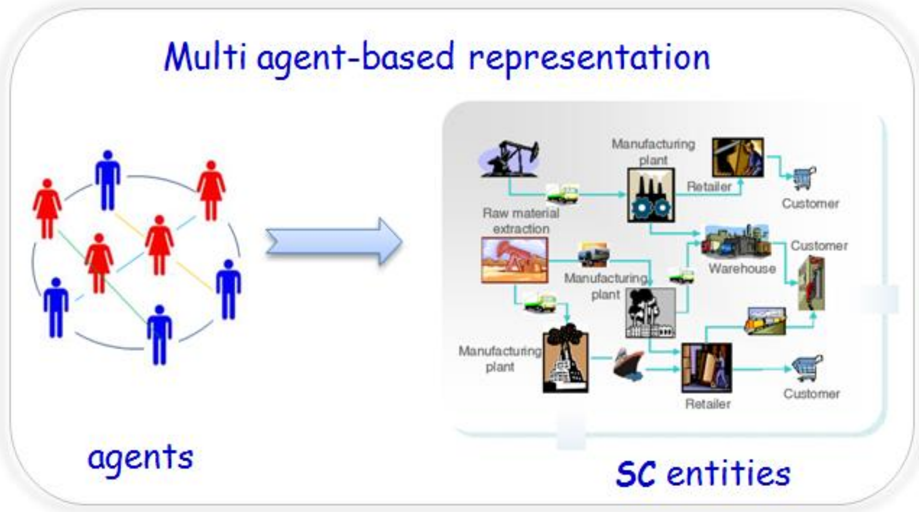


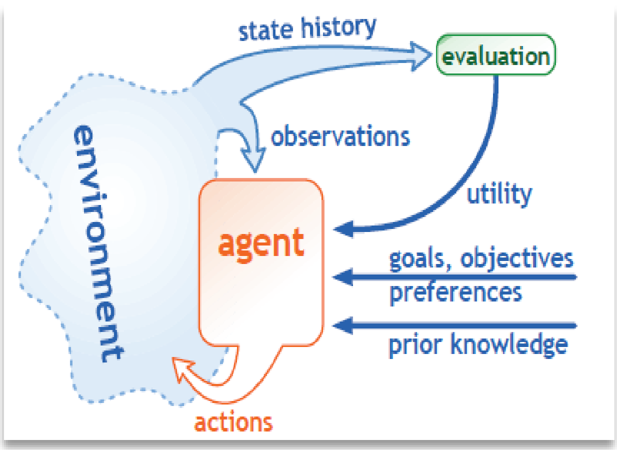
Supply chain matrix

GOAL: predict production targets and material flow over several months (up to one year)

- Generally a simplified representation of the production.
- Formulated as a linear problem
- Separate solution from the scheduling problem can result in infeasibility and sub-optimality

Integration using Agent based Simulation





- A methodology to track the actions of multiple "agents" defined to be objects with some type of behavior as:
  - Autonomy
  - Social ability
  - Reactivity
  - Pro-activeness
- Promotes a natural form of modeling (ability to mimic human organizations)
- Suitable for studying coordination involving multiple (semi)autonomous agents
- Agents can learn, leading to “intelligent” agents

Julka N et al., Agent-based supply chain management--1: framework. *Computers & Chemical Engineering.* 2002
Garcia-Flores R, Wang XZ. A multi-agent system for chemical supply chain simulation and management support. OR Spectrum. 2002

Agent based Simulation

Market

- Generates demand for every planning period
- Demand not met during a period is added as backorder
- Demand distribution depends on the decision making policy

Warehouse

- Maintains an inventory of products (warehouse capacity)
- Regulates its inventory based on a replenishment policy
- Demand distribution depends on the decision making policy (centralized or decentralized)

Production Site

- Maintains a small inventory of raw materials and products
- Regulates its inventory based on a replenishment policy
- Manufactures products based on a schedule generated by an embedded scheduler

Supplier

- Sends raw materials to production sites
- Regulates its inventory based on a replenishment policy

Characteristics of agents

- Individual ordering policy
- Individual replenishment policy
- Individual shipment policy
- Have the flexibility to use inherent optimization for individual operations
- Event-based scheduling

Optimization Model

$$\min \sum_t \sum_{wh} \sum_s h_s^{wh} Inv_s^{wh,t} + \sum_t \sum_p \sum_s h_s^p Inv_s^{p,t} + \sum_t \sum_p \sum_r h_r^p Inv_r^{p,t}$$
$$+ \sum_t \sum_{\sup} \sum_r h_r^{\sup} Inv_r^{\sup,t} + \sum_t \sum_m \sum_s u_s^m U_s^{m,t} + \sum_t \sum_p \sum_s \left(FixCost^p w_t^p + VarCost^p P_s^{p,t} \right)$$
$$+ \sum_t \sum_m \sum_{wh} \sum_s d_s^{wh,m} D_s^{wh,m,t} + \sum_t \sum_{wh} \sum_p \sum_s d_s^{p,wh} D_s^{p,wh,t} + \sum_t \sum_{\sup} \sum_p \sum_r d_r^{\sup,p} D_r^{\sup,p,t}$$

- **Minimize the total cost**
  - Inventory costs
  - Transportation costs
  - Production costs
  - Backorder costs

- **Constraints**
  - Inventory balance constraints
  - capacity constraints

- A simplified model of the actual process
- Model corresponds to an LP problem
- GAMS/CPLEX is used to solve the problem

$$U_s^{m,t} = U_s^{m,t-1} + Dem_s^{m,t} - \sum_{wh \in WH} D_s^{wh,m,t}$$

$$Inv_s^{wh,t} = Inv_s^{wh,t-1} - \sum_{m \in M} D_s^{wh,m,t} + \sum_{p \in PS} D_s^{p,wh,t}$$

$$Inv_s^{p,t} = Inv_s^{p,t-1} + P_s^{p,t} - \sum_{wh \in WH} D_s^{p,wh,t}$$

$$Inv_r^{p,t} = Inv_r^{p,t-1} - C_r^{p,t} + \sum_{\sup \in SUP} D_r^{\sup,p,t}$$

$$Inv_r^{p,t} \le stcap_r^p$$

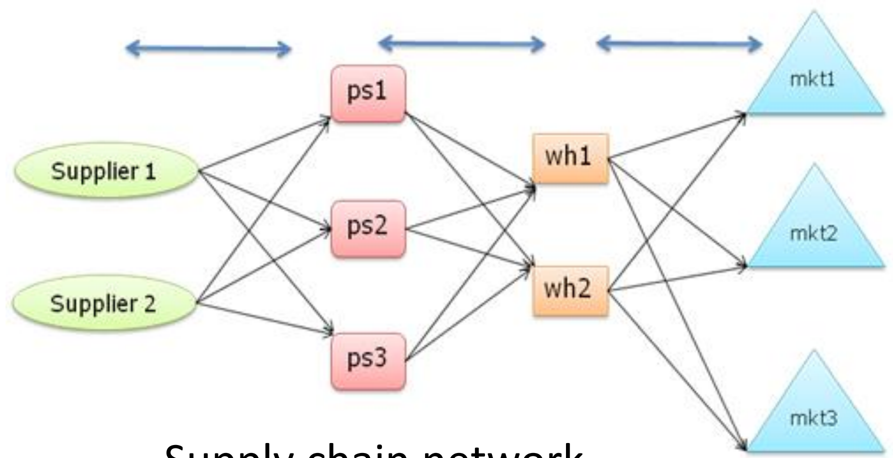
$$Inv_s^{p,t} \le stcap_s^p$$

$$Inv_s^{wh,t} \le stcap_s^{wh}$$

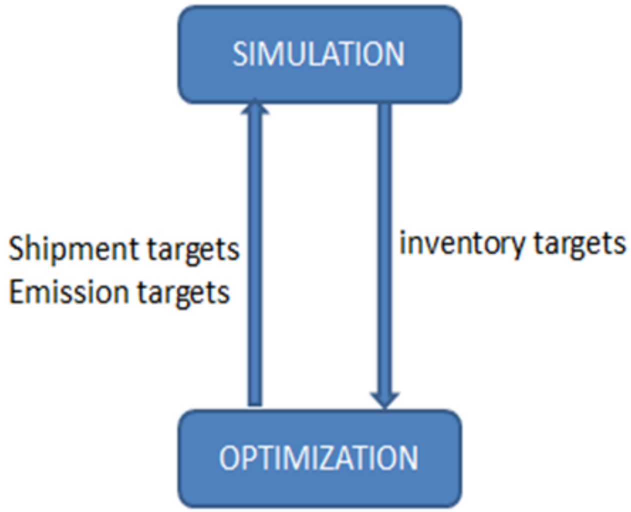
$$P_s^{p,t} \le prcap_s^p$$

Sustainable Supply Chain Operations

- Emissions due to transportation and production
- Conflicting objectives: cost and environmental impacts
- Study the trade-off between economic and environmental performance



Supply chain network

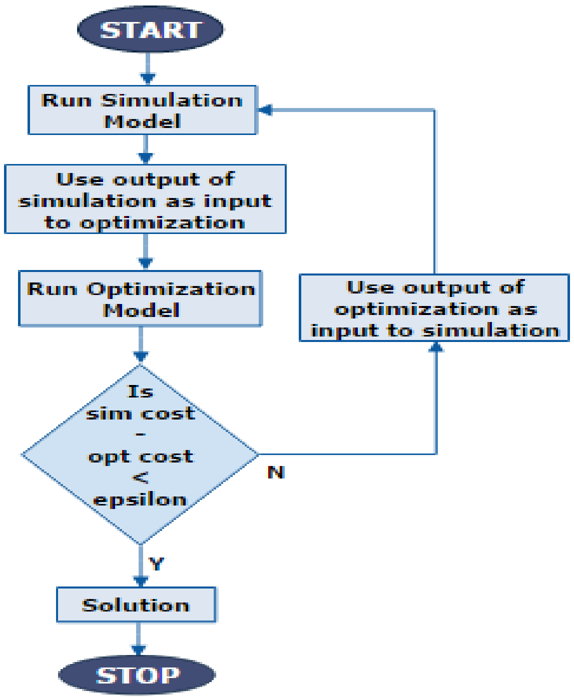


Sim – Opt coupling

- Shipment targets guide simulation towards reduced backorders and inventory
- Emission levels act as additional constraint
- Inventory levels reflect the effect of policies within the simulation

Sahay, N., Ierapetritou, M., Supply chain management using an optimization driven simulation approach. *AIChE Journal* **2013**, 59

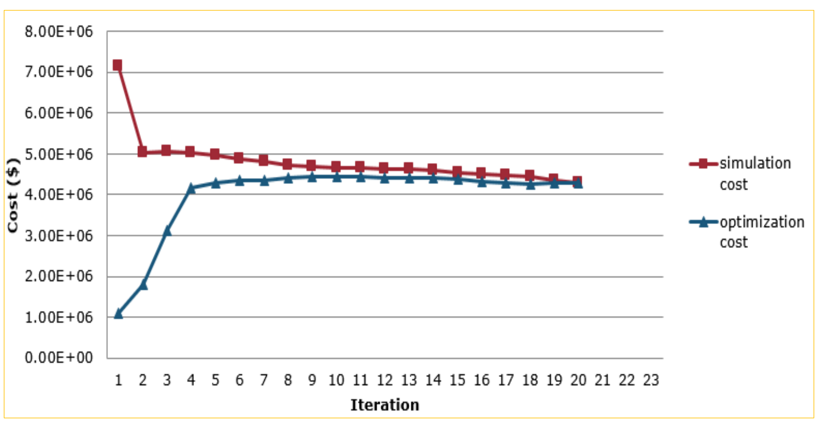
Sustainable Supply Chain Operations



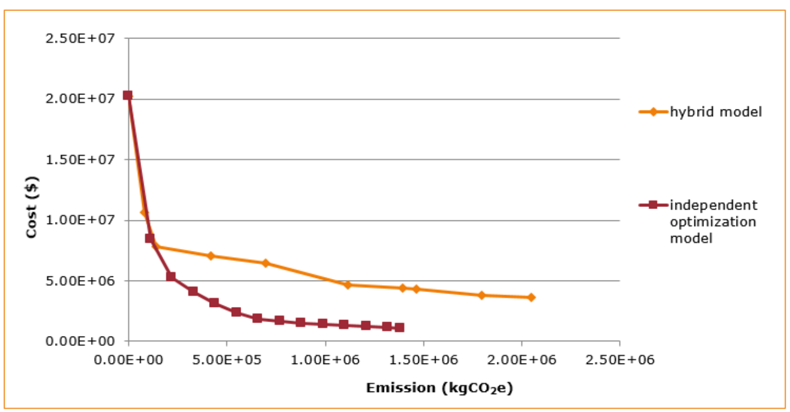
Iterative framework

- Number of iterations required depends on the input parameters
- Gap of 1% between simulation and optimization models used as termination criteria

- ε –constraint method used to solve the multi-objective optimization problem
- Pareto set of solutions obtained. Hybrid simulation based optimization model gives higher cost values than the independent optimization model

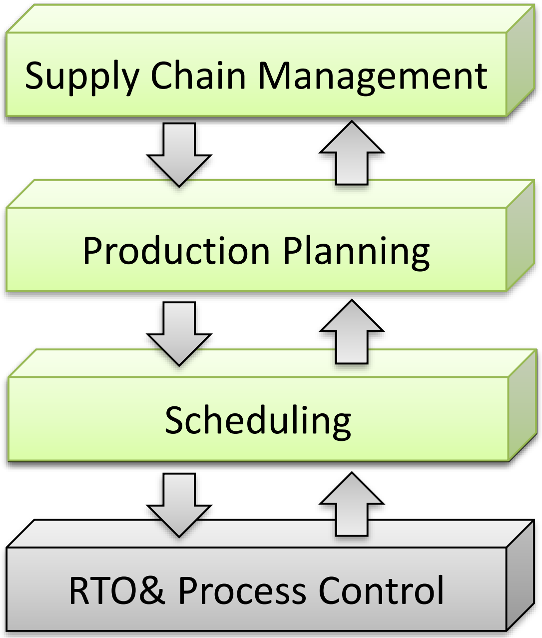


Simulation and Optimization costs



Pareto set of Solutions

Integrated Decision Making



Determine best supply chain network and determine production targets

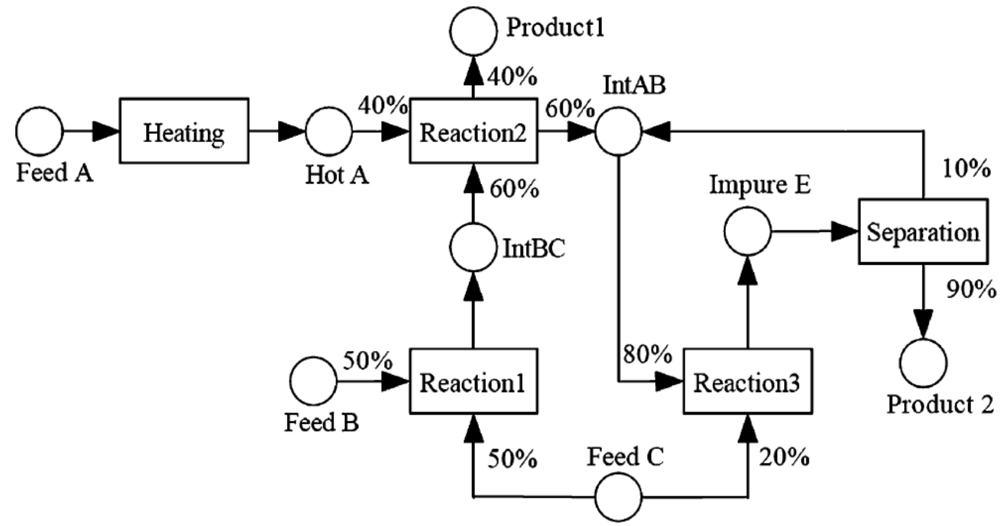
Determine production and inventory targets and feasible schedules

Integrated decisions making

- Ensure accuracy and consistency across decision processes
- Aim to obtain feasible and optimal solution for production process for all manufacturing sites to satisfy warehouse demands

Scheduling in Chemical Processes

Problem formulation



Given (constraints)

- Process flow sheet
- Resource suitability
- Operation constraints
- Market: price, demands

Objective

- Minimize make span
- Minimize production cost
- Maximize process throughput
- Maximize profit

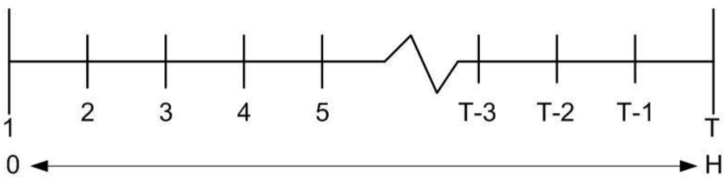
Decisions

- Unit assignments
- Material amounts
- Task sequence
- Task timing

Scheduling Formulations

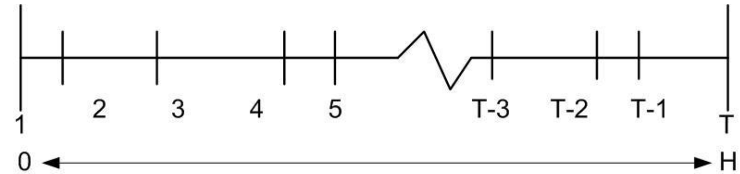
Discrete time

- Uniform time grid



Continuous time

- Event point based

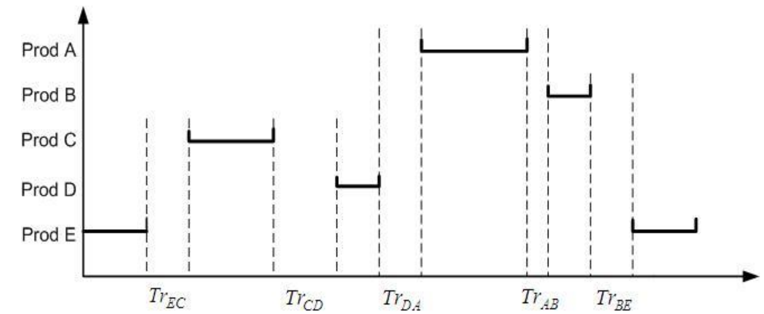


Scheduling Model

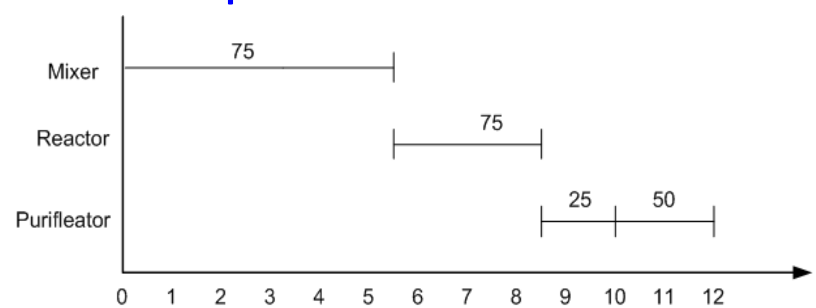
$$\max_{w,y} \; J(w,y)$$

$$s.t. \begin{cases} g_i(w,y) \geq demand(i), \quad \forall i \in product\ set \\ w \in \Omega_w \quad \text{production time} \\ y \in \Omega_y \quad \text{production sequence} \end{cases}$$

Continuous processes



Batch processes



Ierapetritou MG, Floudas CA. Industrial & Engineering Chemistry Research. 1998;37:4341-4359.
Mouret S, Grossmann IE, Pestiaux P. Computers & Chemical Engineering. 2011;35:1038-1063.

Solution Approaches for Scheduling

Lagrangian Decomposition

- Coupling constraints are introduced to decompose large scale model

Wu, D., Ierapetritou, M. G. (2003). Decomposition approaches for the efficient solution of short-term scheduling problems. Computers and Chemical Engineering, 27, 1261-1276.

Shah, N, Iearapetritou, M.G. (2015) . Lagrangian Decomposition Approach to Scheduling of a Large-Scale Refinery Operations. Computers and Chemical Engineering, Accepted

$$\begin{aligned} \min_{x\,y}\quad & b^T x + d^T y \\ \text{s.t.}\quad & A^T x + D^T y \le c \\ & H^T x \le 0 \\ & x \ge 0,\ y \in \{0,1\} \end{aligned}$$

$\Rightarrow$

$$\begin{aligned} \min_{x\,y\,xx}\quad & b^T xx + d^T y \\ \text{s.t.}\quad & A^T x + D^T y \le c \\ & H^T xx \le 0 \\ & x - xx = 0 \\ & x \ge 0,\ xx \ge 0,\ y \in \{0,1\} \end{aligned}$$

$\Rightarrow$

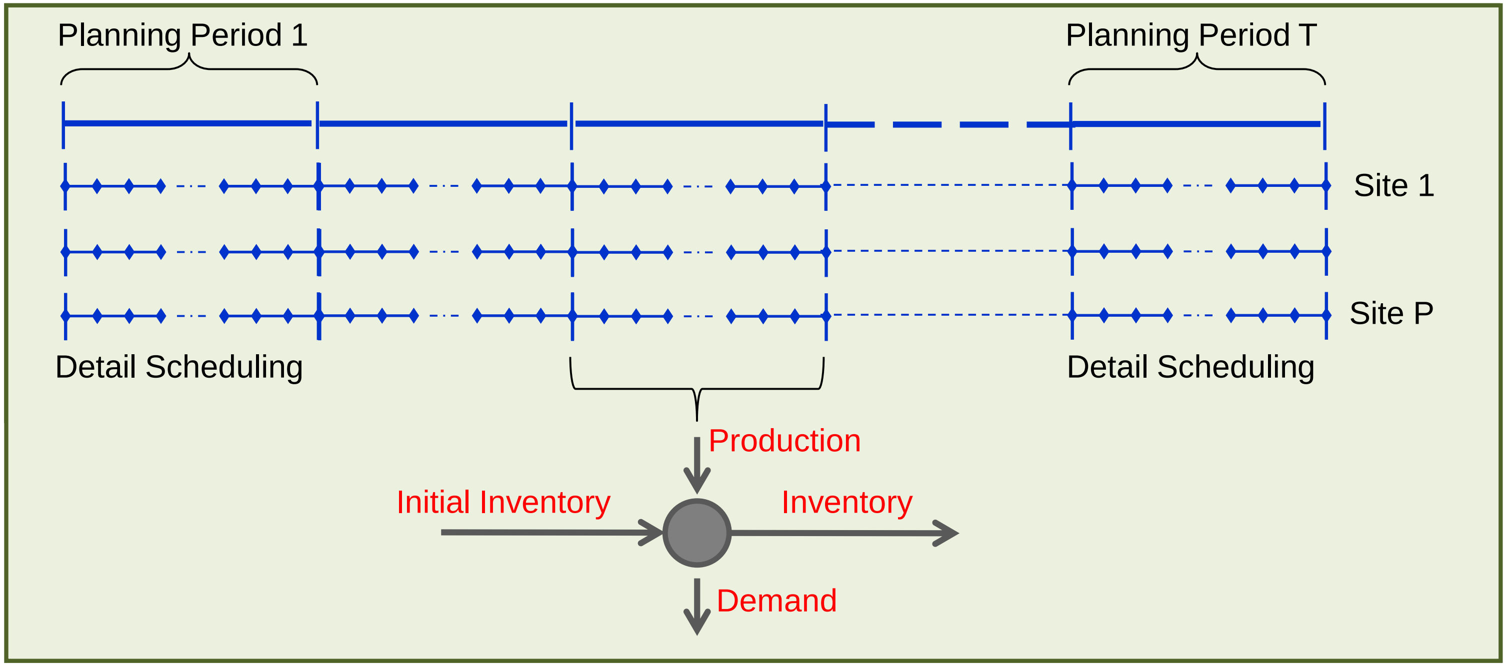
$$\begin{aligned} \min_{x\,y\,xx}\quad & b^T xx + d^T y + \lambda^T (x - xx) \\ \text{s.t.}\quad & A^T x + D^T y \le c \\ & H^T xx \le 0 \\ & x \ge 0,\ xx \ge 0,\ y \in \{0,1\} \end{aligned}$$

Benders Decomposition – Covering cut bundle (CCB) generation

- Primal problem is obtained by fixing binary variables and relaxed master problem (RMP) involves binary decisions variables and optimality and feasibility cuts generated by primal problem.
- Suitable for problems that generates low-density cuts involving a small number of decisions variables of RMP.
- Significantly decreases the number of iterations by producing multiple cuts in each iteration, leading to improved resolution times

Saharidis, G. K. D., et al. (2010). "Accelerating Benders method using covering cut bundle generation." International Transactions in Operational Research **17**(2): 221-237.

Planning and Scheduling



- **Surrogate scheduling model**
  - Incorporating production capacity constraints into the planning problem: Rolling Horizon Application

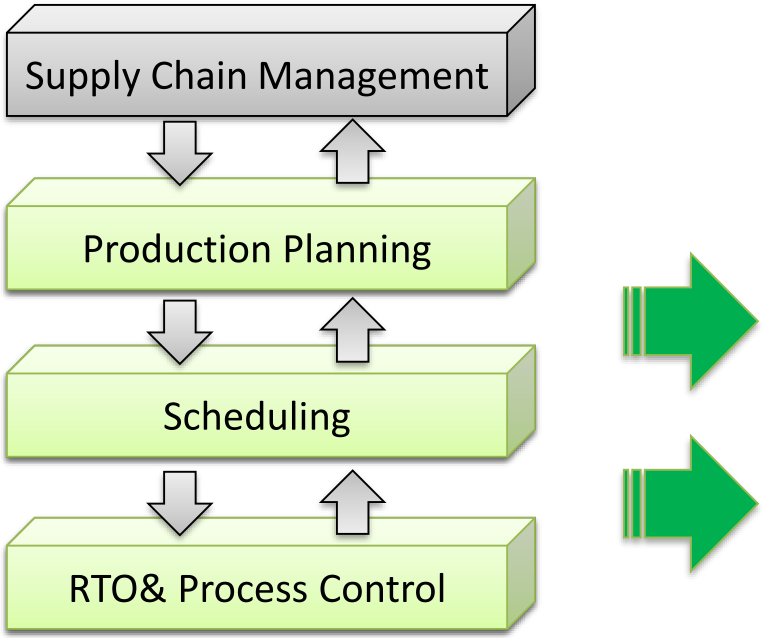
    Li, Z. and M. G. Ierapetritou (2010), *Chem. Eng. Sci.*, 65(22): 5887-5900.
- **Mathematical decomposition of full space model**
  - Cutting plane based decomposition

    Li and Ierapetritou, *Chem. Eng. Sci.*, 2009, 64, 3585
  - Dual decomposition

    Li, Z. and M. G. Ierapetritou (2010), *Chem. Eng. Sci.*, 34(6): 996-1006.

    Shah, N. K. and M. G. Ierapetritou (2012), *Chem. Eng. Sci.*, 37: 214-226.

Integrated Decision Making



Determine production and inventory targets and feasible schedules

Determine production schedule and transition profile for changeovers

Integrated decisions making

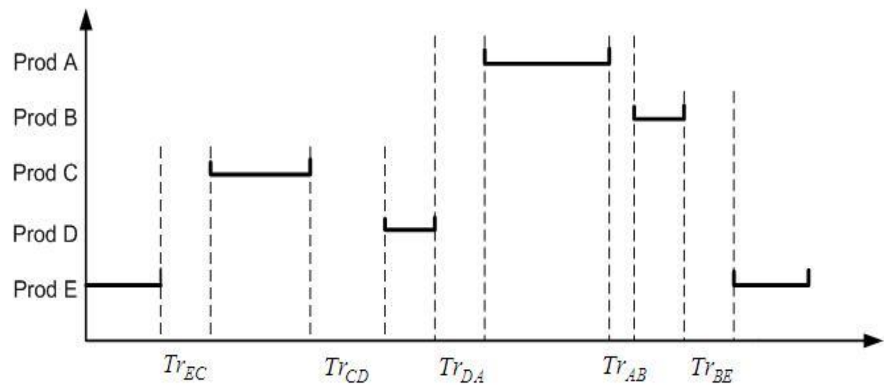
- Ensure accuracy and consistency across decision processes
- Aim to obtain feasible and optimal production schedule and best transition profile during changeovers between different production modes

General Models for Scheduling and Control Problems

Scheduling of production: optimally allocate limited resources to processing tasks over time, while ensuring that demands are met and guarantying profitable operations

$$\max_{w,y} J(w,y)$$

$$s.t. \begin{cases} g_i(w,y) \geq demand(i), \ \ \forall i \in product\ set \\ w \in \Omega_w \ \ \text{production time} \\ y \in \Omega_y \ \ \text{production sequence} \end{cases}$$



Process Control: goal is to ensure stability, robustness, safety and fast tracking

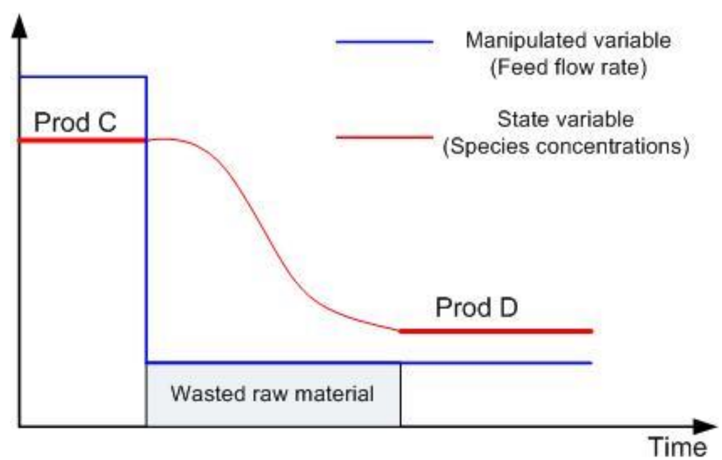
$$\min_{u_k} J_k(x_k, u_k, q_k)$$

$$s.t. \begin{cases} \dot{x}_k = f_k(x_k, u_k) \\ q_k = h_k(x_k, u_k) \\ (x_k, u_k, q_k) \in \Omega_{xuq} \end{cases}$$

Dynamic Model

$$\dot{x}_k = f_k(x_k, u_k)$$

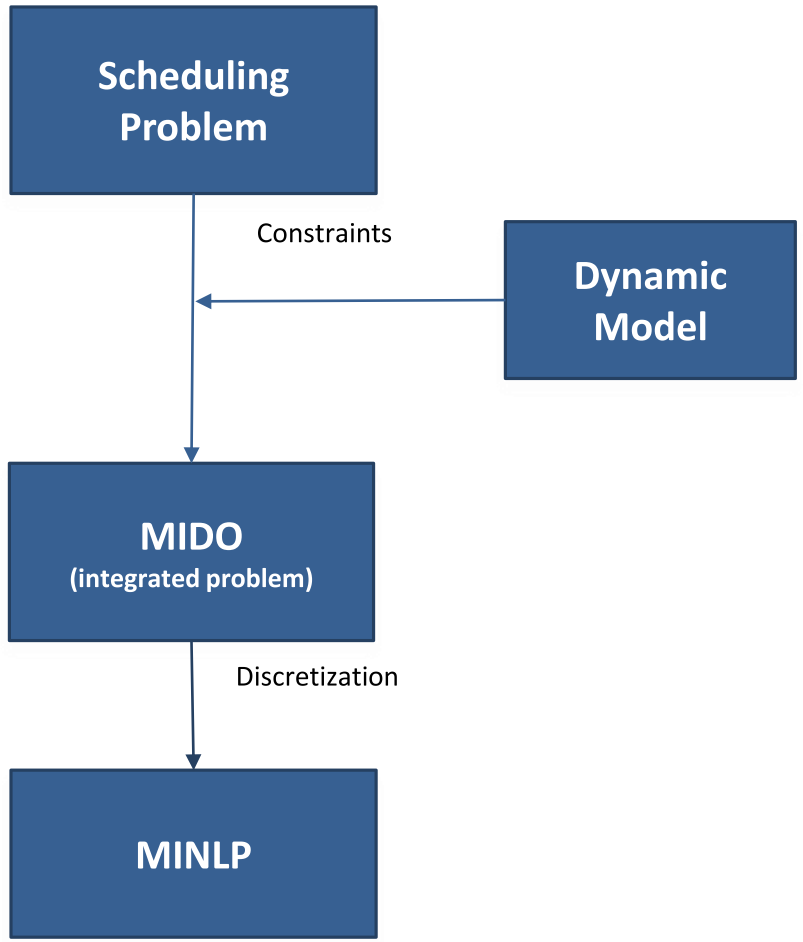
$$q_k = h_k(x_k, u_k)$$



Modeling the Integration

Main ideas

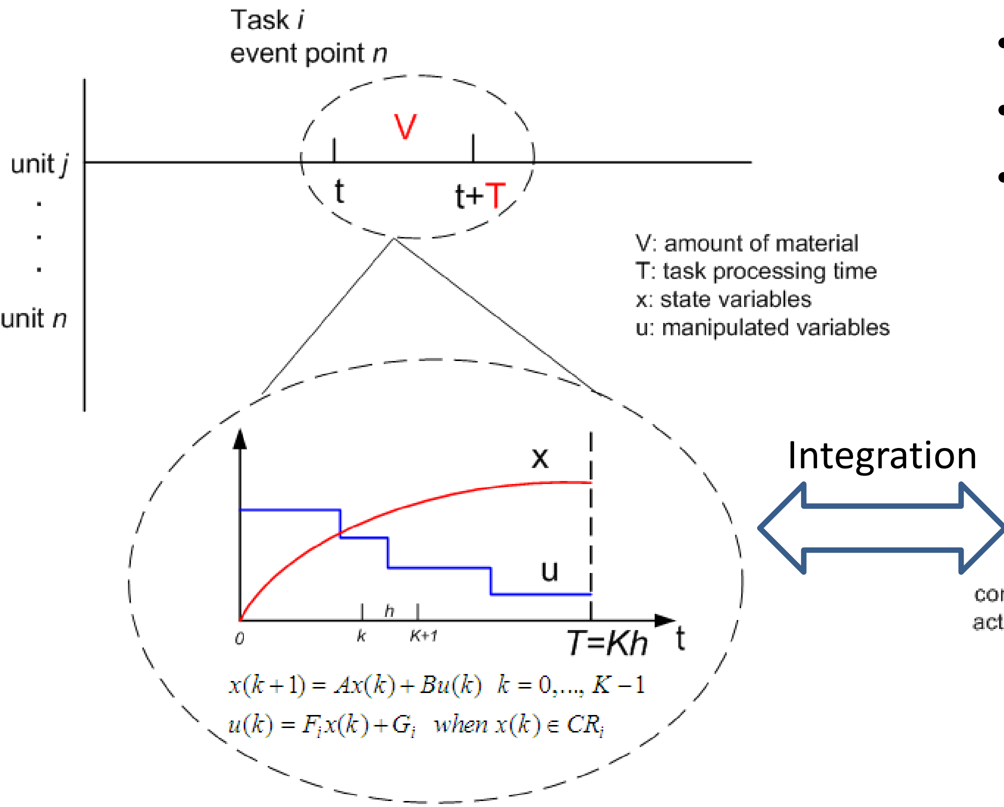
- Incorporate dynamic models in the scheduling problem
- Discretize resulting MIDO
- Several techniques to solve the resulting problem can be found in the literature
- The problem is solved for the **scheduling** and **control actions**

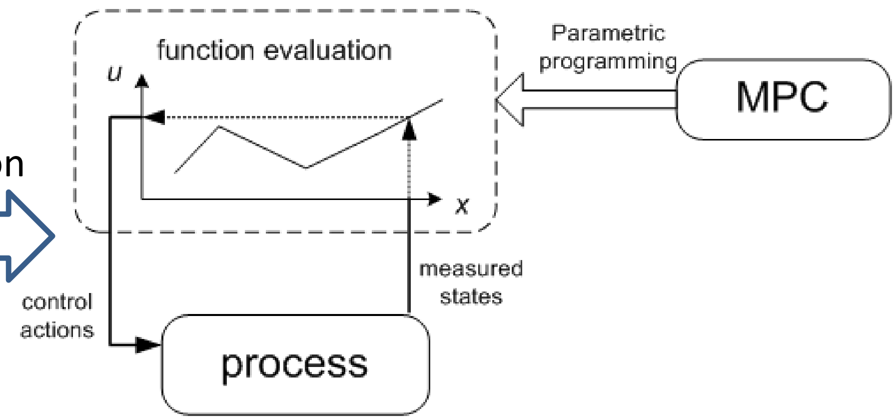


Flores-Tlacuahuac, A., Grossmann, I. (2006). Simultaneous Cyclic Scheduling and Control of a Multiproduct CSTR Reactor

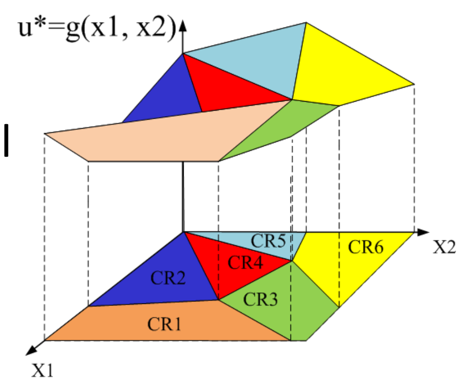
Integration using mp-MPC

- Event Point scheduling formulation
- Multi-parametric MPC, Function evaluation, fast
- Explicit control integrated with scheduling





2-dimensional case



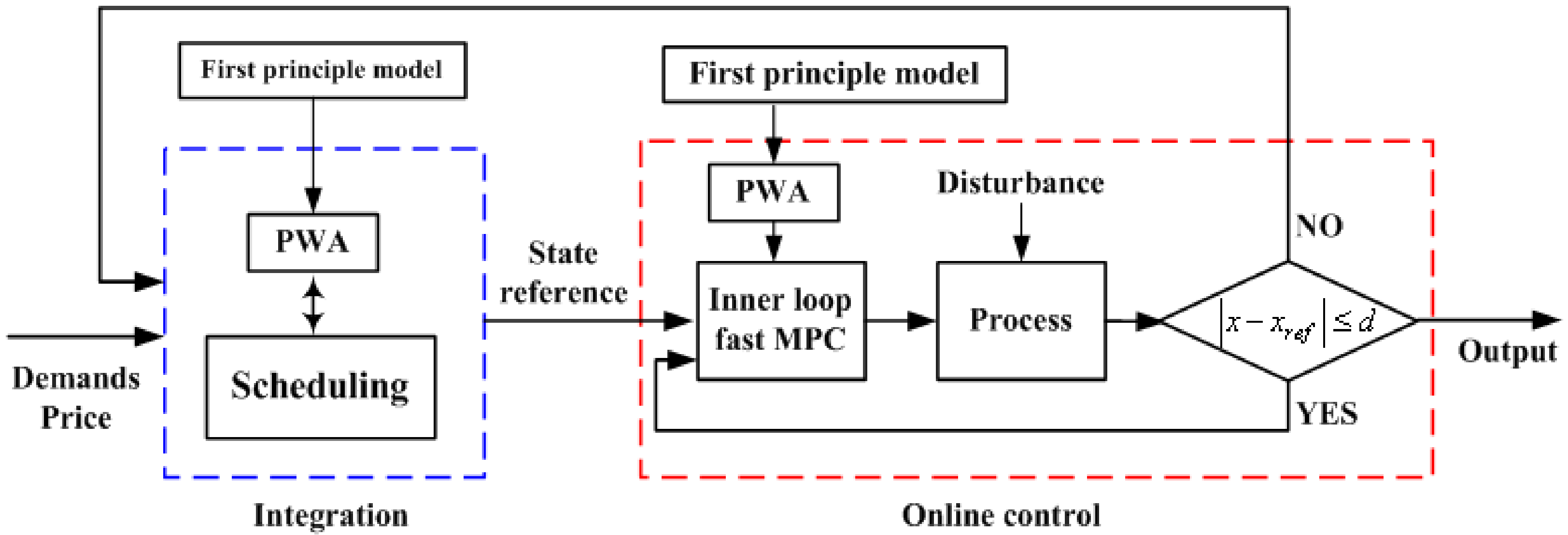
- Number of Critical Regions increases exponentially with problem dimension
- Time consuming in locating critical regions

Bemporad A, Bozinis NA, Dua V, Morari M, Pistikopoulos, E. N. Model predictive control: A multi-parametric programming approach. Computer Aided Chemical Engineering: Elsevier 2000 301-306

Pistikopoulos EN. Perspectives in multiparametric programming and explicit model predictive control. AIChE Journal. 2009;55:1918-1925.

Integration using fast MPC

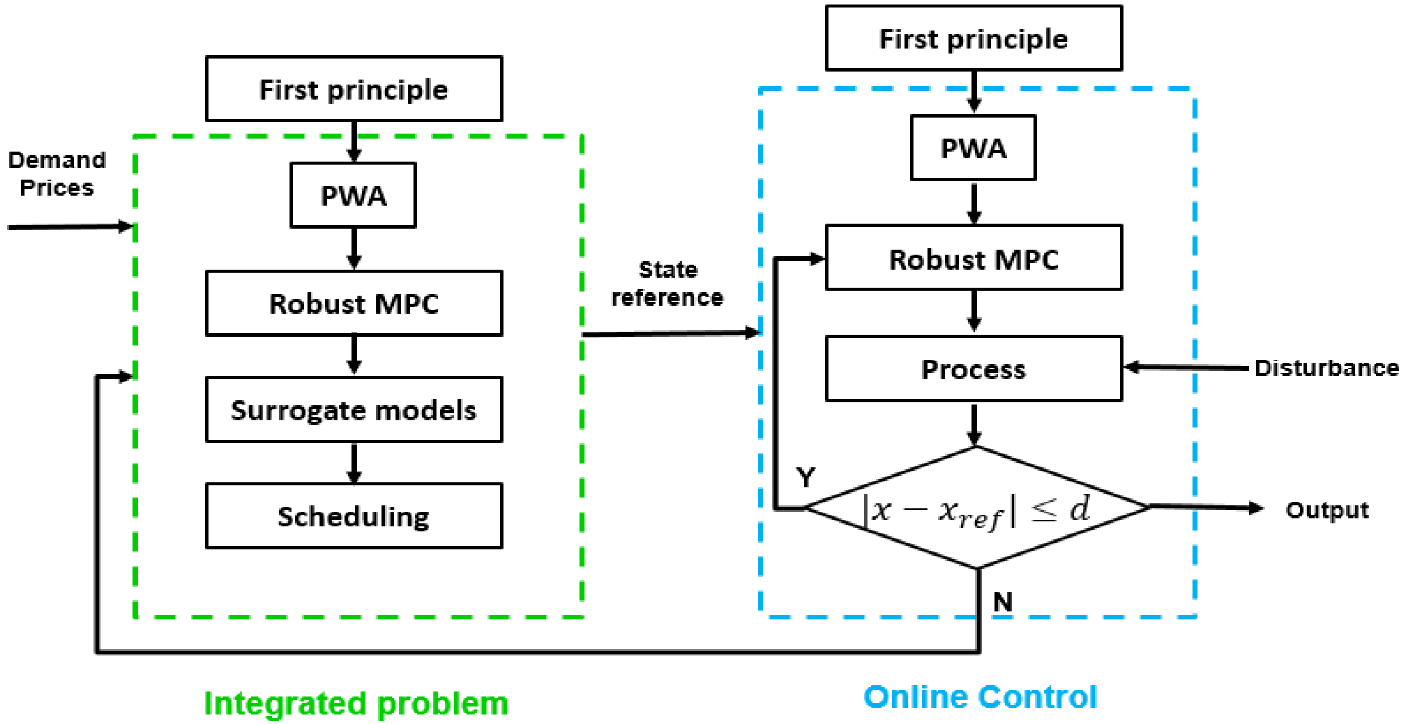
– **targets both goals:** genuine integration and tractable computation



- PWA approximations of nonlinear dynamic, simplify control computation
- Integrated problem incorporating PWA system
- Scheduling solution transfer to Inner loop fast MPC

Zhuge, J. and Ierapetritou, M. G. (2015) An integrated Framework for Scheduling and Control Using Fast Model Predictive Control. AIChE Journal. Under review.

Integration under uncertainty



1. Approximate the nonlinear dynamic behavior of the system with PWA functions
2. Build the MPC scheme
3. Use surrogate models to approximate the closed-loop input-output relationship imposed by the control
4. Incorporate surrogate models to the scheduling formulation
5. Transmit scheduling solutions to the online control