THE UNIVERSITY OF TEXAS AT AUSTIN

Modeling and optimization of complex industrial systems for application to demand response

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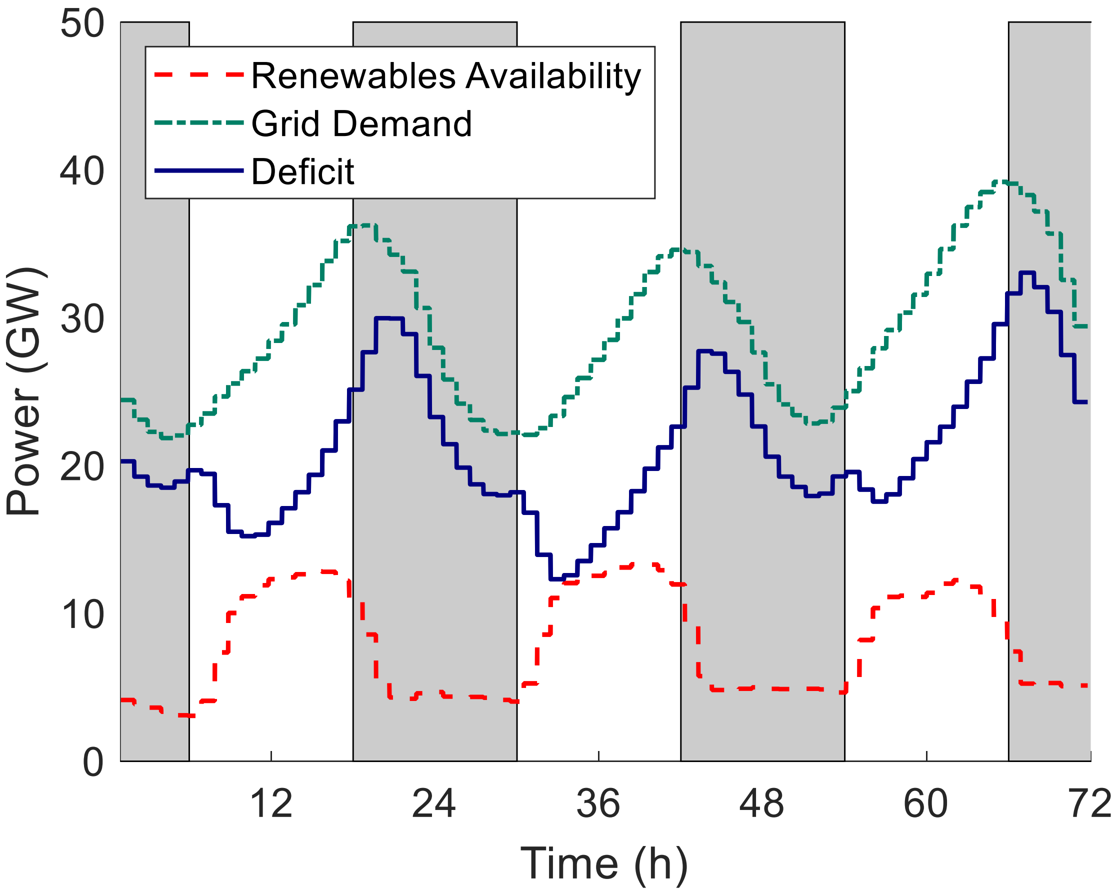
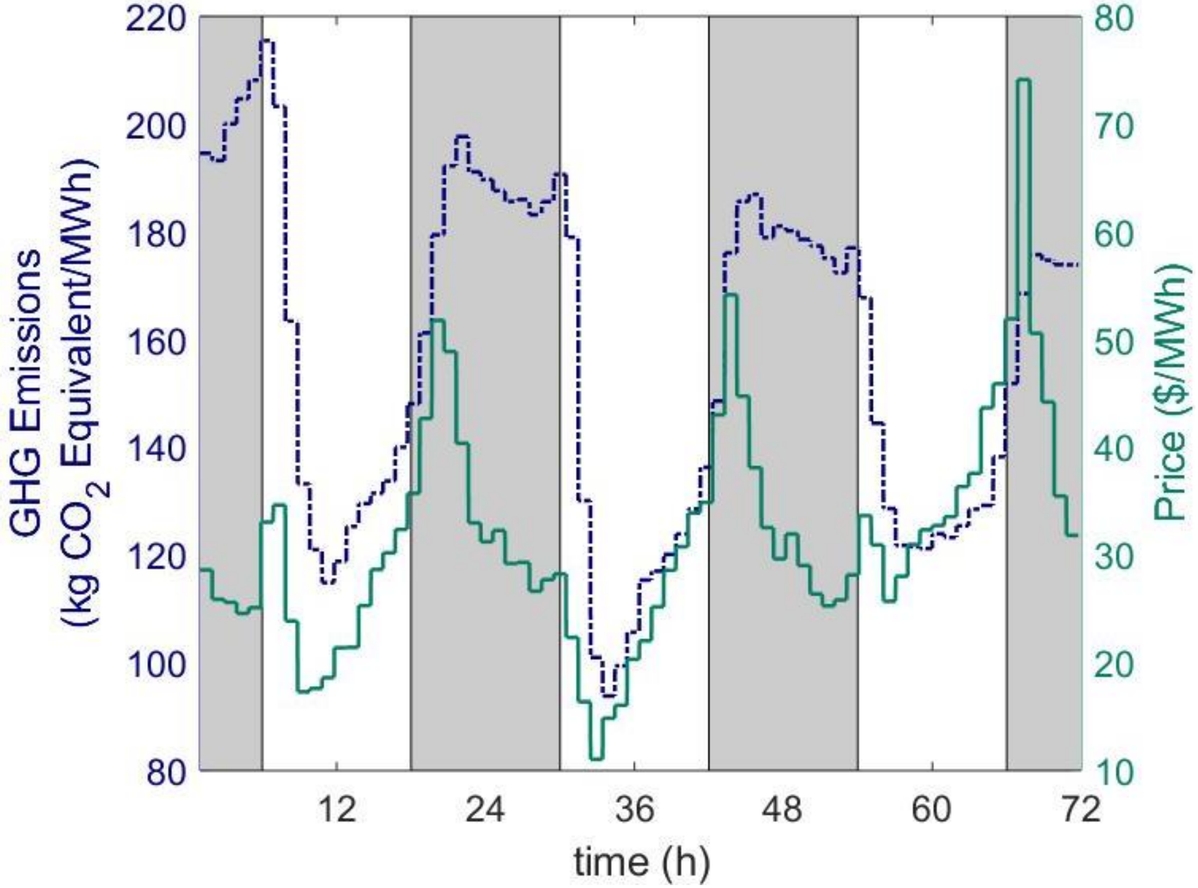
DOE CSGF Program Review

Summer 2021

Demand, Availability, and Price

- Increased capacity from renewables exacerbates variability issues
- This deficit is reflected in the electricity prices

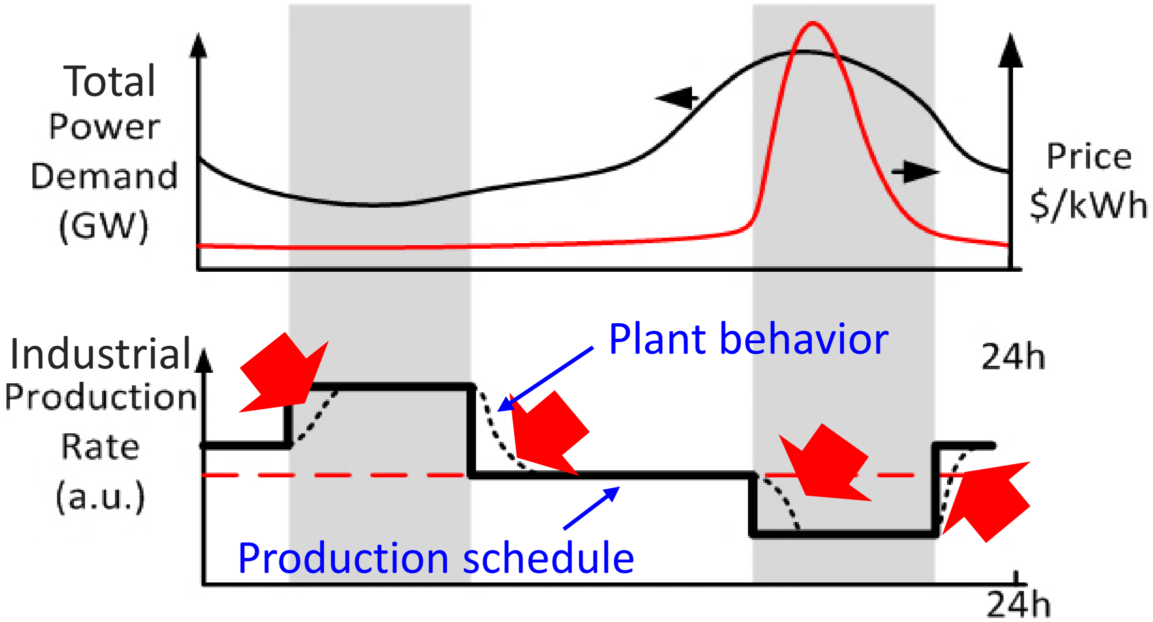




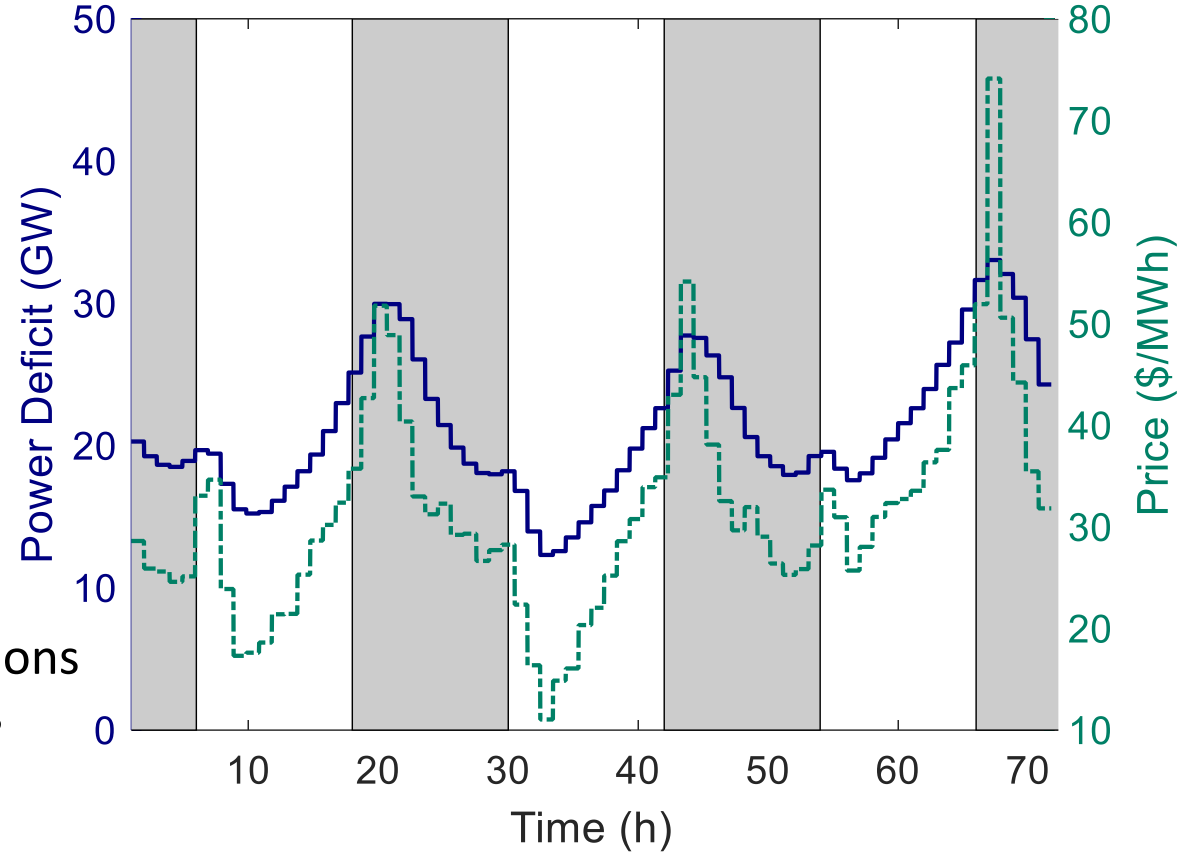
Renewables contribution, grid demand, and prices for July 3-5 2017 from data supplied by CAISO

CAISO. (2017). California Independent System Operator. Retrieved from http://www.caiso.com/Pages/default.aspx

Load Shifting: Industrial Participation



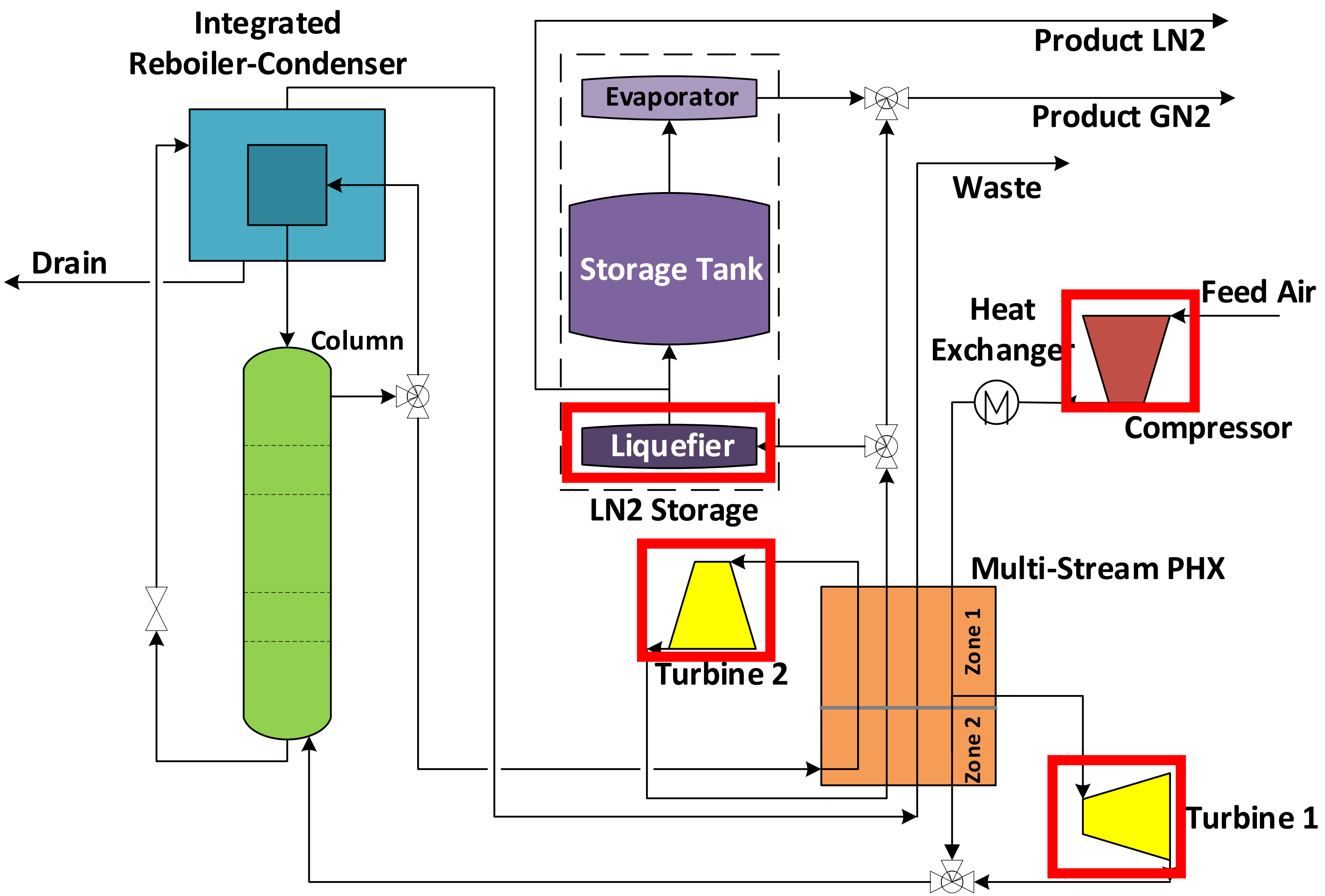
- **Paired events:** overproduce during low demand/emissions times and store extra product to use during peak hours when production is lower
  - Frequent schedule changes, account for process dynamics (same time scale as scheduling decisions)
  - Assumptions: excess capacity, product storage, fast transitions are possible



Renewables contribution, grid demand, and prices for July 3-5 2017 from data supplied by CAISO

CAISO. (2017). California Independent System Operator. Retrieved from http://www.caiso.com/Pages/default.aspx

Case study: Cryogenic Air Separation



Industrial gas sector accounted for 2.62% of industrial electricity consumption in 2014[5]

Products: LN_2, GN_2

Vary the inlet feed flowrate to modulate production levels

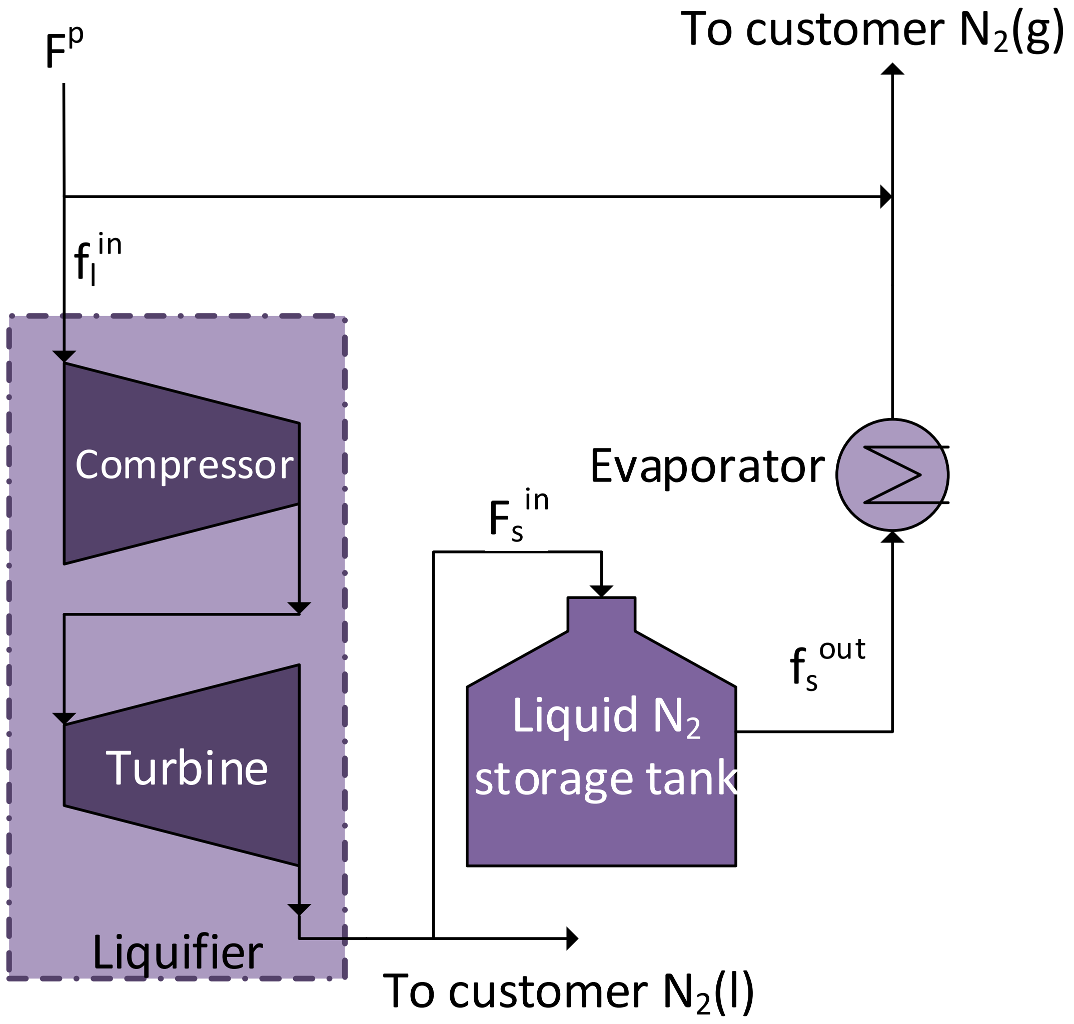
Longer time horizon=more savings

[5] US EIA. (2017). *Manufacturing Energy Consumption Survey 2014*. Washington, D.C.

Storage System and Power Consumption

Storage system:

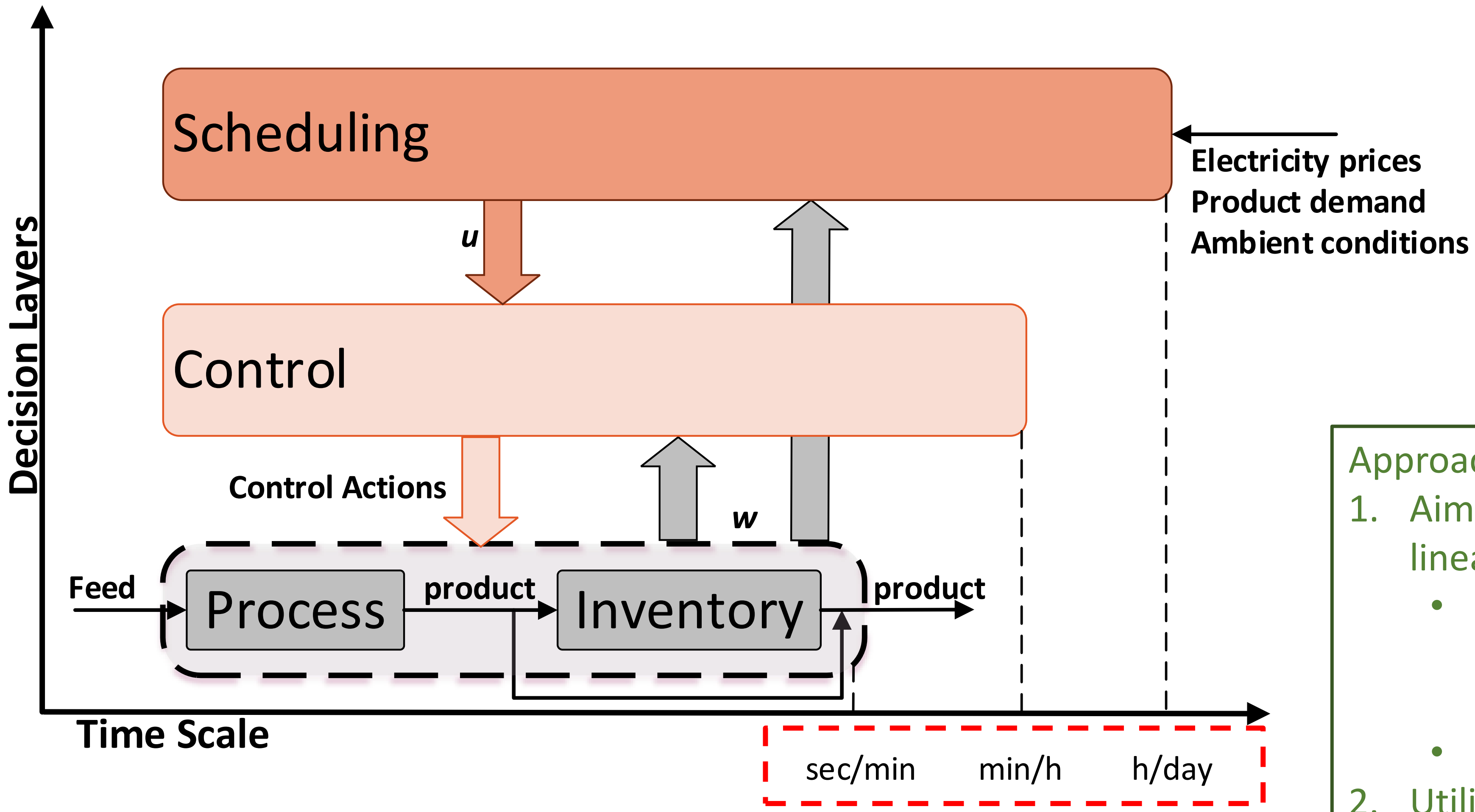
- Product in excess of gas demand is liquefied
  - Product is removed from liquefier and sent to meet liquid demand
  - Excess is sent to storage (as liquid)



Power consumption:

- Linear relationship between net work and flow through unit

Hierarchy of Process Decisions



Key goal:
Solve the optimal scheduling problem in less than an hour on a standard computer

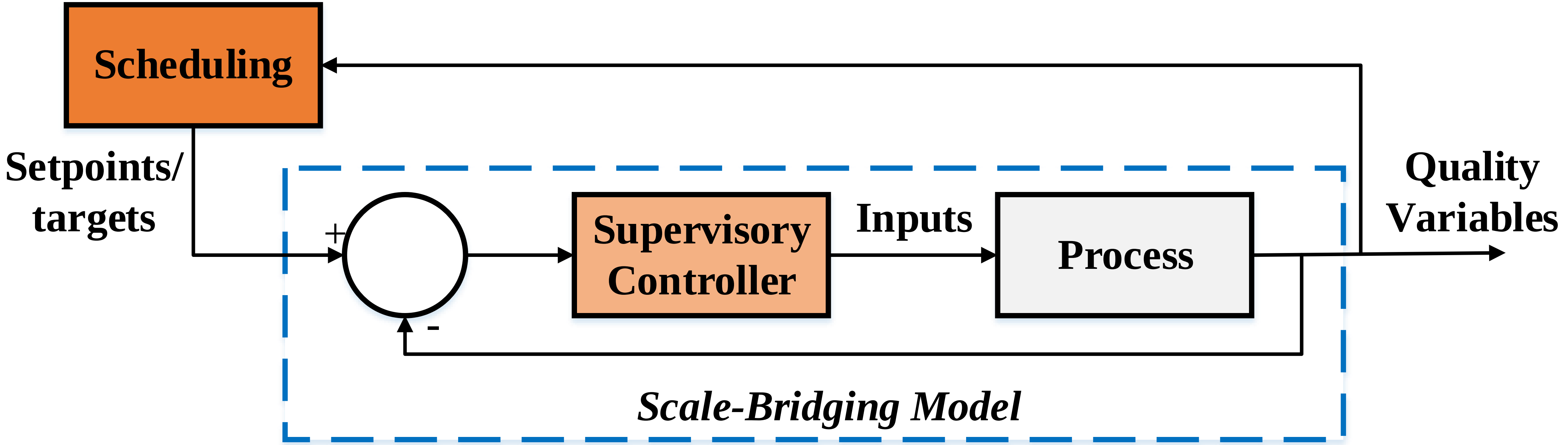
Approach:

1. Aim for a linear (or mixed-integer linear) program
   - Linear programs have guaranteed optimality and fast solution times
   - Grid models are MILPs
2. Utilize problem structure that enables parallel computing

Reduced-order modeling

Bridge disparate time scales between scheduling and process dynamics/control

- Low-order
- Utilize input/output (closed-loop) operating data
- Only capture scheduling-relevant variables



[7] J. Du, J. Park, I. Harjunkoski, and M. Baldea, "A time scale-bridging approach for integrating production scheduling and process control," *Comput. Chem. Eng.*, vol. 79, pp. 59–69, Aug. 2015.

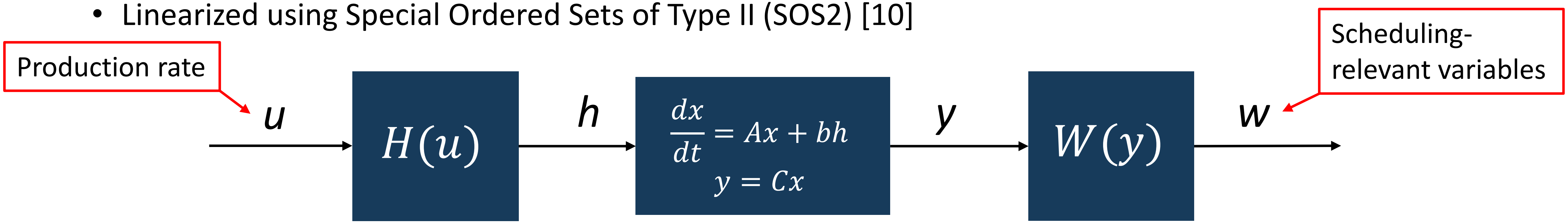
Scale Bridging Models

Finite Step Response (FSR) Models (Linear)

- Data-driven non-parametric models used for unknown model order and time delay

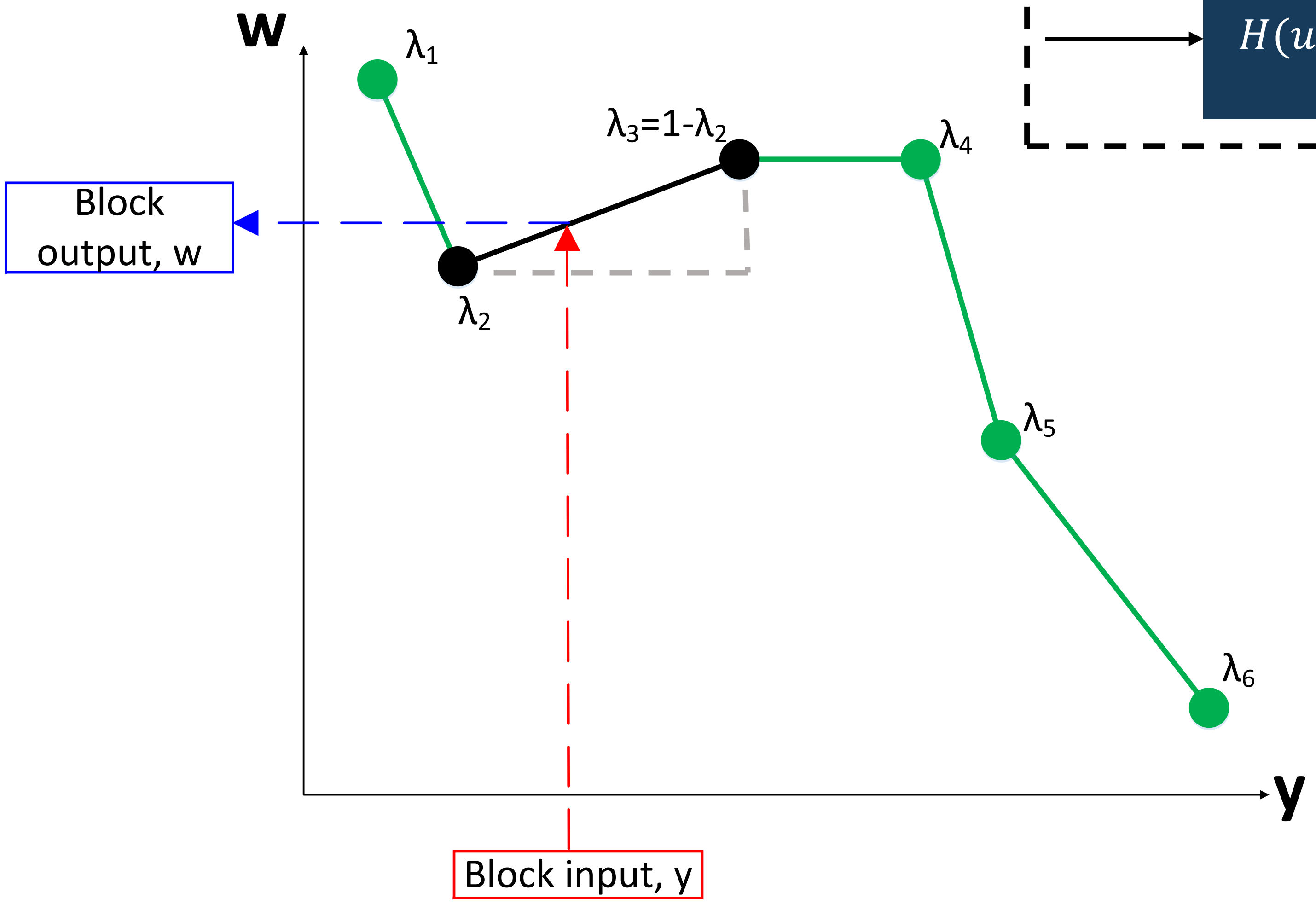
Hammerstein-Wiener (HW) Models (Nonlinear)

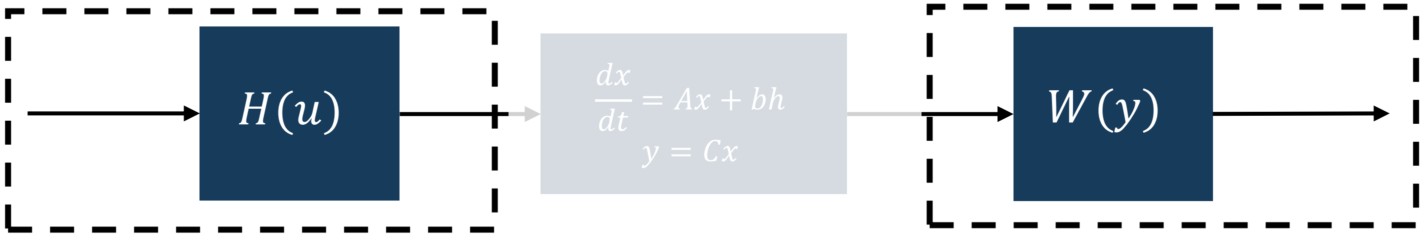
- Linear State-space block
- Static input/output nonlinearities: piece-wise linear (PWL)
  - Linearized using Special Ordered Sets of Type II (SOS2) [10]



Billings, S. A. (2013). *Nonlinear system identification : NARMAX methods in the time, frequency, and spatio-temporal domains*. Chichester, West Sussex: John Wiley & Sons.
MATLAB. (2016). MATLAB 2016a. Natick, MA, USA: The Mathworks, Inc.
M. T. Kelley, R. C. Pattison, R. Baldick, and M. Baldea, “An MILP framework for optimizing demand response operation of air separation units,” *Appl. Energy*, vol. 222, pp. 951–966, Jul. 2018.

Static blocks: Linearize nonlinearities





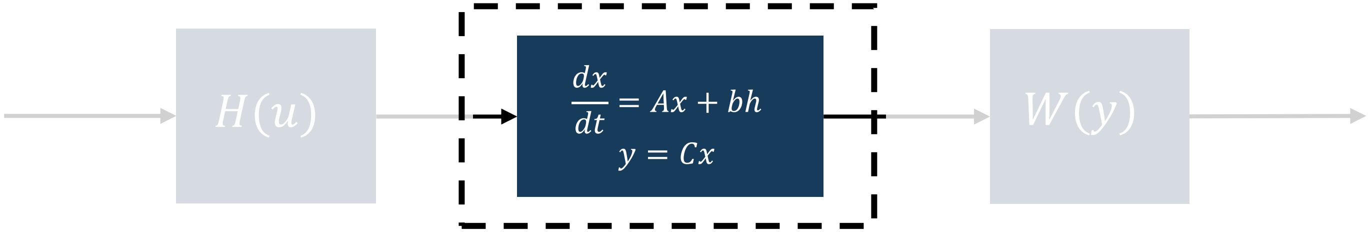
Special Ordered Sets of type 2 (SOS2)

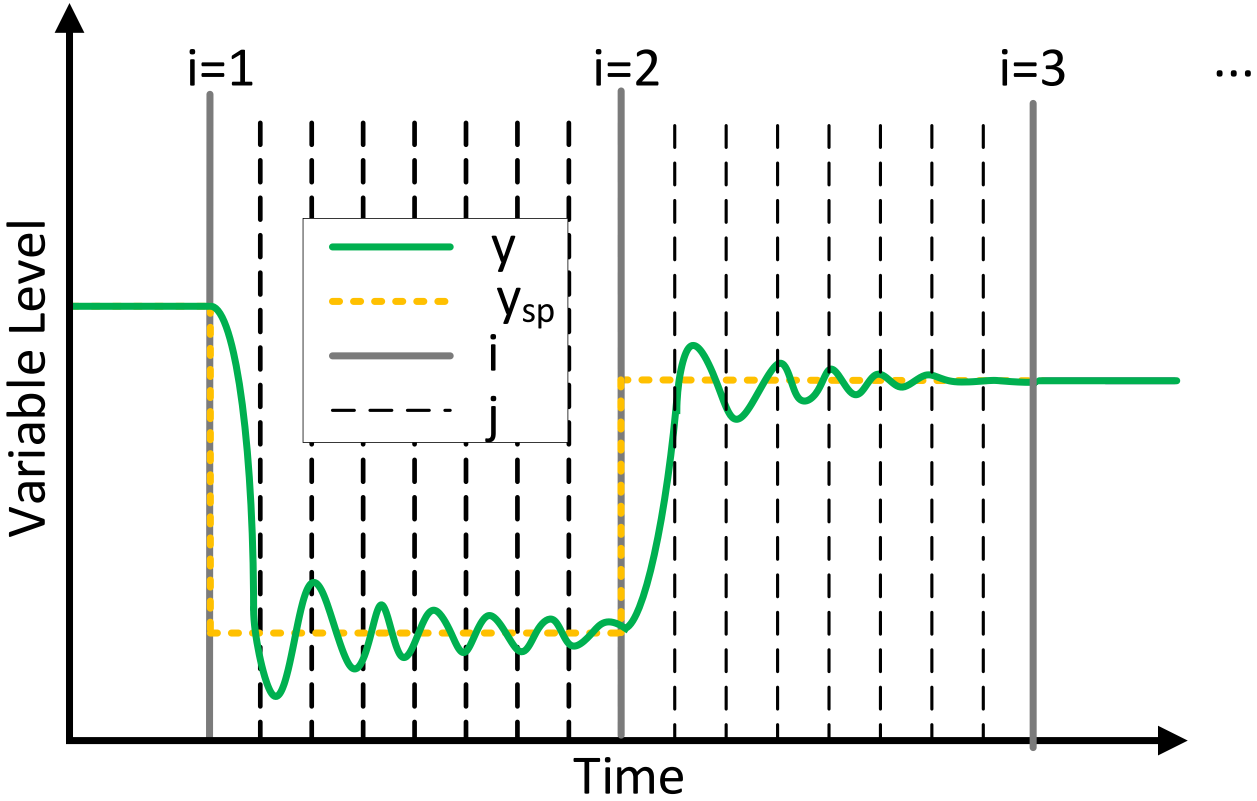
- Benefits:
  - *Most* linear optimization solvers have architecture in place to solve SOS2 variables directly
  - Result in *exact* linearization—no loss of information
- Drawbacks:
  - Introduces multiple integer variables at each time point
    - Exponential increases in solution time with each integer added

Dynamic block: Define discrete time grids

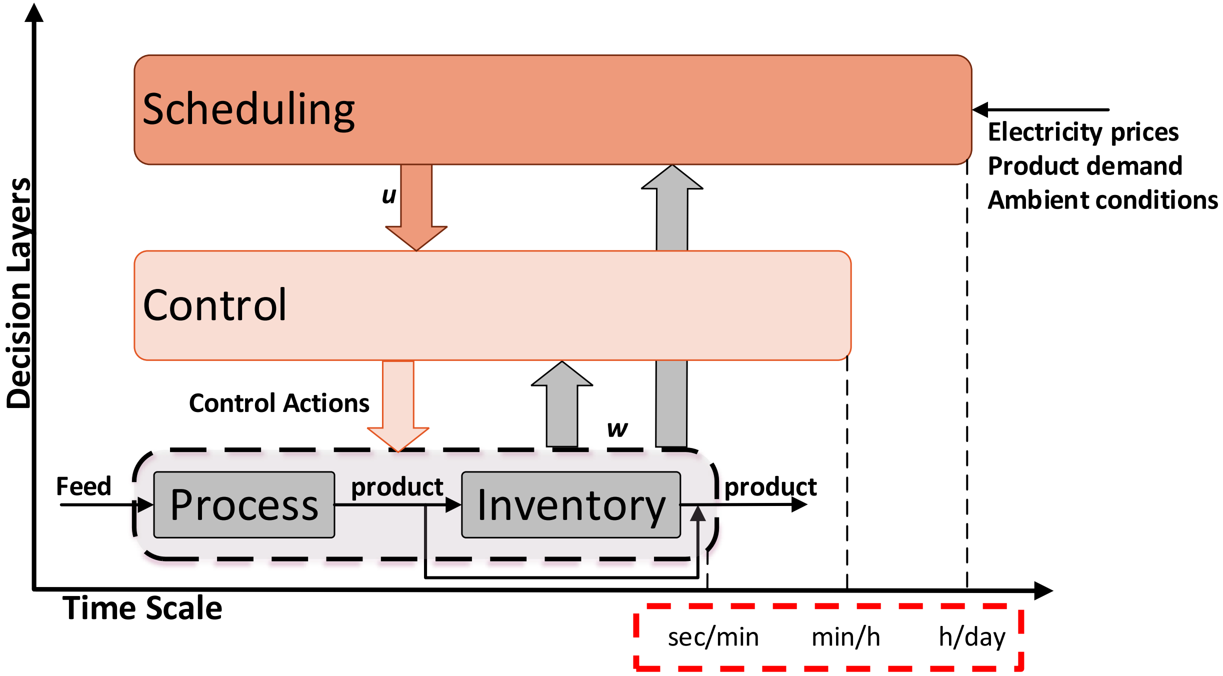
i: Scheduling time slots

j: time points for discretized dynamics





y_{sp} is supplied by the scheduling layer, and y is how the process reacts to y_{sp}



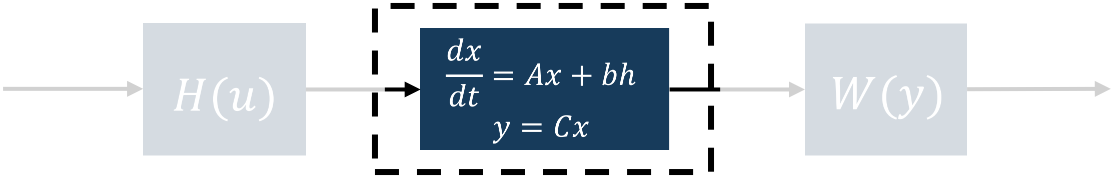
MILP Reformulation: Discretization

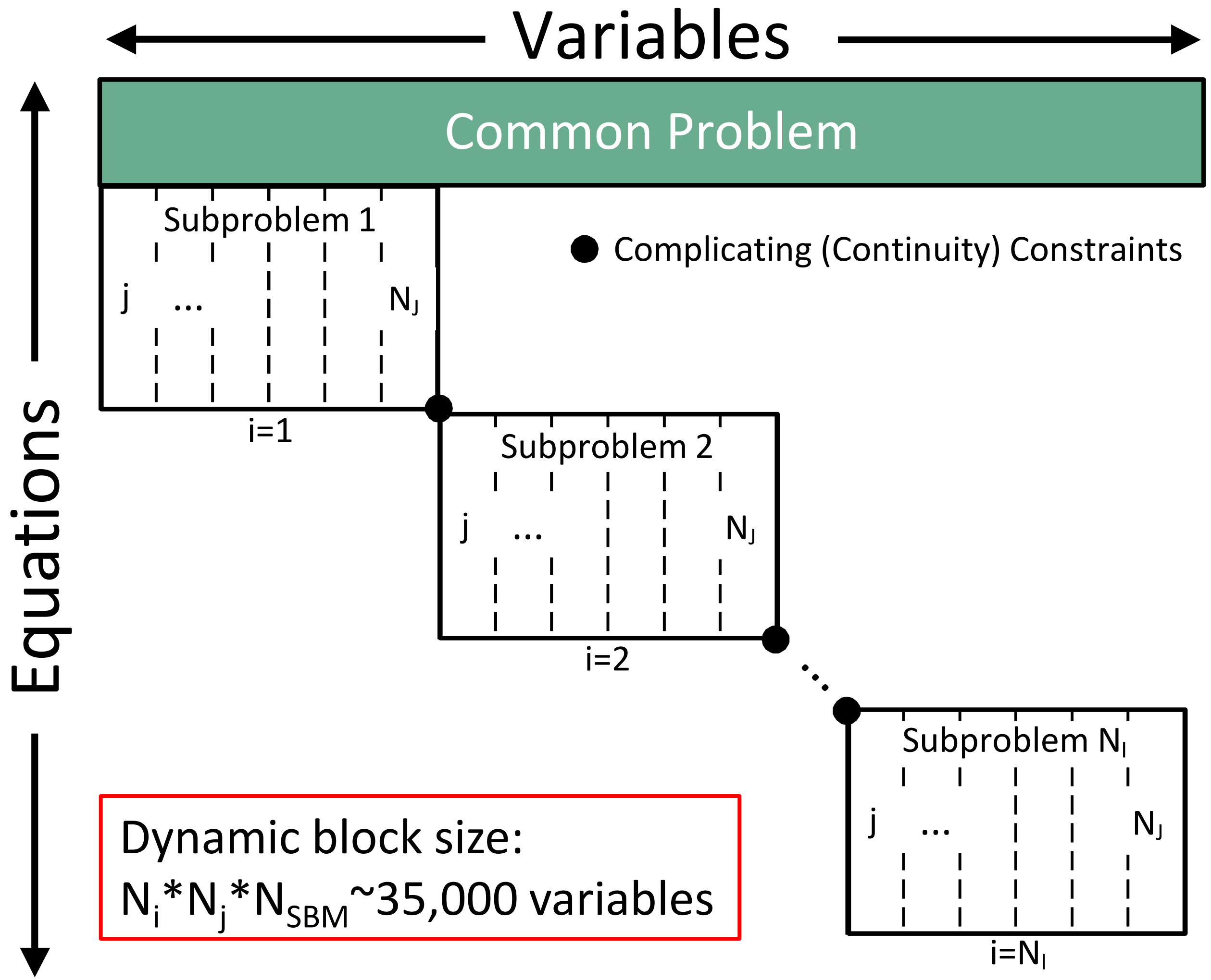
- Discretization:

$$h_i = H(u_i)$$
$$\vec{x}_{i,j+1} = A\vec{x}_{ij} + Bh_i$$
$$y_{ij} = C\vec{x}_{ij}$$
$$w_{ij} = W\left(y_{ij}\right)$$

- Requires state continuity constraint between scheduling time slots:

$$x_{i,j+1} = x_{i-1,j=N_j}$$

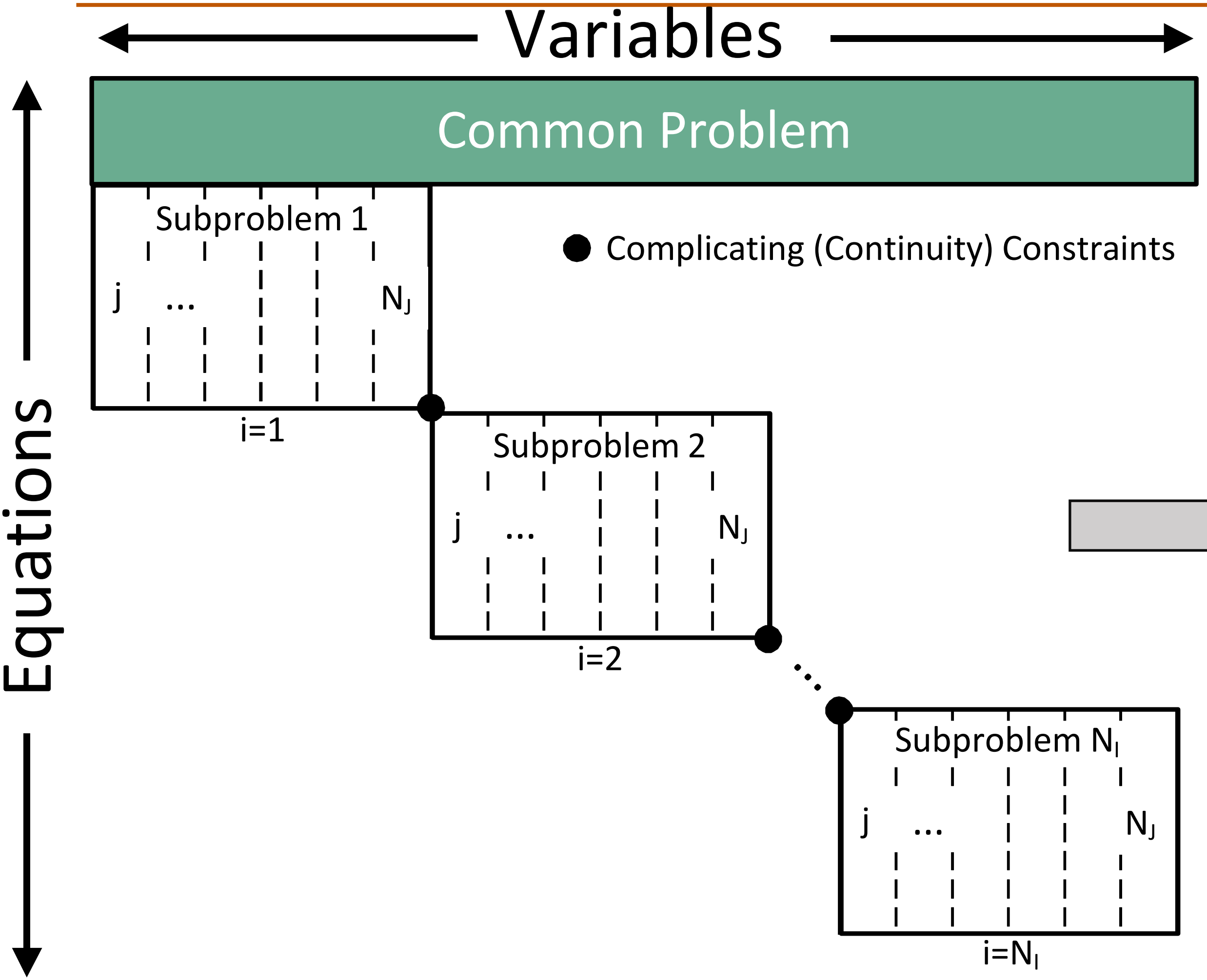




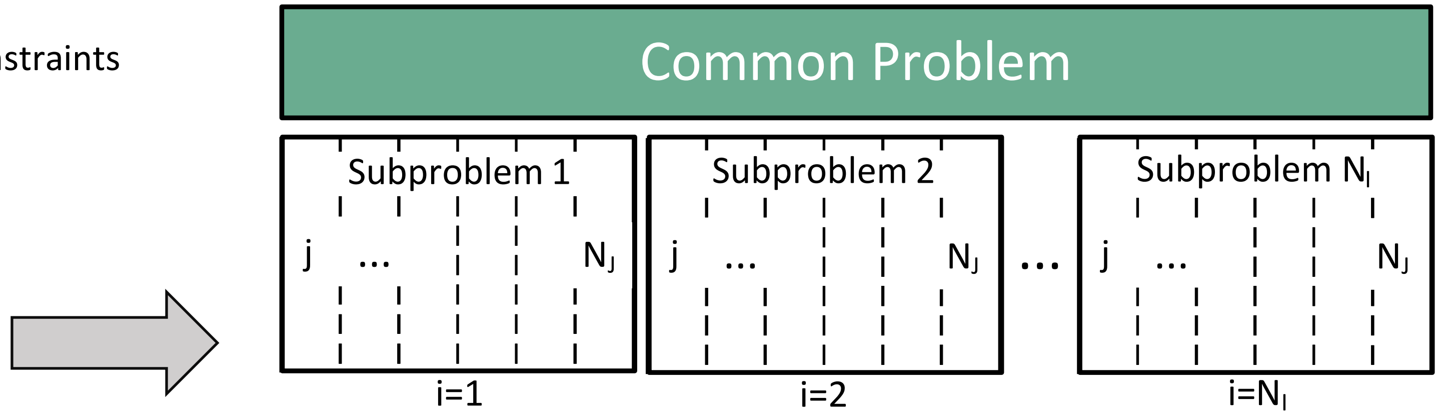
Dynamic block size:
N_i*N_j*N_{SBM}~35,000 variables

Kelley, M. T., Pattison, R. C., Baldick, R., & Baldea, M. (2018). An MILP framework for optimizing demand response operation of air separation units. *Applied Energy*, *222*, 951–966. https://doi.org/10.1016/j.apenergy.2017.12.127

Parallelization



Now each subproblem can be solved independently



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Lagrangian Relaxation

Re-write complicating constraints (continuity conditions):

$$x_{i,j+1} = x_{i-1,j=N_j} \quad \rightarrow \quad \left| x_{i,j+1} - x_{i-1,j=N_j} \right| = \lambda_{i,m}$$

Designate a Lagrangian multiplier: $\gamma_{i,m} = f(\gamma_{i,m-1})$

Optimization problem (m is iteration number):

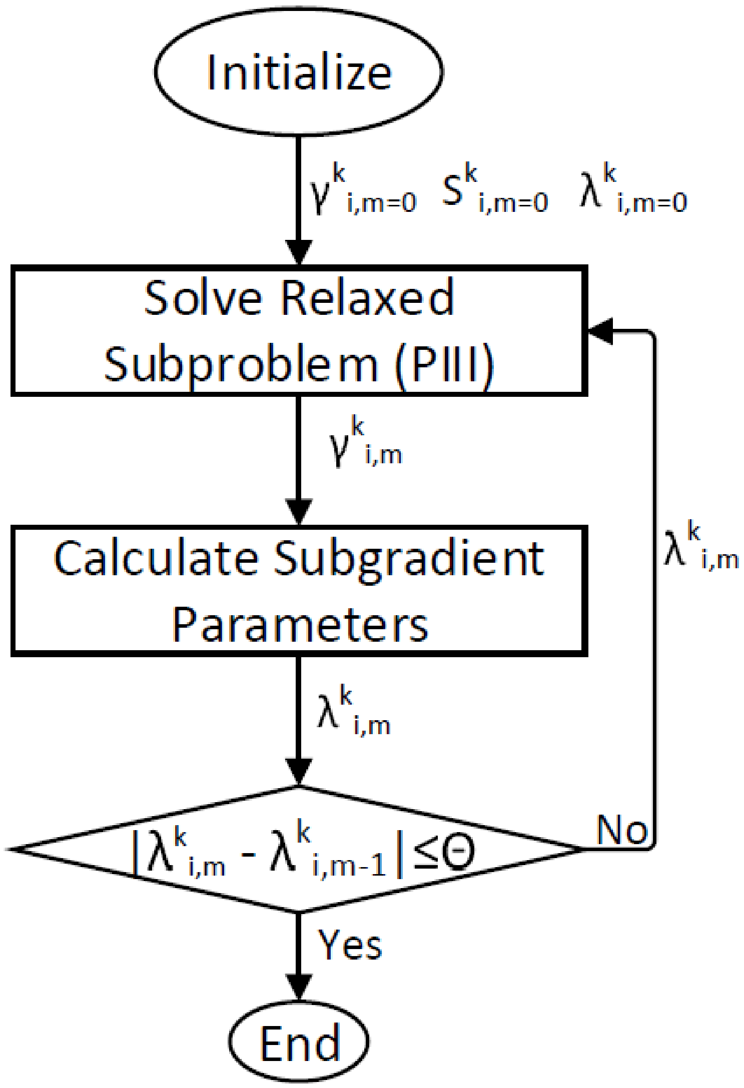
$$\min_{u_i} J_m = \sum_i \sum_j Price_i \mathcal{P}_{ijm} + \gamma_{im}\gamma_{im}$$

s.t.
Timing constraints
Process model (HW/FSR)
Inventory model
Initial Conditions
Process and Quality Constraints

Kelley, M. T., Pattison, R. C., Baldick, R., & Baldea, M. (2018). An MILP framework for optimizing demand response operation of air separation units. *Applied Energy*, *222*, 951–966. https://doi.org/10.1016/j.apenergy.2017.12.127

Solution time: 1.5 mins
Optimal operating cost: $1,014
Cost savings: 1.12%
Optimality gap: 0.09%

Continuous Variables: 90,325
SOS2 Variables: 1,512



Evolution of the solution time

full-order nonlinear model
97 hours
↓
Nonlinear SBMs
5 hours
↓
Linearization
11 minutes
↓
Parallelization
1.5 minutes

1. Demand response scheduling

Kelley, M. T., Pattison, R. C., Baldick, R. & Baldea, M. An MILP framework for optimizing demand response operation of air separation units. Appl. Energy 222, 951-966 (2018).

2. Grid-side emissions minimization

Kelley, M. T., Baldick, R. & Baldea, M. Demand Response Operation of Electricity-Intensive Chemical Processes for Reduced Greenhouse Gas Emissions: Application to an Air Separation Unit. ACS Sustain. Chem. Eng. 7, 1909-1922 (2019).

3. Consideration of electricity price and product demand uncertainty

Kelley, M. T., Baldick, R. & Baldea, M. Demand response scheduling under uncertainty: Chance-constrained framework and application to an air separation unit. AIChE J. 66, (2020).

Kelley, M. T., Baldick, R. & Baldea, M. An empirical study of moving horizon closed-loop demand response scheduling. J. Process Control 92, 137-148 (2020).

4. Additional case studies: Ammonia production, batch reactors

Kelley, M. T., Pattison, R. C., Baldick, R. & Baldea, M. An ecient MILP framework for integrating nonlinear process dynamics and control in optimal production scheduling calculations. Comput. Chem. Eng. 110, 35-52 (2018).

Evaluating the Demand Response Potential of Ammonia Plants, submitted

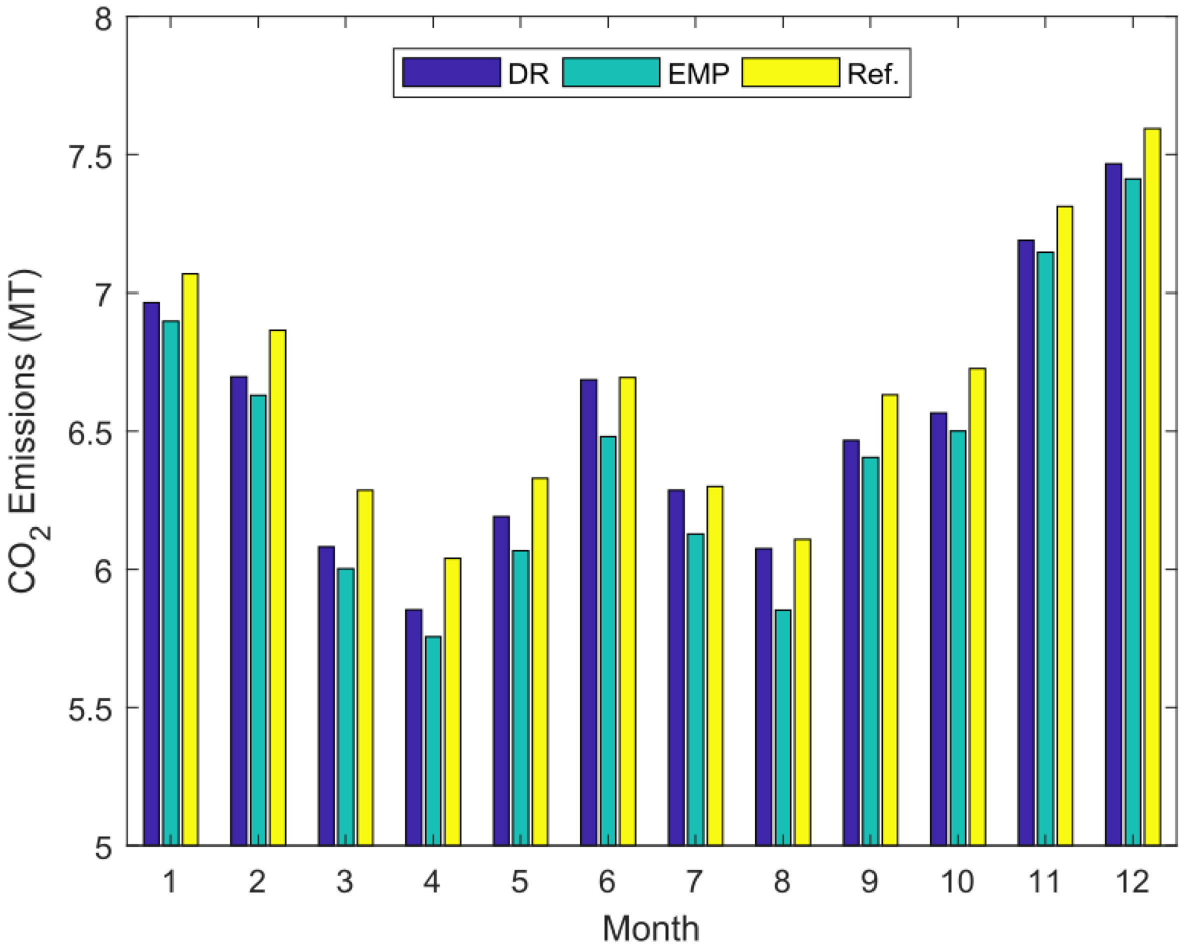
5. Identified SBMs for a year's worth of historical plant data from an industry partner for industrial DR scheduling

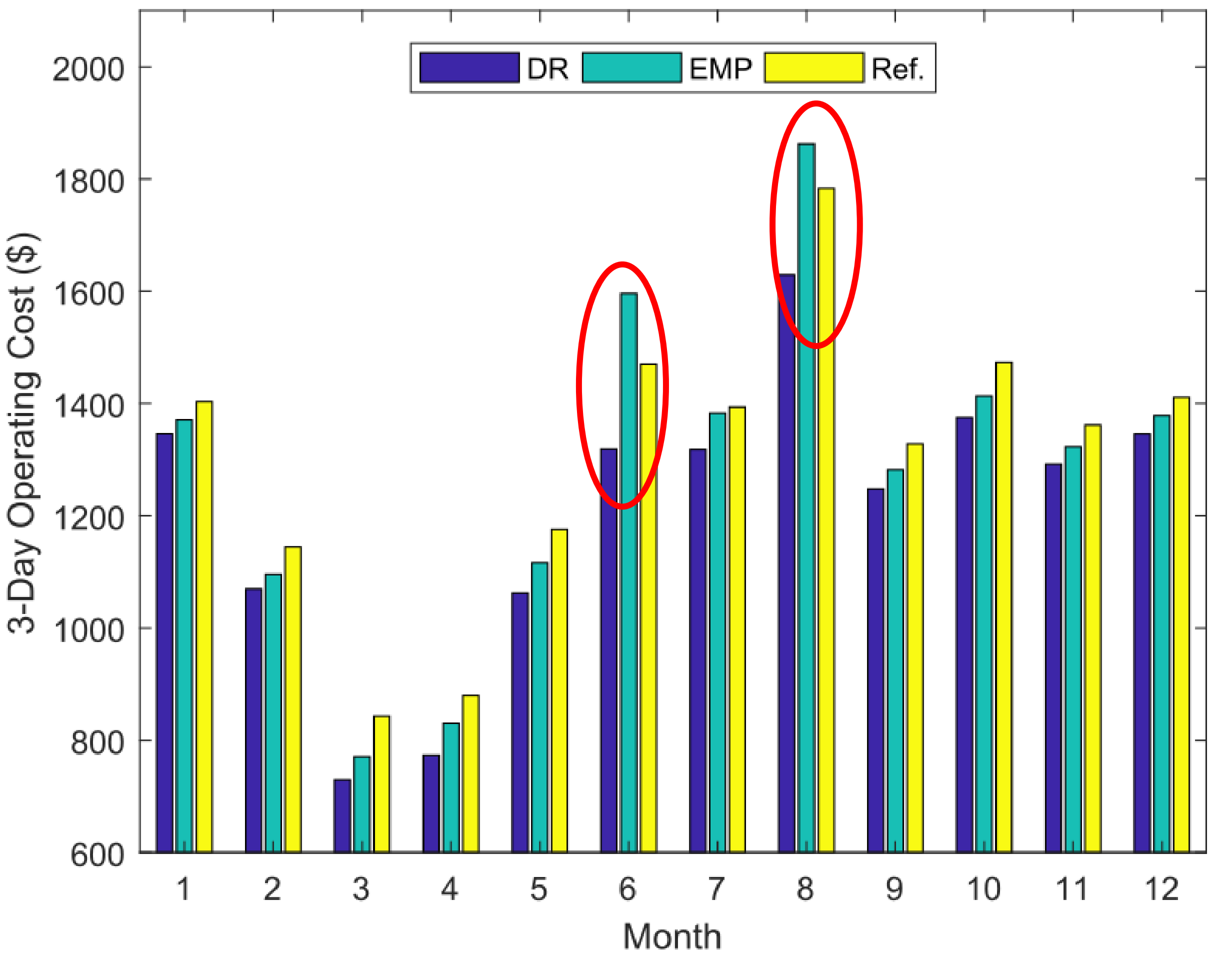
A linear programming formulation for demand response scheduling problem for an industrial air separation unit, in preparation

6. Extension to nonlinear problems

Kelley, M. T., Baldick, R. & Baldea, M. A direct transcription-based multiple shooting formulation for dynamic optimization. Comput. Chem. Eng. 140, 106846 (2020).

Grid-side emissions reduction

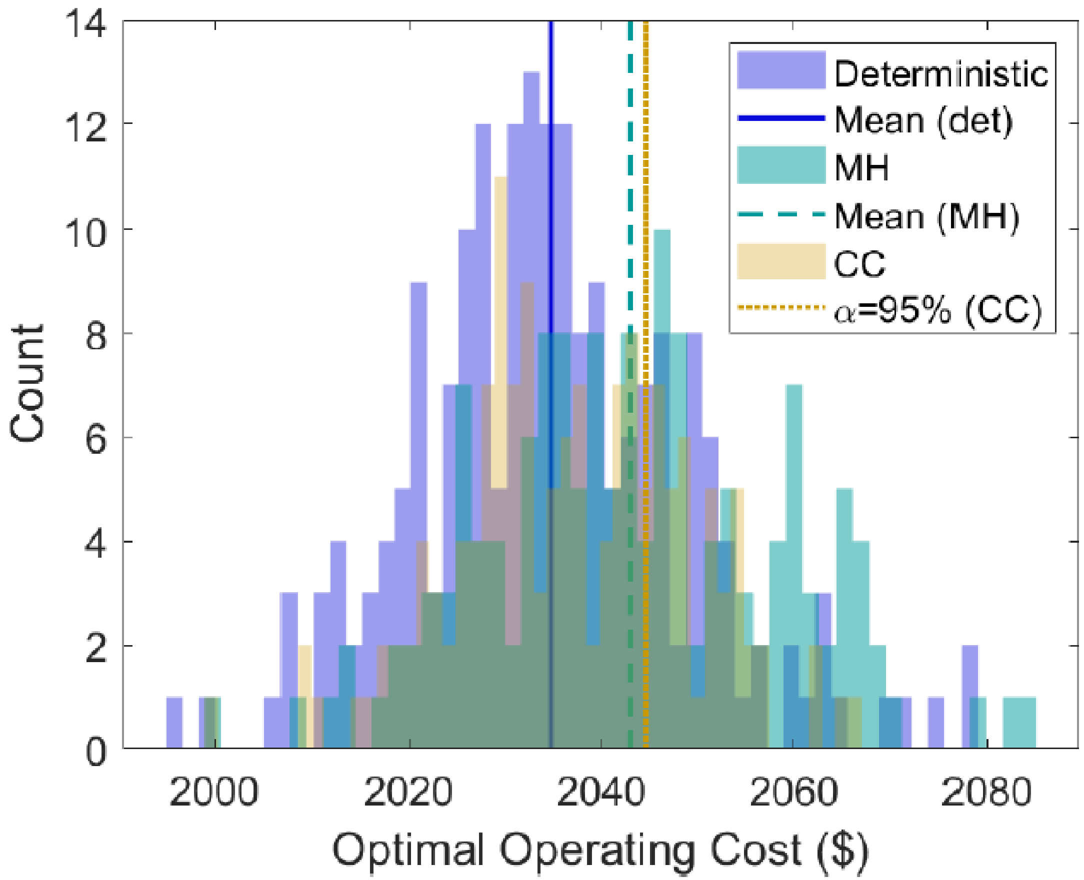




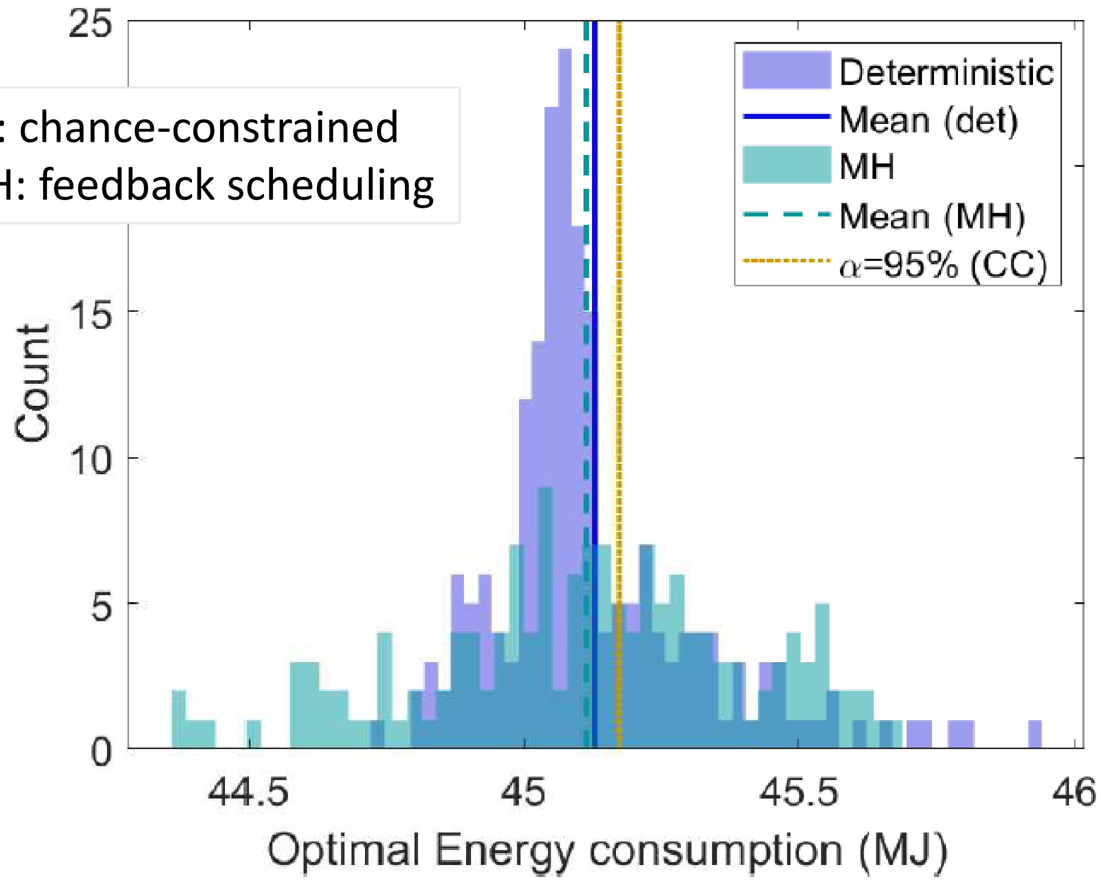
DR consistently lowers emissions even though its aim is to minimize operating cost

Minimizing emissions can increase operating cost during summer months

Consideration of uncertainty



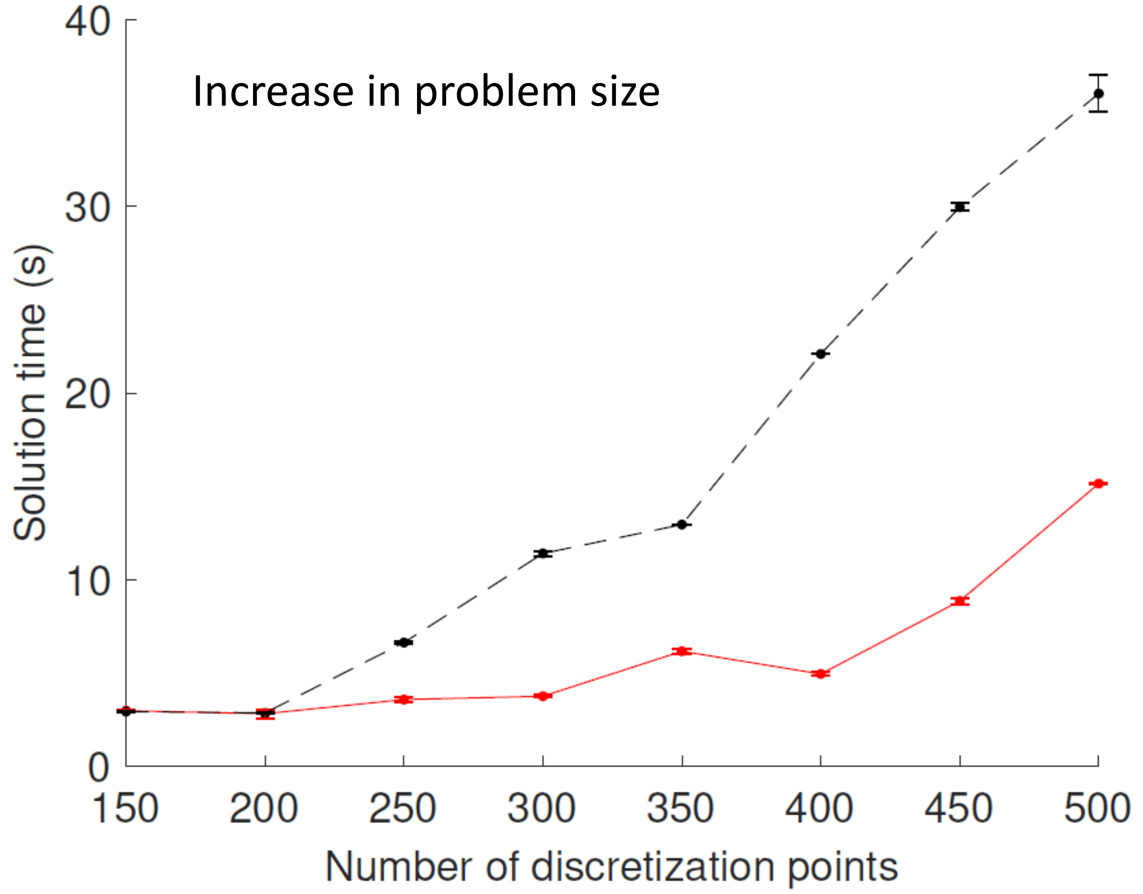
CC: chance-constrained
MH: feedback scheduling

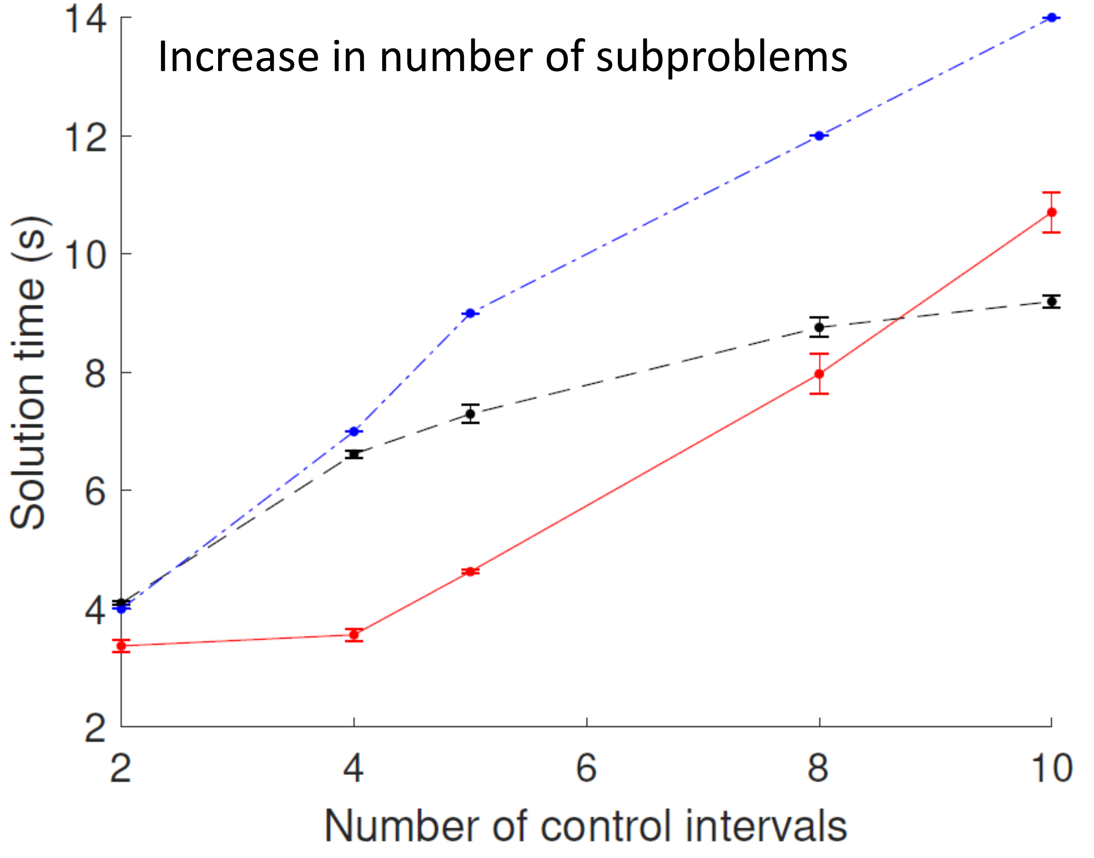


MH and CC methods are comparable, with the MH method allowing more room for correction at rescheduling points

Extension of parallel framework to nonlinear problems

Continuous Sequential: **Blue** dash-dot **Discrete sequential**: **Black** dash **Parallel solution: Red** solid



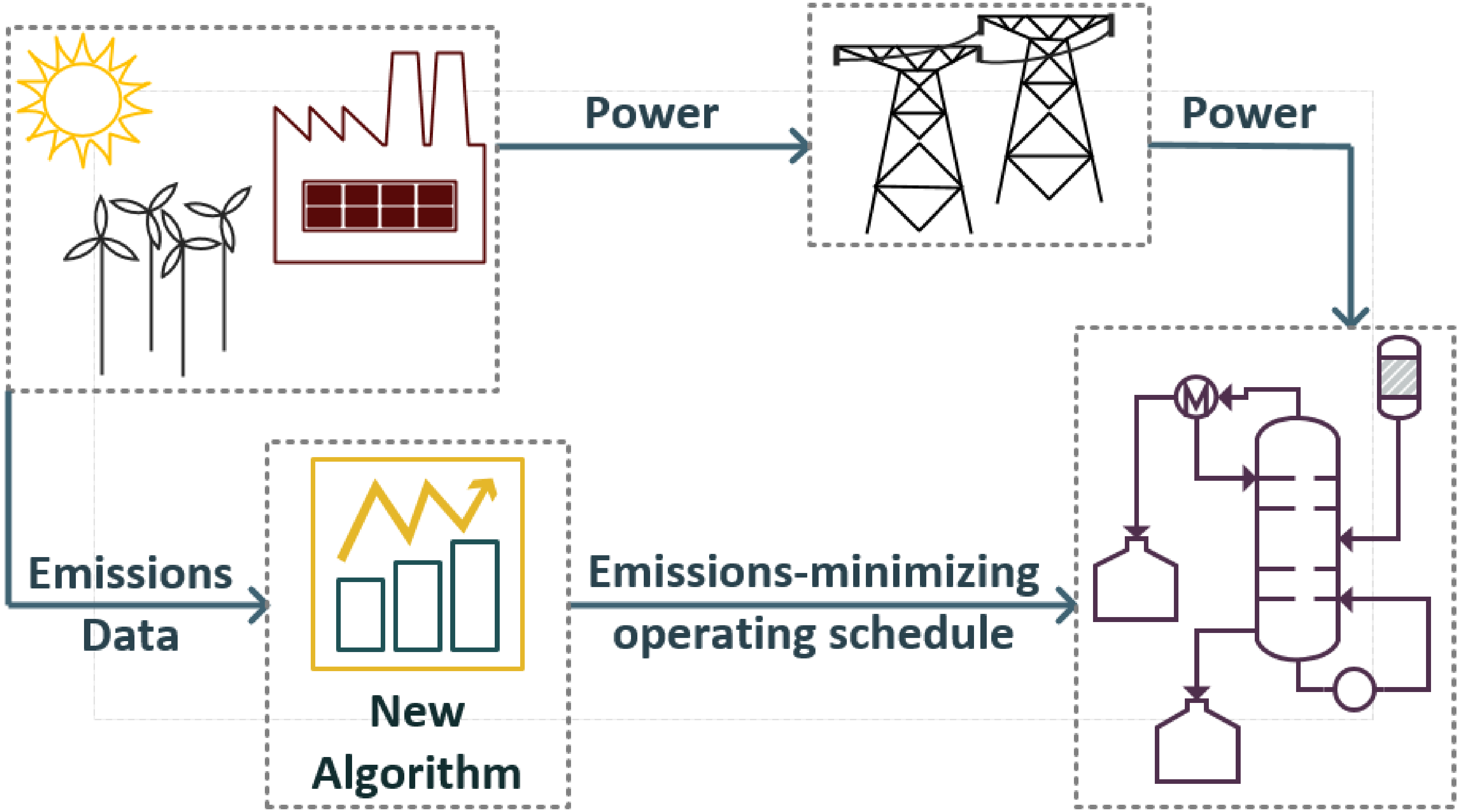


Parallel solution can handle increase in problem size much better than the sequential problem

Parallel solution is beneficial up until a point, where the overhead at generating each independent subproblem is too much

Conclusions

- Developed framework to do optimal scheduling of large chemical entities for participation in load shifting
- Parallelization made a significant difference in terms of solution time and problem flexibility
- The fast solution time enabled many different directions of research



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