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# Enabling effective electrification of the chemical industry via coordinated demand response

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CAPD Energy Systems Initiative (ESI) Seminar

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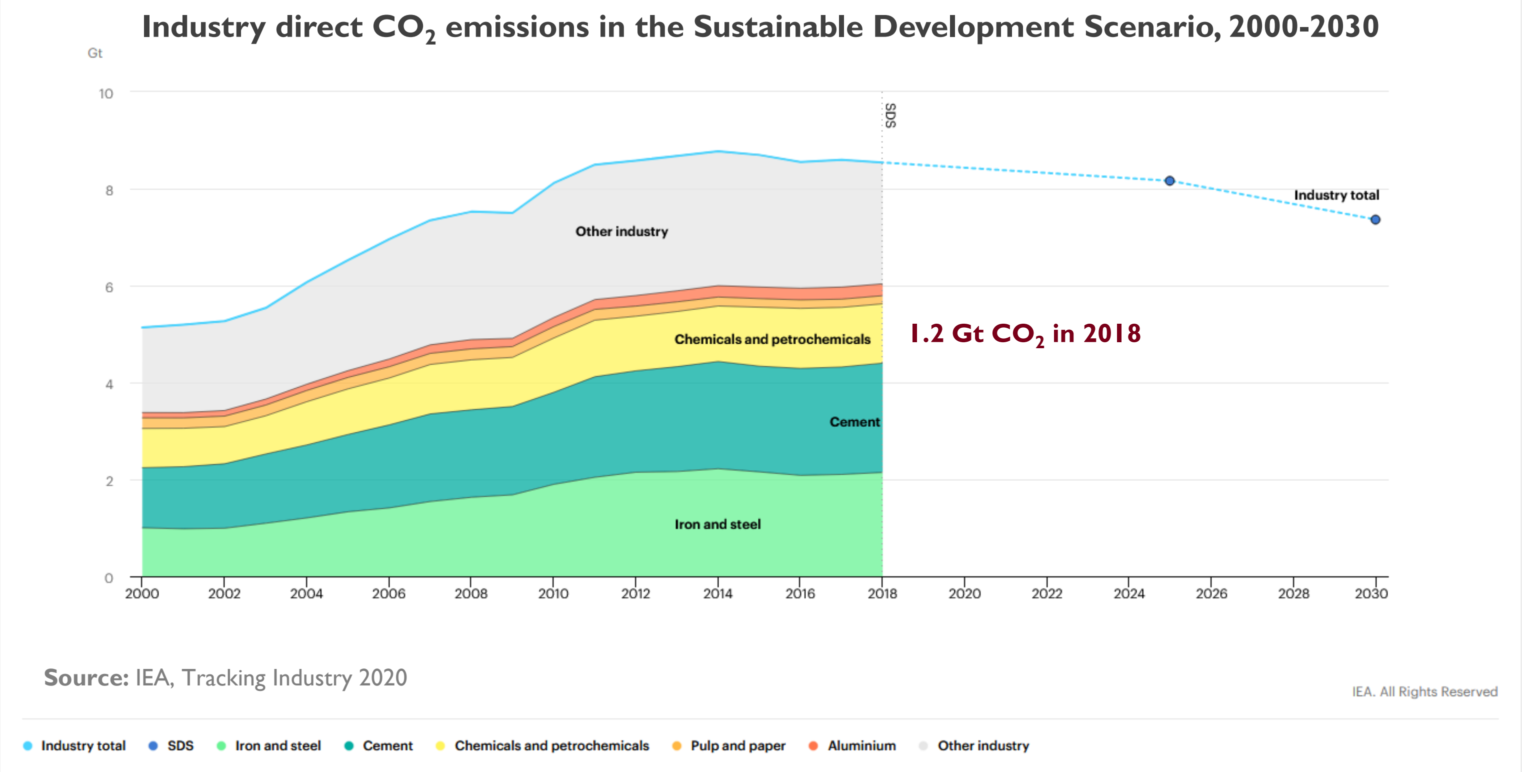
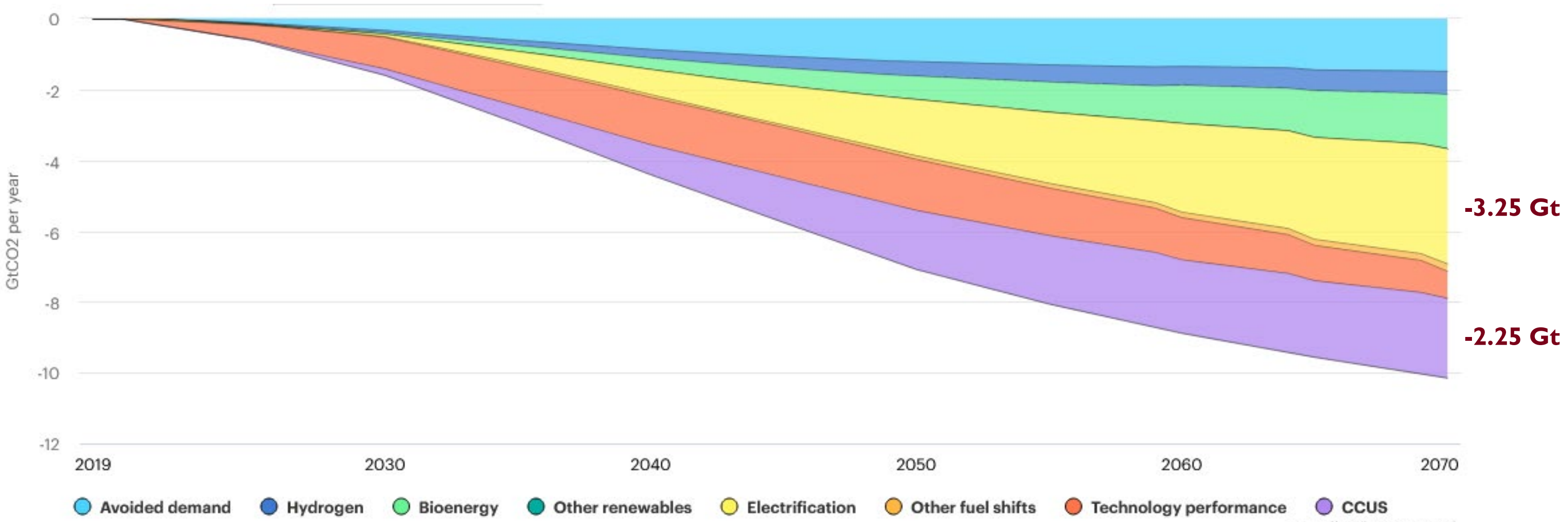
# The chemical industry is a major emitter of $CO_2$




**Source:** IEA, Tracking Industry 2020

# Electrification and CCUS are key emission reduction strategies

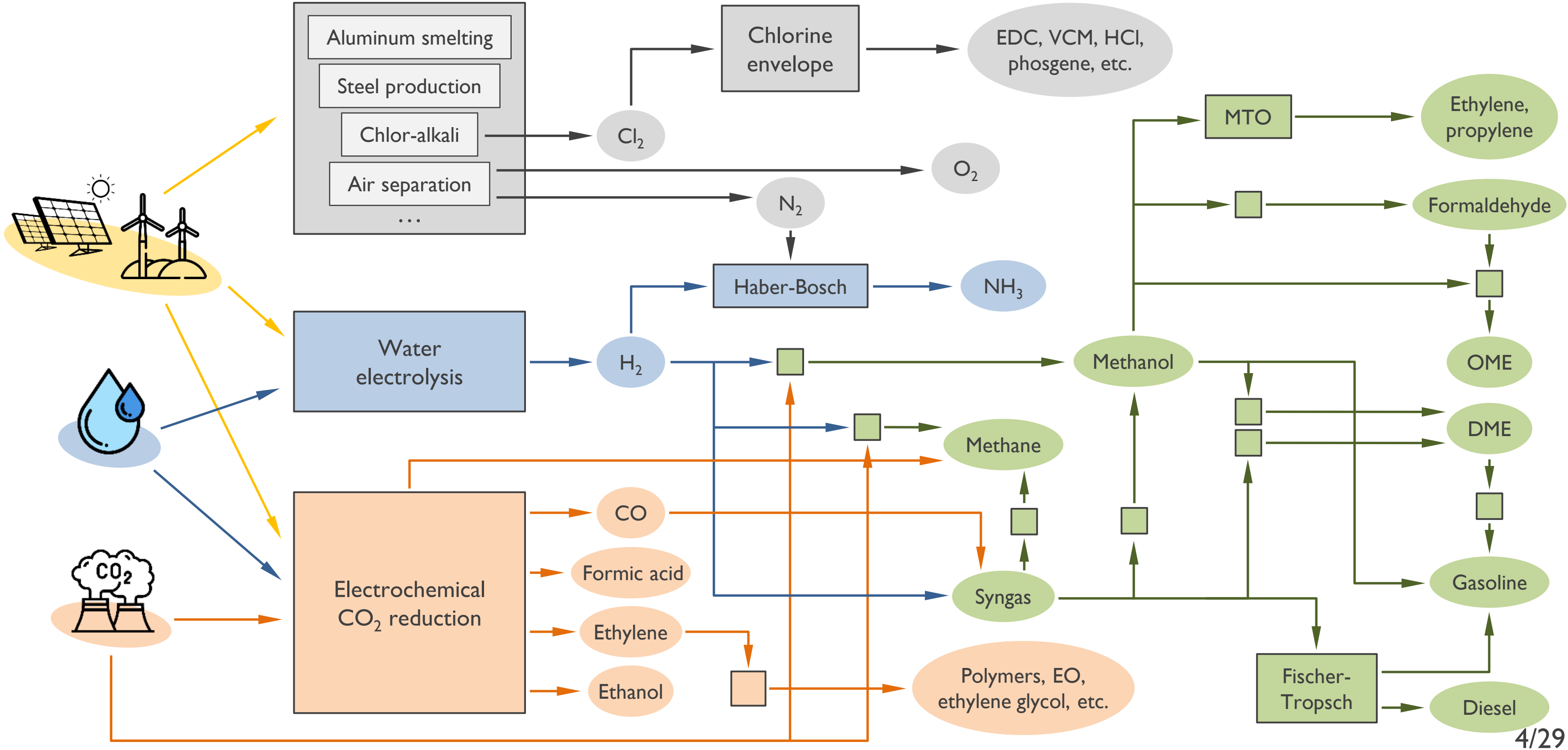
**$CO_2$ emissions reductions in the industrial sector in the Sustainable Development Scenario relative to the Stated Policies Scenario**





**Source:** IEA, Energy Technology Perspectives 2020

# Electrification of the chemical industry



# Challenges and opportunities in an electrified chemical industry

- **Challenge #1:** increasingly time-sensitive availability and pricing of electricity
- **Challenge #2:** significantly greater number of large electricity consumers

→ Requires operational flexibility,

*but also*

**increased demand response (DR) potential**

- **Challenge #3:** highly interconnected networks consisting of a large variety of processes

→ May restrict operational flexibility,

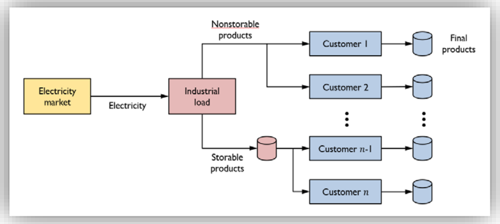
*but also*

**opportunity for non-power-consuming processes to benefit from DR**

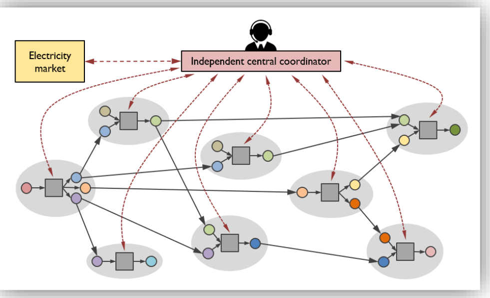
Need **coordinated DR** for maximum operational flexibility and performance

- **Challenge #4:** processes may be owned and operated by different companies/stakeholders

# Outline

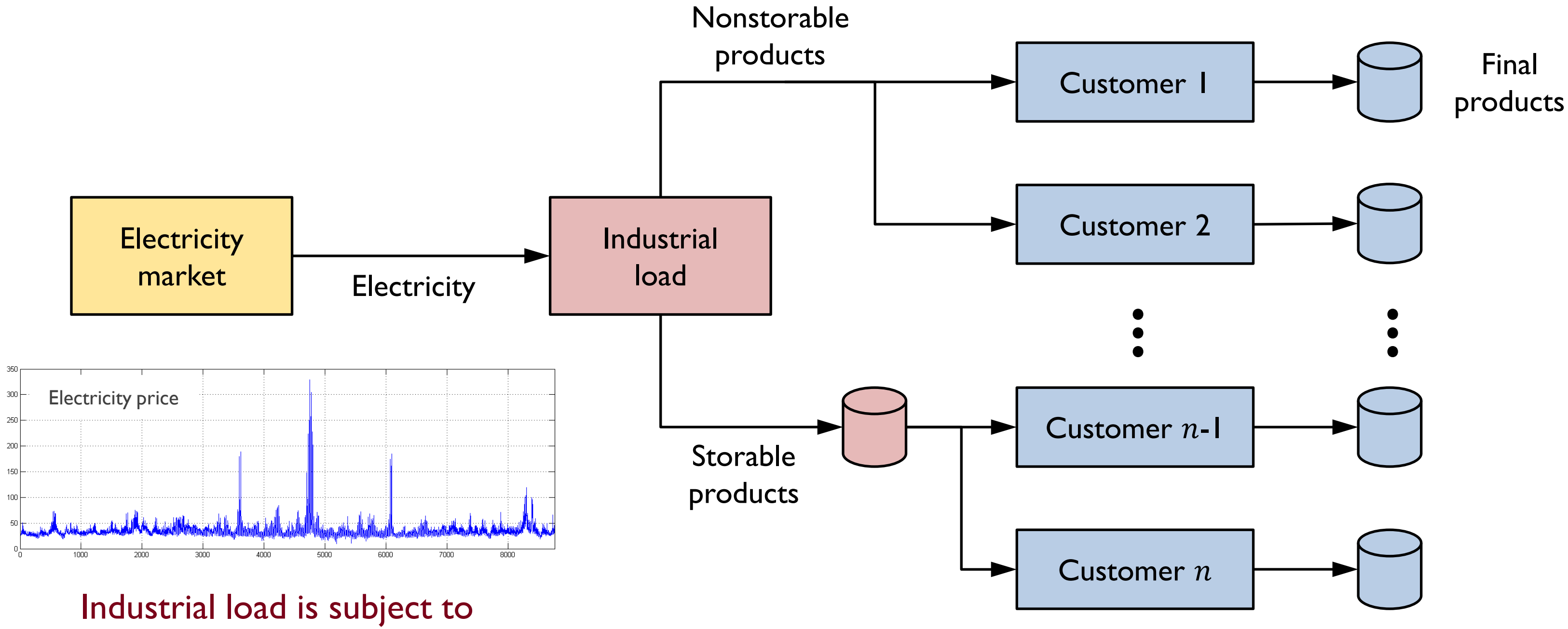



**Coordination between one power-intensive process and its downstream customers**




**Fairness-guided coordinated DR within a general multi-stakeholder process network**

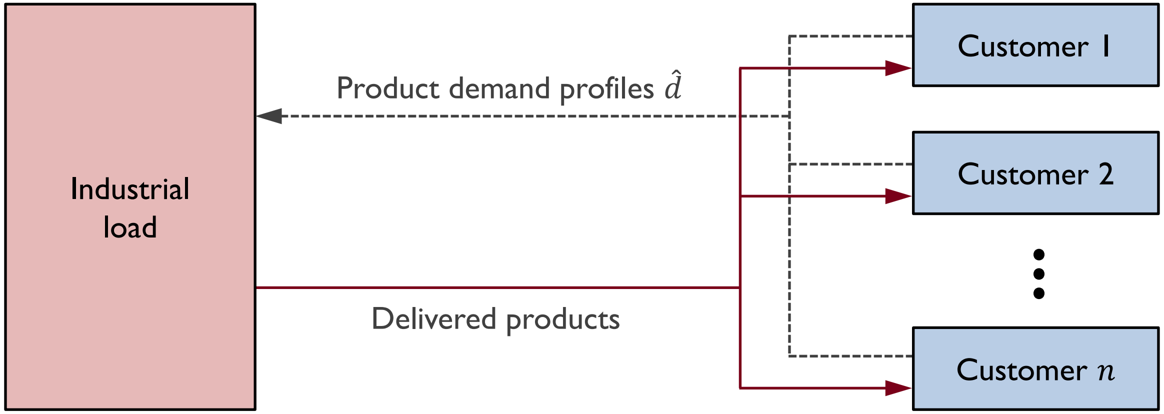
# Single power-intensive process (industrial load) and its customers




Industrial load is subject to time-varying electricity prices

Downstream customers may not be large electricity consumers

# Traditional approach without coordination/cooperation



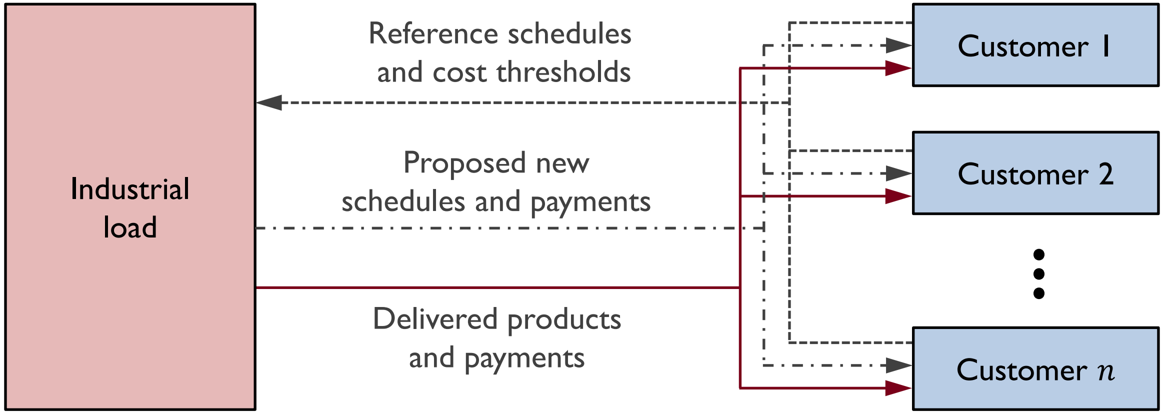

The industrial load solves:

$$\begin{aligned} \hat{f} = \min_{x} \quad & f(x) \\ \text{s.t.} \quad & x \in \mathcal{X}(\hat{d}) \end{aligned}$$

Each customer $i$ solves scheduling problem:

$$\begin{aligned} \hat{c}_i = \min_{y_i, d_i} \quad & c_i(y_i, d_i) \\ \text{s.t.} \quad & y_i \in \mathcal{Y}_i(d_i) \\ & d_{ijt}^{\min} \leq d_{ijt} \leq d_{ijt}^{\max} \quad \forall j \in \mathcal{J}, t \in \mathcal{T} \end{aligned}$$

# Cooperative DR relies on incentives for changing demand profiles




- Solving a cooperative DR problem, the industrial load determines new schedules and proposes payments to the customers
- Implements a solution that benefits both the industrial load and its customers

- Solving the same scheduling problem, each customer $i$ determines a reference schedule including $\hat{d}_i$
- It also submits a cost threshold $\beta_i \hat{c}_i$, indicating when it would agree to deviations in $\hat{d}_i$

# Mathematical formulation of the cooperative DR problem

weighted overall cost function

$$\underset{d,x,y,z,\gamma}{\text{minimize}} \quad \alpha \left( f(x) + \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} \sum_{t\in\mathcal{T}} \gamma_j |d_{ijt} - \hat{d}_{ijt}| \right) + (1-\alpha) \sum_{i\in\mathcal{I}} \left( c_i(y_i, d_i) - \sum_{j\in\mathcal{J}} \sum_{t\in\mathcal{T}} \gamma_j |d_{ijt} - \hat{d}_{ijt}| \right)$$

subject to

$$x \in \mathcal{X}(d)$$

feasibility for industrial load

$$y_i \in \mathcal{Y}_i(d_i) \quad \forall i \in \mathcal{I}$$

$$d_{ijt}^{\min} \leq d_{ijt} \leq d_{ijt}^{\max} \quad \forall i \in \mathcal{I},\ j \in \mathcal{J},\ t \in \mathcal{T}$$

feasibility for customers

$$f(x) + \sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{J}} \sum_{t\in\mathcal{T}} \gamma_j |d_{ijt} - \hat{d}_{ijt}| \leq \hat{f}$$

industrial load's cost must not exceed the reference

$$c_i(y_i, d_i) - \sum_{j\in\mathcal{J}} \sum_{t\in\mathcal{T}} \gamma_j |d_{ijt} - \hat{d}_{ijt}| \leq \beta_i \hat{c}_i + (1-\beta_i)\hat{c}_i(1-z_i) \quad \forall i \in \mathcal{I}$$

customer $i$ only agrees to deviate if its cost gets below $\beta_i \hat{c}_i$

$$|d_{ijt} - \hat{d}_{ijt}| \leq M_i\, z_i \quad \forall i \in \mathcal{I},\ j \in \mathcal{J},\ t \in \mathcal{T}$$

can deviate from the reference only if $z_i = 1$

$$z_i \in \{0,1\} \quad \forall i \in \mathcal{I}$$

$$\gamma_j \geq 0 \quad \forall j \in \mathcal{J}$$

new variables

**Can be interpreted as a (uniform-price) market for *product* DR**

# Need to solve cooperative DR problem in a distributed manner

Reformulation:

$$\min_{d,[d],x,y,z,\gamma,[\gamma]} \quad \alpha\left(f(x)+\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}}\sum_{t\in\mathcal{T}}\gamma_j|d_{ijt}-\hat{d}_{ijt}|\right)+(1-\alpha)\sum_{i\in\mathcal{I}}\left(c_i(y_i,[d]_i)-\sum_{j\in\mathcal{J}}\sum_{t\in\mathcal{T}}[\gamma]_{ij}|[d]_{ijt}-\hat{d}_{ijt}|\right)$$

subject to

$$x\in\mathcal{X}(d)$$

$$f(x)+\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}}\sum_{t\in\mathcal{T}}\gamma_j|d_{ijt}-\hat{d}_{ijt}|\le\hat{f}$$

$$d_{ijt}^{\min}\le d_{ijt}\le d_{ijt}^{\max}\quad\forall i\in\mathcal{I},\ j\in\mathcal{J},\ t\in\mathcal{T}$$

$$\gamma_j\ge 0\quad\forall j\in\mathcal{J}$$

industrial load's subproblem

$$y_i\in\mathcal{Y}_i([d]_i)\quad\forall i\in\mathcal{I}$$

$$c_i(y_i,[d]_i)-\sum_{j\in\mathcal{J}}\sum_{t\in\mathcal{T}}[\gamma]_{ij}|[d]_{ijt}-\hat{d}_{ijt}|\le\beta_i\hat{c}_i+(1-\beta_i)\hat{c}_i(1-z_i)\quad\forall i\in\mathcal{I}$$

$$|[d]_{ijt}-\hat{d}_{ijt}|\le M_i z_i\quad\forall i\in\mathcal{I},\ j\in\mathcal{J},\ t\in\mathcal{T}$$

$$d_{ijt}^{\min}\le[d]_{ijt}\le d_{ijt}^{\max}\quad\forall i\in\mathcal{I},\ j\in\mathcal{J},\ t\in\mathcal{T}$$

$$z_i\in\{0,1\}\quad\forall i\in\mathcal{I}$$

$$[\gamma]_{ij}\ge 0\quad\forall i\in\mathcal{I},\ j\in\mathcal{J}$$

each customer's subproblem

$$d_{ijt}=[d]_{ijt}\quad\forall i\in\mathcal{I},\ j\in\mathcal{J},\ t\in\mathcal{T}$$

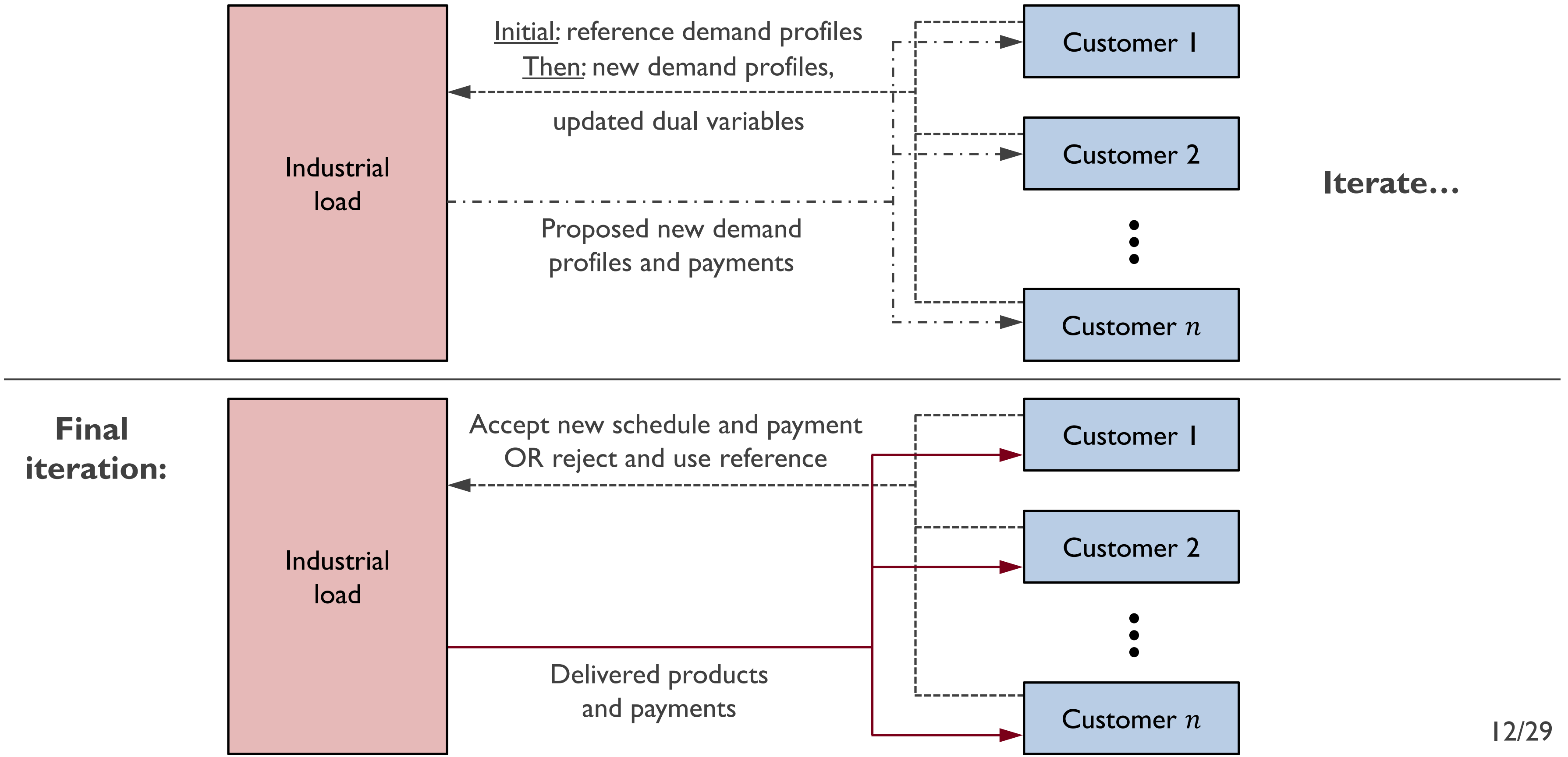
$$\gamma_j=[\gamma]_{ij}\quad\forall i\in\mathcal{I},\ j\in\mathcal{J}$$

introduce copy variables → linking constraints

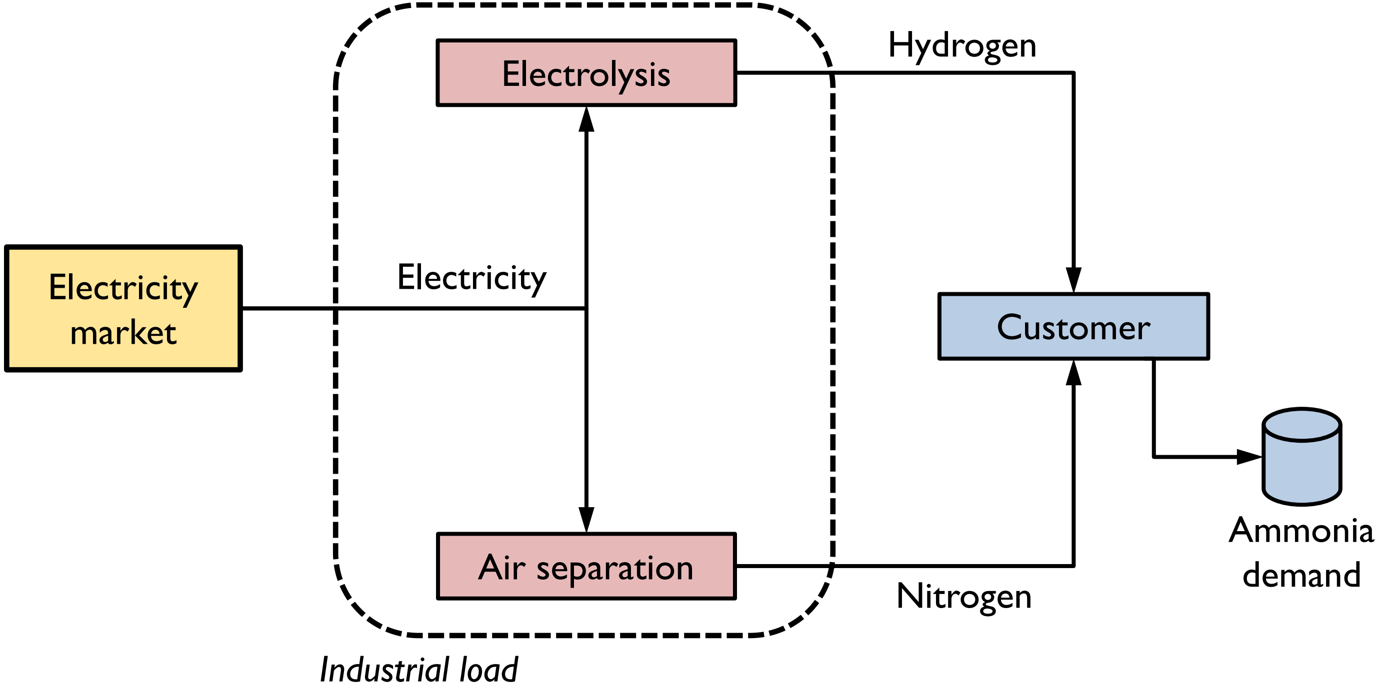
Dualize linking constraints and solve using the alternating direction method of multipliers (ADMM)[1]

1. Boyd et al. (2011). *Foundations and Trends in Machine Learning, 3,* 1-122.

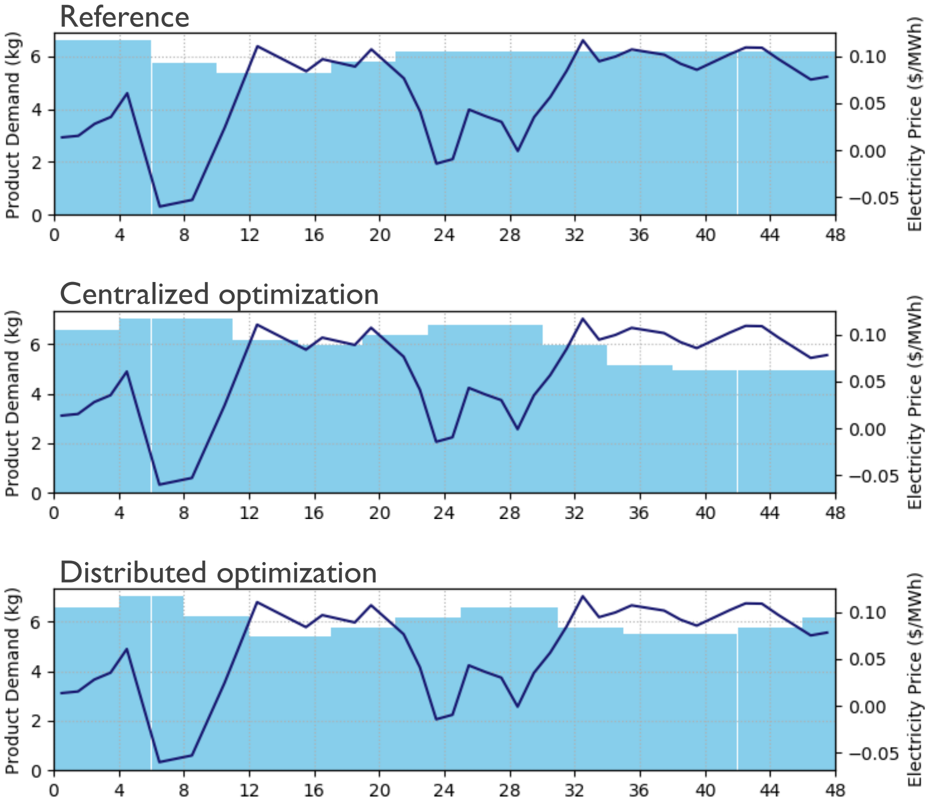
# Illustration of ADMM algorithm



# Green ammonia case study



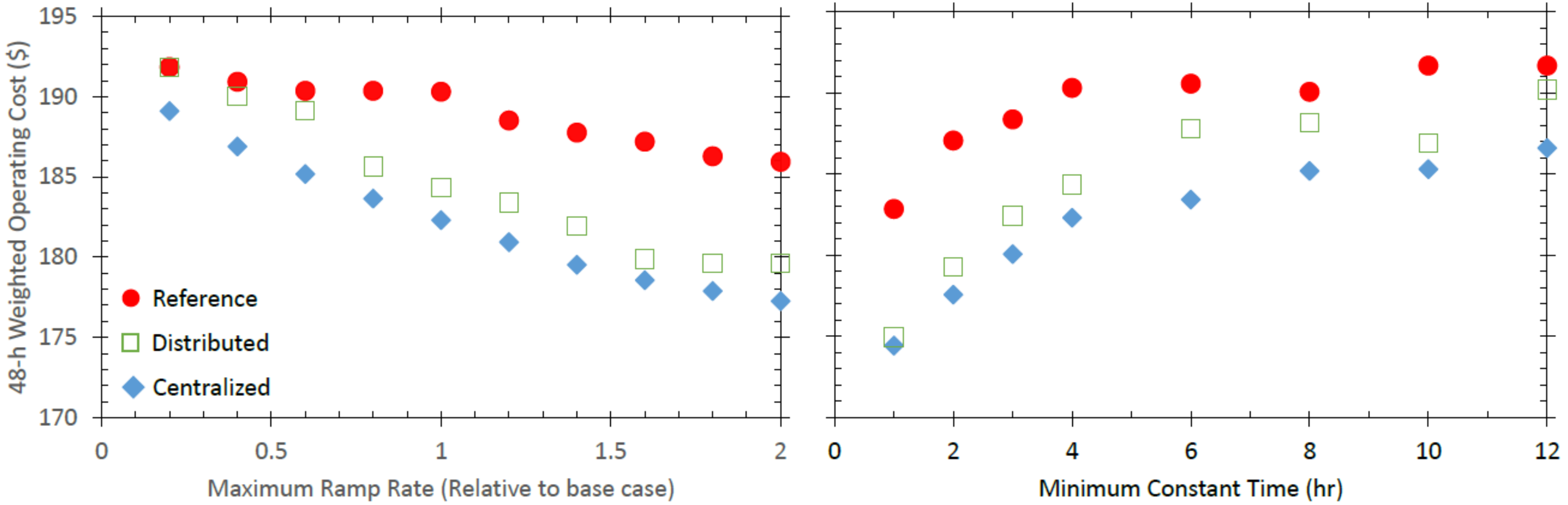
# Cooperative DR achieves cost savings for both load and customer



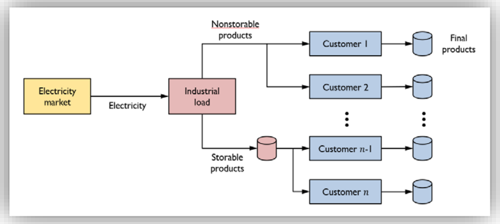

| | Load | Customer |
|---|---|---|
| **Ref.** | $286 | $42 |
| **Cent.** | $276 (4.4% savings) | $41 (2% savings) |
| **Dist.** | $280 (3.2% savings) | $41 (2% savings) |

# Sensitivity analysis: effect of dynamic flexibility

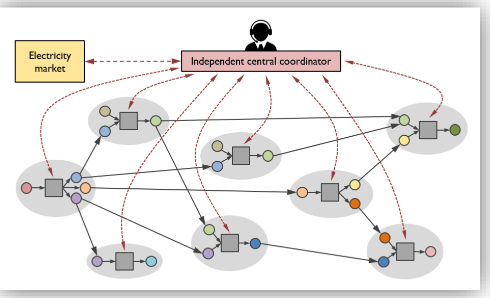
- Ammonia reactor's dynamics is characterized by the maximum ramp rate and the minimum constant time



# Outline



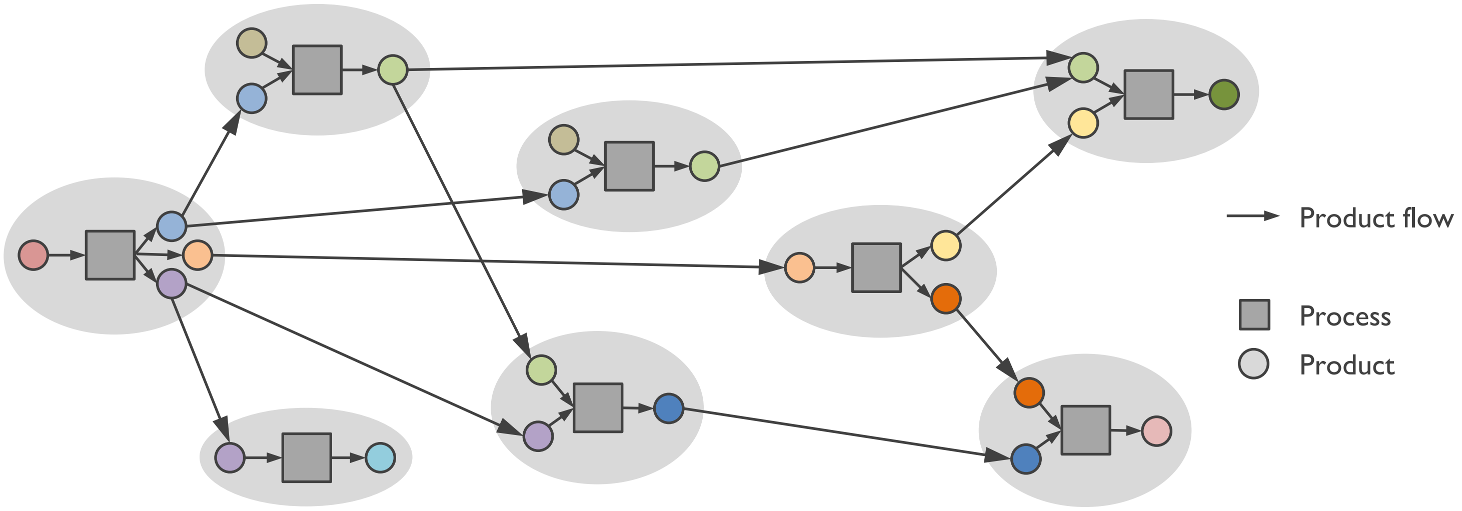

**Coordination between one power-intensive process and its downstream customers**



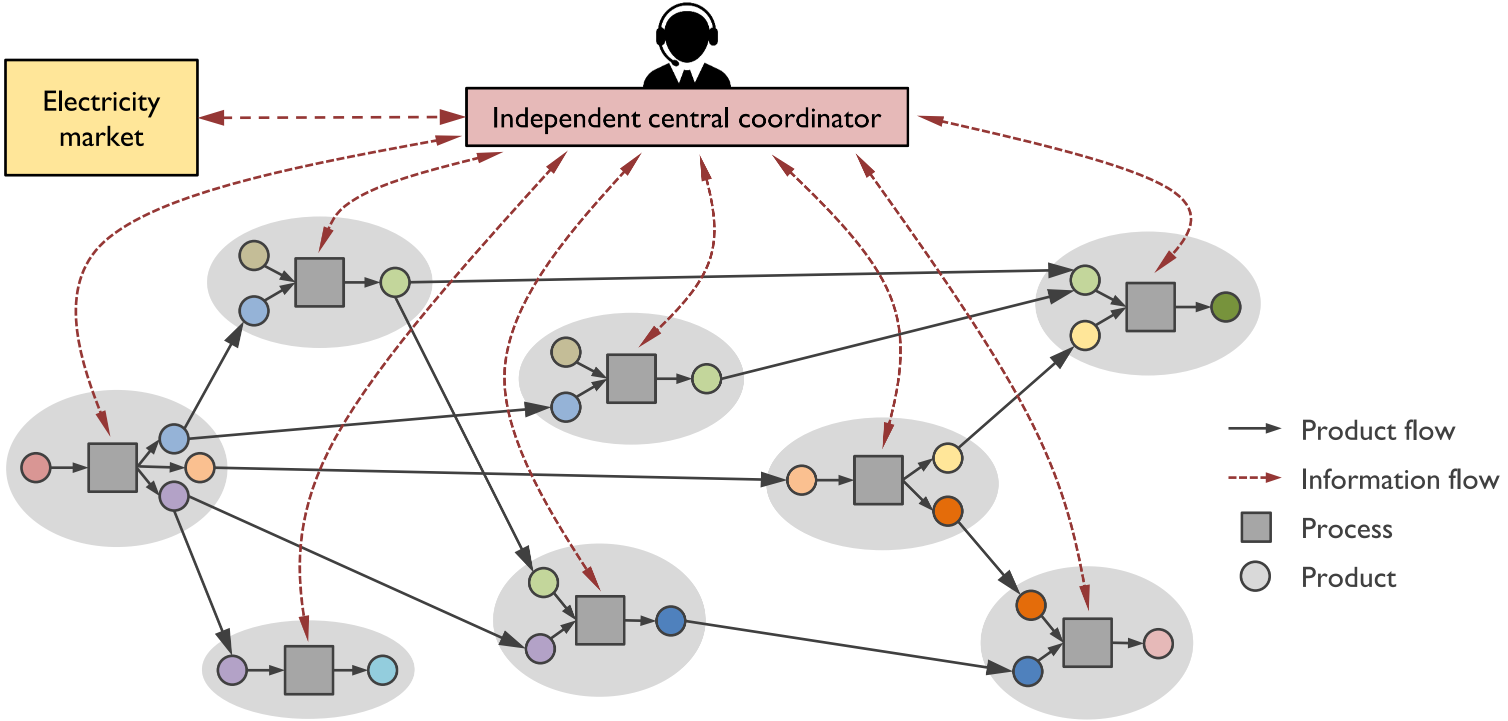

**Fairness-guided coordinated DR within a general multi-stakeholder process network**

# Need different coordination approach for general process networks

- Previous method does not directly extend to more complex networks
- **Main question:** How to distribute jointly generated benefits? → **fair allocation**



# Envisioned coordinated DR framework



# Network model with DR aggregation

For each process $i$, we have:

$$s_{ijt} = s_{ij,t-1} + q_{ijt} - \sum_{i' \in \bar{\mathcal{I}}_{ij}} y_{ii'jt} \quad \forall\, j \in \bar{\mathcal{J}}_i,\, t \in \mathcal{T}$$

$$s_{ijt} = s_{ij,t-1} - q_{ijt} + \sum_{i' \in \widehat{\mathcal{I}}_{ij}} y_{i'ijt} \quad \forall\, j \in \widehat{\mathcal{J}}_i,\, t \in \mathcal{T}$$

$$y_{ii'jt} \in \mathbb{R}_+ \quad \forall\, j \in \bar{\mathcal{J}}_i,\, i' \in \bar{\mathcal{I}}_{ij},\, t \in \mathcal{T}$$

material balances

$$(q_i, s_i, r_i) \in \mathcal{X}_i$$

general operational constraints

$$u_i(q_i, s_i, r, y) = \sum_{t \in \mathcal{T}} \left( \sum_{j \in \bar{\mathcal{J}}_i} \sum_{i' \in \bar{\mathcal{I}}_{ij}} \alpha_{ii'jt}\, y_{ii'jt} - \sum_{j \in \widehat{\mathcal{J}}_i} \sum_{i' \in \widehat{\mathcal{I}}_{ij}} \beta_{i'ijt}\, y_{i'ijt} \right) - f_i(q_i, s_i) - h_i(r)$$

utility function

$$h_i(r) = \sum_{t \in \mathcal{T}} \frac{r_{it}}{\bar{r}_t} \bar{h}_t(\bar{r}_t) \quad \text{with} \quad \bar{r}_t = \sum_{i' \in \mathcal{I}} r_{i't}$$

disaggregated electricity cost, $\bar{h}_t(\bar{r}_t)$ assumed to be convex

# What should be optimized?

- Total utility maximization (TUM):

$$\begin{aligned} \underset{q,s,r,y}{\text{maximize}} \quad & \sum_{i \in \mathcal{I}} u_i(q_i, s_i, r, y) \\ \text{subject to} \quad & (q, s, r, y) \in \mathcal{F} \end{aligned}$$

- Does not respect individual stakeholders' objectives
- May lead to solutions that favor some processes over others

→ **Need a fair allocation scheme that all stakeholders can agree to**

# Use Nash bargaining as the fair allocation scheme

- There are several notions of fairness and corresponding fairness metrics[1]
- We apply the definition of fairness proposed by Nash[2], which involves four axioms:
  1. Symmetry
  2. Pareto optimality
  3. Scale invariance
  4. Independence of irrelevant alternatives

- Fair utility allocation (FUA), maximizing the Nash product:

$$\begin{aligned} \underset{q,s,r,y}{\text{maximize}} \quad & \prod_{i \in \mathcal{I}} [u_i(q_i, s_i, r, y) - \tilde{u}_i] \\ \text{subject to} \quad & (q, s, r, y) \in \mathcal{F} \end{aligned}$$

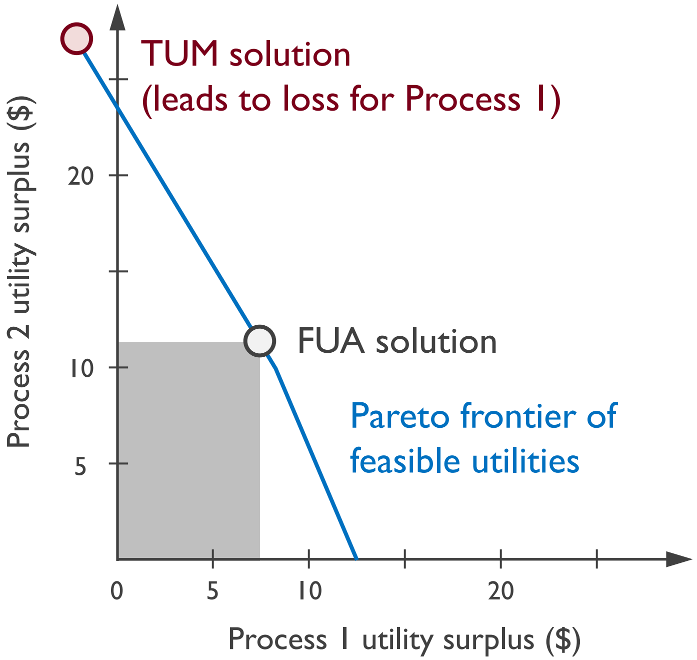
Reformulation →

$$\begin{aligned} \underset{q,s,r,y}{\text{maximize}} \quad & \sum_{i \in \mathcal{I}} \ln \left( u_i(q_i, s_i, r, y) - \tilde{u}_i \right) \\ \text{subject to} \quad & (q, s, r, y) \in \mathcal{F} \end{aligned}$$

Status-quo solution ("disagreement point") — $\tilde{u}_i$

1. Sampat & Zavala (2019). *Optimization & Engineering*, *20*, 1249-1272.
2. Nash (1950). *Econometrica*, 155-162.

# Geometrical interpretation of TUM and FUA



# Increase overall and individual utilities through revenue sharing

- Some processes may only be able to increase their utilities if additional revenues are made
- Fair allocation with revenue sharing (FRS):

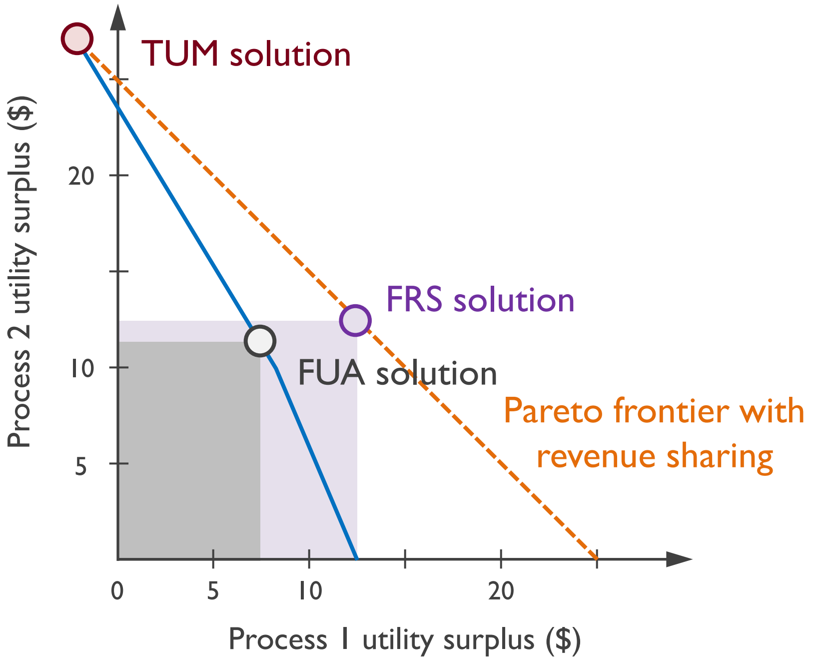
$$\underset{q,s,r,y,z}{\text{maximize}} \quad \sum_{i\in\mathcal{I}} \ln\left(u_i(q_i, s_i, r, y) - z_i - \tilde{u}_i\right)$$

$$\text{subject to} \quad (q, s, r, y) \in \mathcal{F}$$

$$\sum_{i\in\mathcal{I}} z_i = 0,$$

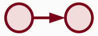
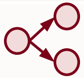
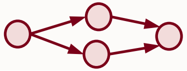
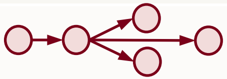
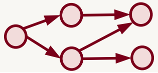
Money exchanged

- **Useful property:** FRS can be solved exactly in two steps
  1. Solve TUM
  2. Obtain shared revenues by solving a set of linear equations

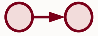
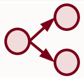
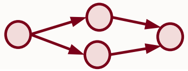
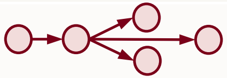
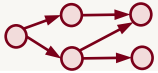



**TUM, FUA, and FRS can all be solved in a distributed manner using ADMM**

# Computational experiments

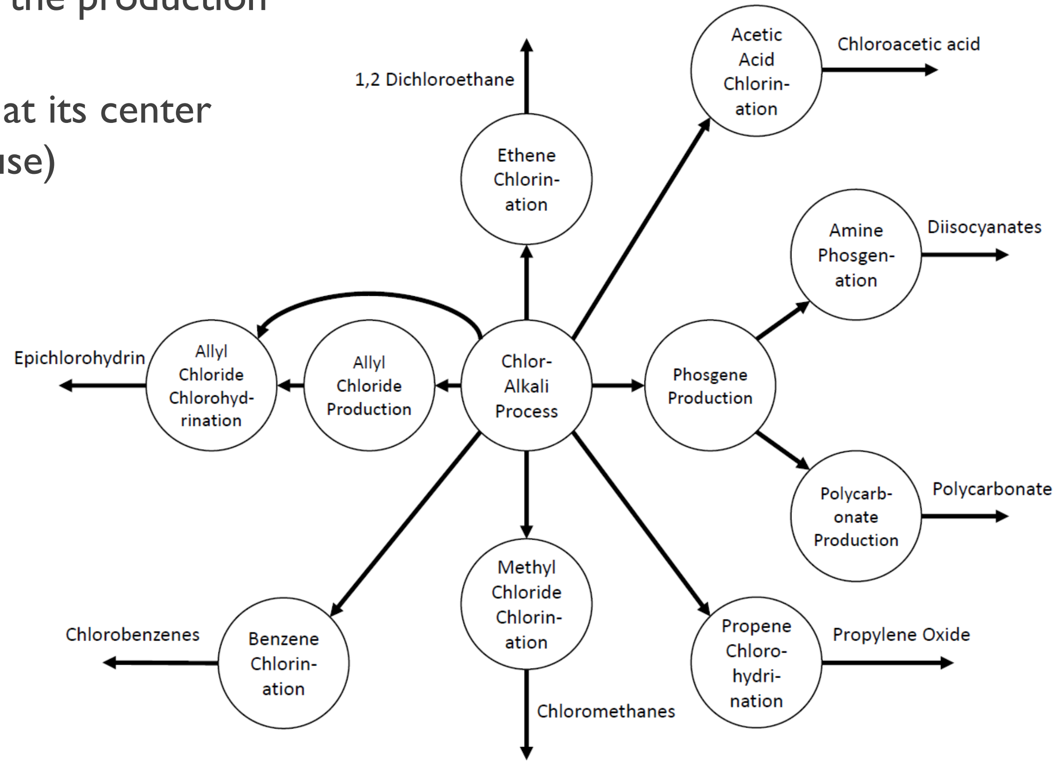
| | Nash product | | | Total savings ($) | |
|---|---|---|---|---|---|
| **Configuration** | TUM | FUA | FRS | TUM/FRS | FUA |
|  | 7.044 | 7.062 | 7.547 | 4,481 | 4,403 |
|  | 7.235 | 7.304 | 7.983 | 9,230 | 8,608 |
|  | 6.673 (1) | 6.944 | 8.157 | 12,903 | 9,804 |
|  | 6.658 | 6.997 | 7.784 | 9,948 | 8,609 |
|  | 7.085 | 7.388 | 8.34 | 25,006 | 17,400 |
|  | 5.980 | 6.278 | 7.097 | 10,878 | 9,106 |
|  | 6.186 (3) | 6.553 | 8.023 | 18,290 | 11,671 |
|  | 5.891 (2) | 7.187 | 8.569 | 33,844 | 21,786 |

# Comparison of distributed solution methods (for FRS)

| | Direct | | | 2-phase | | |
|---|---|---|---|---|---|---|
| **Configuration** | Quality | Time (s) | Iterations | Quality | Time (s) | Iterations |
|  | 100 | 373 | 1,289 | 100 | 73 | 540 |
|  | 100 | 370 | 982 | 100 | 103 | 633 |
|  | 99.9 | 386 | 993 | 100 | 94 | 693 |
|  | 100 | 654 | 1,206 | 100 | 182 | 773 |
|  | 100 | 535 | 1,047 | 100 | 153 | 828 |
|  | 99.9 | 1,381 | 1,510 | 100 | 201 | 878 |
|  | 99.5 | 750 | 1,208 | 100 | 207 | 800 |
|  | 99.4 | 845 | 1,028 | 100 | 157 | 798 |

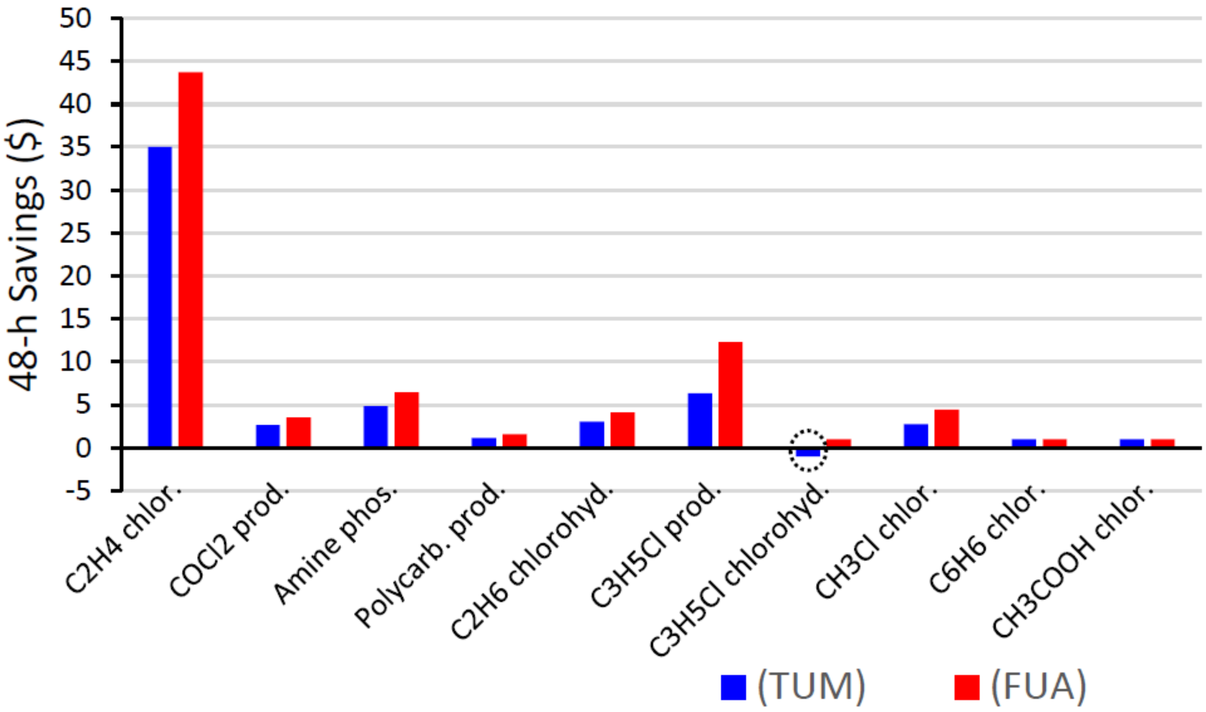
# Chlorine network case study

- Chlorine network is responsible for the production of various important chemicals
- Power-intensive chlor-alkali process at its center (accounts for 2% of U.S. electricity use)
- Involved processes exhibit different characteristics in terms of demands and dynamic flexibility[1]
- Case study with 11 processes




1. Klaucke et al. (2020). *Applied Energy, 276,* 115366.

# Revenue sharing increases overall cost savings by 54%

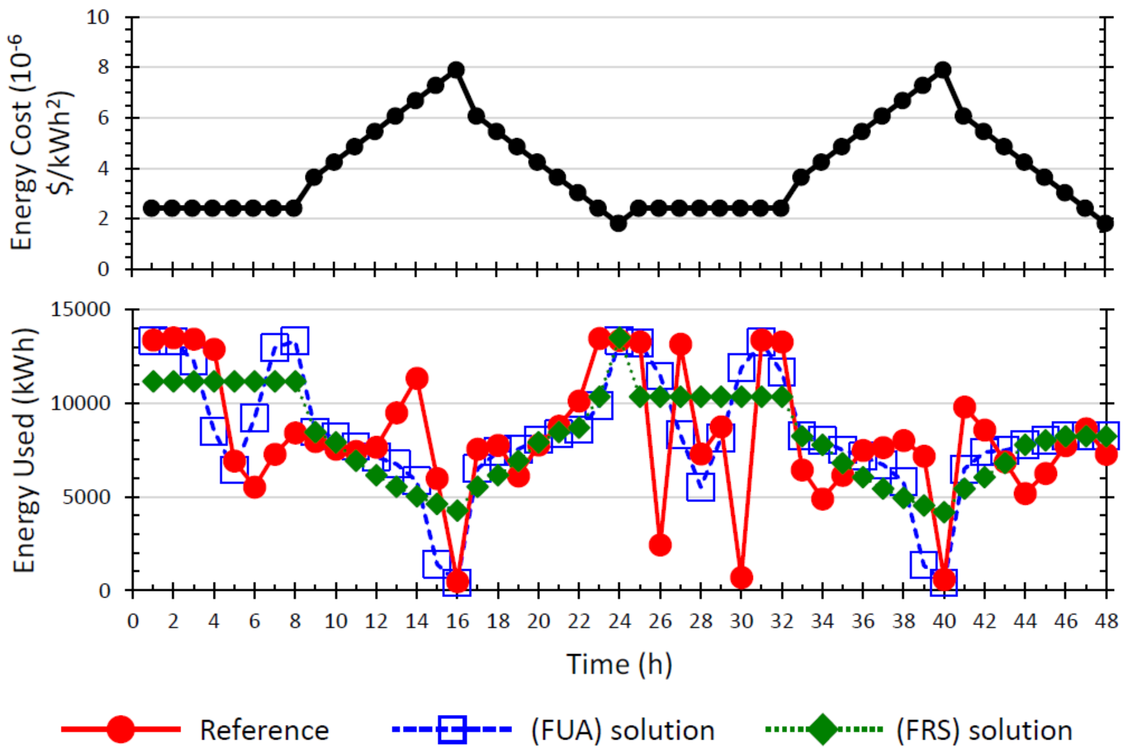



**TUM:** loss for one process

**FUA:** $1,329 cost savings, 94% of which attributed to the chlor-alkali process

**FRS:** $2,048 cost savings, evenly divided between the processes/stakeholders

# Overall energy consumption profiles



# Concluding remarks

- Coordinated DR can increase operational flexibility in process networks, which translates into significant cost savings under time-sensitive electricity pricing

- **Coordinated DR requires:**
  - a mechanism that provides appropriate incentives for cooperation
  - a framework that allows distributed decision making with minimum information sharing

- **Not perfect:** the FRS solution evenly distributes the surpluses without accounting for the effort made by each process → introducing weights may help

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