

PUBLIC

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Inspire the Next

# Scheduling and Energy

Industrial Challenges and Opportunities

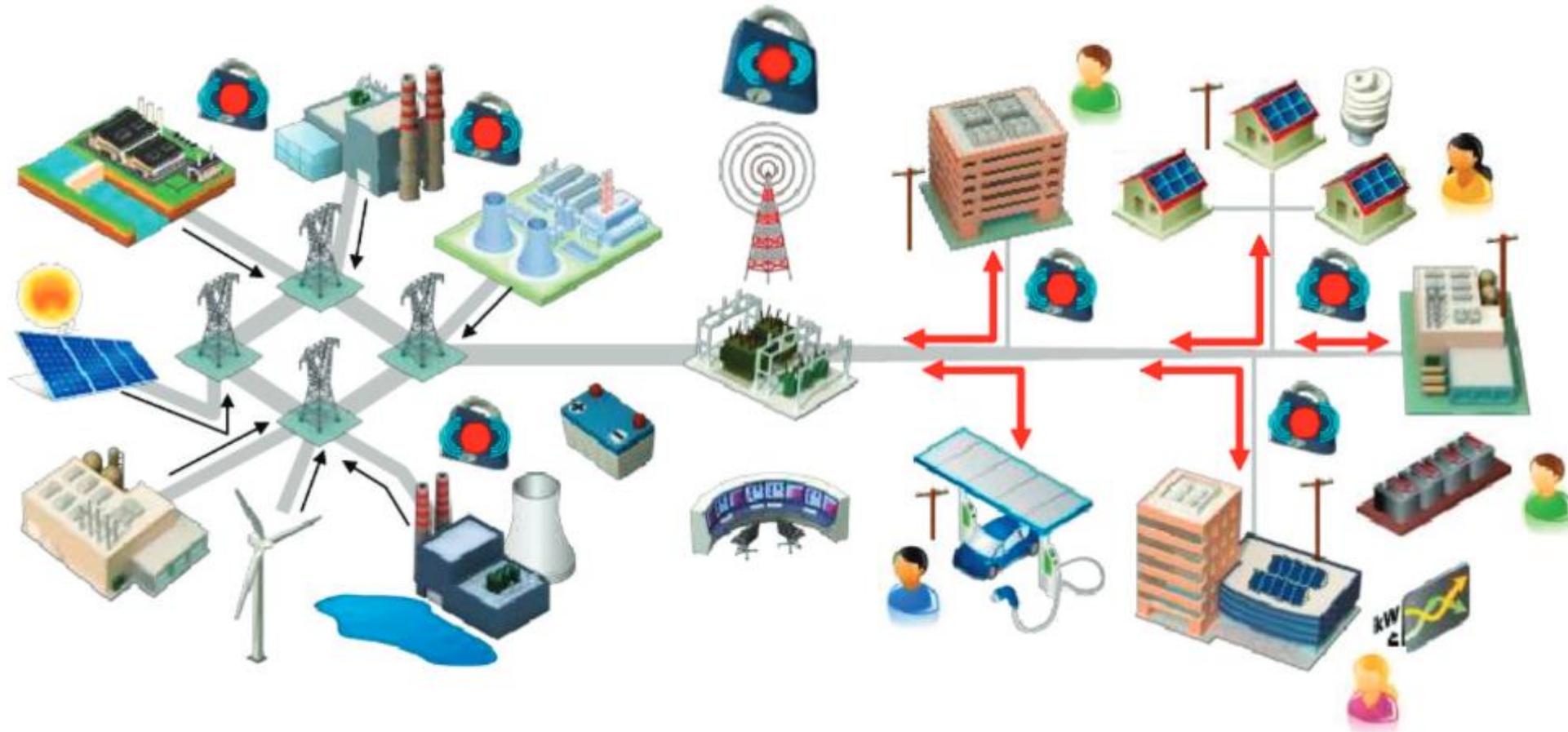
Scheduling Seminar - 2022-04-27, Iiro Harjunkoski

2022-04-27

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 **Hitachi Energy**

# The Future of Electric Power is Bi-Directional and Smart(er)





“  
Electricity will be the backbone of the entire energy system

**01**

Accelerated shift from fossil-based to renewable power generation

**02**

Growing electrification of Transportation, Industry and Buildings sectors

**03**

Sustainable energy carriers, complementary to direct electrification

## Fast facts

“  
Global electrification will be more than 50% of total energy demand

“  
Electrification improves energy efficiency

“  
All market sectors converting towards electrification

“  
Energy sector-coupling beneficial

## So what?

Digital and energy platforms are needed...

...to manage the enormous power system energy transition challenges:

increased complexity  
additional capacity

**for reduction of CO<sub>2</sub> emissions**

**Accelerating the transition to a carbon-neutral energy system requires adapting and adopting policies and regulations to enable technology and new business models to support Scalable, Flexible and Secure energy systems**

- Highlight the importance of energy / electricity
- Give insights to solving industrial-scale scheduling problems (demand-side management)
- Present some strategies to speed up large-scale optimization problems
- Share some personal experiences from working with MILP problems
  - Melt-shop (steel) scheduling
  - Unit Commitment



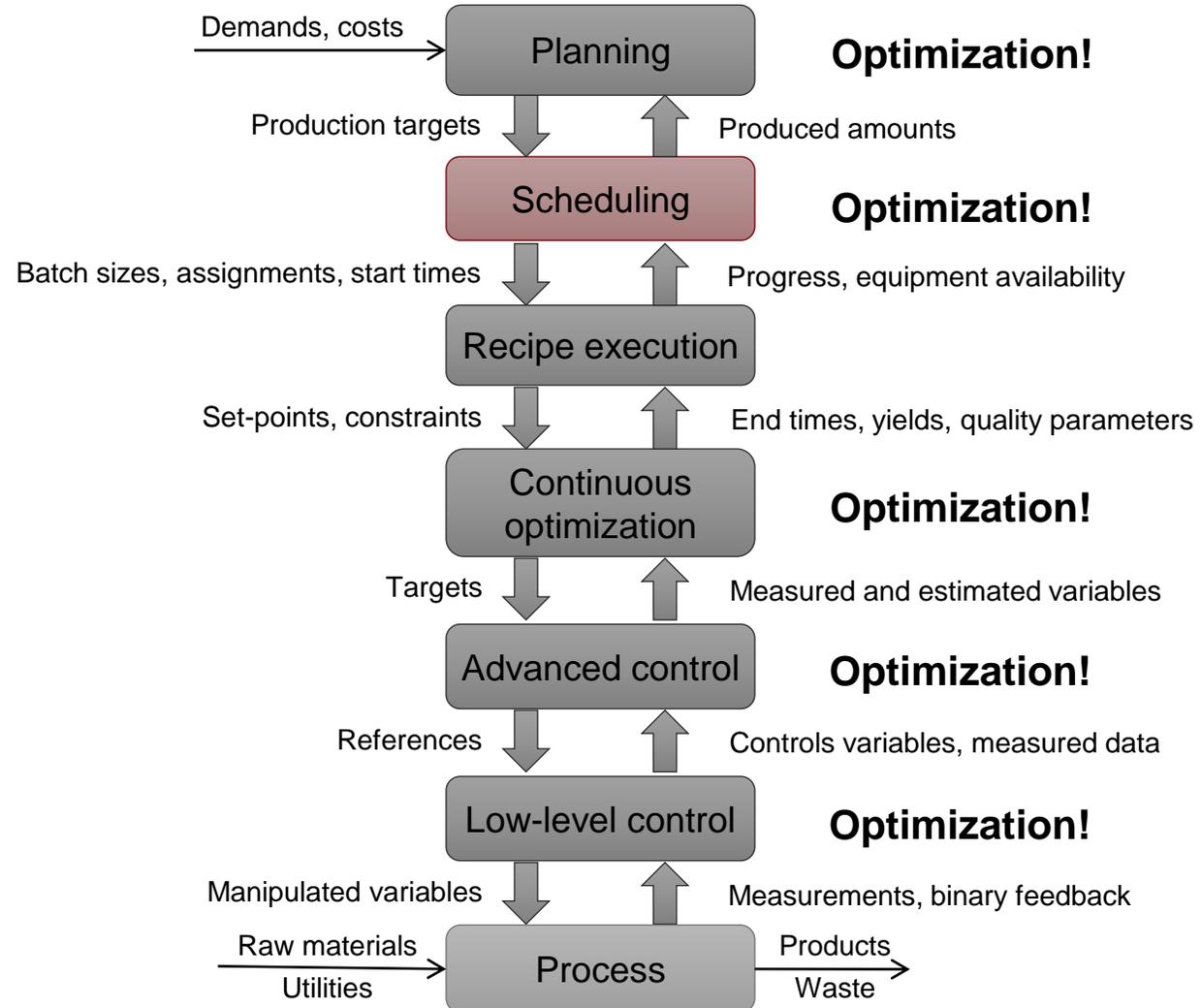
**MILP is an important (although not only) component in solving industrial scheduling problems**

# Outline of the Talk

1. Why MILP?
2. Demand-side Management – Short Introduction
3. Steel Production Scheduling (continuous-time)
4. Unit Commitment Problem (discrete-time)
5. Conclusions

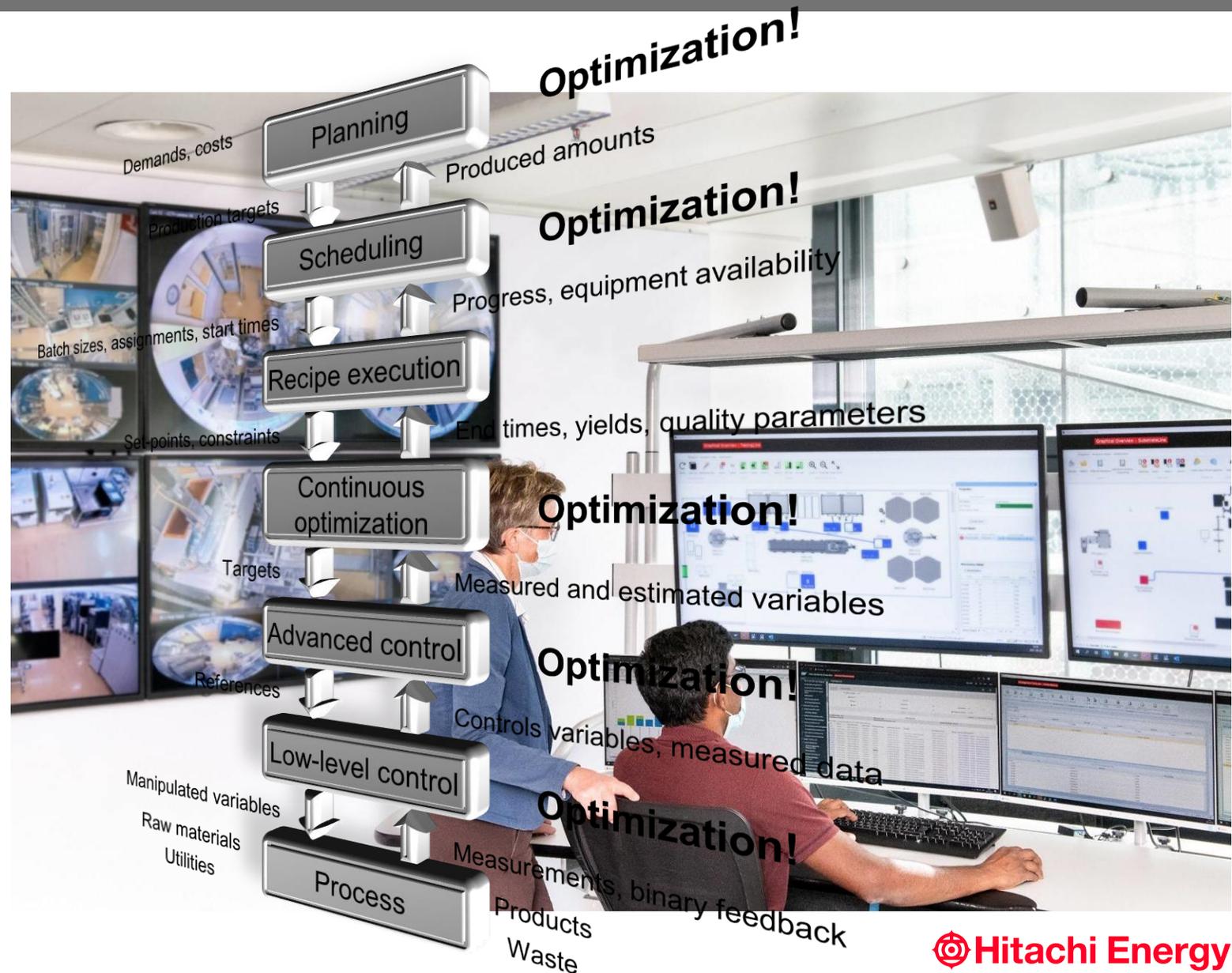
# Why MILP?

# Several Optimization Layers – Potential of Conflicting Actions



MILP models are flexible and “elastic”

- Consider physical and business constraints
- No adaptation to old model needed when adding new constraints
- Commercial solvers – benefit from top OR achievements
- Separate modeling experts and software developers
- Scheduling only one part of automation systems

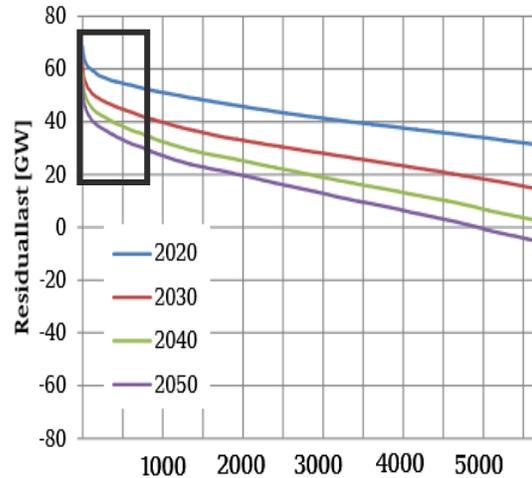


# Demand-side Management

## Short Introduction

## Volatile energy prices

Renewable generation



source: dena – Integration EE

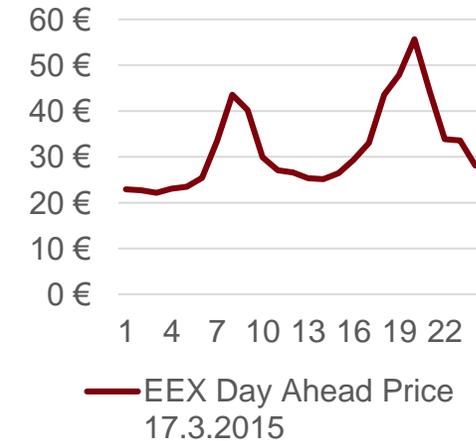
## Consumption & generation

Covering consumption peaks



## Market liberalization

Grid availability and stability



**Demand side management offers benefits in new market environment**

## Using process flexibility for iDSM

Shifting loads of energy intensive process steps to low-cost times

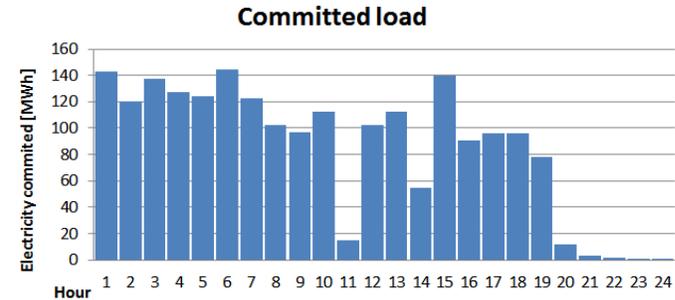
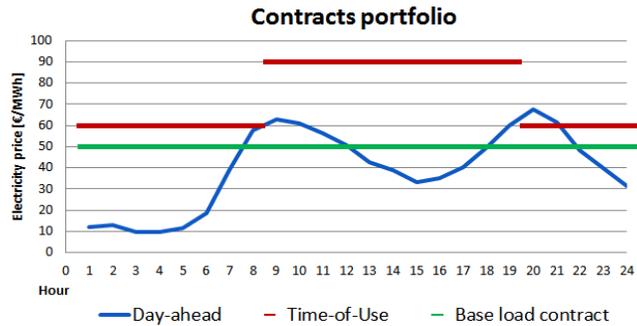


## Reduce critical load of power grids



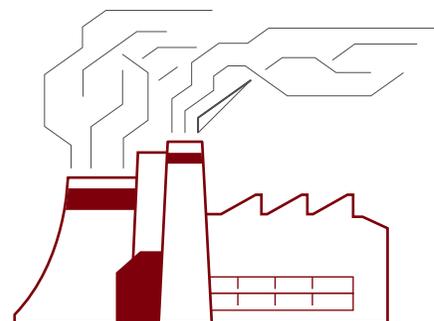
**iDSM allows important cost savings**

# Scheduling of Energy-Intensive Processes



Multiple contracts – time dependent price levels

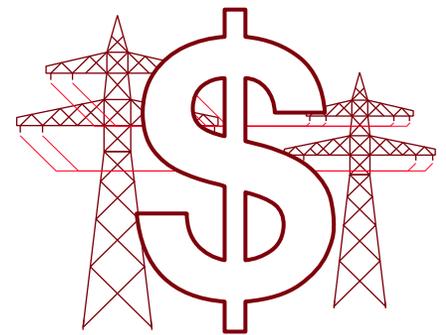
Pre-agreed load curve – penalties for deviation



On-site generation – with special constraints



Demand from production process



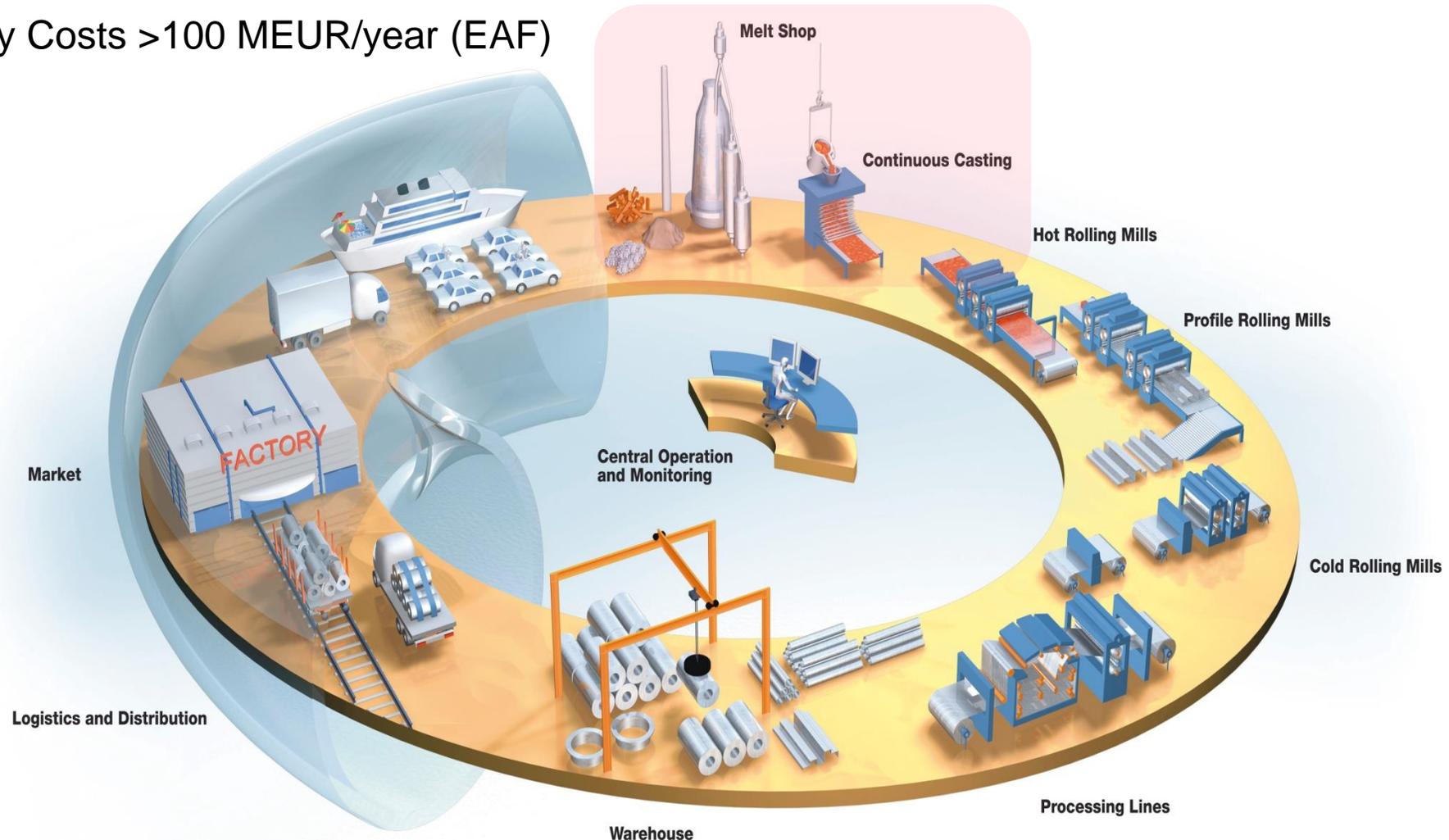
Selling back to grid

# Steel Production Scheduling

## Continuous Time

# Melt Shop in the Steel Production Supply Chain

Typical Electricity Costs >100 MEUR/year (EAF)



## From scrap to steel

### Step 1: Electric Arc Furnace (EAF)

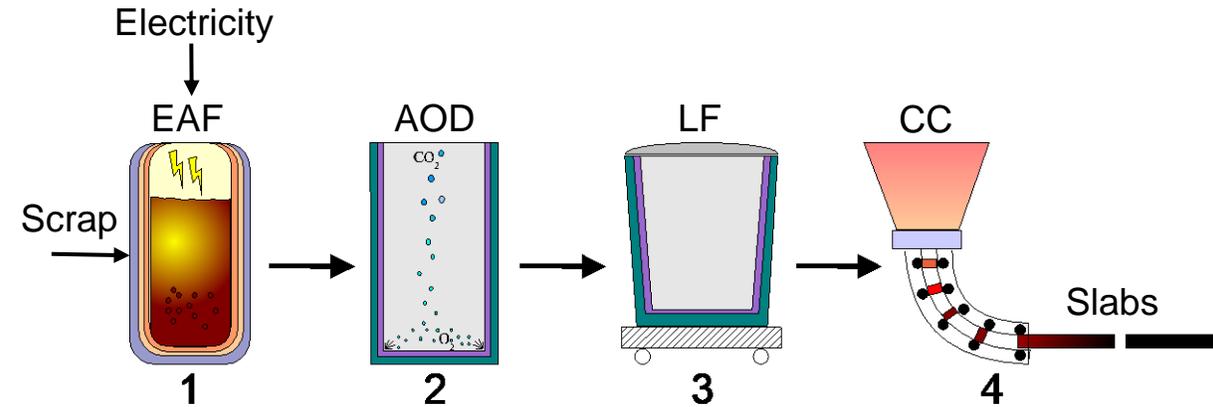
- The largest electricity consumer
- Done in batches (called heats)

### Steps 2-3: Adapt the chemical properties

- Argon-oxygen decarburization (AOD)
- Ladle Furnace (LF)

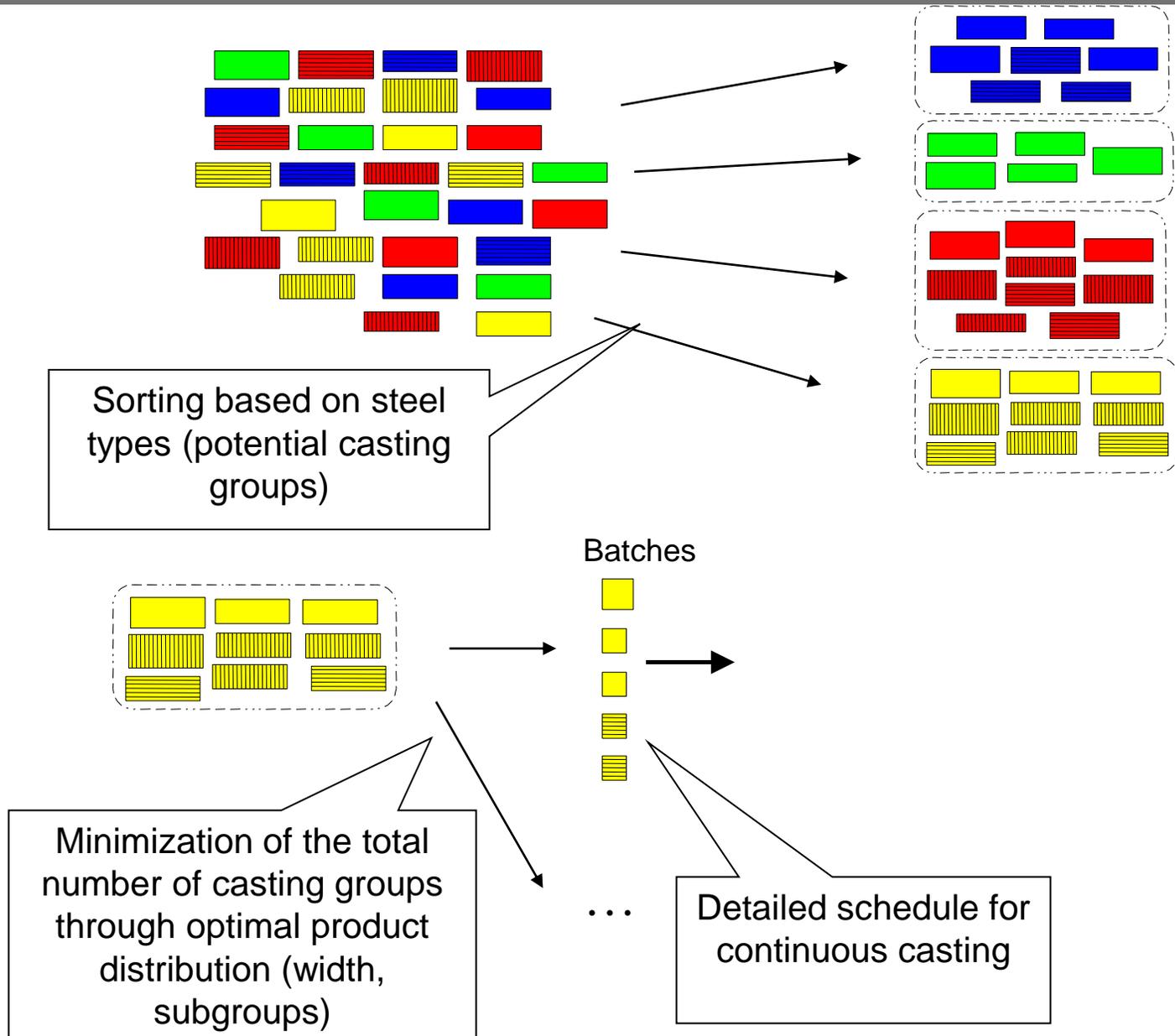
### Step 4: Continuous Casting (CC)

- Cast multiple heats without interruption

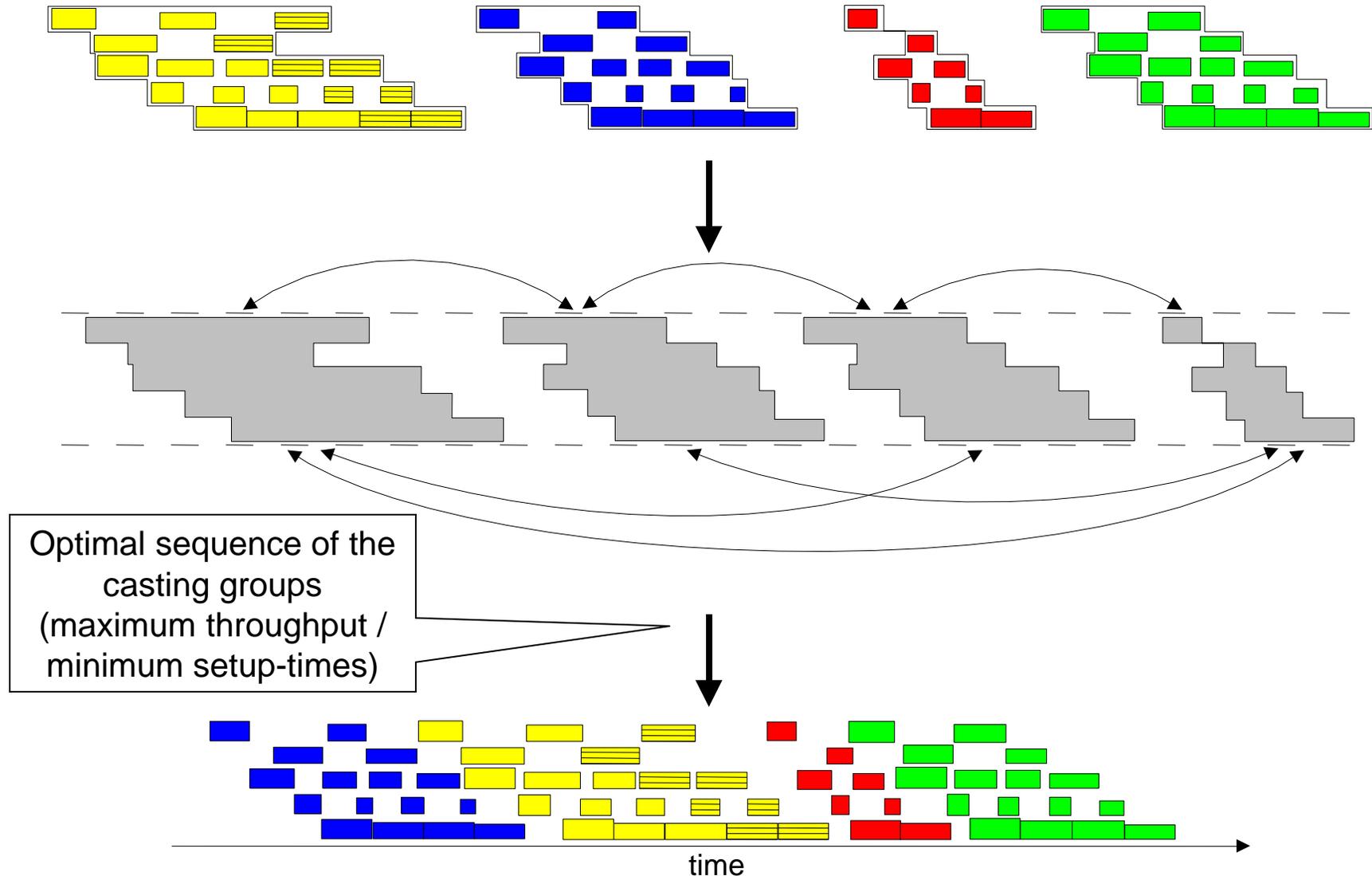


### Electricity-intensive process with many constraints

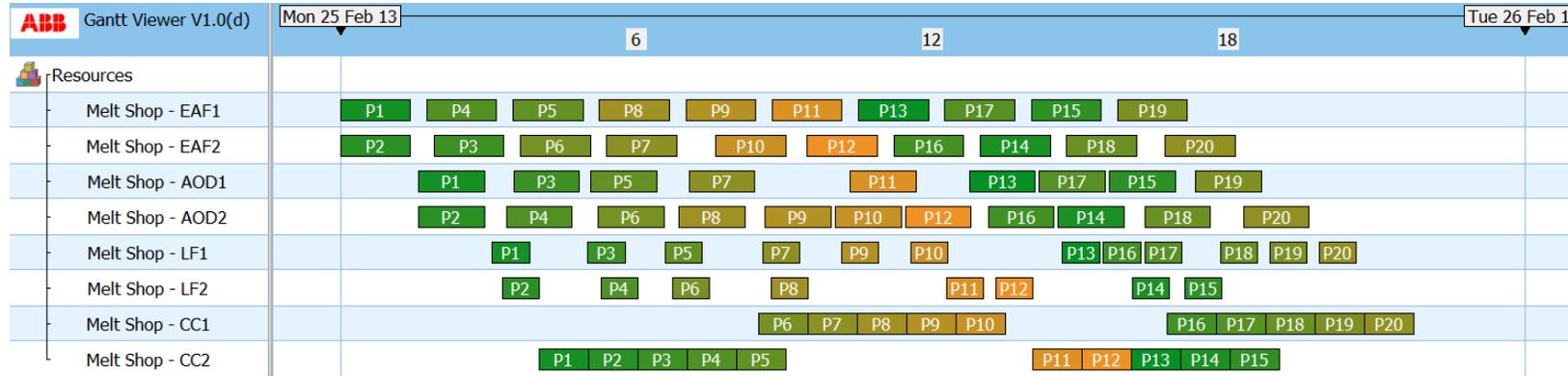
- Avoid intermediate cooling (quality problems)
- Sequence-dependent changeovers
- Grade incompatibilities
- Transfer times between equipment
- Coordination of production steps



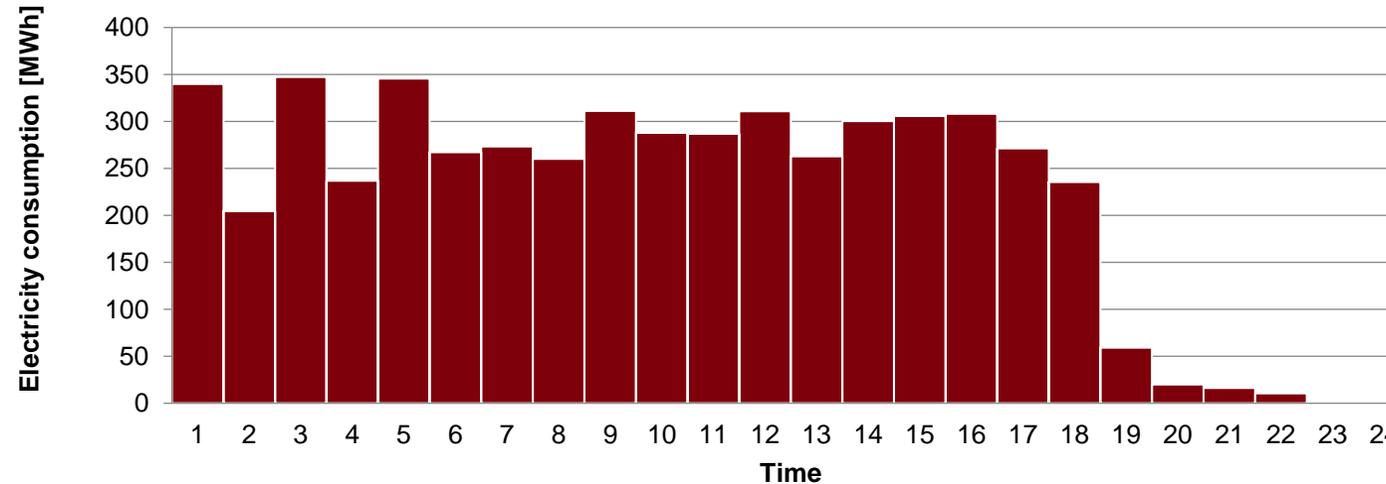
# Optimization step II – Aggregation and Finalization



## Volatile Prices as Opportunity



### Load schedule



## Volatile Prices as Opportunity

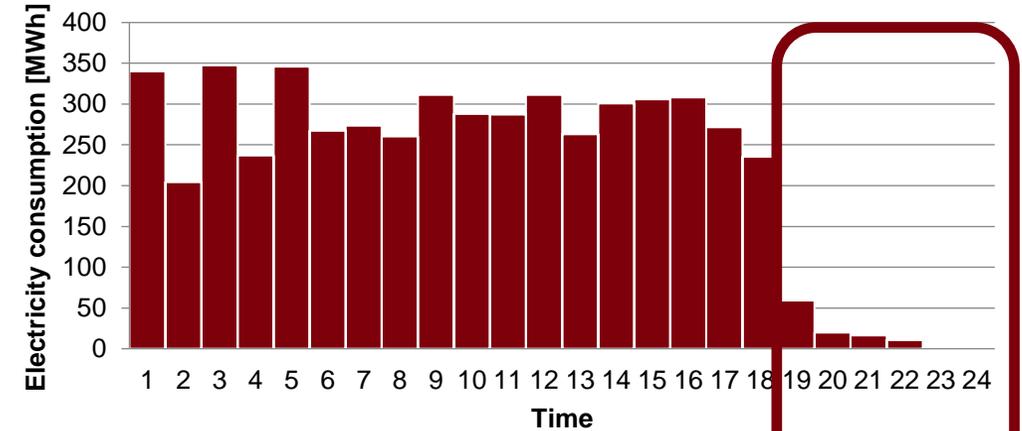
Enable energy-intensive industry to

- Participate in future energy markets (virtual power plant)
- Actively support grid stability and reliability

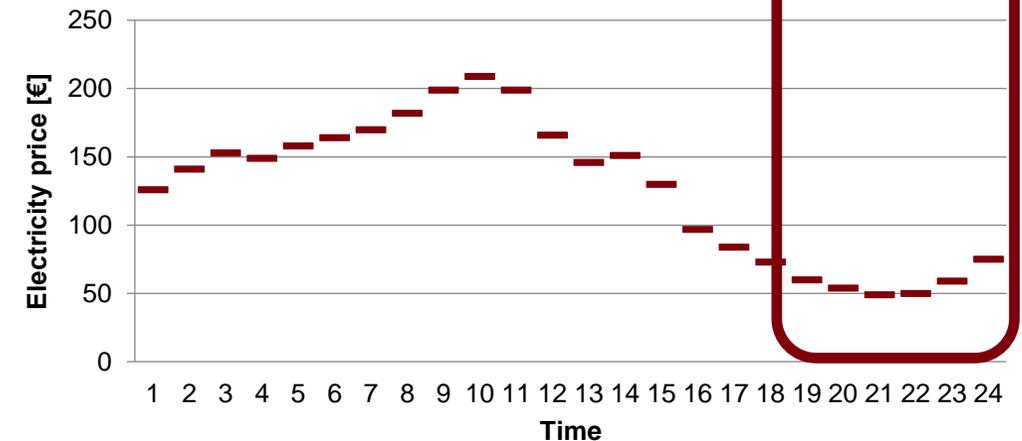
Use process flexibility to intelligently schedule the production in order to

- Lower energy cost
- Efficiently manage resources

### Load schedule

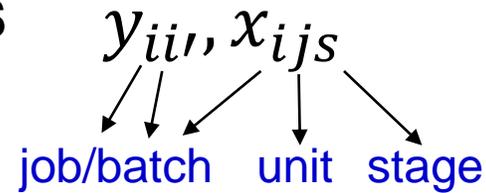


### Day-ahead market



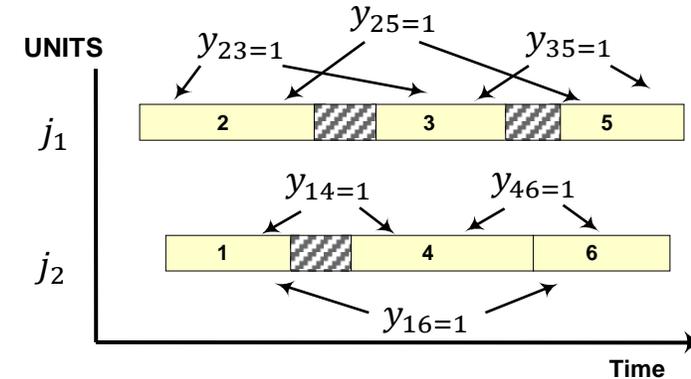
## MAJOR MODEL VARIABLES

### BINARY VARIABLES



Note: The same unit may be used in multiple stages!

$y_{i i'} = 1$  if batch  $i'$  is processed after batch  $i$ , else zero (global precedence)  
 $x_{i j s} = 1$  if batch  $i$  is processed in unit  $j$  on stage  $s$  (stage-based assignment)



**6 BATCHES, 2 UNITS**  
 **$(6*5)/2 = 15$  SEQUENCING VARIABLES**

### CONTINUOUS VARIABLES

$t_{i s}^s$  = start time of batch  $i$  on stage  $s$   
 $t_{i s}^f$  = end time of batch  $i$  on stage  $s$

**Can be easily generalized to  
 multistage processes  
 and to several resources**

(Méndez and Cerdá, 2003)

$$\sum_{j \in J_{is}} x_{ijs} = 1 \quad \forall i \in I, s \in S_i$$

**ALLOCATION CONSTRAINT**

$$t_{is}^f = t_{is}^s + \sum_{j \in J_{is}} T_{ijs} x_{ijs} \quad \forall i \in I, s \in S_i$$

**PROCESSING TIME**

End time = start time + duration  
(depends on equipment choice)

$$t_{i's'}^s \geq t_{is}^f + T_{is,i's'}^{clean} + T_{i's'}^{setup} \\ \forall i, i' \in I, i < i', s \in S_i, s' \in S_{i'}, j \in J_{is,i's'}$$

Sequencing only makes sense  
for jobs on the same machine

**SEQUENCING CONSTRAINTS**

$$t_{is}^s \geq t_{i's'}^f + T_{i's',is}^{clean} + T_{is}^{setup} \\ \forall i, i' \in I | i < i', s \in S_i, s' \in S_{i'}, j \in J_{is,i's'}$$

**Indices and variables**

$i$  = job  
 $j$  = unit or machine  
 $s$  = production stage  
 $x$  = assignment variable  
 $y$  = sequencing variable

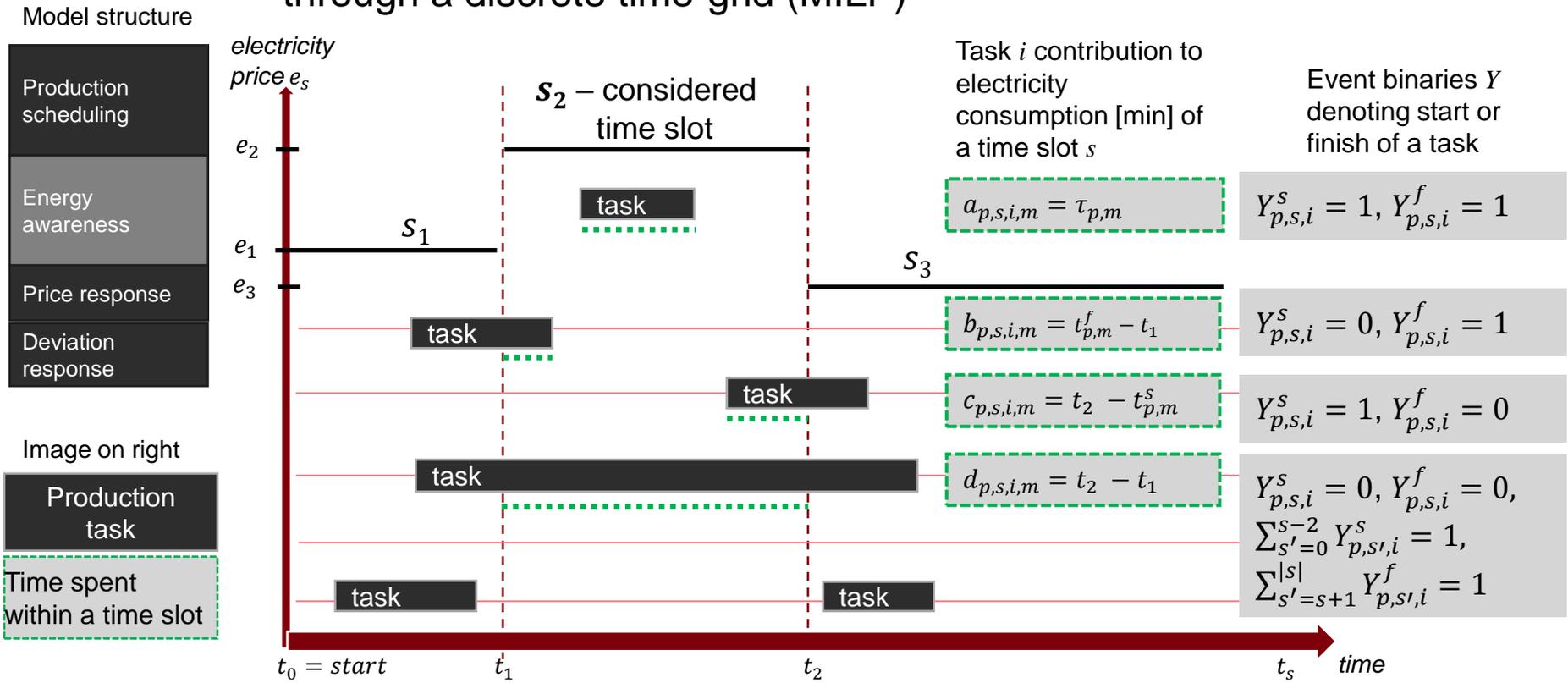
$$t_{is}^s \geq t_{i,s-1}^f + T_{i,s-1,s}^{tr} \quad \forall i \in I, s \in S_i, s > 1$$

**STAGE PRECEDENCE**

Continuous-time scheduling model

## Accounting for Electricity Consumption

Model the relation between tasks  $i$  and time slots  $s$  through a discrete time-grid (MILP)



Source: Nolde, K., & Morari, M. (2010). Electrical load tracking scheduling of a steel plant. Computers and Chemical Engineering, 34, 1899-1903; Hadera, H. et al. (2015). Optimization of steel production scheduling with complex time-sensitive electricity cost. Computers and Chemical Engineering, 76, 117-136

$ST$ : stages in the original scheduling formulation

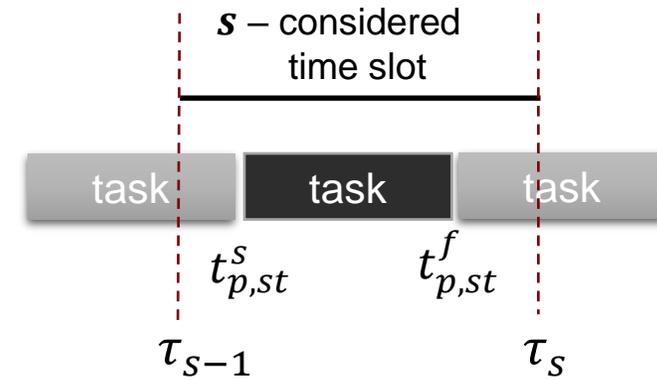
$S$ : time slots for electricity tracking

$$t_{p,st}^s \geq \tau_{s-1} \cdot Y_{p,st,s}^s \quad \forall p \in P, st \in ST, s \in S$$

$$t_{p,st}^s \leq \tau_s + (M - \tau_s) \cdot (1 - Y_{p,st,s}^s) \quad \forall p \in P, st \in ST, s \in S$$

$$t_{p,st}^f \geq \tau_{s-1} \cdot Y_{p,st,s}^f \quad \forall p \in P, st \in ST, s \in S$$

$$t_{p,st}^f \leq \tau_s + (M - \tau_s) \cdot (1 - Y_{p,st,s}^f) \quad \forall p \in P, st \in ST, s \in S$$



For more information on how to link the auxiliary variables  $a, b, c, d$  to the scheduling problem, see paper by Hadera et al. (2015)

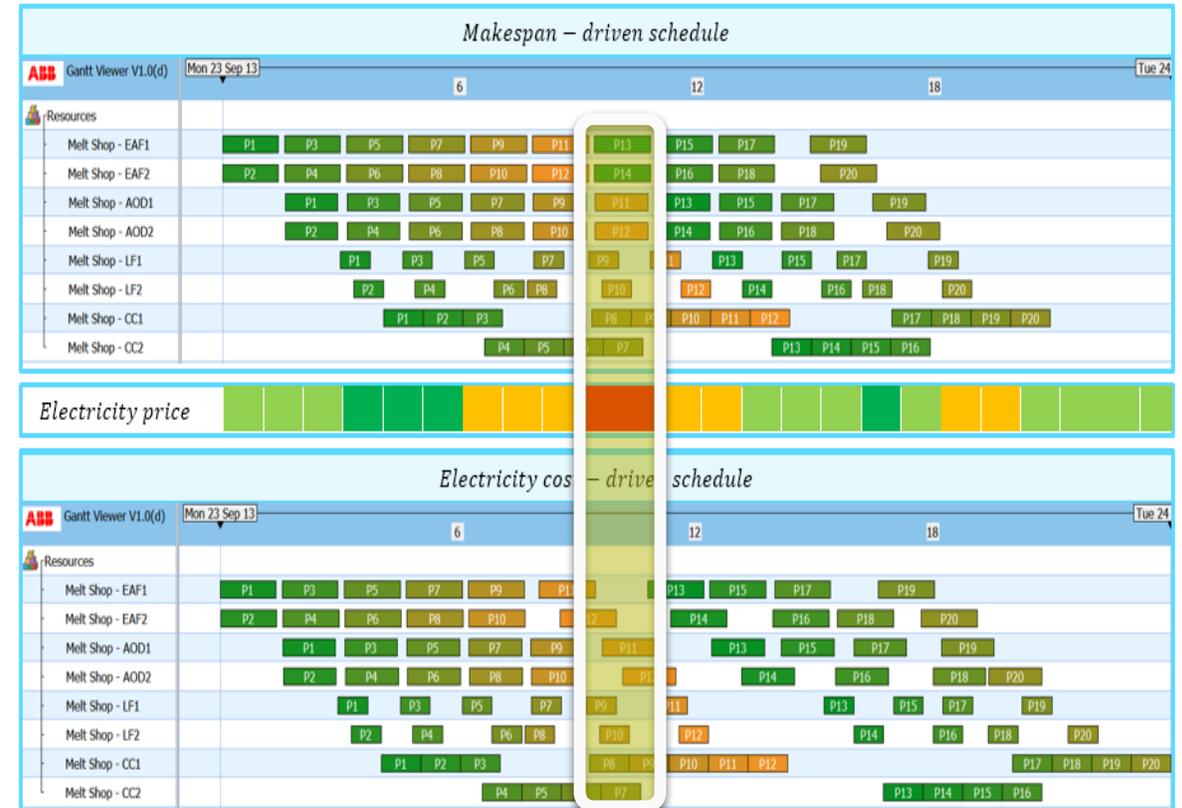
## Intelligent Production Planning

Lower energy costs by

- Utilization of variable pricing
- Keeping committed load profiles



Scenario	Bin	Vars	MIP (600 s)	Gap (600 s)	MIP (3600 s)	Gap (3600 s)
1 (20-hi)	4065	29508	247838	29,30%	241136	26,80%
2 (20-lo)	4065	29508	200038	24,90%	180023	16,10%
3 (16-hi)	3229	23428	155226	22,81%	146339	17,93%
4 (16-lo)	3229	23428	204173	22,50%	180965	12,10%



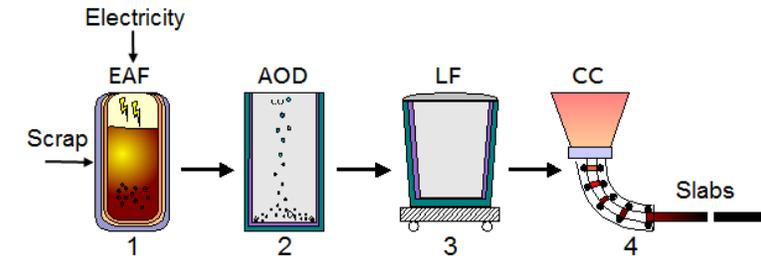
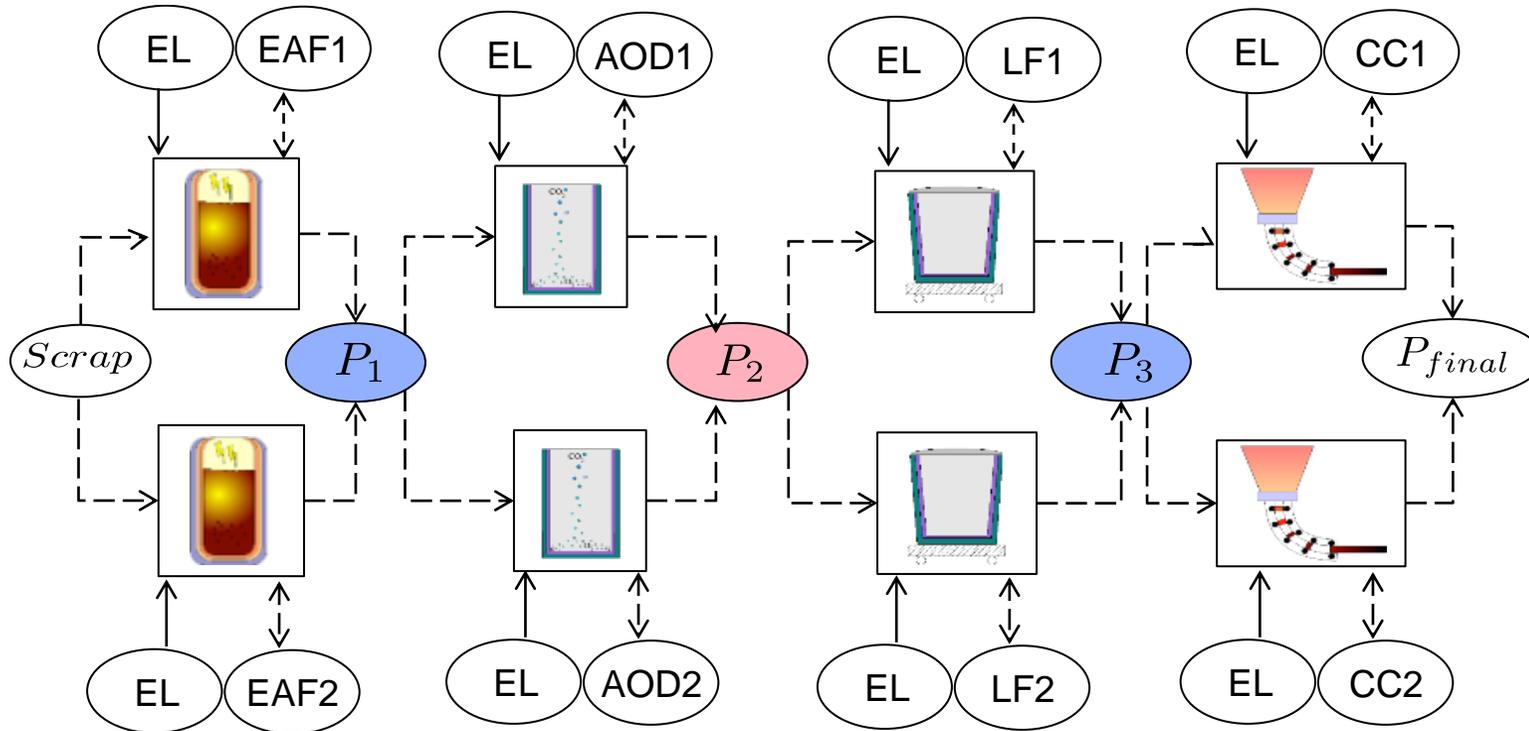
Hadera et al. (2015), Merkert et al. (2015), Castro et al. (2013)

**Benefits of Collaboration: 5% Savings at pilot plant**

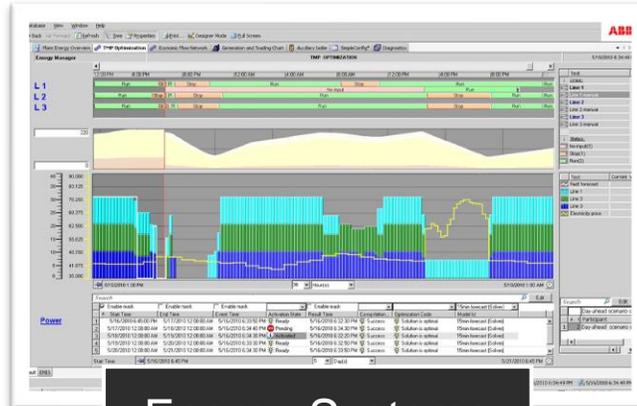
Discrete-time scheduling model

## Modeling Approach Based on Resource Balances

$$Re_{r,t} = Re_{r,t-1} + \sum_k \sum_i N_{k,i,t} \mu_{r,k,i} + \sum_k \sum_i N_{k,i,t-\theta_{k,i}} \bar{\mu}_{r,k,i} + \sum_k \sum_i \sum_{t'=t-\theta_{k,i}+1}^h N_{k,i,t'} \xi_{k,i,r} + \pi_{r,t} \forall r,t$$



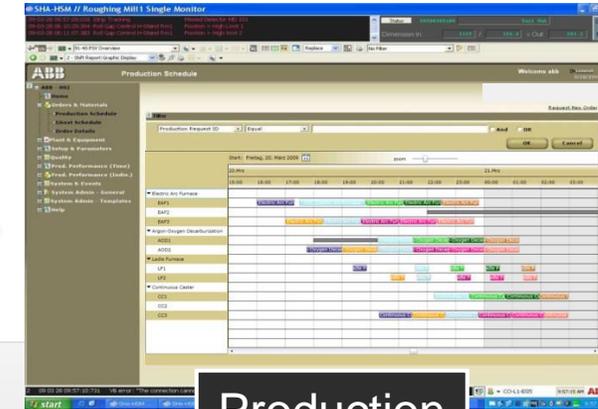
## Integrated Production Planning & Energy Management



Energy Systems Scheduling



iDSM module



Production Planning

Coordination through

- Monolithic model (PP&EM)
- Model decomposition
- Data exchange

- + Reduce energy cost using time varying energy prices
- + Increase flexibility / agility wrt. energy availability

- + Connect to existing environment
- + Steel/TMP mills: 3-20% energy cost savings

Source: Hadera, H. et al. (2015). Optimization of steel production scheduling with complex time-sensitive electricity cost. Computers and Chemical Engineering, 76, 117-136; Hadera, H. et al. (2019). Integration of production scheduling and energy-cost optimization using mean value cross decomposition. Computers and Chemical Engineering, 129, 106436

## Power Grids Focus



## Different Industrial Processes



**Coordination of Energy Production and Consumption is a Very Large Scheduling Problem**

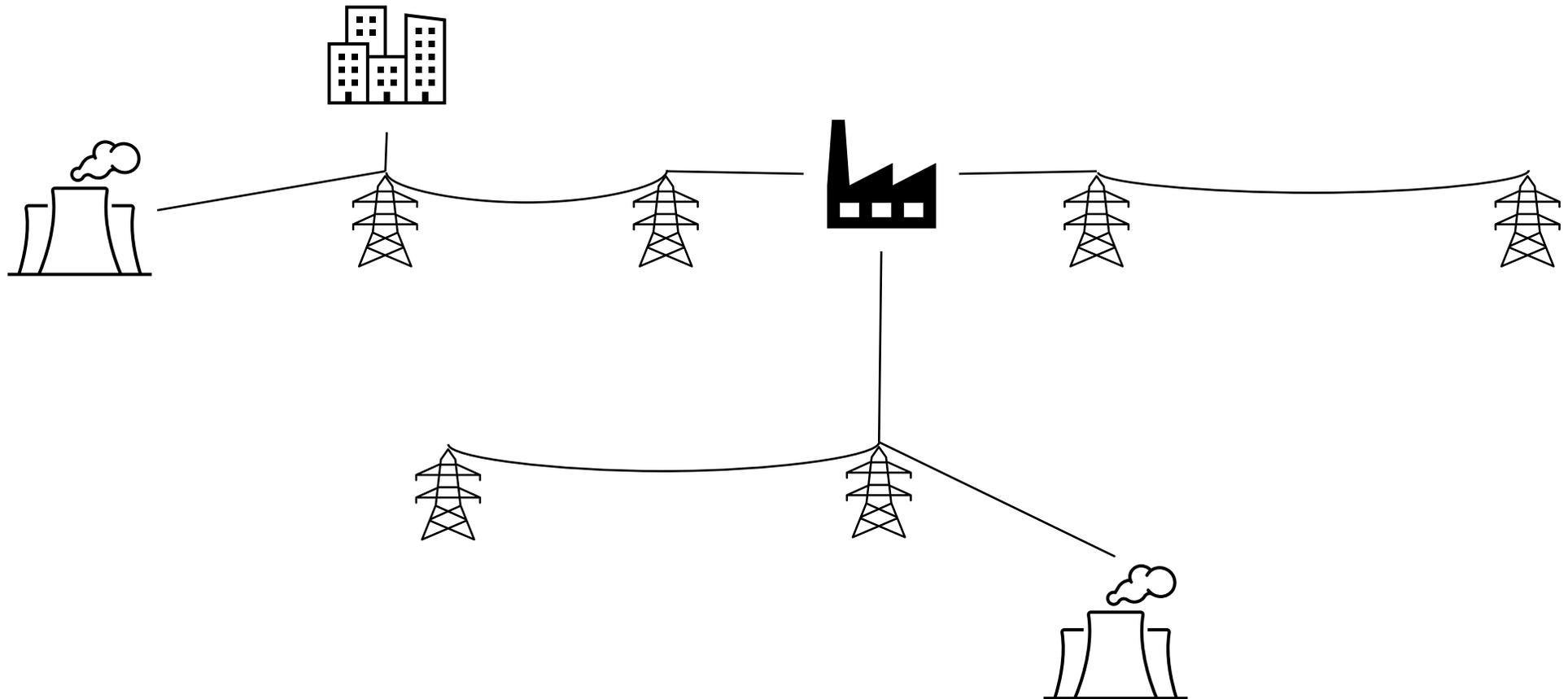
# Two Worlds Separated – Cannot See all Details of the Other



© Scott Grietler  
Bluewater Photo

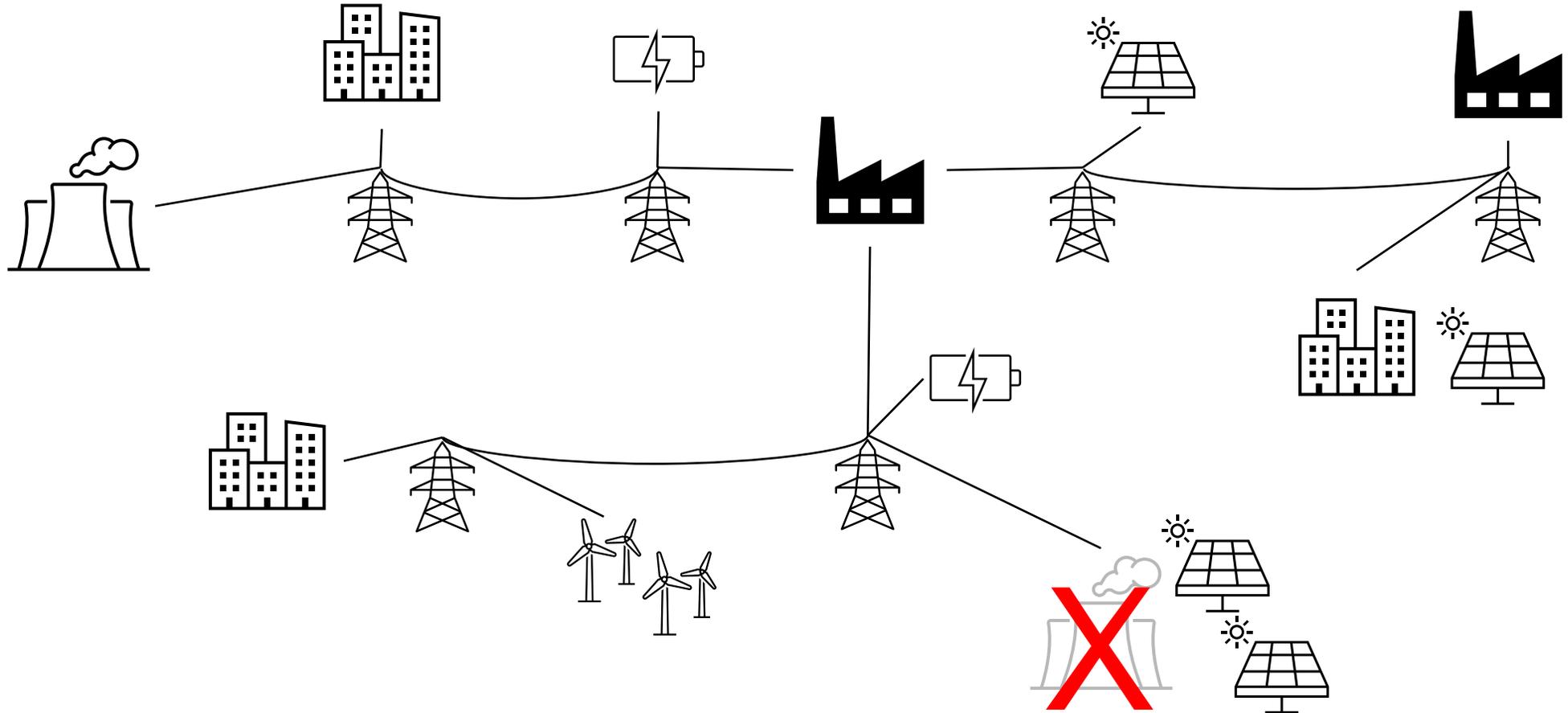
# How Are Things Related Together?

Traditional Power System – main concern sufficient electricity availability at each time



# How Are Things Related Together?

Modern Power System – main concerns electricity availability at each time as well as network capacity



# Unit Commitment Problem

## Discrete Time

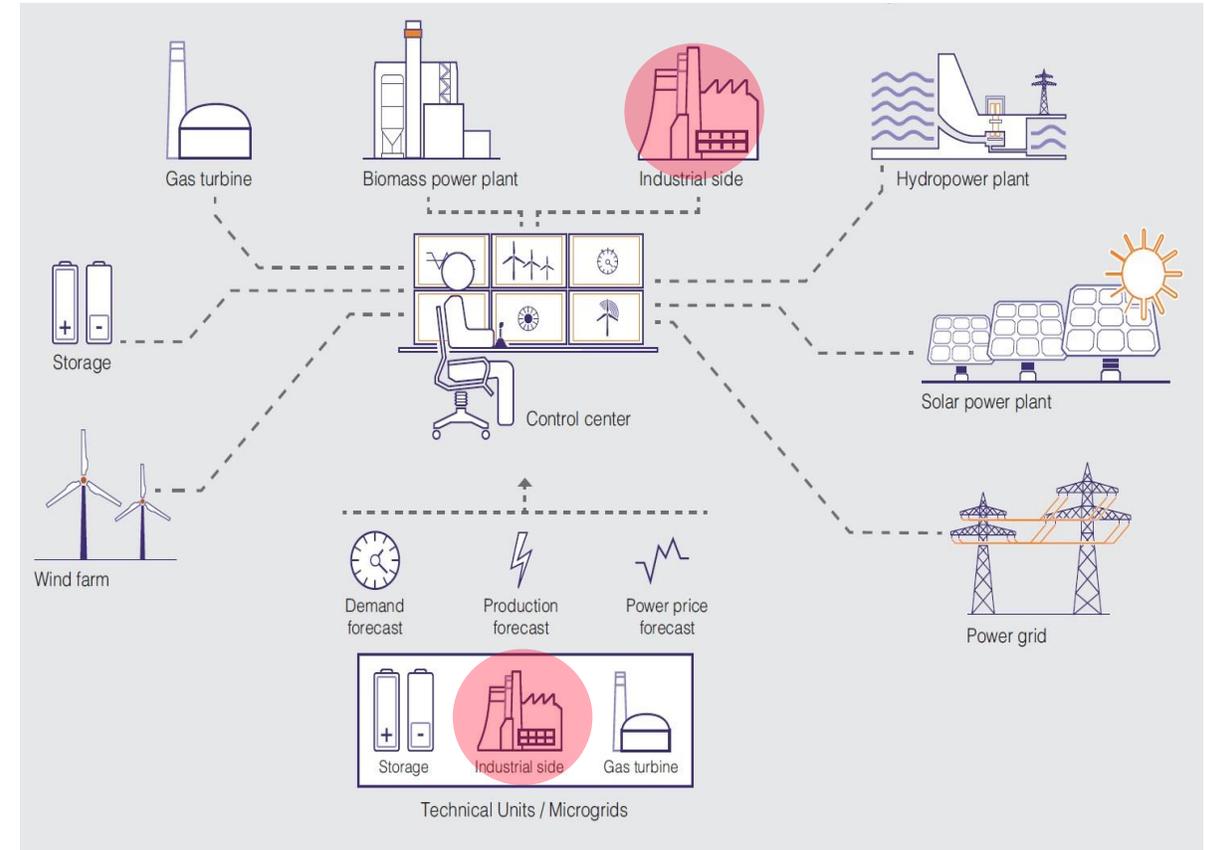
## Electricity Production = Consumption

Ensure that the Electricity Production = Consumption

- Schedule and coordinate electrical generation in order to match the energy demand and supply at minimum cost

Optimal (lowest cost) balance between the “players” by solving MILP-based models

- Including: Generators, Renewables, Energy storage, Industrial sites, Power markets (buy & sell)
- Ensuring: Demand being met also with strong renewable participation
  - Most economical operations
  - Healthy ramp-up / ramp-down phases
  - Feasible w.r.t. power grid limitations



## Mathematical Formulation (5 units, 5 time points) Illustration

### Indices

$i$  generation unit ( $I$ )

$t$  time slot ( $T$ )

### Parameters

$P_t^{dem}$  electricity demand at time  $t$  (MW)

$C_i^{var}$  variable generation cost (EUR/MW)

### Variables

$p_{i,t}$  generation level, e.g. in MW (continuous)

### Constraints

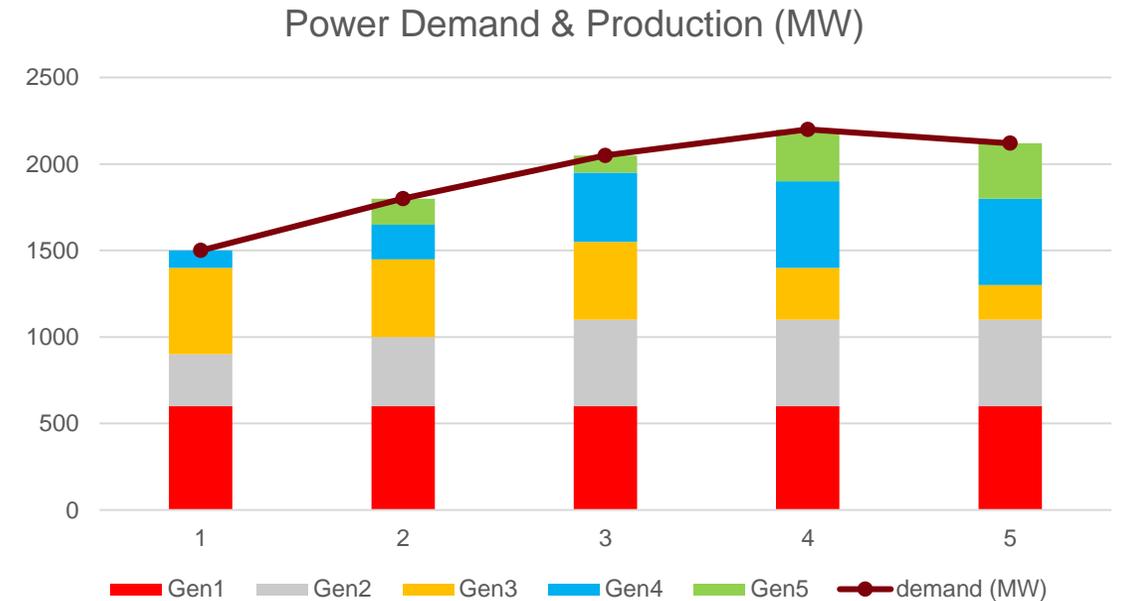
$$\sum_i p_{i,t} = P_t^{dem} \quad \forall t$$

### Objective function

$$\min \sum_t \sum_i C_i^{var} \cdot p_{i,t}$$

Unit allocation can be done based on unit-specific costs (still simple)!

- However, a unit may be turned on/off... (we need a binary variable)
- Each unit also has a lower and upper operation limits (MW)



## Individual Generator Limitations

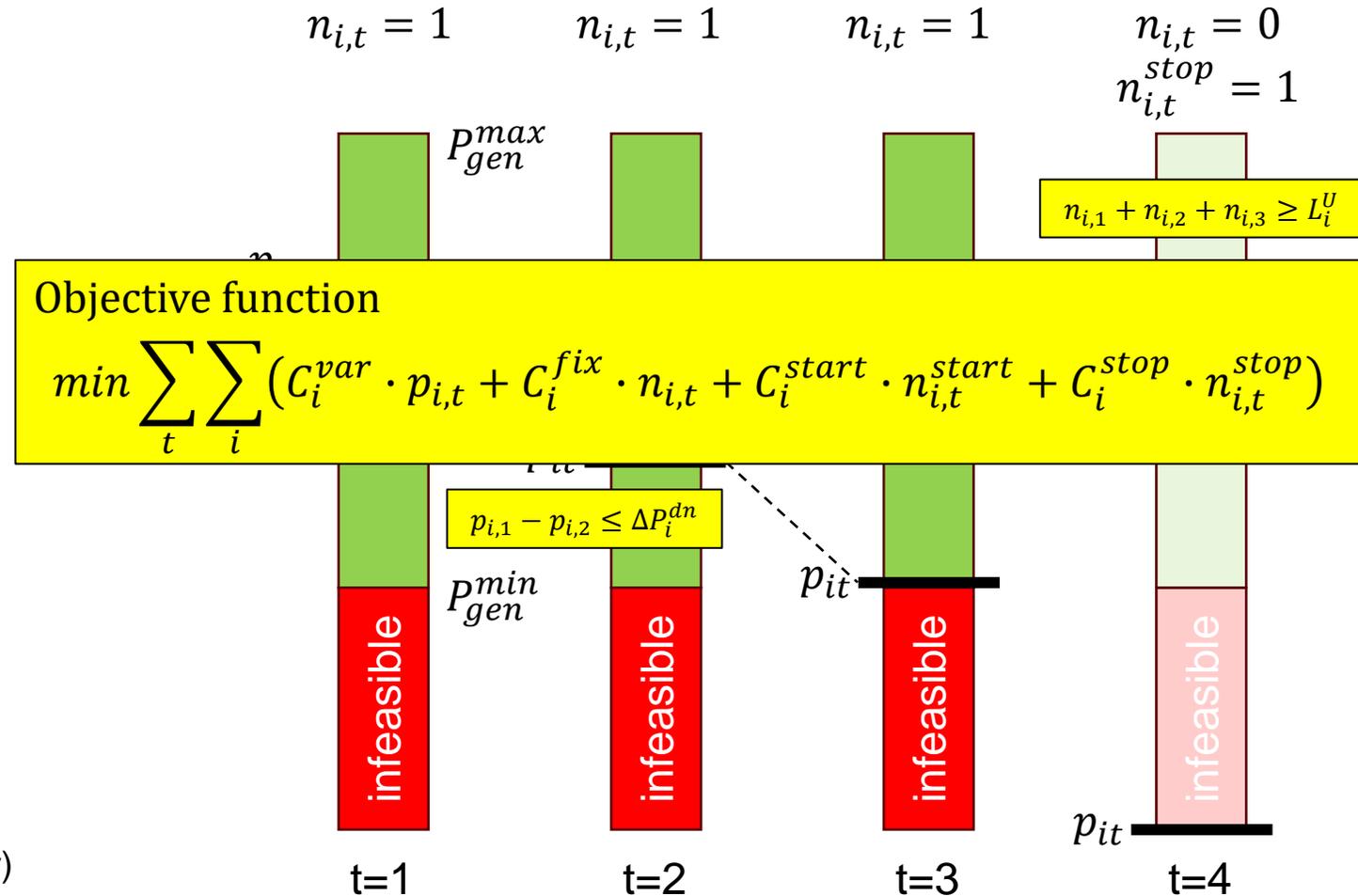
### Parameters

- $C_i^{fix}$  fixed generation cost (EUR/time step)
- $C_i^{start}$  start-up cost of generator (EUR)
- $C_i^{stop}$  shut-down cost of generator (EUR)
- $L_i^U$  minimum uptime (time steps)
- $L_i^D$  minimum downtime (time steps)
- $\Delta P_i^{up}$  ramp-up limit (MW/time step)
- $\Delta P_i^{dn}$  ramp-down limit (MW/time step)
- $P_i^{min}$  minimum feasible (stable) generation (MW)
- $P_i^{max}$  maximum feasible (stable) generation (MW)

### Variables

- $p_{i,t}$  generation level, e.g. in MW (continuous)
- $n_{i,t}$  state of generator  $i$  at time  $t$ : on/off (binary)
- $n_{i,t}^{start}$  start-up indicator of generator  $i$  s at time  $t$  (binary)
- $n_{i,t}^{stop}$  shut-down indicator of generator  $i$  at time  $t$  (binary)

## Illustration



## Additional Constraints for Every Generator

Generation level

$$P_i^{min} \cdot n_{i,t} \leq p_{i,t} \leq P_i^{max} \cdot n_{i,t} \quad \forall i, t$$

Ramp-up/down limits

$$p_{i,t} - p_{i,t-1} \leq \Delta P_i^{up} + P_i^{min} \cdot n_{i,t}^{start} \quad \forall i, t > 1$$

$$p_{i,t-1} - p_{i,t} \leq \Delta P_i^{dn} + P_i^{min} \cdot n_{i,t}^{stop} \quad \forall i, t > 1$$

Start-stop constraints

$$n_{i,t} - n_{i,t-1} = n_{i,t}^{start} - n_{i,t}^{stop} \quad \forall i, t > 1$$

$$n_{i,t}^{start} + n_{i,t}^{stop} \leq 1 \quad \forall i, t > 1$$

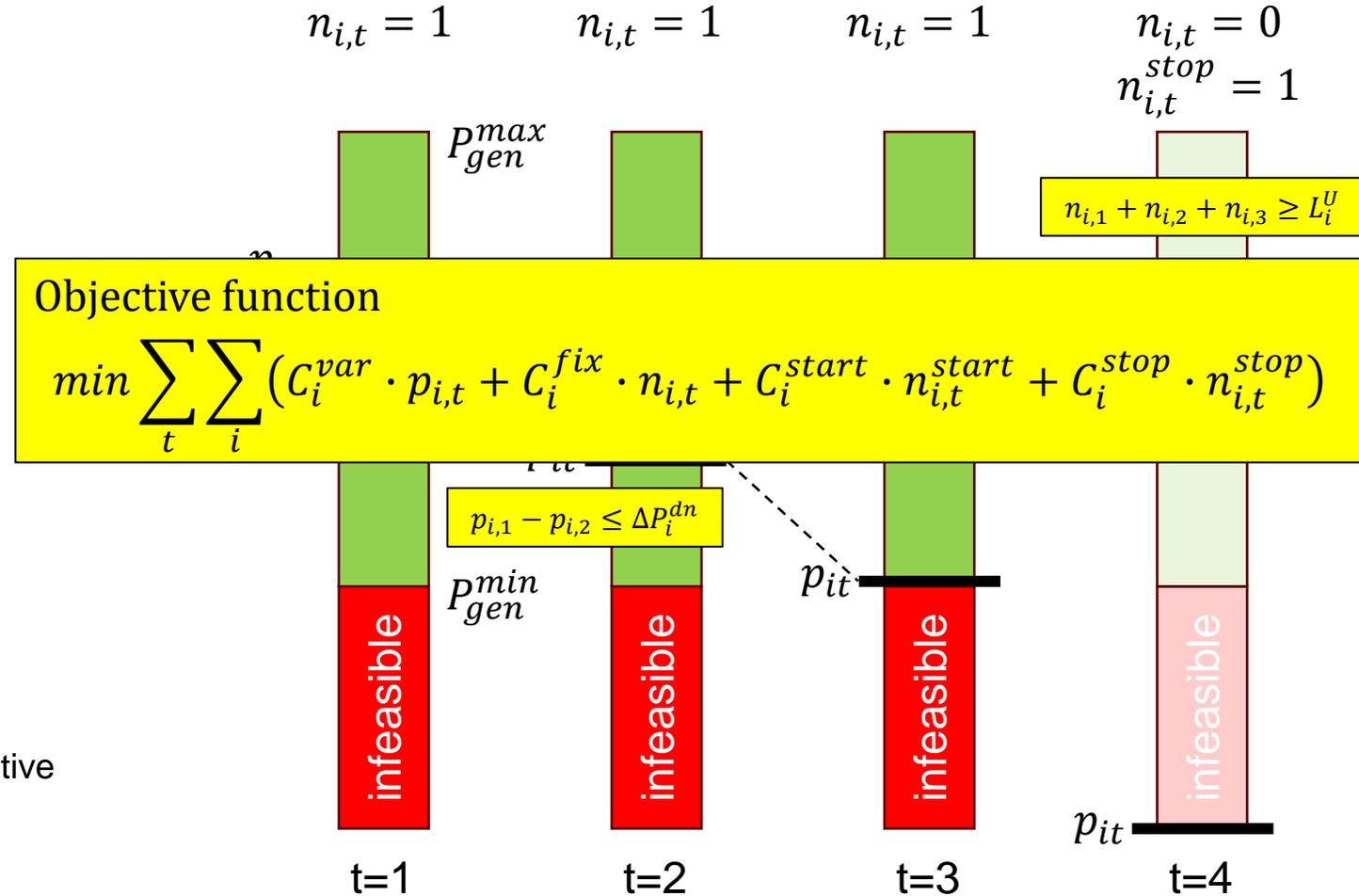
Minimum up/down-times

$$n_{i,\tau} \geq n_{i,t}^{start} \quad \forall i, t, \tau = t + 1, \min\{t + L_i^U - 1, T\}$$

$$n_{i,\tau} \leq 1 - n_{i,t}^{stop} \quad \forall i, t, \tau = t + 1, \min\{t + L_i^D - 1, T\}$$

+ Reserve variables & constraints, network constraints (iterative process), ...

## Illustration



## Problem Size

Number of units significantly increasing (small renewable units, energy storage units, ...)

- Yesterday: 50-200 generation units
- Today: >1000 plannable units
- Future: >5000+ units...

Planning horizon: 24 hours, time grid of 1 hour, 30 or 15 min → 24, 48 or 96 time points.

- A problem with at least 24000 binary variables (1000 units) →  $5.24 \cdot 10^{7224}$  combinations

Any brute force method will fail ...

We need to be able to solve several UC problem runs (iterative procedure) typically within 5-10 minutes!

## Optimality

Optimization plays a crucial role as we are often optimizing the power use for an entire country or state

Assume

- a typical consumption of 40 GW...
- Average power price 40 EUR/MWh (4 cents / kWh)

This result in a daily generation cost of 38.4 MEUR (in a year 14 billion EUR)

- Each 1% away from the optimal solution means 384 kEUR loss / day (this is still acceptable) → 140 MEUR / year

**Optimization matters!!!**

## Proposed Approach

Basic target: Speed up the solution of the UC problem without loss off (near) optimality!

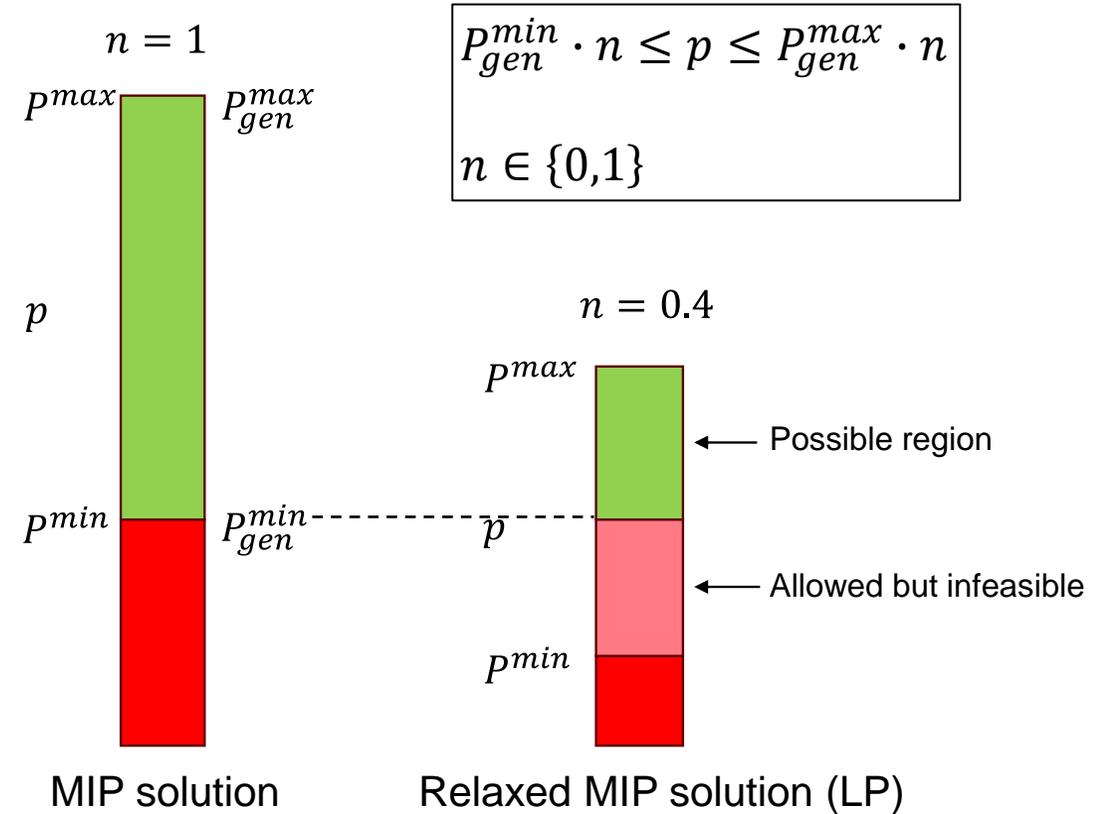
LP problem much faster than corresponding MILP

- Rounding e.g. fractional values  $0.9 \rightarrow 1$  (binary) does not work well!

Idea: Analyze LP solution and fix binary variables for generators respecting the physical generation limits  $(P_{gen}^{min}, P_{gen}^{max})$  in the relaxed solution by checking the key equation:

$$n_{i,t} \cdot p_{i,t} \geq P_i^{min}$$

If this is satisfied, then the generator operates on a valid region even in the relaxed solution  $\rightarrow$  **assume** also needed in MIP  $\rightarrow$  fix  $n_{i,t} = 1$



## Proposed Approach

Basic target: Speed up the solution of the UC problem without loss off (near) optimality!

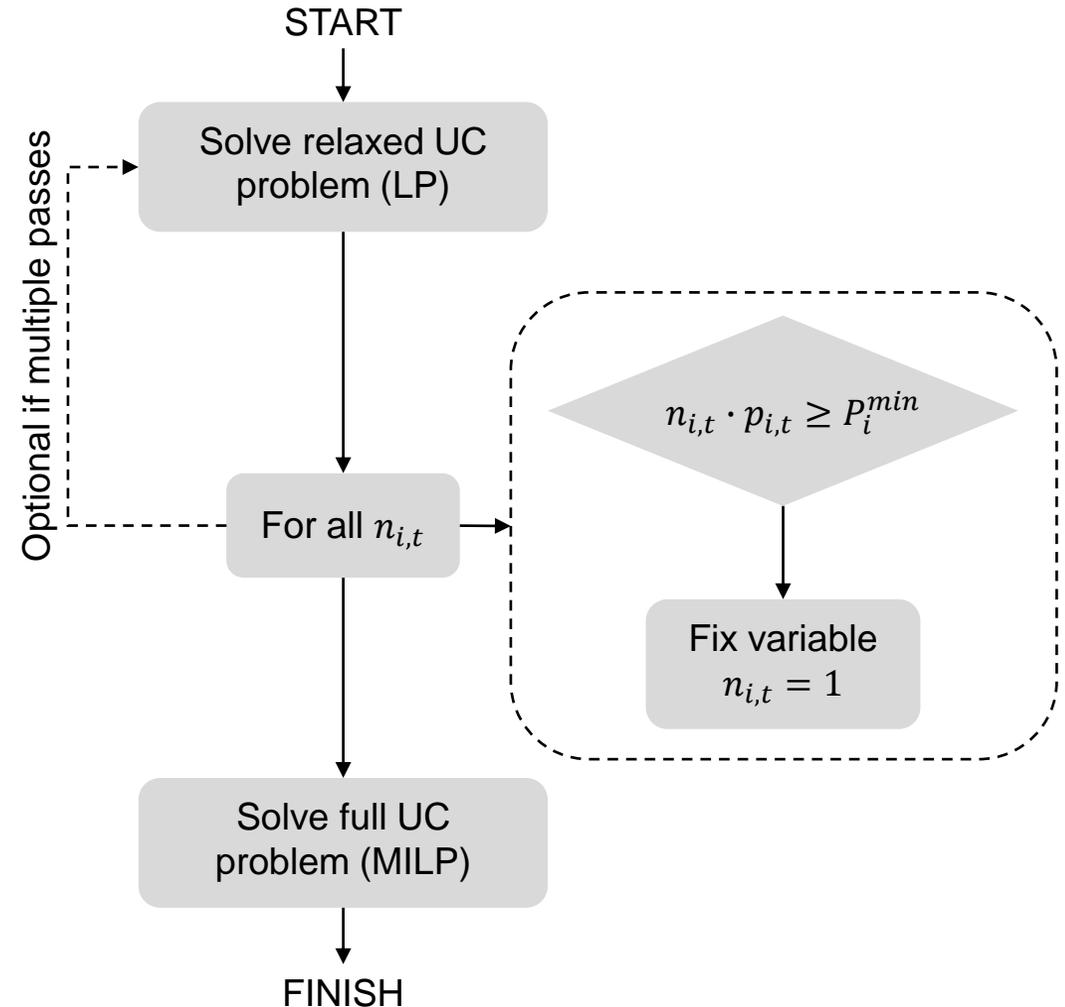
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If this is satisfied, then the generator operates on a valid region even in the relaxed solution  $\rightarrow$  **assume** also needed in MIP  $\rightarrow$  fix  $n_{i,t} = 1$



## Test Cases with 1200/50 Units

Results: 1200 units (large example)

- Average speed-up: 3.7
- Longest solution time (critical): 132 → 13 seconds!
- Average solution improvement

Results: 50 units (small example)

- Average speed-up: 1.8
- Longest solution time: 226 → 65s
- In average 0.7% worse solutions
  - One outlier case with 41% (caused by inflexible units)

Many runs: Better than MIP

- All runs: mipgap = 1%

### First UC example (1200 units, 44 instances)

Solution times (s)	MIP	LPHeur	FixedVars	Speed-Up	ObjDiff
Min	9.24	7.24	8002	0.944	0.992
Max	<b>131.99</b>	<b>12.72</b>	10494	13.918	1.004
Average	36.63	9.82	10053	<b>3.731</b>	0.999
Median	25.37	9.76	10086	2.553	0.999
Total (sum)	1611.78	432,00		N/A	N/A

### Second UC example (50 units, 225 instances)

Solution times (s)	MIP	LPHeur	FixedVars	Speed-Up	ObjDiff
Min	0.168	0.208	29	0.130	0.994
Max	<b>226.825</b>	<b>65.418</b>	355	6.093	1.410
Average	9.797	5.154	137	<b>1.863</b>	<b>1.007</b>
Median	1.074	0.565	128	1.515	1.001
Total (sum)	1498.903	788.570	N/A	N/A	N/A

Harjunoski, I. et al. (2021). Matheuristics for speeding up the solution of the unit commitment problem. Paper presented at the Proceedings of 2021 IEEE PES Innovative Smart Grid Technologies Europe: Smart Grids: Toward a Carbon-Free Future, ISGT Europe 2021

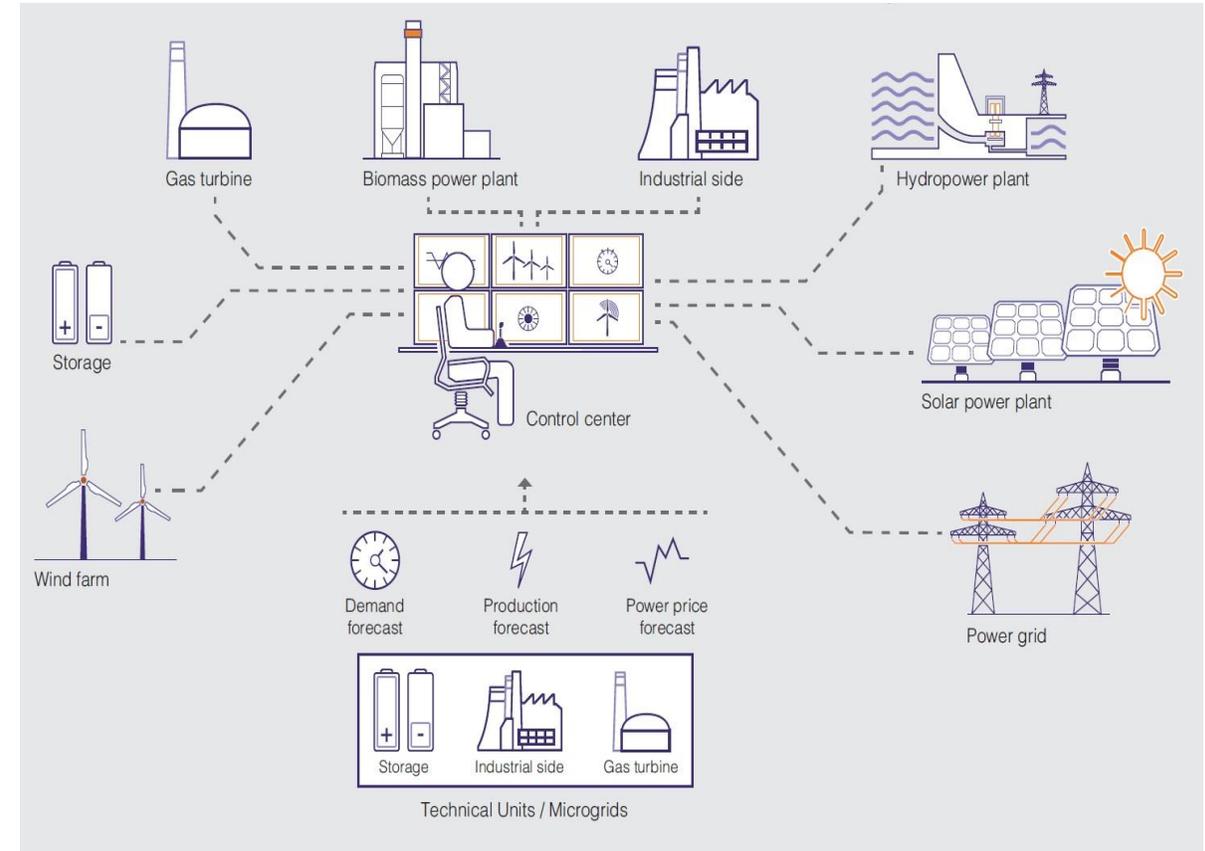
## Promising results

A simple approach can make a big difference!

- Increasing the robustness of solving the UC problem
- All instances on the same grid → large variations
- Possible to build up on this, combine it with ML etc.
  - Nevertheless, due to strong optimality need and many cost types optimal cost balancing can be challenging
  - Important: enough problem-specific data for training

Deployment of proposed LP-based heuristic relatively straightforward in an existing product environment

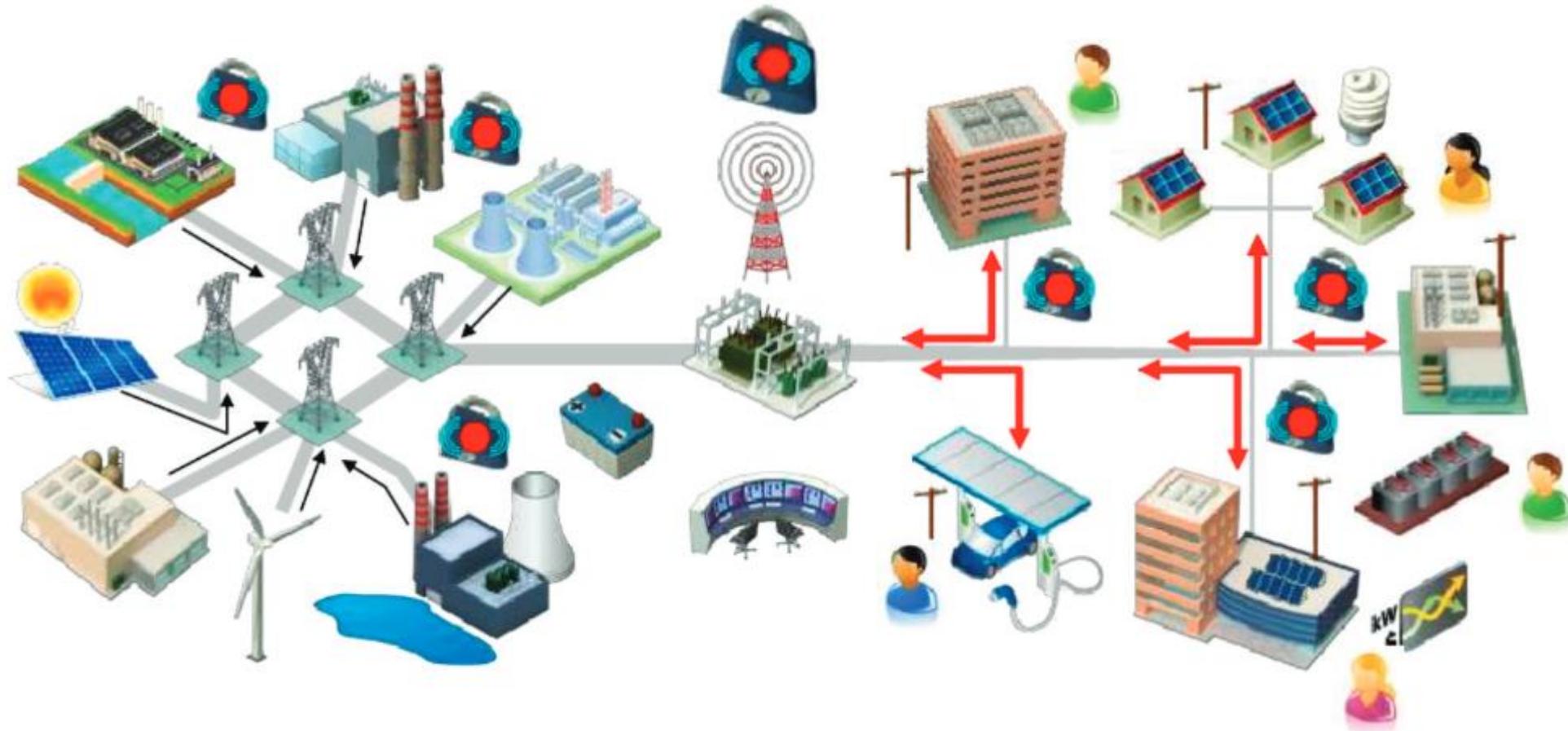
- Sometimes, relaxed LP-solution took > 50% of total time (done twice in LP-based heuristics)



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# Conclusions

# The Future of Electric Power is Bi-Directional and Smart(er)



- Highlight the importance of energy / electricity
- Give insights to solving industrial-scale scheduling problems (demand-side management)
- Present some strategies to speed up large-scale optimization problems
- Share some personal experiences from working with MILP problems
  - Melt-shop (steel) scheduling
  - Unit Commitment



**MILP is an important (although not only) component in solving industrial scheduling problems**

Optimization is critical to many industrial problems

- MILP a good tool, especially for modeling complex constraints
- Commercial MILP solvers embed most advanced algorithms

MILP alone not sufficient in solving many real-size problems

- Need supporting heuristics, decomposition schemes, AI/ML, ...
- Models must be both very tight and expandable

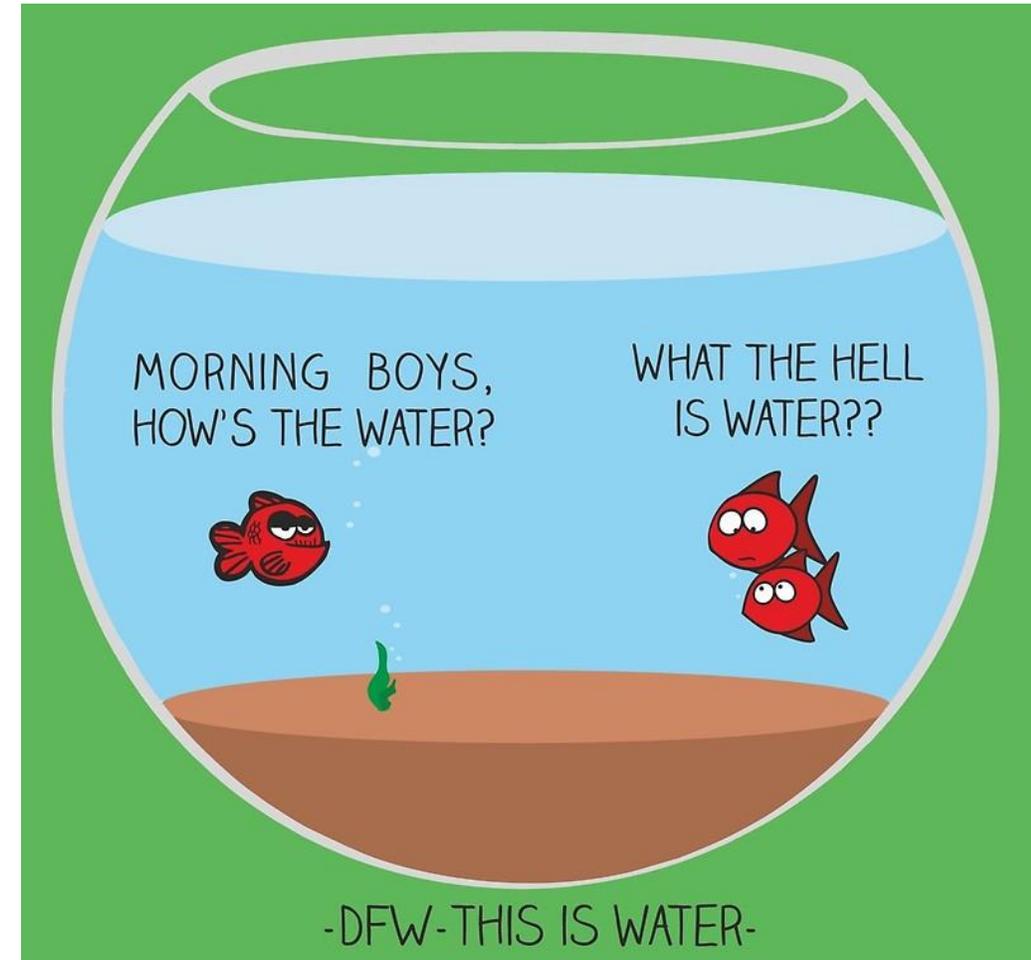
Energy combines different players and becomes more important

- Demand-side management seek to identify process flexibility
- Combination of scheduling processes and energy is hard but necessary: Need more solutions crossing the domain borders!

Important: Research cultures meet and collaborate: Math, CS/OR, Engineers (ChemE, Elec, SW, ...) and Natural Scientists

- Not to forget about industrial/academic collaboration...

Still many industrial challenges not even yet been modeled!



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