Characterization of the Flexibility of an Energy Consumer and Optimization of its Energy Usage – A Multiform Problem

Claude Le Pape and many contributors (C. Desdouits, V. Boutin, J.-L. Bergerand, A. Samperio, …)
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ACPSS 2017

Schneider Electric, the Global Specialist in Energy Management and Automation

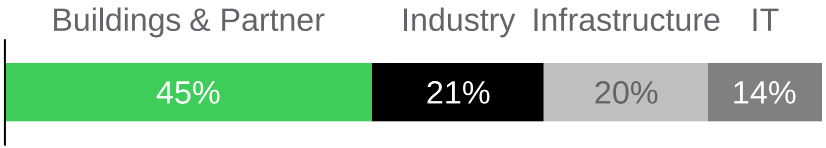
€26.6 billion
FY 2015 revenues

~5%
of FY revenues devoted to R&D

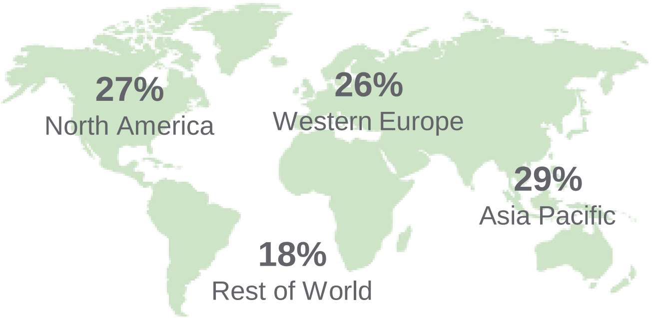
160,000+
people in 100+ countries

Four integrated and synergetic businesses

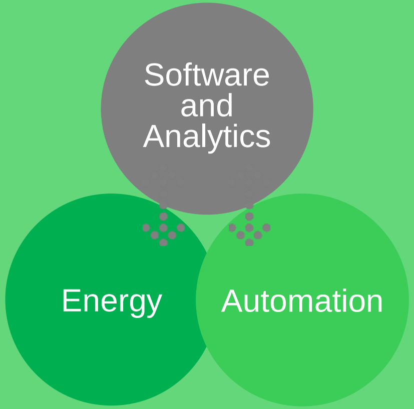
FY 2015 revenues



Balanced geographies – FY 2015 revenues



At Schneider Electric, we combine **Energy Management, Automation** and **Software** serving 4 markets, i.e. 70% of the world energy consumption



% are calculated on final energy

Source: IEA Explore 2015

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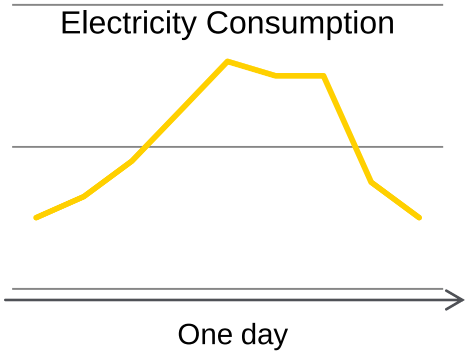
Electricity Consumption

One local consumer



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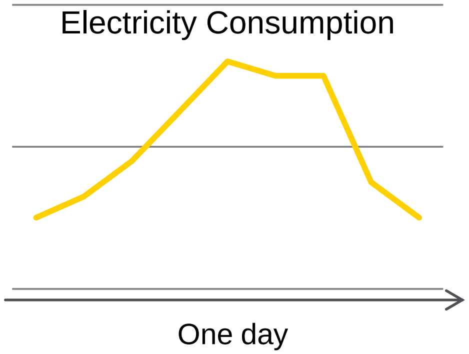
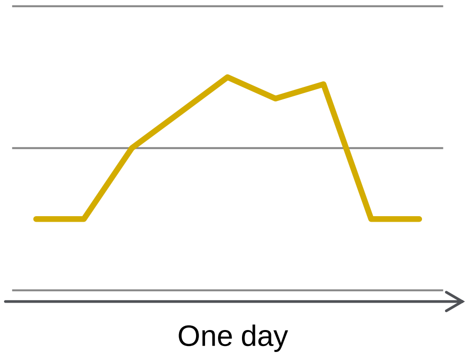
Electricity Consumption

Two local consumers





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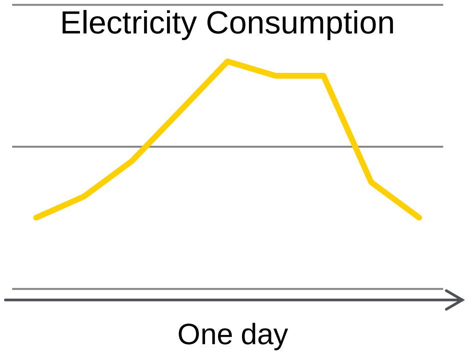
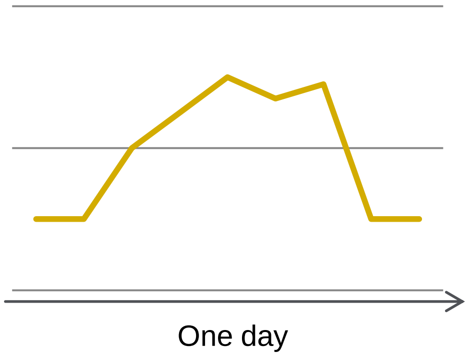
Electricity Consumption versus Production





Production means …

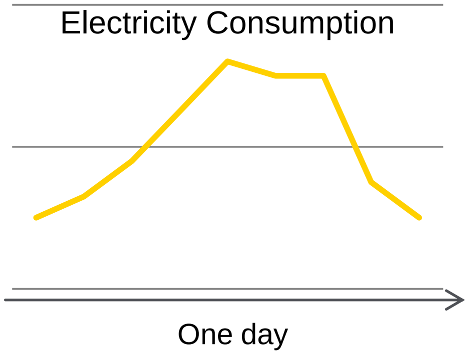
- Intermittent and roughly non-controllable, e.g., solar, wind
- Stable, controllable under given limits, e.g., nuclear
- Totally controllable but highly polluting, e.g., oil, gas, coal

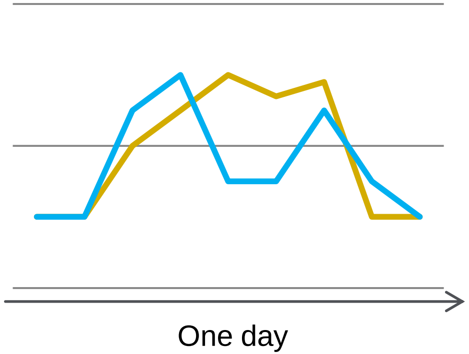
Representing costly investments

- ➢ Can we lower consumption peaks?
- ➢ Or the difference between consumption and clean production?
- ➢ Using (energy) storage?

Electricity Consumption versus Production

Flexible consumers





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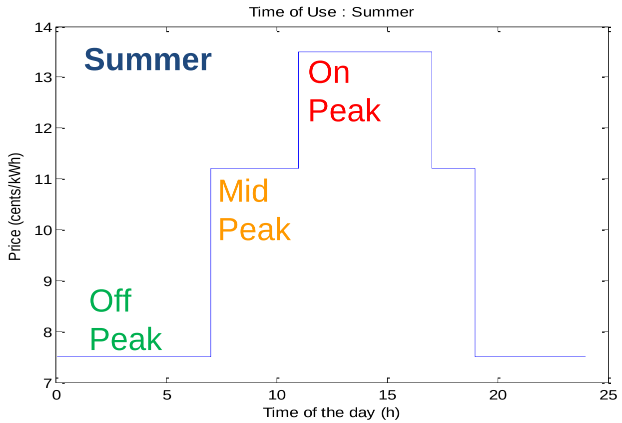
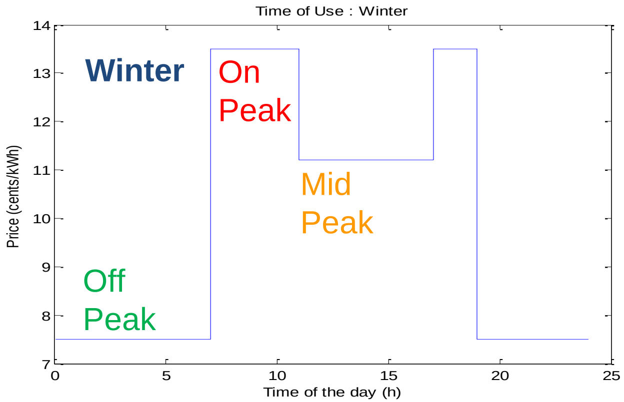
Time of Use (agreed tariff) and Critical Peak Pricing (on event)

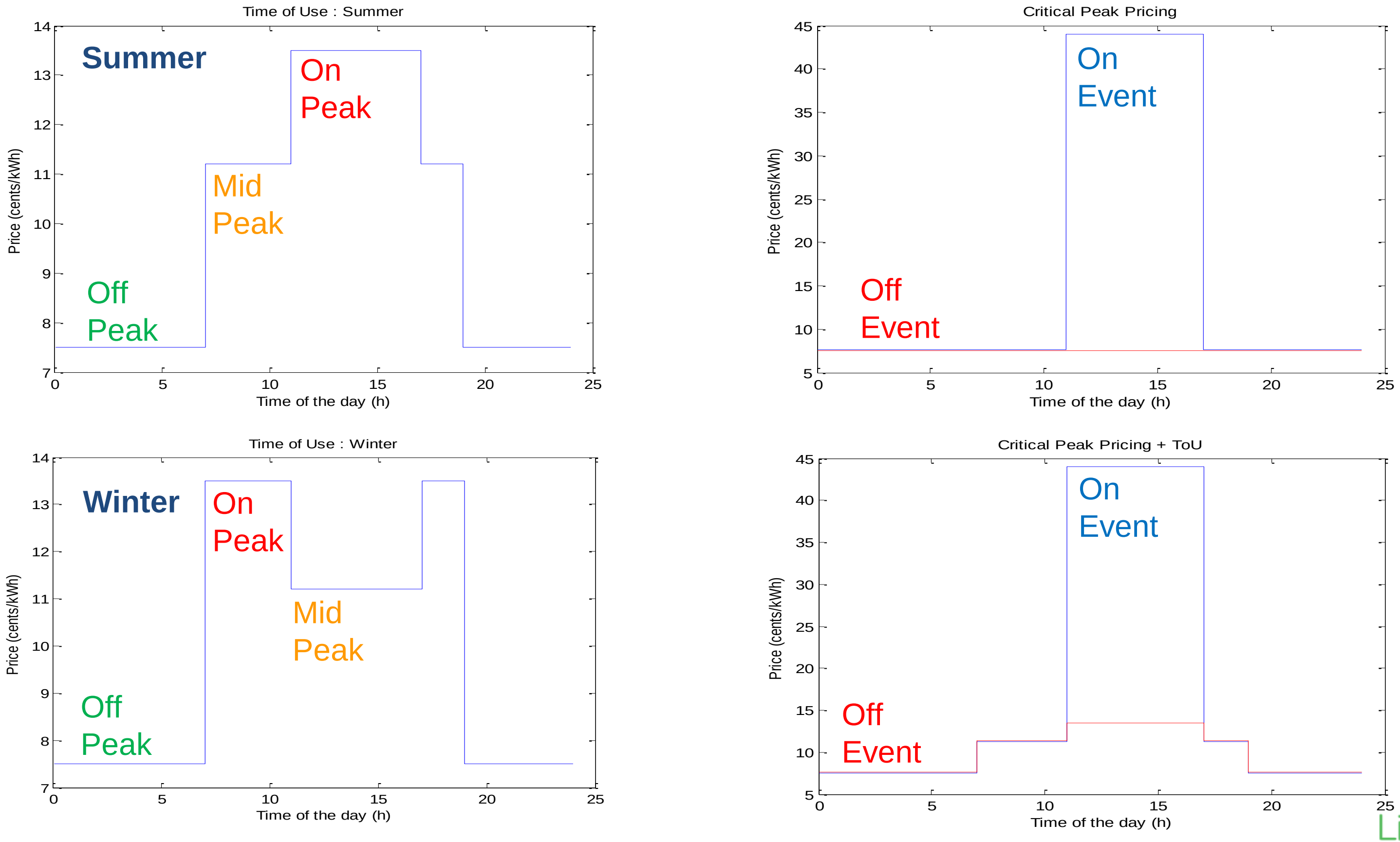




Question:

Guess why the peak times change with the season?

Time of Use (agreed tariff) and Critical Peak Pricing (on event)



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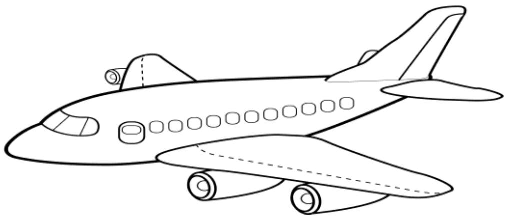
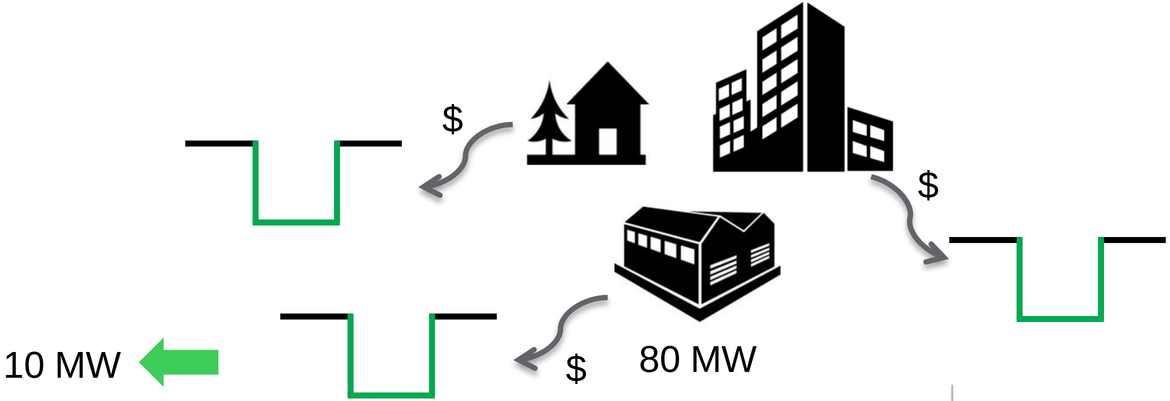
Demand Response



70

80

70 MW

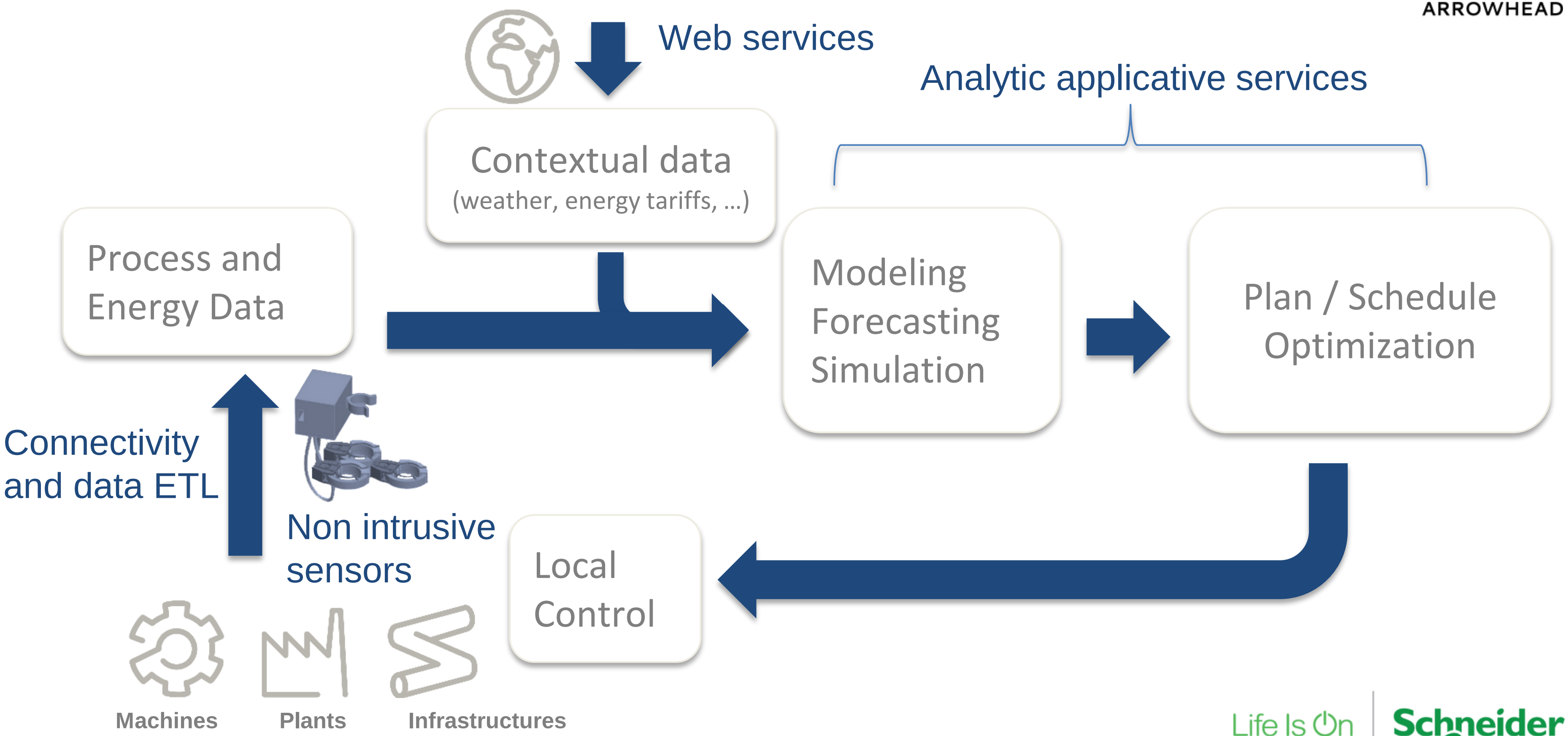


Most Consumers …

Focus for today

- Know their global bill (e.g., 1.2M€ per year) but do not have precise figures about when, where, and under which conditions the corresponding electricity is used
  - Measurements
  - Classification and disaggregation (profiling) problems
- Cannot predict precisely enough (with the appropriate time grain) their consumption for the next day, week, month …
  - Forecasting problems
- Have to balance their energy consumption against other (more) important costs and criteria related to their own activity (due-date satisfaction in manufacturing plants, comfort in buildings, …)
  - Multi-criteria planning and scheduling problems
- Have to react in real-time to unforeseen changes
  - Context-dependent control problems (with consumption commitments?)
- Might need to redesign or resize their systems to enable significant energy cost savings
  - Design and sizing (investment decision support) problems

Arrowhead Project – Energy Management Applications



Energy Management Pilot Demonstrators

ARROWHEAD

ELEVATOR

Energy recovery | Distributed energy resources | Variable energy tariffs

OPTIMIZE PLANNING and CONTROL of the multiple energy sources, leveraging batteries and variable tariffs

- ❑ Reduce the electrical cost and the environmental footprint
- ❑ Maintain sufficient autonomy in case of grid failure in order to ensure safety

MANUFACTURING

Variable energy tariffs | Process flexibilities

OPTIMIZE SCHEDULE of manufacturing operations, leveraging sub-assembly storage and variable tariffs

- ❑ Minimize cost without taking risks regarding satisfaction of customer demand

WATER NETWORK

Variable energy tariffs | Process flexibilities

OPTIMIZE SCHEDULE of pumping, leveraging water tower storage and variable tariffs

- ❑ Minimize cost without taking risks regarding satisfaction of customer demand

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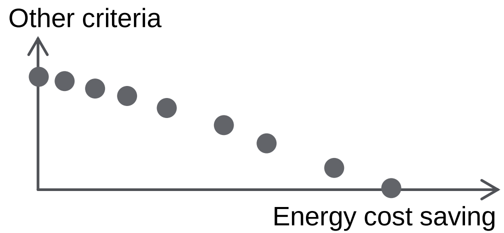
Three Main Sources of Flexibility

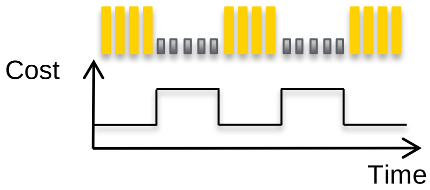
- Making compromises to achieve definitive energy savings
  - When the impact on the process for which the energy is used is not too significant
  - Example: up to a certain limit, one can dim the light in an elevator → Direct and definitive energy savings, acceptable provided that it does not occur too often, depending on the context
- Delaying high consumption
  - When a highly consuming activity can be delayed (or performed in advance) or, more generally, when savings are possible at a given time but at the expense of further consumption before or after this time
  - Example: if enough water is available in a water tower, one can delay for a while the pumping of water into this water tower → At some point, however, pumping will be needed to ensure the water tower gets enough water to serve the local customers
  - Example: highly consuming activities in a manufacturing plant might be avoided during a given interval of time, provided these activities are not time-critical and the corresponding products are available in stock → At some point, however, it will become necessary to perform these activities, and consume the corresponding amount of energy, in order to replenish the stock
- Storing energy
  - When energy can be stored (e.g., in batteries, in the form of hot water, etc.)
  - Example: part of the energy stored in the battery of an elevator can be used to temporarily operate the elevator with no other impact on the elevator's process → At some point, however, it will become necessary to recharge the battery

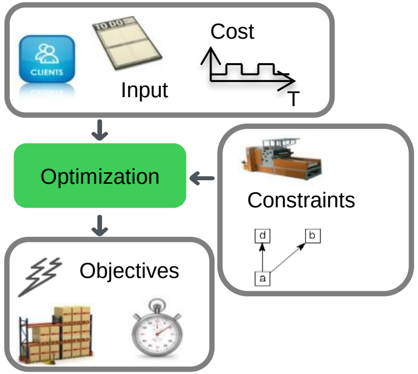
Typical Optimization Models

- Making compromises to achieve definitive energy savings
  - Multi-criteria optimization
  - Sometimes considering past accumulation of inconvenience
  - Sometimes with fairness consideration

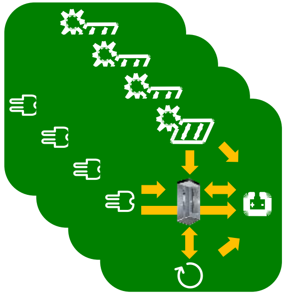


- Delaying high consumption
  - Multi-criteria planning, lot sizing, scheduling models
  - Most often with energy cost as a secondary criterion





- Storing energy
  - Constrained network flow optimization problem
    - Nodes correspond to energy producers and consumers at given times
    - Arcs correspond to potential flows of energy in time
  - With costs and losses …
  - In general, a lot of energy cost savings can be achieved without impacting other process-specific criteria → multi-criteria optimization is only an option



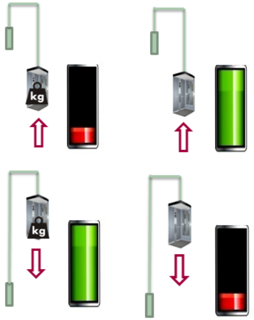
Sources of Flexibility Coexist

Worth decomposing – especially if one holds most of the potential benefit

	Complexity	Potential Benefit		
		Elevator	Manufacturing (plant-dependent)	Water
Making compromises to achieve definitive energy savings	Medium	Small (and can be looked at separately)	Small	Not applicable
Delaying high consumption	High	Not applicable	**High**	**High**
Storing energy	Small	**High**	Not applicable	Not applicable

Power (or Energy) Consumption Modeling

→ Define a model enabling to evaluate the power (or energy) consumption as a function of controlled and uncontrolled inputs



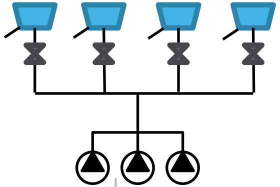
Elevator

- P(t) = f(origin, destination, load, elevator and control parameters)

Manufacturing

- If the electrical power does not vary during the execution of an activity and does not depend on environmental conditions then $P(t) = \text{baseload} + \Sigma_{A \text{ executing at } t} P(A)$
- Need to determine P(A) for each A
- The model can be much more complex than this (e.g., for activities requiring heating or cooling)

Water

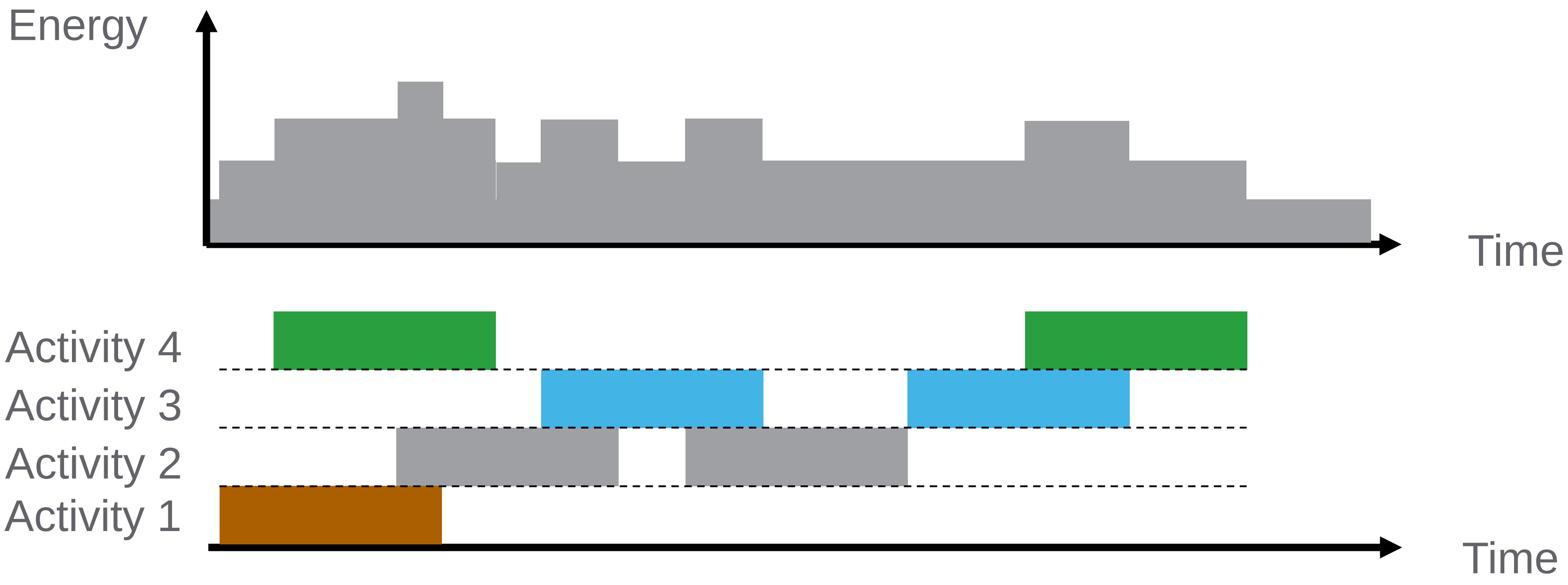


- P(t) = f(pump and valve settings) with f depending on many (unknown) characteristics of the network

C. Desdouits
P.-A. Berseneff

Zoom on the Manufacturing Case

Multivariate Regression Problem



Multivariate Regression Problem Statement – Data

- Energy has been measured over intervals $[t_i\ t_{i+1})$

  $\tau_i = t_{i+1} - t_i$ is the duration of the time interval

  $energy_i$ is the energy consumed over the time interval

- Start and end times of activities and quantities of product processed are known

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	PRODUCTION_ORDER_ID	ACTIVITY_ID	MODE_NUMBER	START_TIME	END_TIME	RECIPE_ID	BATCH_SIZE	RESOURCE_ID	FIXED_PROCESSING_TIME	VARIABLE_PROCESSING_TIME	CHOCOLATE	NUTS	SHAPE
2	7	3	0	01/01/2001 06:00	01/01/2001 09:45	1	1	0	0	13500	Milk	None	Egg
3	10	8	0	01/01/2001 06:00	01/01/2001 09:15	2	1	2	0	11700	Milk	Hazelnut	Rabbit
4	11	8	0	01/01/2001 09:15	01/01/2001 12:30	2	1	2	0	11700	Milk	Hazelnut	Rabbit
5	8	3	0	01/01/2001 09:45	01/01/2001 13:30	1	1	0	0	13500	Milk	None	Egg
6	7	4	0	01/01/2001 09:45	01/01/2001 15:01	1	1	1	0	19000	Milk	None	Egg
7	16	13	0	01/01/2001 12:30	01/01/2001 14:00	3	1	2	0	5400	Dark	Coconut	Egg

Assuming regularity throughout each activity execution, this enables to compute, for each (recipe, activity, mode) reference r the amount $batchSize_{r,i}$ of reference r executed over each interval $[t_i\ t_{i+1})$

For example, between 06:00 and 06:01, we assume that 60/13500 of (recipe 1, activity 3 in mode 0) and 60/11700 of (recipe 2, activity 8 in mode 0) have been executed

When fixed / setup times exist, activities must be decomposed in sub-activities

Multivariate Regression Problem Statement – Variables

- **baseload** $=$ the energy consumed per unit of time at all times, i.e., even when no activity executes

  (can be constrained to be non-negative)

- **energy**$_r$ $=$ the energy consumed per unit of reference r

  (can be constrained to be non-negative)

- **error**$_i$ $=$ the difference between

  the measured energy consumption energy_i

  and the regression value $\Sigma_{r \in \text{References}} (\mathbf{energy}_r * \text{batchSize}_{r,i}) + \mathbf{baseload} * \tau_i$

  due to lack of precision of the energy meter, lack of precision in activity start and end times, invalidity of our assumptions, random fluctuations, etc.

➢ We want to minimize a non-decreasing function of $|\mathbf{error}_i|$ for all i

➢ A classical one is $\Sigma_i\ \mathbf{error}_i^2$ but …

Multivariate Regression Problem Statement – Difficulties

- Depending on the energy measurement system, intervals $[t_i\ t_{i+1})$ may have different durations
  - Need to process the energy data (making assumptions again) to get intervals of the same duration
  - Or weigh the errors $|\mathbf{error_i}|$ or $\mathbf{error_i^2}$
- A lot of data are needed to statistically make sense but problem size can be an issue
  - Need time intervals on which diversified combinations of activities execute (usual rule of thumb is a factor 10 between the number of variables and the number of constraints) → a lot of time intervals means a lot of constraints
- The problem may have equivalent solutions
  - If a machine (unary resource) is never idle, you can increase/decrease the value of **baseload** and correspondingly decrease/increase the values of $\mathbf{energy_r}$ for the references using this machine → check data or get baseload elsewhere
- More or less co-linear constraints tend to create numerical issues (depending on the solver)
  - If $\tau_i = \tau = 1$ minute, all the minutes between 06:00 and 09:45 lead to
  - $energy_i = \Sigma_{r \in References}\ (\mathbf{energy_r} * batchSize_{r,i}) + \mathbf{baseload} * \tau_i + \mathbf{error_i}$ with the same coefficients $batchSize_{r,i}$ and τ_i
  - Hence a need to select or aggregate intervals, but this impacts the definition of the error

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	PRODUCTION_ORDER_ID	ACTIVITY_ID	MODE_NUMBER	START_TIME	END_TIME	RECIPE_ID	BATCH_SIZE	RESOURCE_ID	FIXED_PROCESSING_TIME	VARIABLE_PROCESSING_TIME	CHOCOLATE	NUTS	SHAPE
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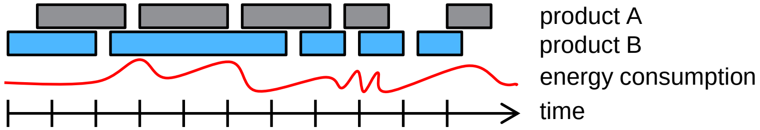
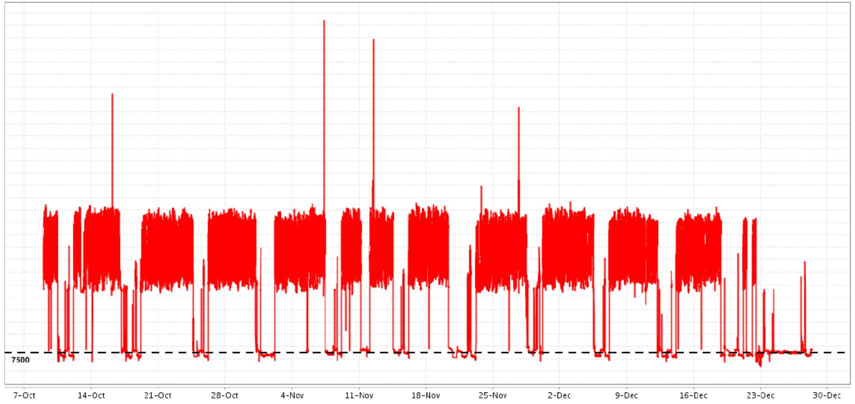
Multivariate Regression Problem Statement – Summary





baseline power: about 7500W

Time discretization:

Linear regression of:

- **$\mathbf{energy_r}$** is the energy consumed by producing one unit of reference r;
- **baseload** is the power consumed by the line whatever the production;
- **$\mathbf{error_i}$** is a term that represents regression model errors.

$\forall t_i \leq H,$

$$energy_i = \sum_{r \in References} (\mathbf{energy_r} \times batchSize_{r,i}) + \mathbf{baseload} \times \tau_i + \mathbf{error_i}$$

Works well in principle but is sensitive to the level of noise in the data → Practice much harder than theory

C. Desdouits, J.-L. Bergerand, P.-A. Berseneff, C. Le Pape and D. Yanculovici.
Energy Study of a Manufacturing Plant.
ECEEE International Conference on Industrial Efficiency, 2016.

Forecasting

→ Forecast either consumption or elements that will influence consumption

- Usually looking at time intervals with an appropriate time grain

Elevator

- Two options:
  - Either forecast the (statistical) demand for the elevator and simulate the elevator to forecast the energy production and consumption
  - Or forecast directly the energy production/consumption on the basis of historical data

Manufacturing

- The forecast depends on the manufacturing work plan, based on the previously identified model

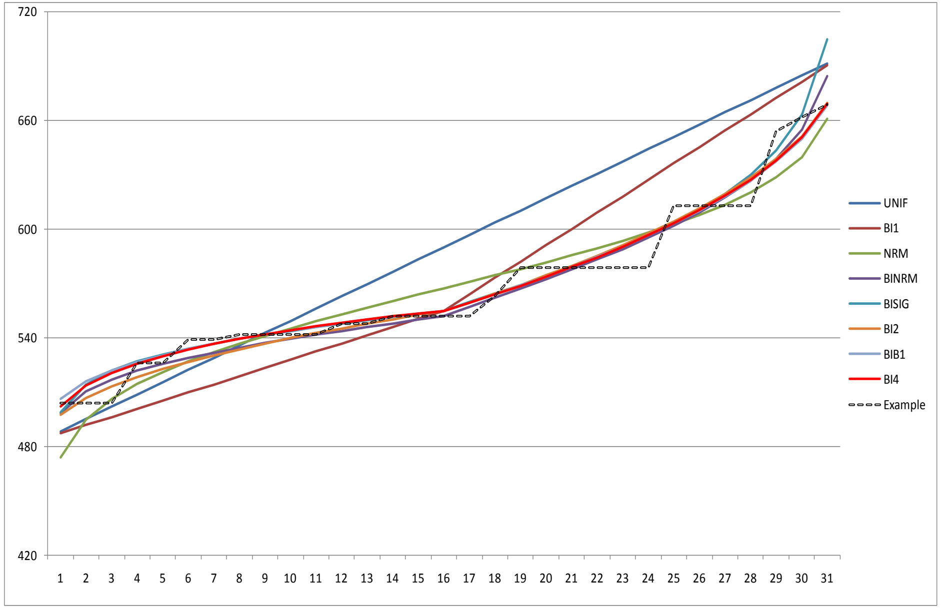
Water

- Forecast the demand for water (input for planning)

Forecasting

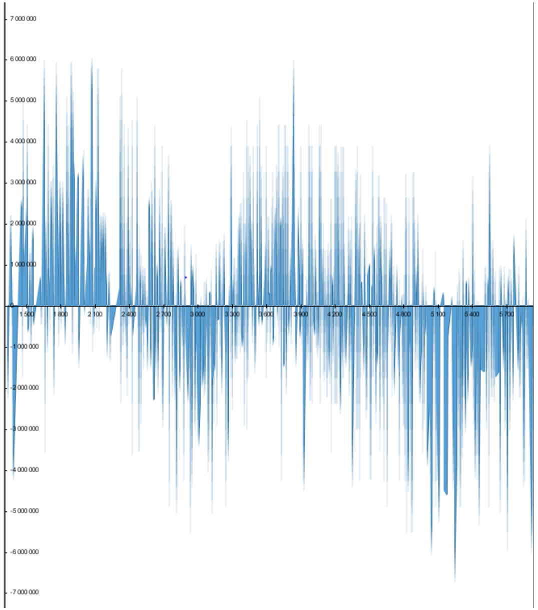
Energy production and consumption forecasting from a statistical demand model

Identification of statistical laws



Arrival times of people in the morning for a given floor
Sample and approximating statistical laws (arrival number / minute)

→Simulation



Elevator trips over time
Δ altitude * (load – counterweight)

→Forecast of energy production and consumption (per quarter)

Average over N simulations

Distribution enabling to check the level of uncertainty

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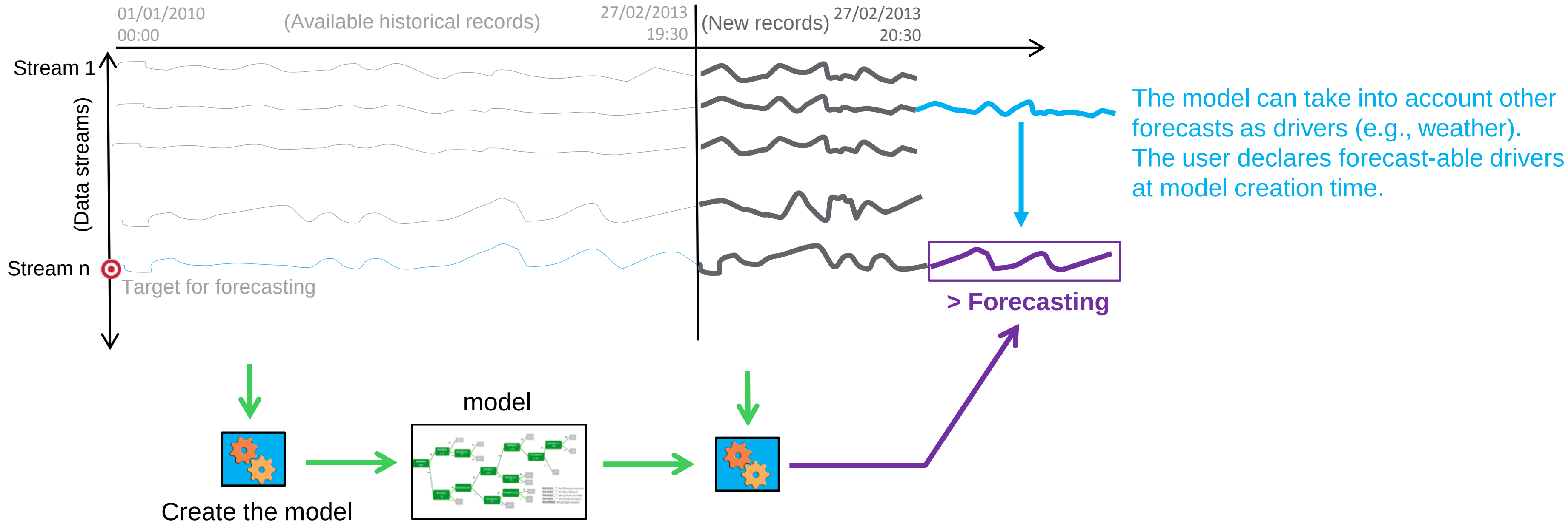
Forecasting

Direct forecasting of energy production and consumption from historical data



Main risk is to forget important drivers (e.g., number of people with an office at each floor), especially if these did not vary much in the historical data → Drift detection and model re-learning might be required

Forecasting

An anecdote about water consumption forecasting

Solve the following apparent paradox:

- Silvio the Social Scientist: “We have studied the water consumption behavior of our customers: weather has no impact on their consumption.”
- Francesca the Financial Officer: “The weather last year has not been good, so we sold less water.”
- *Jacques Bodoin: “Qui c’est qui va se le cloquer, le robinet qui perd, le bassin qui fuit?”*

Hints:

- We are on the seaside, 100 kilometers from a big city
- The weather forecast established on Thursday for the week-end is an important driver of the week-end consumption.

Planning / Scheduling

C. Desdouits M. Haouassi G. German G. Bonvin

→ Build a plan / schedule to reduce energy costs

Elevator

- Focus on the good usage of energy storage → Linear Programming

Manufacturing

- Focus on delaying high consumption → Scheduling → Mixed-Integer Programming, Constraint Programming, forms of Local Search
- With a big difficulty to relate energy cost with the main variables of the problem → Multiple approximations tried over the years of the project

Water

- Focus on delaying high consumption → Scheduling → Mixed-Integer Quadratic Programming, due to non-linearity in the relation between energy and water flow

C. Desdouits, M. Alamir, V. Boutin and C. Le Pape. Multisource Elevator Energy Optimization and Control. European Control Conference, 2015.

C. Desdouits, M. Alamir, R. Giroudeau and C. Le Pape. The Sourcing Problem: Energy Optimization of a Multisource Elevator. International Conference in Informatics in Control, Automation and Robotics, 2016.

G. German, C. Desdouits and C. Le Pape. Energy Optimization in a Manufacturing Plant. ROADEF, 2015.

M. Haouassi, C. Desdouits, R. Giroudeau and C. Le Pape. Production Scheduling with a Piecewise-Linear Energy Cost Function. IEEE Symposium Series on Computational Intelligence, 2016.

G. Bonvin, S. Demassey, C. Le Pape, N. Maïzi, V. Mazauric, and A. Samperio. A convex mathematical program for pump scheduling in a class of branched water networks. Applied Energy, 2017.

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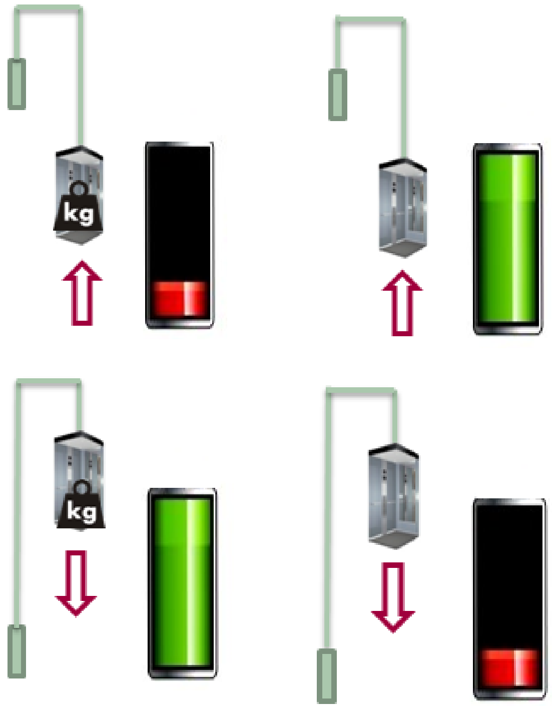
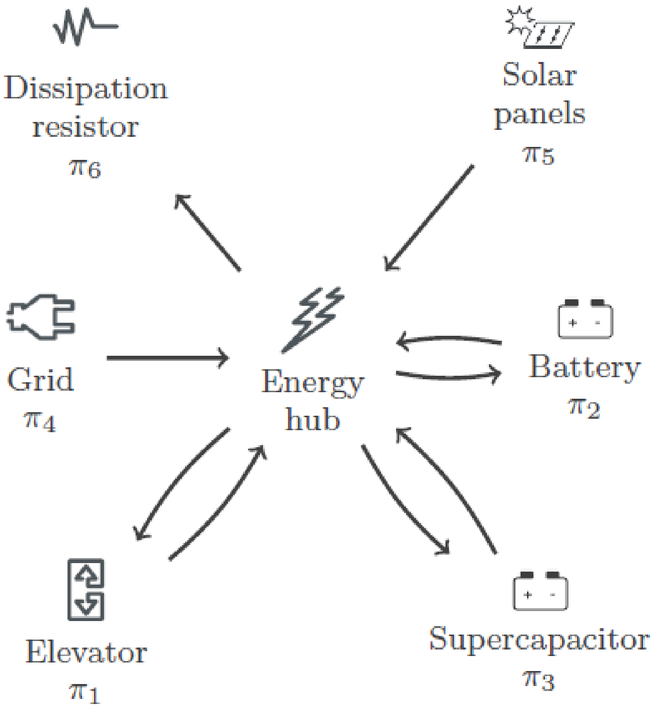
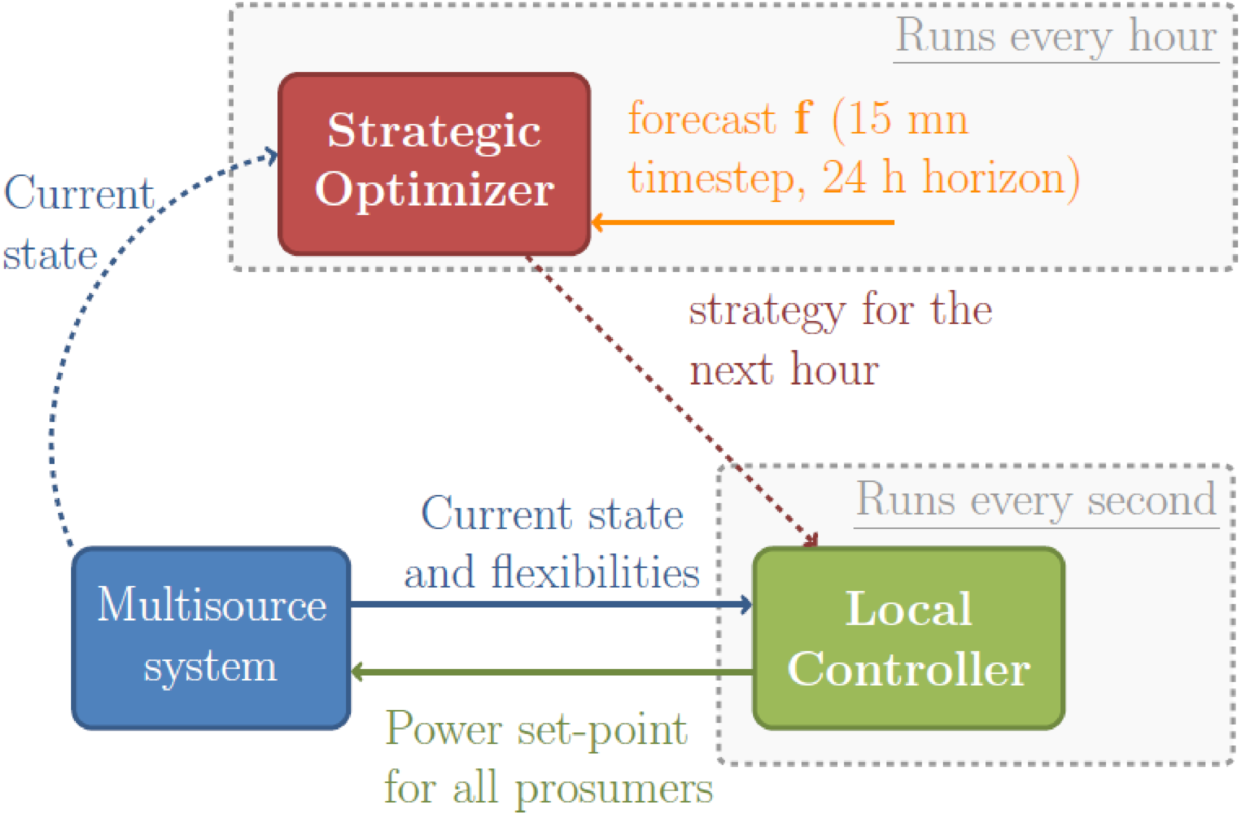
Zoom on the Elevator Case – Energy Hub Structure





Zoom on the Elevator Case – Control Strategy



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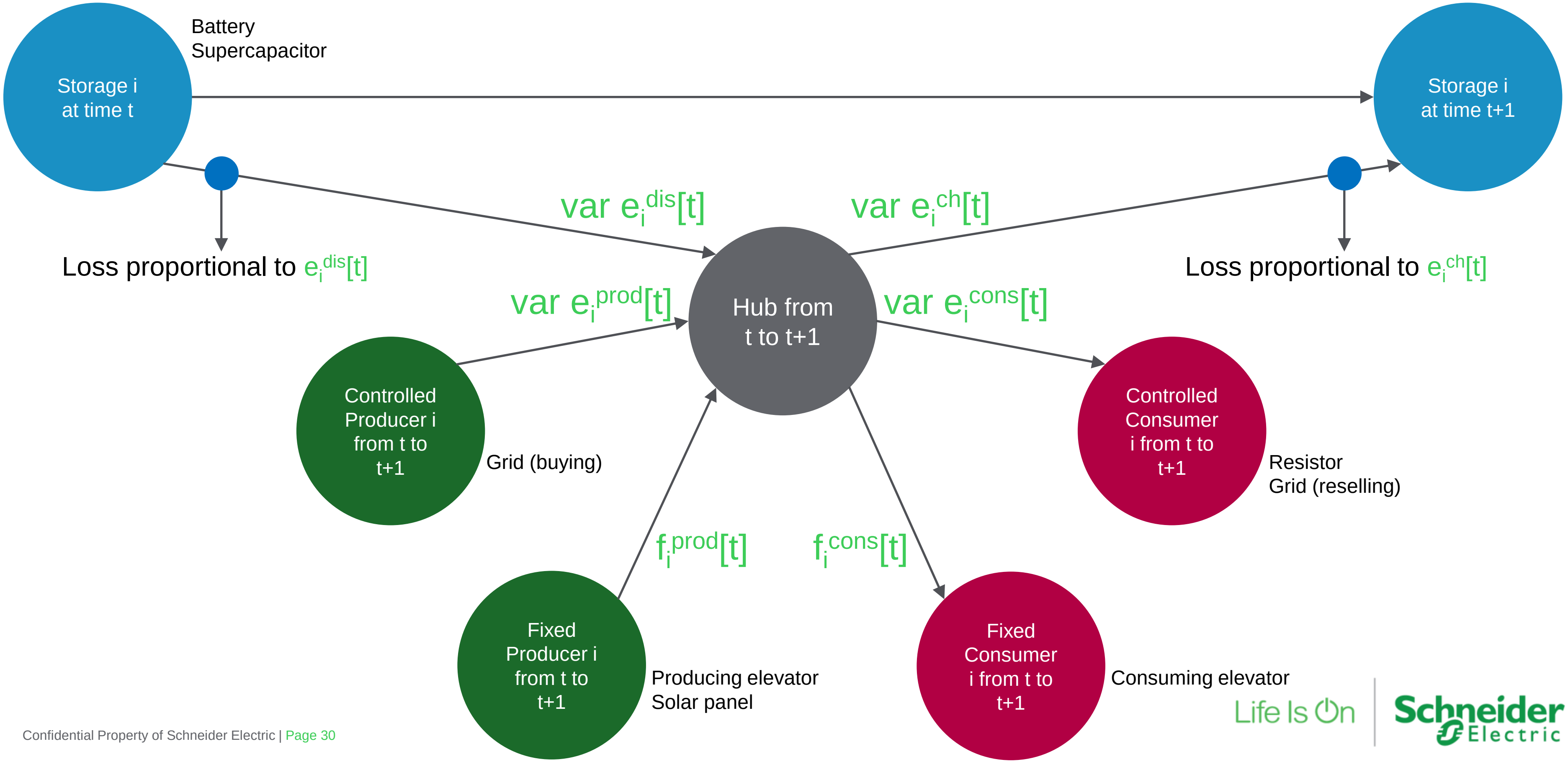
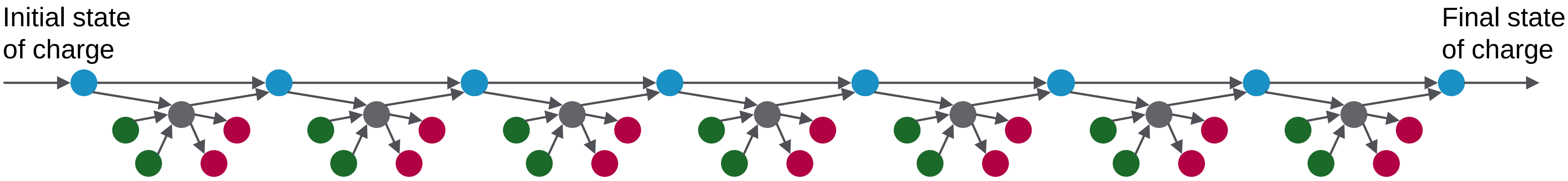
Zoom on the Elevator Case – Network Flow Structure



Zoom on the Elevator Case – Network Flow Structure



Constraints:

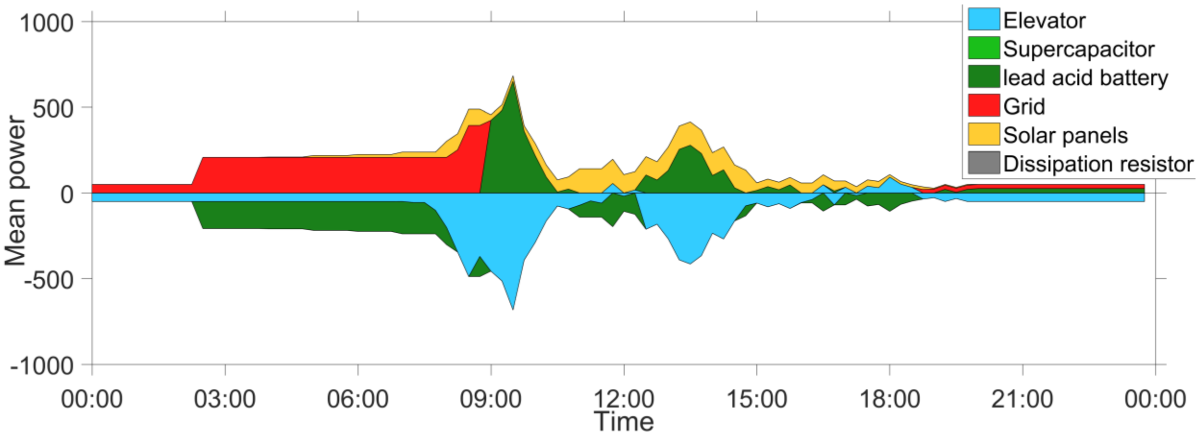
- Minimal and maximal values for each variable, including amounts stored at each time t
- Energy conservation at the hub
- Energy conservation at each storage unit (taking losses into account)

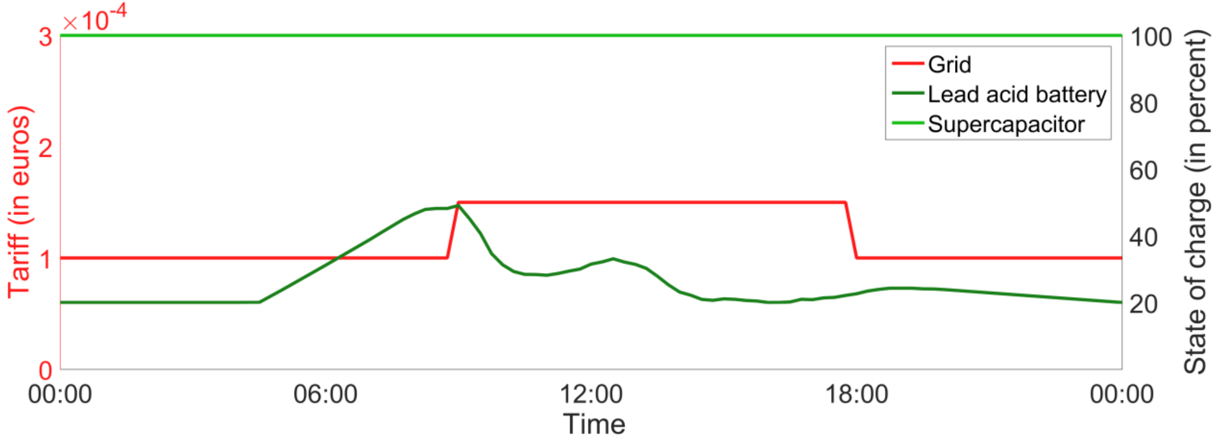
Costs on the arcs:

- Between storage and hub: usage costs of the storage unit, proportional to $e_i^{dis}[t]$ and/or $e_i^{ch}[t]$
- Between grid and hub: buying/reselling prices, proportional to $e_i^{prod}[t]$ and $e_i^{cons}[t]$, with coefficients depending on t

➢ Easily solved by linear programming

Zoom on the Elevator Case – Typical Day





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Zoom on the Manufacturing Case: Job-Shop Scheduling with Minimal and Maximal Delays and Electricity Costs

- For each manufacturing order, we have a set of activities
  - Non-interruptible
  - With known duration
  - Linked together with precedence constraints with minimal and maximal delays
  - Requiring unary resources (machines)
  - Requiring electrical power
- Three antagonistic optimization criteria
  - Ensure due date satisfaction, i.e., deliver each manufacturing order on time, or as little late as possible
  - Reduce storage costs, for both intermediate and final products
  - Reduce the electricity bill

➢ In practice, the first criterion is considered as much more important than the others

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Zoom on the Manufacturing Case: Activity Variables

Three variables

start(A)

end(A)

duration(A) (a constant in our case)

for each activity A

With finite domain (bit vector) or interval domain (pair of numbers)

$start_{min}(A)$, $start_{max}(A)$,

$end_{min}(A)$, $end_{max}(A)$

$duration_{min}(A)$, $duration_{max}(A)$

Zoom on the Manufacturing Case: Relation Between the Variables

Constraint of the form $end(A) = start(A) + duration(A)$

Linear

- $end_{min}(A) = \max(end_{min}(A), start_{min}(A) + duration_{min}(A))$
- $end_{max}(A) = \min(end_{max}(A), start_{max}(A) + duration_{max}(A))$

- $start_{min}(A) = \max(start_{min}(A), end_{min}(A) - duration_{max}(A))$
- $start_{max}(A) = \min(start_{max}(A), end_{max}(A) - duration_{min}(A))$

- $duration_{min}(A) = \max(duration_{min}(A), end_{min}(A) - start_{max}(A))$
- $duration_{max}(A) = \min(duration_{max}(A), end_{max}(A) - start_{min}(A))$

Zoom on the Manufacturing Case: Precedence Constraints with Minimal and Maximal Delays

Linear

Constraints of the form

$$\text{start}(A) + \text{delay} \leq \text{start}(B)$$

$$\text{start}(A) + \text{delay} \leq \text{end}(B)$$

$$\text{end}(A) + \text{delay} \leq \text{start}(B)$$

$$\text{end}(A) + \text{delay} \leq \text{end}(B)$$

with delay positive or negative

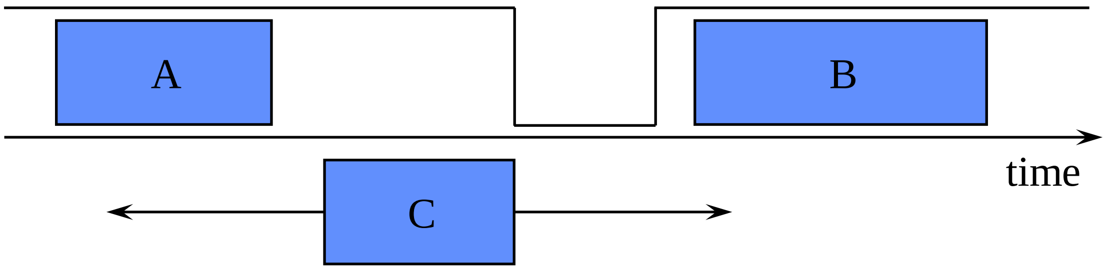
$$\text{var}(A) + \text{delay} \leq \text{var}(B)$$

- $\text{var}_{min}(B) = \max(\text{var}_{min}(B), \text{var}_{min}(A) + \text{delay})$
- $\text{var}_{max}(A) = \min(\text{var}_{max}(A), \text{var}_{max}(B) - \text{delay})$

Zoom on the Manufacturing Case: Unary Resource Constraints

Machines

- Some times unavailable
- Processing one activity at a time



Multiple models and propagation algorithms in the literature

Among them, the disjunctive constraint, i.e.,

if A and B require the same machine,

then [end(A) $\leq$ start(B)] OR [end(B) $\leq$ start(A)]

- [end_{min}(A) > $start_{max}$(B)] implies [end(B) $\leq$ start(A)]
- [end_{min}(B) > $start_{max}$(A)] implies [end(A) $\leq$ start(B)]

Non Linear

precede(A, B) = 0 or 1

precede(A, B) + precede(B, A) = 1

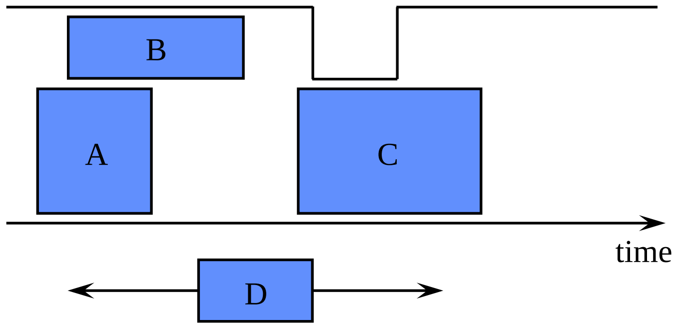
end(B) $\leq$ start(A) + M $*$ precede(A, B)

end(A) $\leq$ start(B) + M $*$ precede(B, A)

Zoom on the Manufacturing Case: Cumulative Resource Constraints and Electricity Cost (1/2)

Each activity requires a given power

- Possibly limited
- Inducing cost



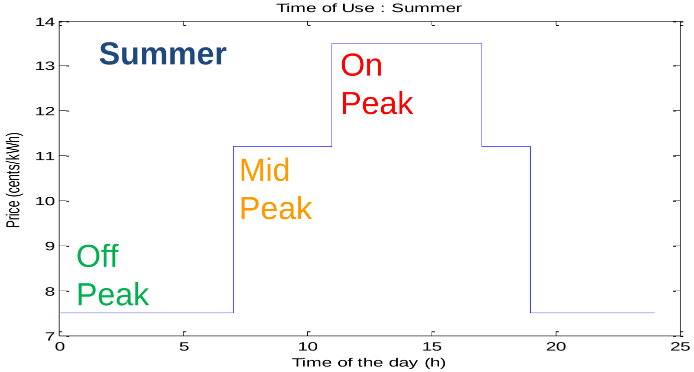
$\forall A, \forall t, W_A(t) = [start(A) \leq t < end(A)]$

$\forall t, \Sigma_A \,(W_A(t) * power(A)) = power(t)$

General case:

$$\text{total electricity cost} = \Sigma_t \, f_t\,(power(t))$$

Particular case: price per kWh c_I over given intervals I



$$\text{total electricity cost} = \Sigma_I \,(c_I * \Sigma_{t \in I}\, power(t)) = \Sigma_I \, \Sigma_A \,(c_I * power(A) * \Sigma_{t \in I}\, W_A(t))$$

Zoom on the Manufacturing Case: Cumulative Resource Constraints and Electricity Cost (2/2)

$\text{overlap}(A, I) = \Sigma_{t\in I}\, W_A(t) = \min(\alpha_A(I), \beta_A(I), \delta(I), \delta(A))$

where

$\alpha_A(I) = \max(0, \text{end}(A) - \text{start}(I))$

$\beta_A(I) = \max(0, \text{end}(I) - \text{start}(A))$

$\delta(I) = \text{end}(I) - \text{start}(I)$

$\delta(A) = \text{duration}(A)$

Non Linear

$\text{bound}(A, I) \leq \text{end}(A) - \text{start}(I)$

$\text{bound}(A, I) \leq \text{end}(I) - \text{start}(A)$

$\text{bound}(A, I) \leq \text{end}(I) - \text{start}(I)$

$\text{bound}(A, I) \leq \text{duration}(A)$

$\text{disjoint}(A, I) = 0 \text{ or } 1$

$0 \leq \text{overlap}(A, I)$

$\text{overlap}(A, I) \leq (\text{end}(I) - \text{start}(I)) * (1 - \text{disjoint}(A, I))$

$\text{overlap}(A, I) \leq \text{bound}(A, I) + M * \text{disjoint}(A, I)$

$\Sigma_I\, \text{overlap}(A, I) = \text{duration}(A)$

$\text{total electricity cost} = \Sigma_I\, \Sigma_A\, (c_I * \text{power}(A) * \text{overlap}(A, I))$

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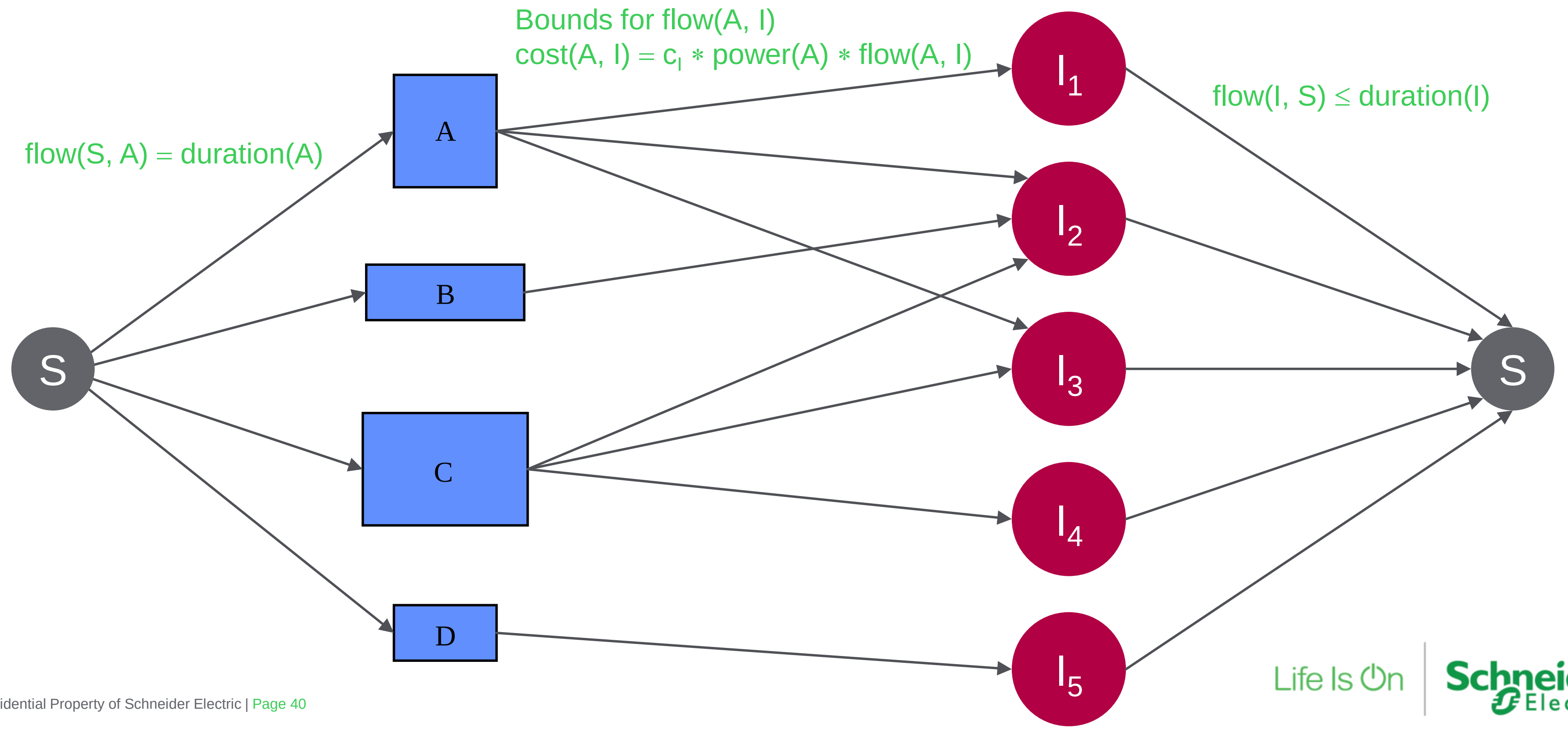
Zoom on the Manufacturing Case: Global Constraint Mixing a Machine and Electricity Cost (Preemptive Relaxation)



Zoom on the Manufacturing Case: Tardiness and Storage Costs

Linear

Tardiness

- Each activity A delivering an order has a due date duedate(A) and a tardiness weight weight(A)
- $0 \leq \text{tardiness}(A)$
- $\text{end}(A) - \text{duedate}(A) \leq \text{tardiness}(A)$
- total tardiness cost $= \Sigma_{\text{A with a due date}}\ \text{weight}(A) * \text{tardiness}(A)$

Earliness / Storage of final products

- Same principle

Storage of intermediate products between A and B

- total intermediate storage cost $\Sigma_{\text{A,B with intermediate storage}}\ \text{weight}(A, B) * (\text{start}(B) - \text{end}(A))$

Zoom on the Manufacturing Case: Search Strategies (1/2)

Pure constraint programming with classical variable and value selection strategies

- Variable selection strategy → select an activity A with the smallest $end_{max}(A)$ (or an equivalent computed from due dates)
- Value selection strategy → $end(A) = end_{min}(A)$ on the first branch and then some "smart" exploration

Pure constraint programming starting with ordering decisions

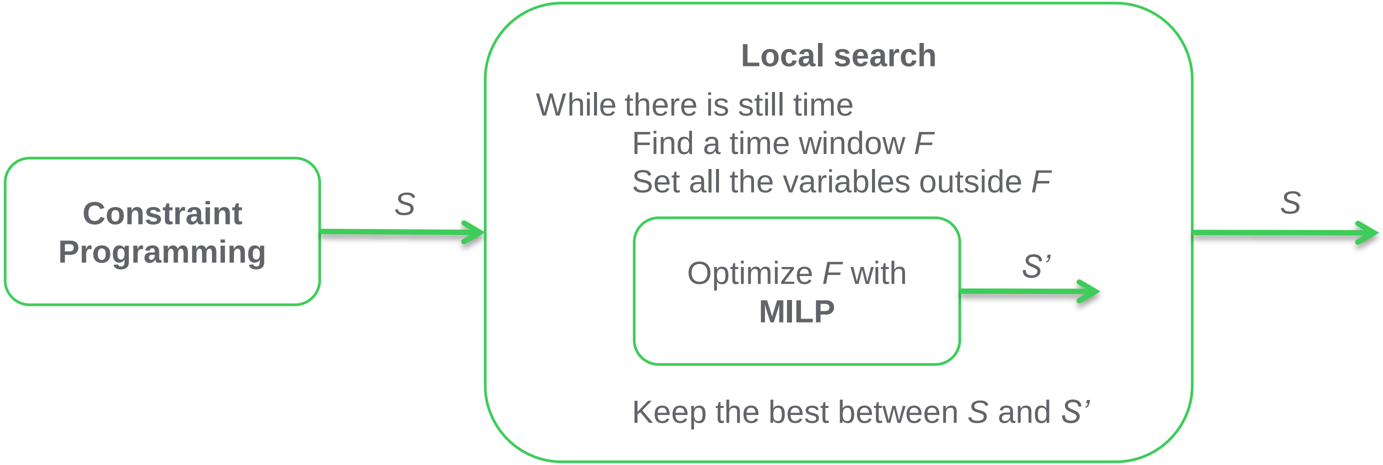
- Select two unordered activities A and B requiring the same machine and impose $end(A) \leq start(B)$
- Reverting to the above once all ordering decisions are made

Pure mixed-integer linear programming

Mixed-integer linear programming once all ordering decisions are made

Zoom on the Manufacturing Case: Search Strategies (2/2)

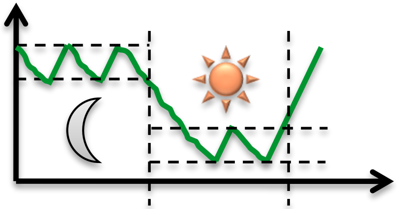
Constraint programming followed by MILP-based local search



With a weighted sum of the three criteria …

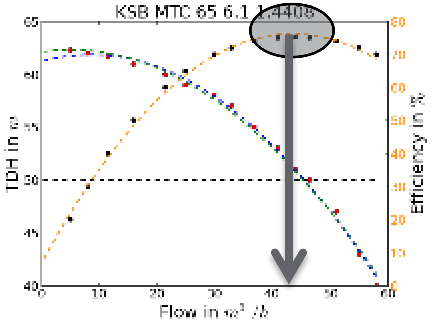
Or optimize tardiness first and then electricity and storage costs without compromising tardiness …

Zoom on the Water Case – Pumping Plan Optimization



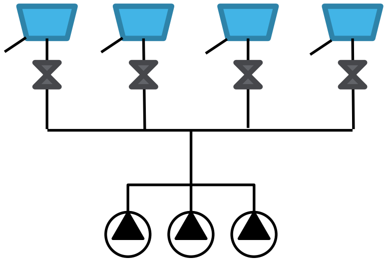
Multiple opportunities for optimization

- **Time-varying tariffs**: if the tariff is attractive, it is worth pumping water in advance, e.g., pumping during the night
- **Head loss versus flow physics**: if a branch is lower in diameter, it is better to avoid activating this branch simultaneously with the other branches
- **Pump efficiency**: it is better to operate pumps at their highest efficiency level



Which depend on what is controllable

- Pumps (with or without drives)
- Valves
- Water levels in tanks
- ➢ Not a single solution for all networks



Benefits:

- Energy cost (and possibly investment) savings
- Plan robustness versus demand and other uncertainties
- Capacity to run what-if scenarios (in predictive or reactive mode)

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Pumping Plan Optimization

An example

Variable tariff

- Water towers are filled during the night

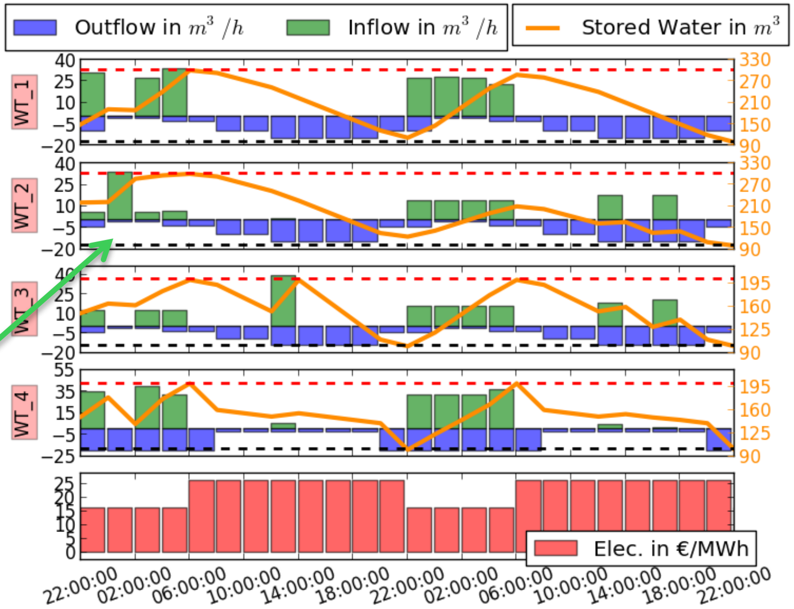
Head losses

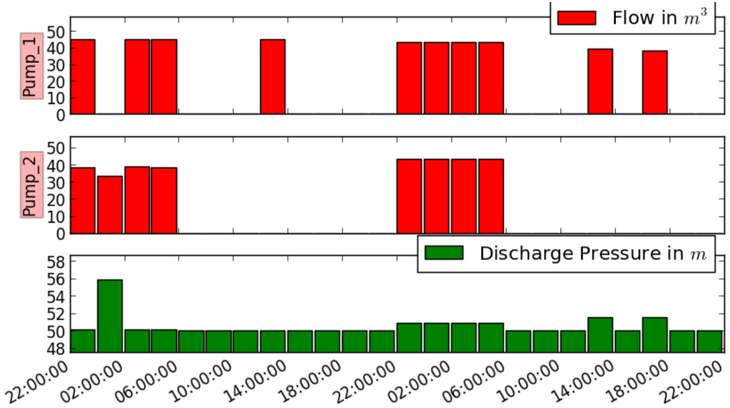
- Water towers 1, 3 and 4 require ~50 bar
- Water tower 2 requires ~56 bar
- The plan sometimes differentiates WT_2

Pump efficiency

- Valves flows are set so that pumps always work at their maximum efficiency point

➢Global compromise between these 3 conflicting elements





Potential Gains

With current electricity tariffs

Elevator

- The overall system can make the elevator almost self-sufficient
- With little due to the optimization itself
- Low quantities → Worthwhile only if multiple elevators share the same system (or if the elevator is considered as one component in the building)

Manufacturing

- Typical savings in the range of 5-10%
- Return on investment depends on the plant, the load of the plant, the tariff structure, etc.

Water

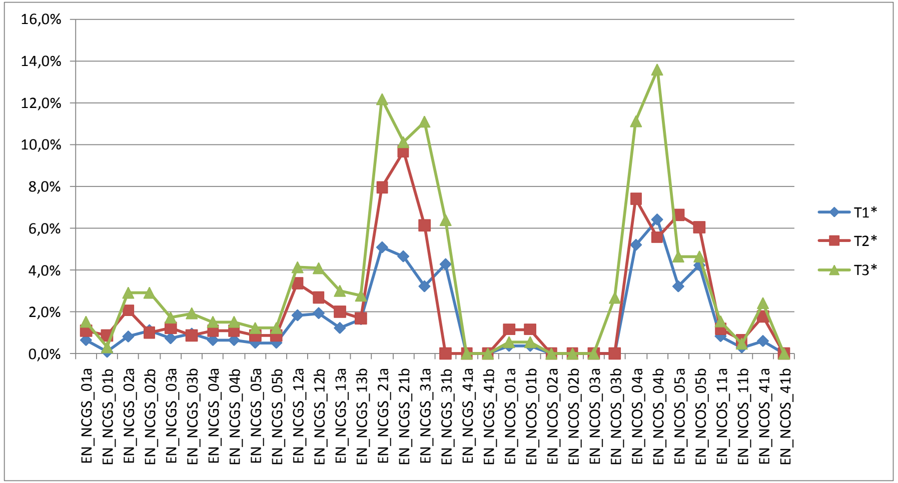
- Intermediate situation

P.-A. Berseneff

Potential Gains Sensitivity Analysis

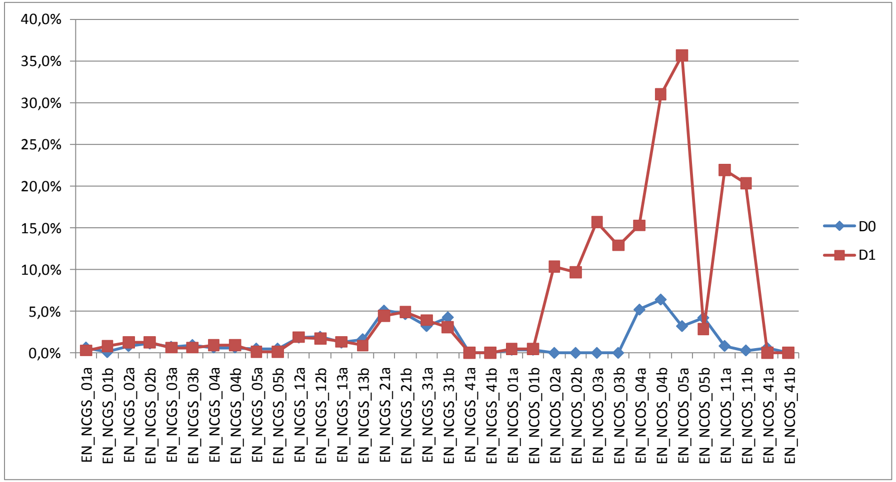
Test on a public manufacturing scheduling benchmark

From: C. Le Pape and A. Robert. Jeux de données pour l’évaluation d’algorithmes de planification et ordonnancement. FRANCORO/ROADEF 2007.



Dependency on tariff (day-night difference)

Dependency on flexibility (due-date tightness)



Conclusion

A lot learned …

Sources of flexibility

- Making compromises to achieve definitive energy savings
- Delaying high consumption
- Storing energy

➢ Which coexist but do not necessarily need to be considered together

Consumption modeling

- First (physical) principles versus measurements and data analysis
- Intermediate: first principles for the form of the function, data analysis to set parameters
- Measurement and display already provide value (e.g., visualizing baseload and peaks)
- Regression and other machine learning methods work, provided there is not "too much" noise in the data

Conclusion

A lot learned …

Forecasting

- Direct or through an intermediate “first principles” model
- Regression and other machine learning methods work, provided there is not “too much” noise in the data and all relevant “drivers” are present → Caution, drift detection and relearning might be needed

Planning / Scheduling

- A general function but no general and no perfect optimization model → Remember that we always solve an approximated problem
- Forecast data is uncertain → Robustness is a dimension to be considered, especially as energy consumption cost is a secondary criterion
- Scheduling with complex energy tariffs is a very hard problem
- Gains (savings) depend on multiple factors including tariffs and application-specific factors of flexibility (e.g., due-date tightness)

Conclusion

A lot remains to be done …

But I’ll stop here for questions …

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