

Actemium-leerstoel duurzame energie: energie-bewuste planning en optimalisatie

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Energy-aware planning and optimisation

Help companies get ready for the upcoming energy transition

Energy becomes a valuable but flexible resource

'Bill of Energy'

Existing sustainable technologies

What infrastructure does the company need? What to invest in?

- ▶ Energy generation: solar, wind, CHP in-plant or buy?
- ▶ Energy storage: batteries, chemical, reservoirs, tanks cost?
- ▶ Energy conversion: turbines, heat pumps, fuel cells losses?

clean, renewable,
sustainable
but variable &
limited capacity

But how to be smart about using these technologies?

Develop innovative and efficient energy-aware planning tools for production & logistics:

When to produce what, *using which source of energy?*



Mathematical optimisation

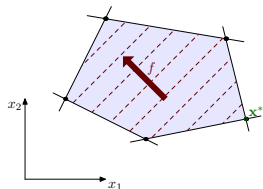
$$\text{Find } \mathbf{x}^* = \arg \min_{\mathbf{x}} f(\mathbf{x}), \quad \mathbf{x} \in \mathcal{S} \subset \mathbb{R}^n$$

- ▶ \mathbf{x} a solution
a particular setting of all n decision variables: $\mathbf{x} = (x_1, x_2, \dots, x_n)$
e.g. production/transportation schedule,
when to charge/discharge battery,
when to convert H2 to electricity
- ▶ \mathcal{S} solution space, search space
set of all feasible solutions
- ▶ f the objective function
typically combination of: production costs, CapEx/OpEx, lead times, makespan, energy costs
- ▶ \mathbf{x}^* an optimal solution (not necessarily unique)

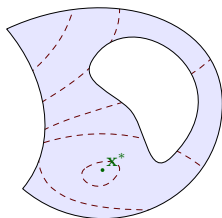


Mathematical optimisation

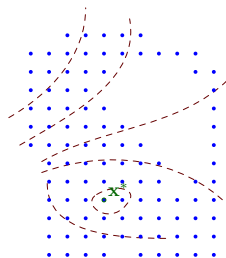
Formulations of a problem



Linear Programming (LP)
Simplex algorithm (Dantzig)
work horse of OR since 1950s



Nonlinear



Integrality of $\mathbf{x} \in \mathcal{S}$

(Computational) challenges for real-life problems

Actually solving a formulation can be difficult because of:

- ▶ very **large** solution space \mathcal{S} , high number of decision variables
- ▶ **shape** of solution space: many constraints, nonlinear constraints, feasibility pockets, integrality constraints
- ▶ **nonlinear, nonconvex** objective function f

Mathematical optimisation

Fundamental tradeoff between computation time and quality of solution

- ▶ Exact algorithms: guarantee **optimality**, but possibly after very long time

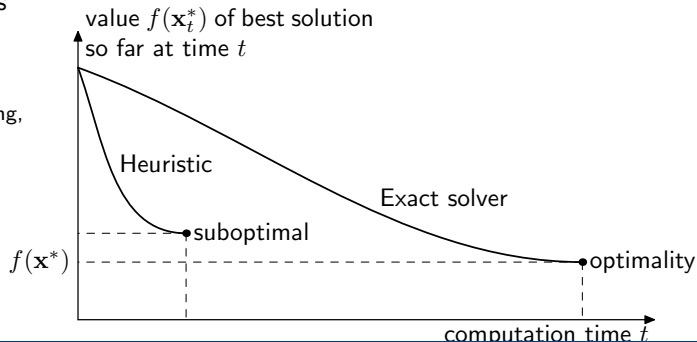
Solvers: advanced general-purpose algorithms that take full advantage of the *formulation's* structure



- ▶ Heuristic algorithms: no guarantee for optimality, but **fast** a good heuristic cleverly exploits the *problem's* structure

genetic algorithms, simulated-annealing, ant-colony, ...

'the heuristics zoo'

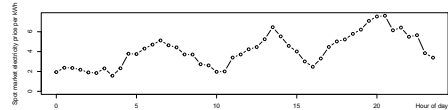


Application energy-aware scheduling

Client

- ▶ Assembly station: schedule 48 **orders** over one day
All orders take 30 minutes to assemble,
but require different amounts of **electric energy** (in kWh)
- ▶ Grid electricity at spot market prices

Price evolution over day known beforehand



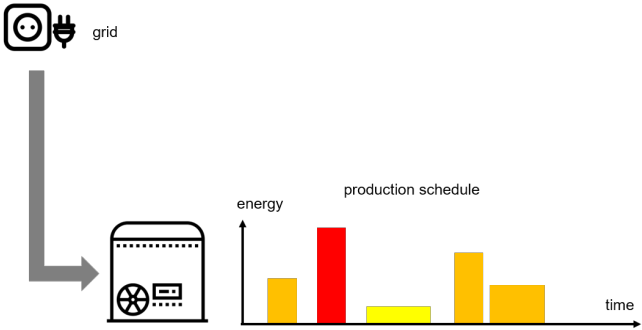
Phases of increasing commitment for client

0. **As-is** situation: existing schedule, regardless of energy cost
Current objective: lead-time of orders, assembly cost, set-ups, changeovers, ...
1. Change assembly schedule to minimise energy cost
2. Invest in on-site **wind turbine** ... and schedule to minimise energy cost
3. Additionally invest in on-site **battery**
optimal assembly schedule, optimal charge/discharge plan for battery
→ Good problem formulation?



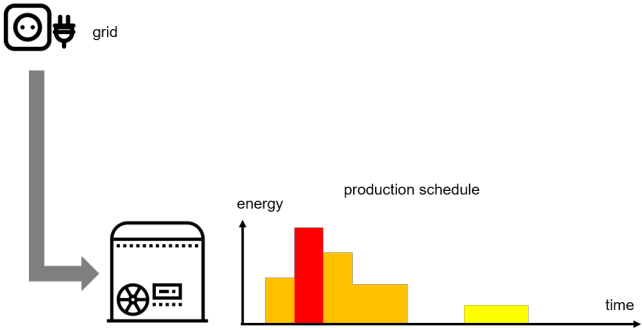
Application energy-aware scheduling

Phase 0, as is



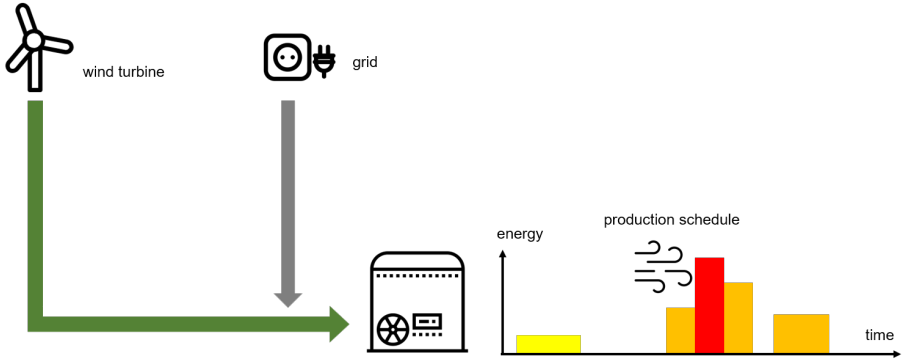
Application energy-aware scheduling

Phase 1, optimise schedule: produce when electricity is cheap



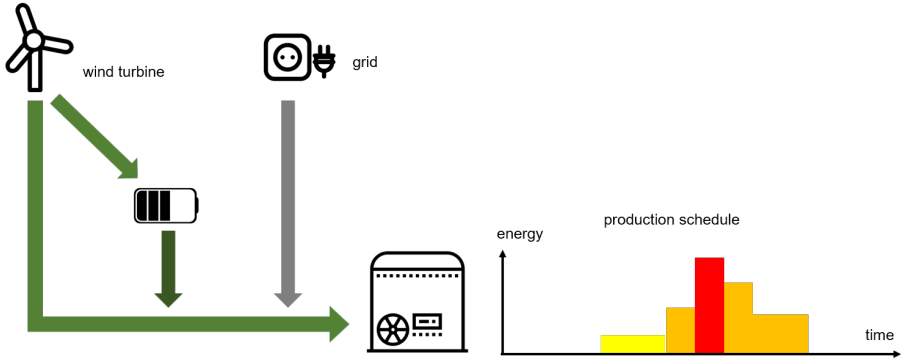
Application energy-aware scheduling

Phase 2, invest in wind turbine



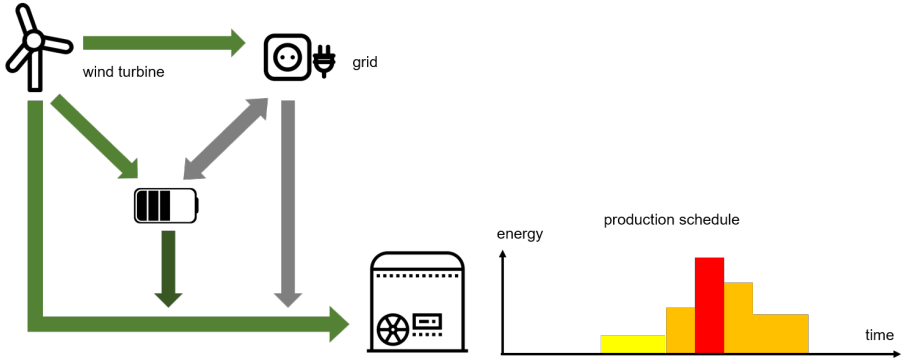
Application energy-aware scheduling

Phase 3, invest in battery



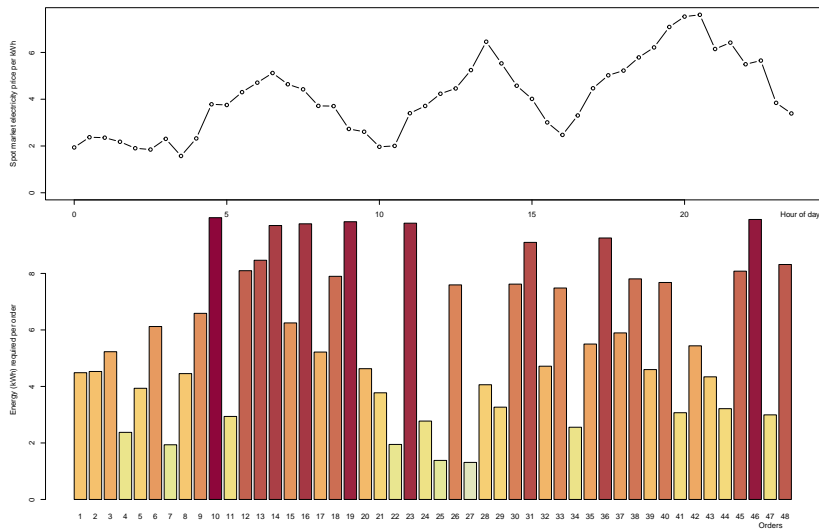
Application energy-aware scheduling

Phase 4, possibly, use battery and wind turbine to supply electricity back to the grid



Application energy-aware scheduling

Phase 0, as is



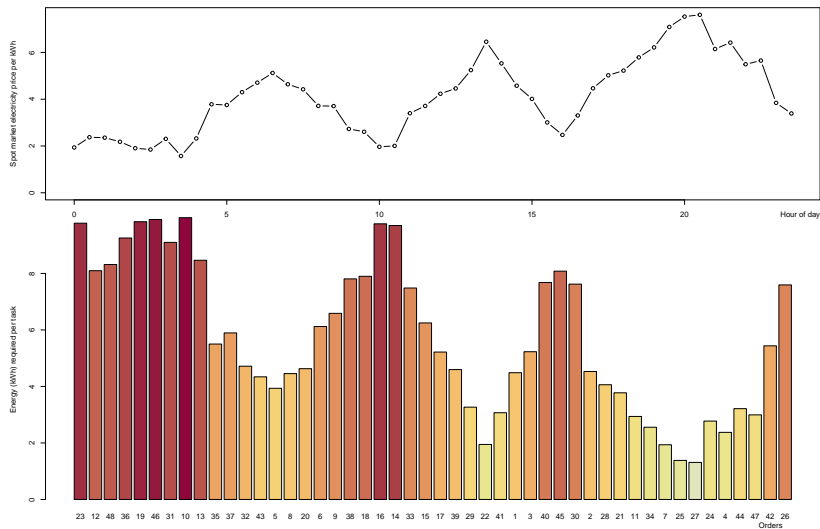
Energy cost

1155 €



Application energy-aware scheduling

Phase 1, schedule to electricity prices



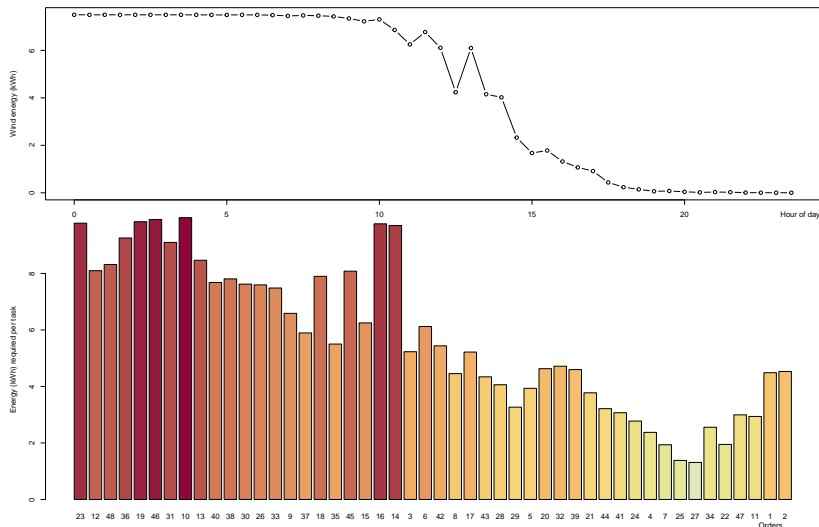
Energy cost

932 €



Application energy-aware scheduling

Phase 2, wind turbine



wind energy (kWh)
per half-hour interval

wind drops around noon

use wind if available
but grid otherwise

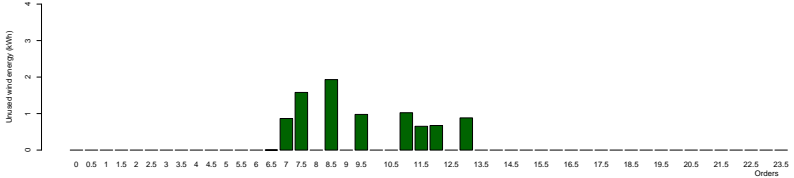
Energy cost

289 €

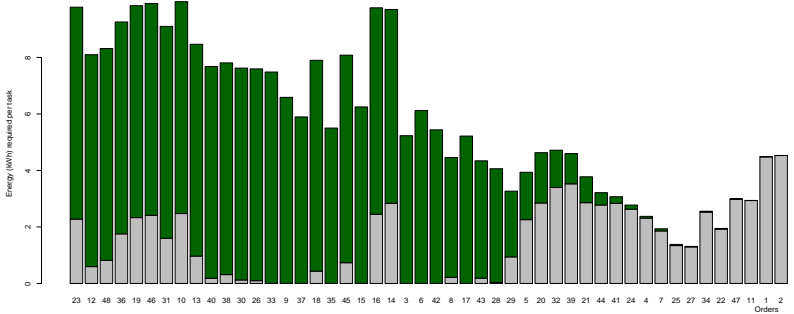


Application energy-aware scheduling

Phase 2, wind turbine



8.6 kWh of wind energy is not used



Application energy-aware scheduling

Phase 3, wind turbine and battery

In this case, a battery with optimal charge/discharge control will likely allow to use *all* generated wind energy of the day

Energy cost

255 €

Generalisation to real-life cases

- ▶ Optimal control of energy storage devices (e.g. batteries) is active area of research
nonlinear charging characteristics, conversion losses, storage losses, transmission losses
- ▶ Multiple sources of energy,
Many more degrees of freedom in the schedule
→ complexity
When to use energy for what? When to convert one form of energy to another?

Requires detailed modeling of client's **Bill of Energy**

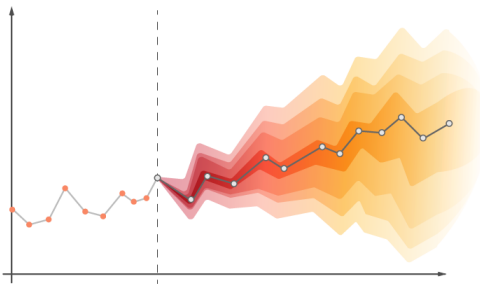


Modeling uncertainty

Obviously, **future evolution** of energy prices, yield of solar, wind are **uncertain** at time of scheduling.

We can propose a **stochastic generative model** (SGM) that generates possible futures ω

- ▶ A **scenario** ω_i is one possible future outcome
- ▶ The **ensemble** of all possible scenarios according to SGM is $\Omega = \{\omega_1, \omega_2, \dots\}$



'Forecasting trumpet of doom'

Limits on predictability!

SGM: state-space models, Markov models, ...

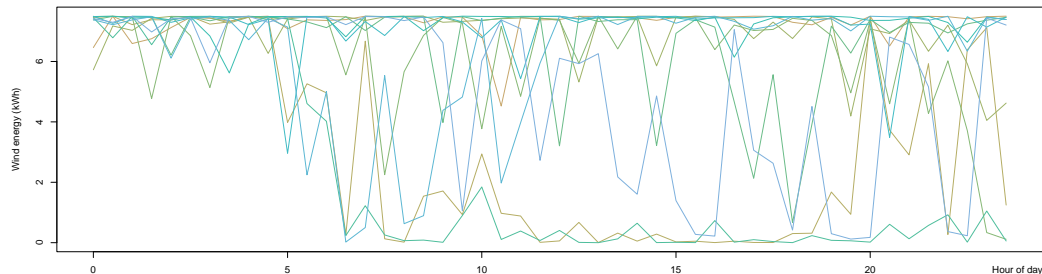
Modeling uncertainty

Scenarios wind turbine yield for client

10 scenarios $\omega_1, \dots, \omega_{10}$ for half-hourly wind turbine yield

SGM: 6-state Markov-modulated Gaussian process (not necessarily most realistic)

→ Useful predictability only for a few hours



Modeling uncertainty

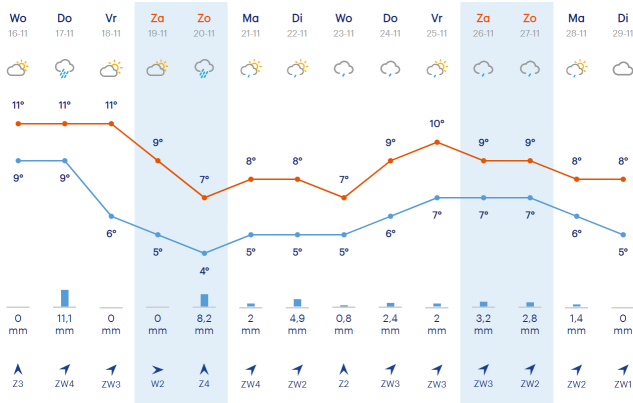
Scheduling pitfalls

- × Scheduling based on a **single scenario** ω
... even if it is the most likely one

- × Scheduling based on an **average scenario** $\bar{\omega} = \frac{1}{n} \sum_{i=1}^n \omega_i$
... note that often $\bar{\omega} \notin \Omega$
is impossible scenario (!)

- × Scheduling based on a **single forecast** without any idea of the forecast's precision
e.g. today's Buienradar for Ghent

14-daagse verwachting



Stochastic optimisation

$$\text{Find } \mathbf{x}^* = \arg \min_{\mathbf{x}} \mathbb{E}_{\omega \in \Omega} [f(\mathbf{x}, \omega)], \quad \mathbf{x} \in \mathcal{S} \subset \mathbb{R}^n$$

- ▶ $f(\mathbf{x}, \omega)$ objective function assuming the future plays out to be scenario ω
- ▶ $\mathbb{E}_{\omega \in \Omega} [f(\mathbf{x}, \omega)]$ is the expected objective cost over the ensemble Ω

Often difficult to evaluate for infinite Ω , but for k (small) possible scenarios:

$$\mathbb{E}_{\omega \in \Omega} [f(\mathbf{x}, \omega)] = \sum_{i=1}^k f(\mathbf{x}, \omega_i) \text{Prob}[\omega_i]$$

Now, the scheduling is based on all or a representative subset of scenarios $\{\omega_1, \dots, \omega_k\}$

However, more scenarios \rightarrow higher complexity:

any considered solution \mathbf{x} must be evaluated in all the scenarios

Robust optimisation

Can we find a solution \mathbf{x} that, limits the risk of a high cost, whatever scenario plays out:

$$\mathbf{x}^{**} = \arg \min_{\mathbf{x}} \max_{\omega \in \Omega} f(\mathbf{x}, \omega)$$



Takeaways

- ▶ Actemium leerstoel: onderzoek naar modellen en snelle optimalisatiemethodes voor energiebewuste planning en scheduling
 - softwaretools
- ▶ **Onzekerheid** expliciet in rekening brengen, robuuste oplossingen
- ▶ Toelaten dat productieplanning wordt gewijzigd op basis van energie-objectief kan veel kosten besparen
- ▶ Welk contracttype met energieleverancier is ideaal voor uw bedrijf?
 - variabiliteit van de energiekost ook belangrijk
 - balanceringsmarkt, spot market, . . .
- ▶ Energiemarkt op dit moment in snelle verandering.
Bedrijven worden meer en meer naast afnemers ook producenten

