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Which optimization “flavor” for sizing Microgrid energy systems?

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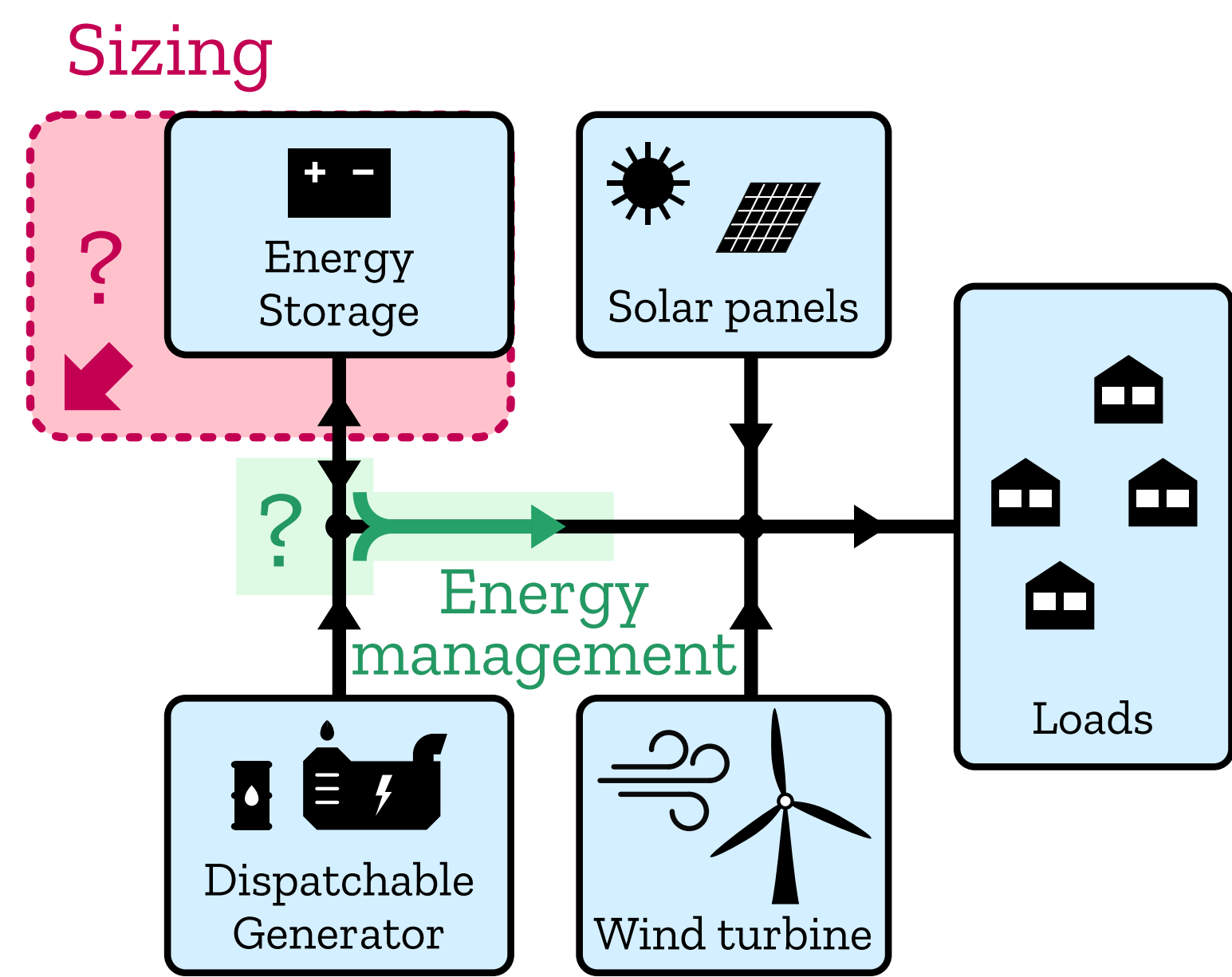
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Microgrid optimal design: definition & challenges

Microgrids

Definition: **standalone energy systems**, e.g. needed for rural electrification



Microgrid design objectives:
 (min) Lifecycle cost = Investment + Operation + Replace
 (max) Quality of Service (→ min load shedding)
 and also: environmental impact...

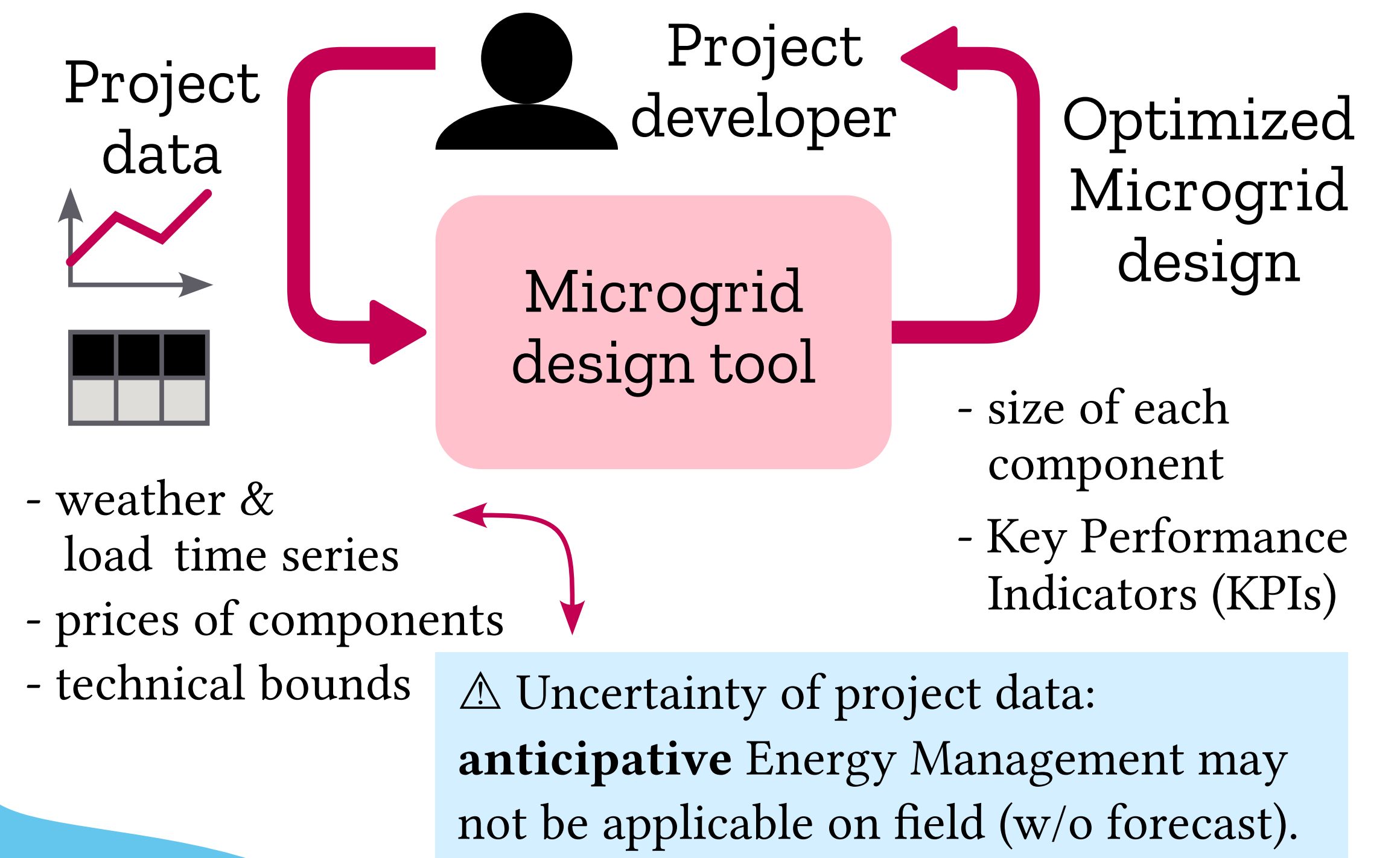
Two *intertwined* optimization problems
 ○ Microgrid **sizing**: find the optimal components' size
 ○ **Energy management (EM)**: choose, at each instant, the optimal power flows

Fact: model type **restricts** choice of optimization method

Q: Which **microgrid model & optim methods** yield:
 ○ **fast** convergence? (~ in seconds)
 ○ **reliable** convergence? (close to global optimum)
 ○ robustness against data uncertainty?

Microgrid sizing tool

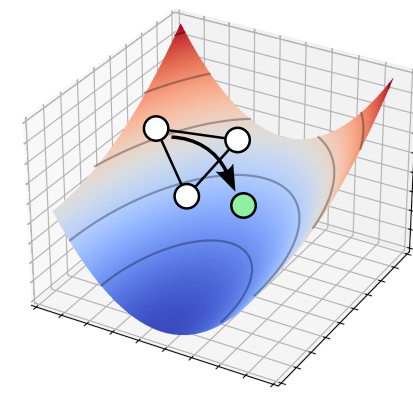
Since each project is a specific design → need for reliable microgrid sizing tool



Two ½ flavors of optimization

1a. Derivative-free

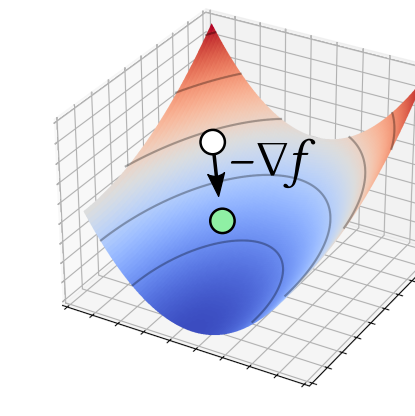
Microgrid model: **imperative** code ("simulator")
 Simulator: sizing $x \mapsto \text{KPIs}(x)$
 Fact: $T_{\text{optim}} \approx T_{\text{sim}} \times n_{\text{eval}} \rightarrow$ Needs:
 ○ **fast** simulation code: $T_{\text{sim}} \searrow$ (i.e. Julia's JIT)
 ○ frugal optimizer: $n_{\text{eval}} \searrow$ (but also reliable)



1. Blackbox (BB)

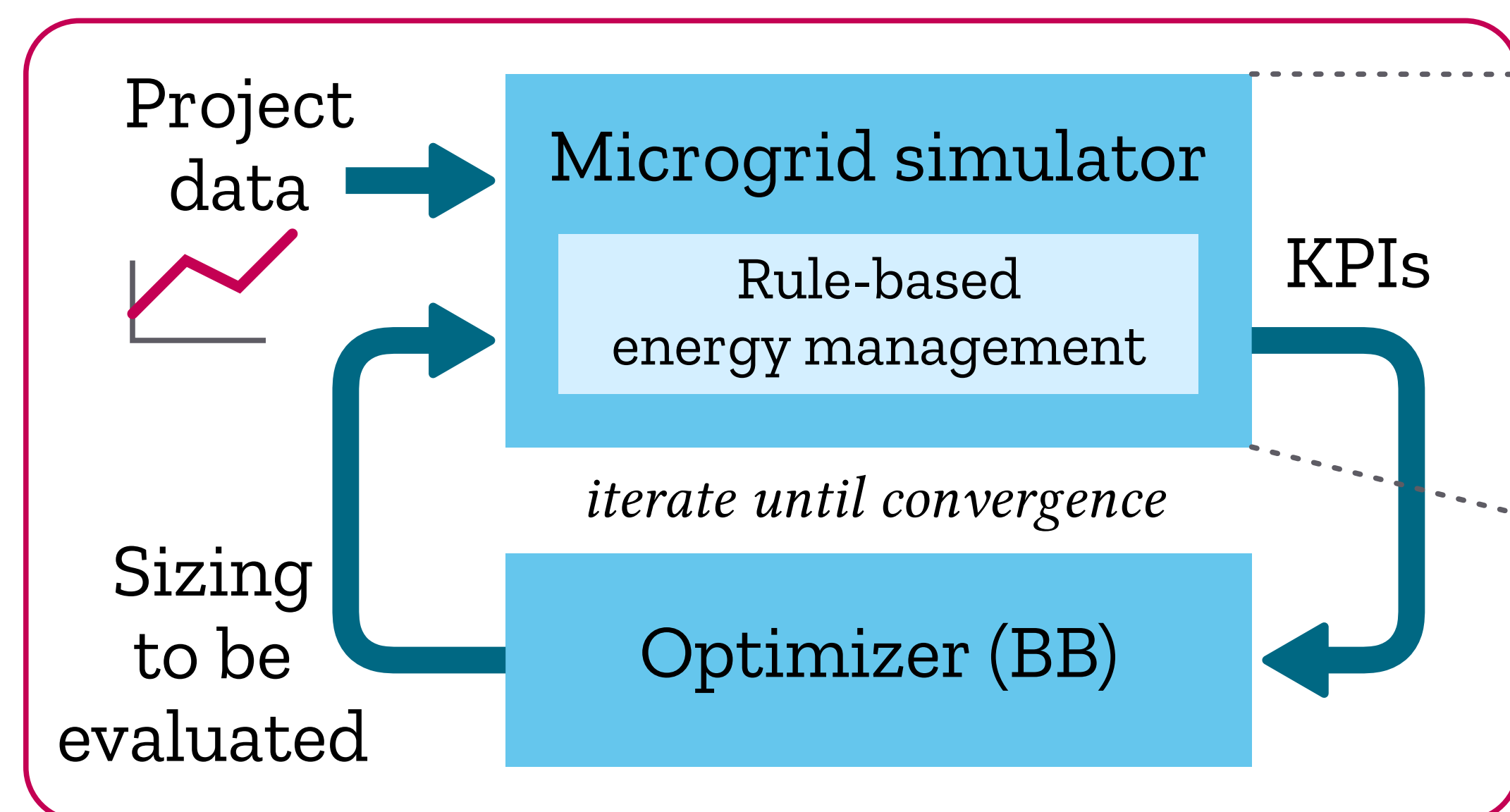
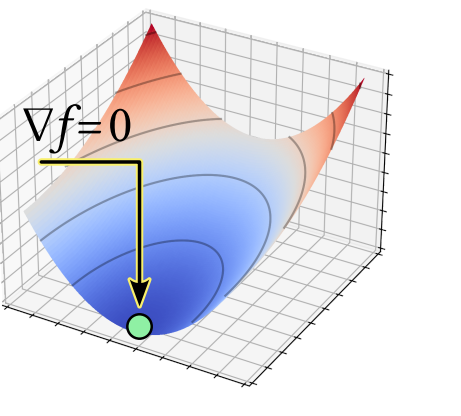
1b. Gradient-based

Idea: gradient-based optimization can **converge faster** (neval \searrow):
 ○ Compute gradients of simulator with **Automatic Differentiation (AD)**
 ○ Tools: ForwardDiff.jl

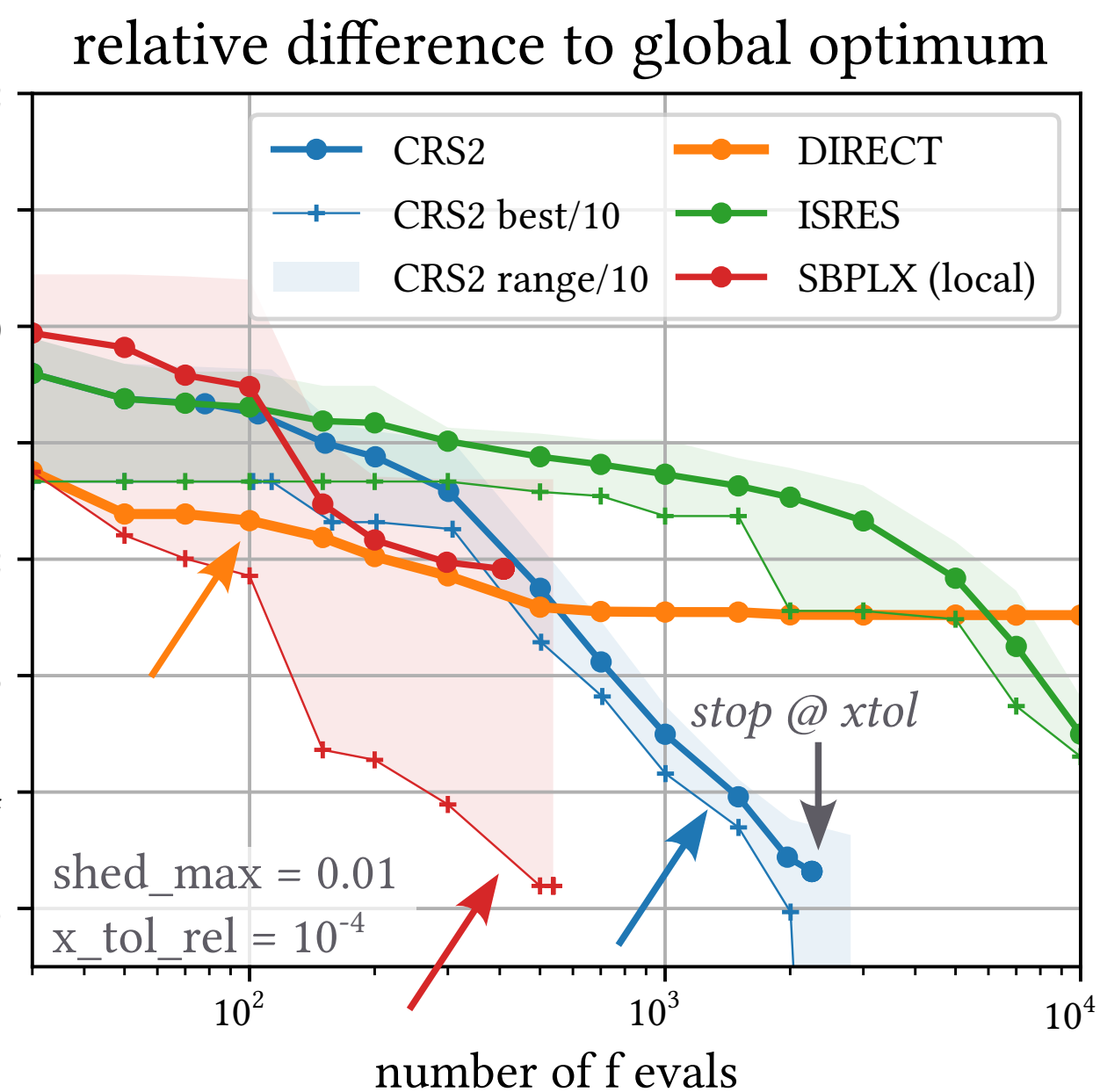


2. Algebraic

Microgrid model: **acausal** & algebraic
 Simulator: sizing \leftrightarrow KPIs
 Fact: convexity allows **reliable convergence**
 ○ Need to linearize models (for Linear Prog.)
 ○ Tools: JuMP.jl + LP solver (Clp...)

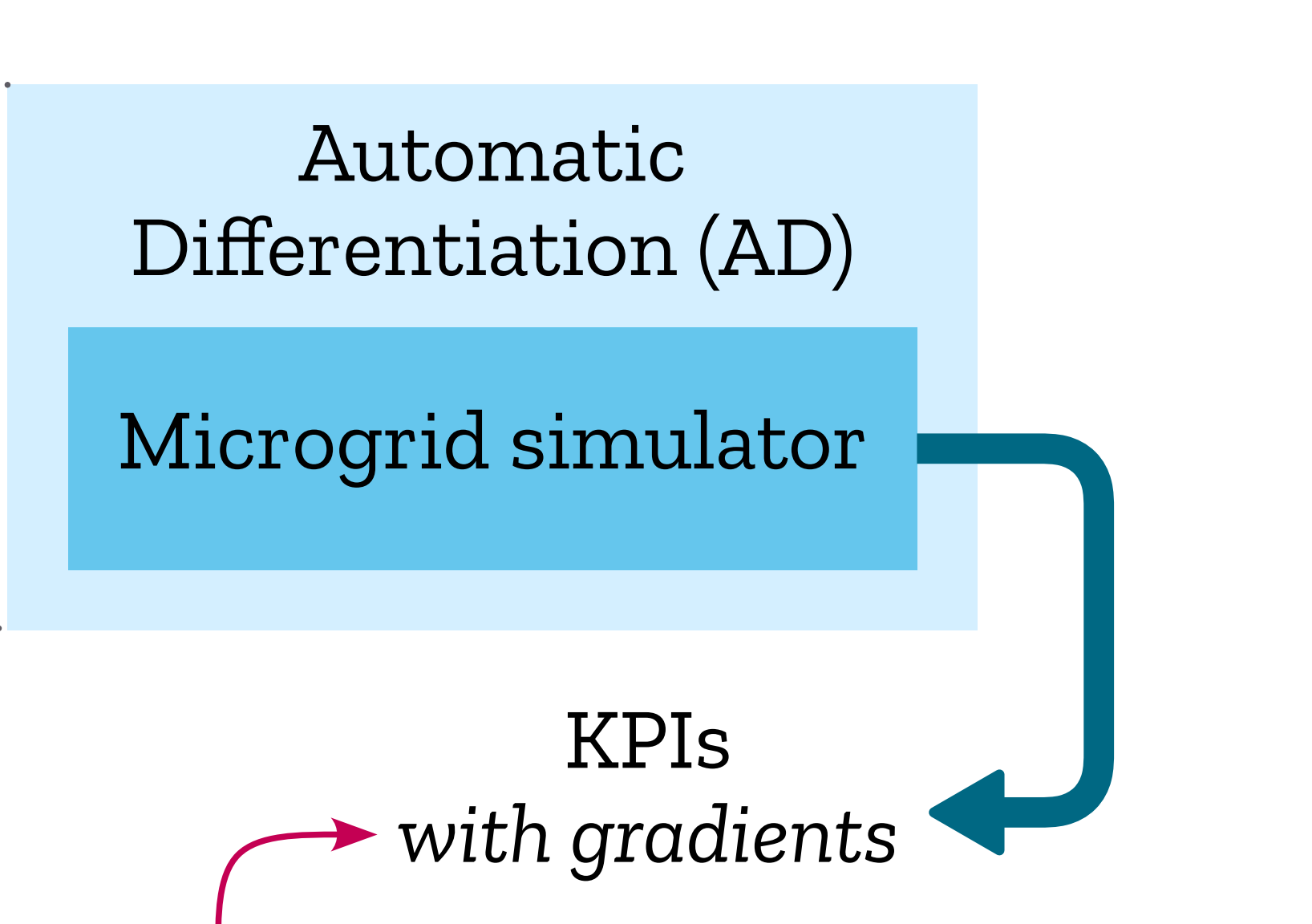


Optimality vs Computational budget: relative difference to global optimum

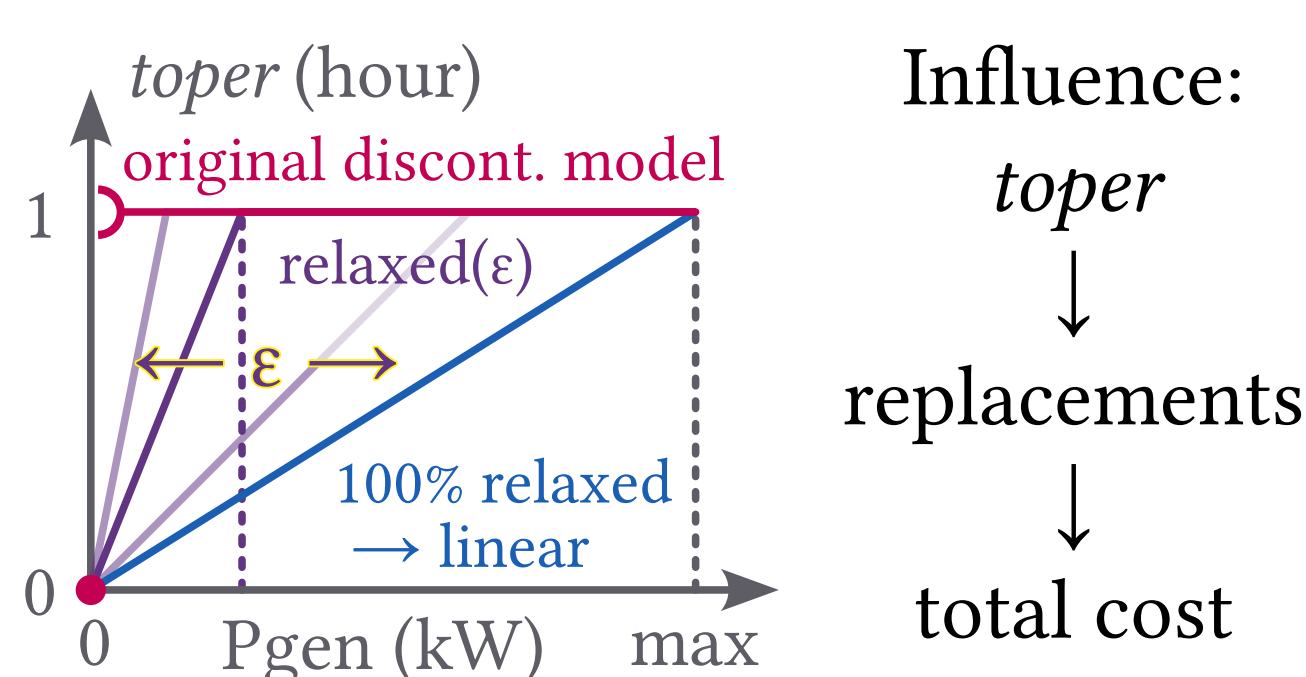


Q: **choice of optimizer?**
 ○ Tools: NLOpt.jl library of optimization algorithms

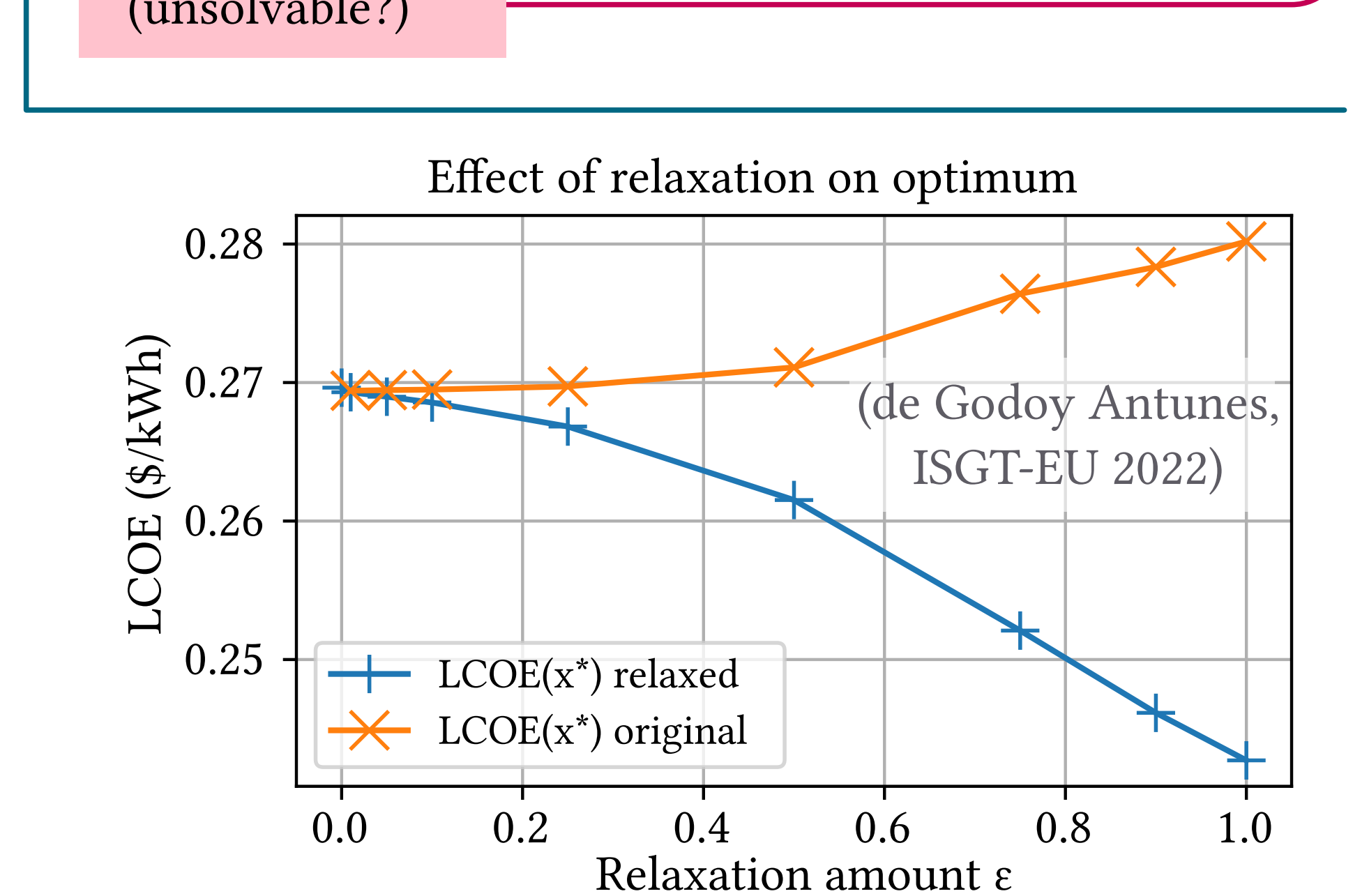
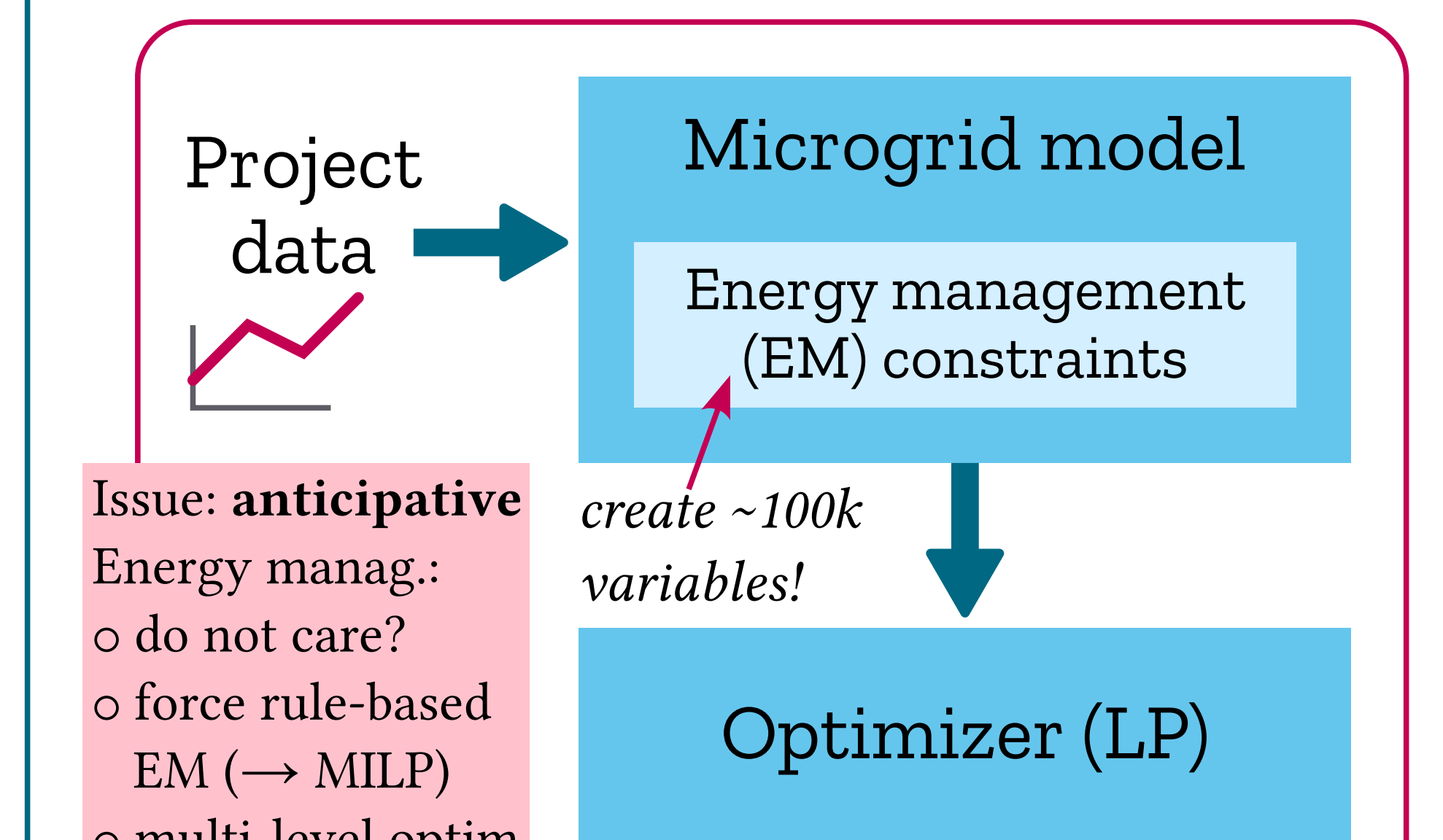
- Benchmark lessons:
- if small budget (~100 iter):
 ● DIRECT best & fully reliable
 - if medium budget (~1k iter):
 ● CRS2 best & pretty reliable
 - if local method (SBPLX●):
 multistart is required



Issue: **discontinuities** of some model expressions
 Example: counting of the operation time of generator



Q: **Tuning relaxation amount ϵ ?** → **Compromise:** more accurate model ← → easier convergence



Tools

<https://pierreh.eu/Microgrids-X/>
 Github: Microgrids-X/Microgrids.jl

Operational & economic simulation of Microgrids
 - with simple rule-based energy management
 - with sizing optimization example

Simulator performance in three languages:

Julia	Matlab	Python
0.15 ms	~0.5 ms inside VM	11 ms no JIT compilation!

Conclusions

Choice of optimization approach

- **Derivative free BB:** more physical model ☺, non anticipative ☺ but simplistic ☹ Energy Management
 - **Gradient-based BB:** discontinuities require smoothing, faster convergence ☺, but multistart needed?
 - **Algebraic (Linear Prog):** guaranteed convergence ☺, but simplified physics ☹, not so fast with 100k variables and anticipative EM yields "overoptimistic" design ☹
- No clear winner, all are useful!

Perspectives

- For blackbox optimization:
- Study effect of **more optimization variables** for mid-project resizing (**recourse** against **uncertainty**: a few → dozens of variables): ranking of BB algorithms unchanged?
 - Add more algorithms in benchmark (GAs, PSO... often used in literature)
 - Test **multi-objective** optimization algorithms
- For algebraic optim.: is there an efficient way to enforce **non anticipative** Energy Management?