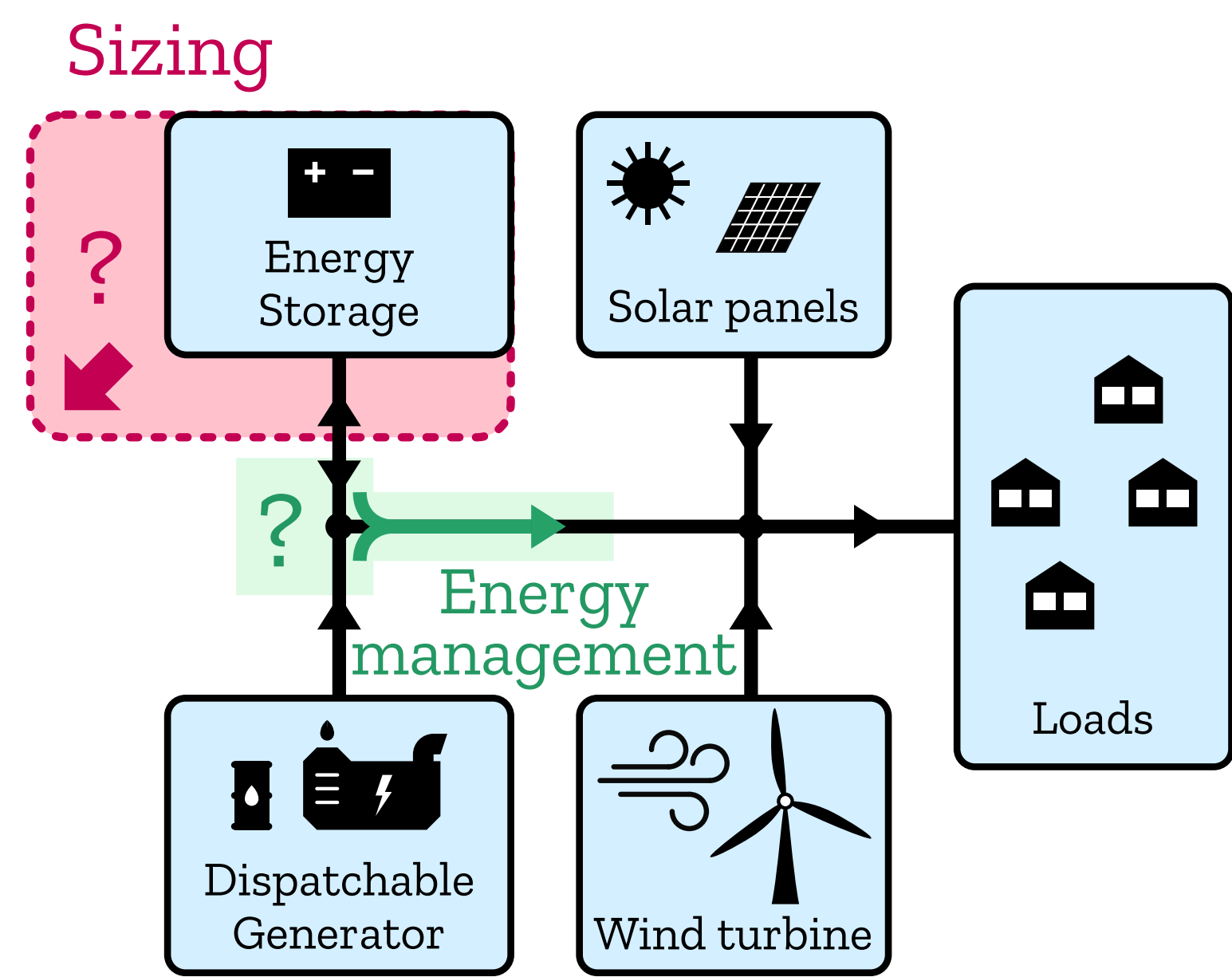


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## Microgrid optimal design: definition & challenges

### 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...

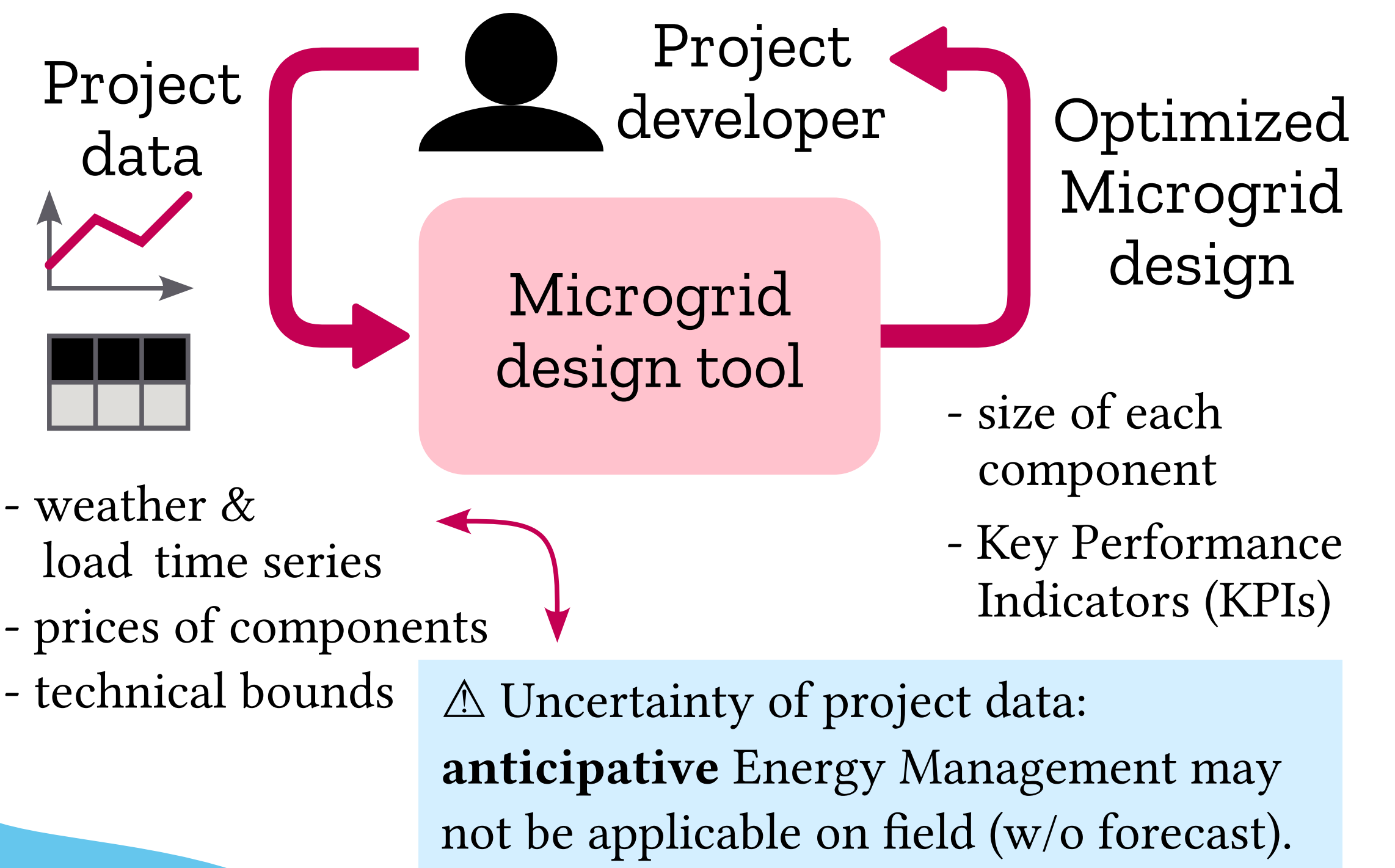
Two *intertwined* optimization problems  
 ○ Microgrid **sizing**: find the optimal components' size  
 ○ **Energy management (EM)**: choose, at each instant, the optimal power flows

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

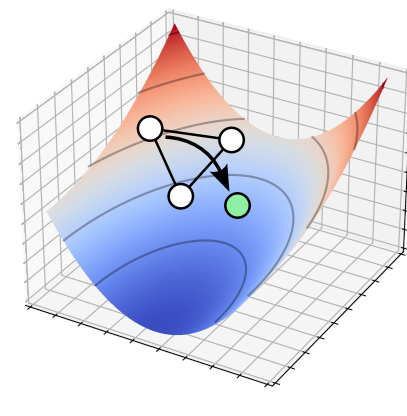
Since each project is a specific design → need for reliable microgrid sizing tool



## Two ½ flavors of optimization

### 1a. Derivative-free

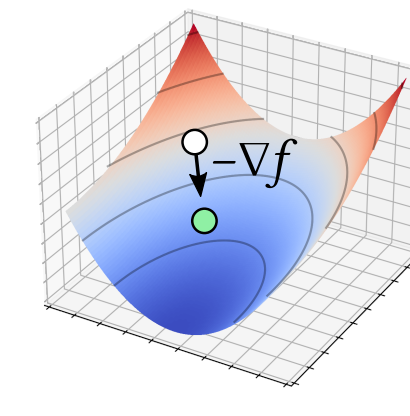
Microgrid model: **imperative** code ("simulator")  
 Simulator: sizing  $x \mapsto \text{KPIs}(x)$   
 Fact:  $T_{\text{optim}} \approx T_{\text{sim}} \times n_{\text{eval}} \rightarrow$  Needs:  
 ○ **fast** simulation code:  $T_{\text{sim}} \searrow$  (i.e. Julia's JIT)  
 ○ frugal optimizer:  $n_{\text{eval}}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



### 1. Blackbox (BB)

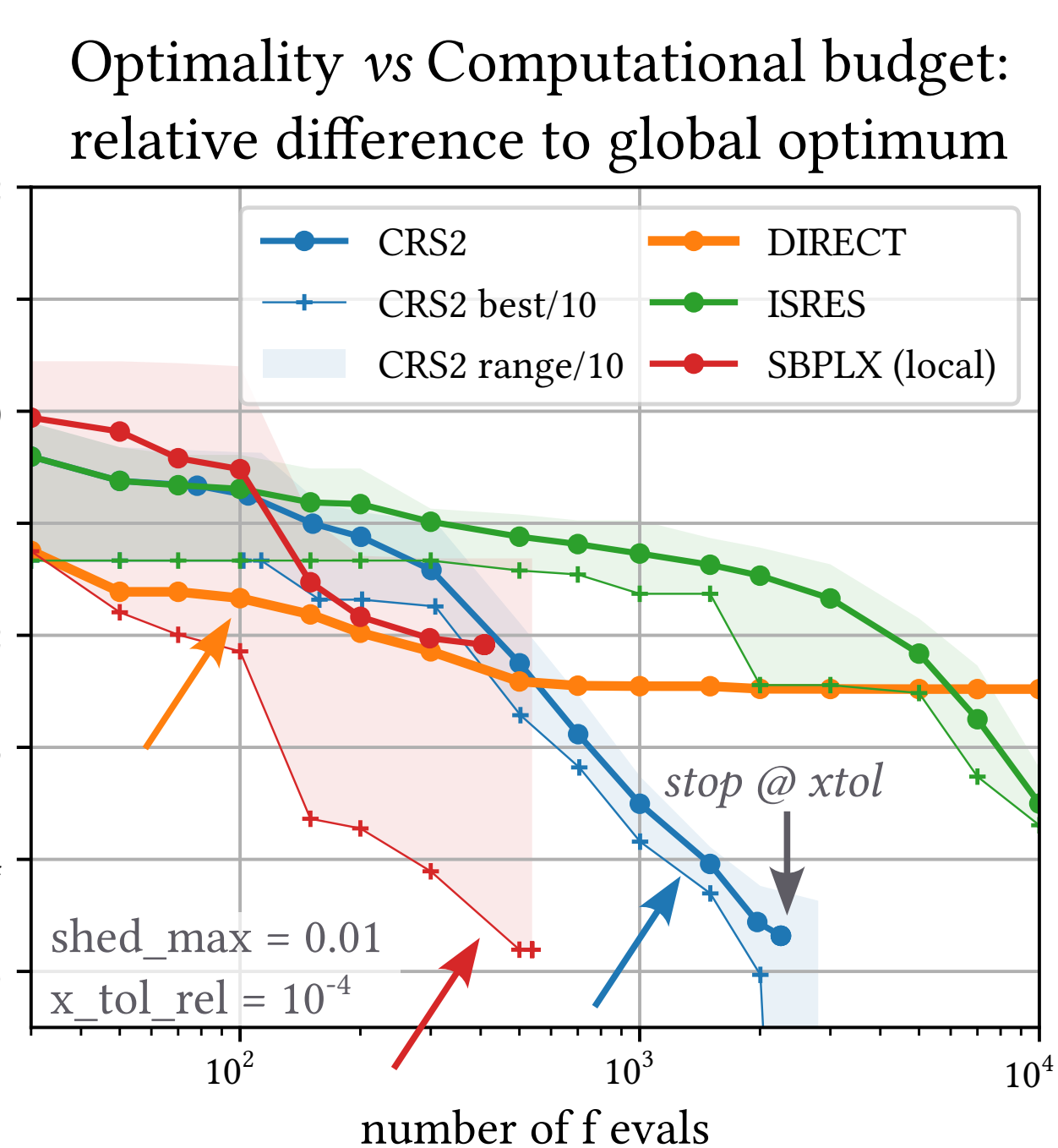
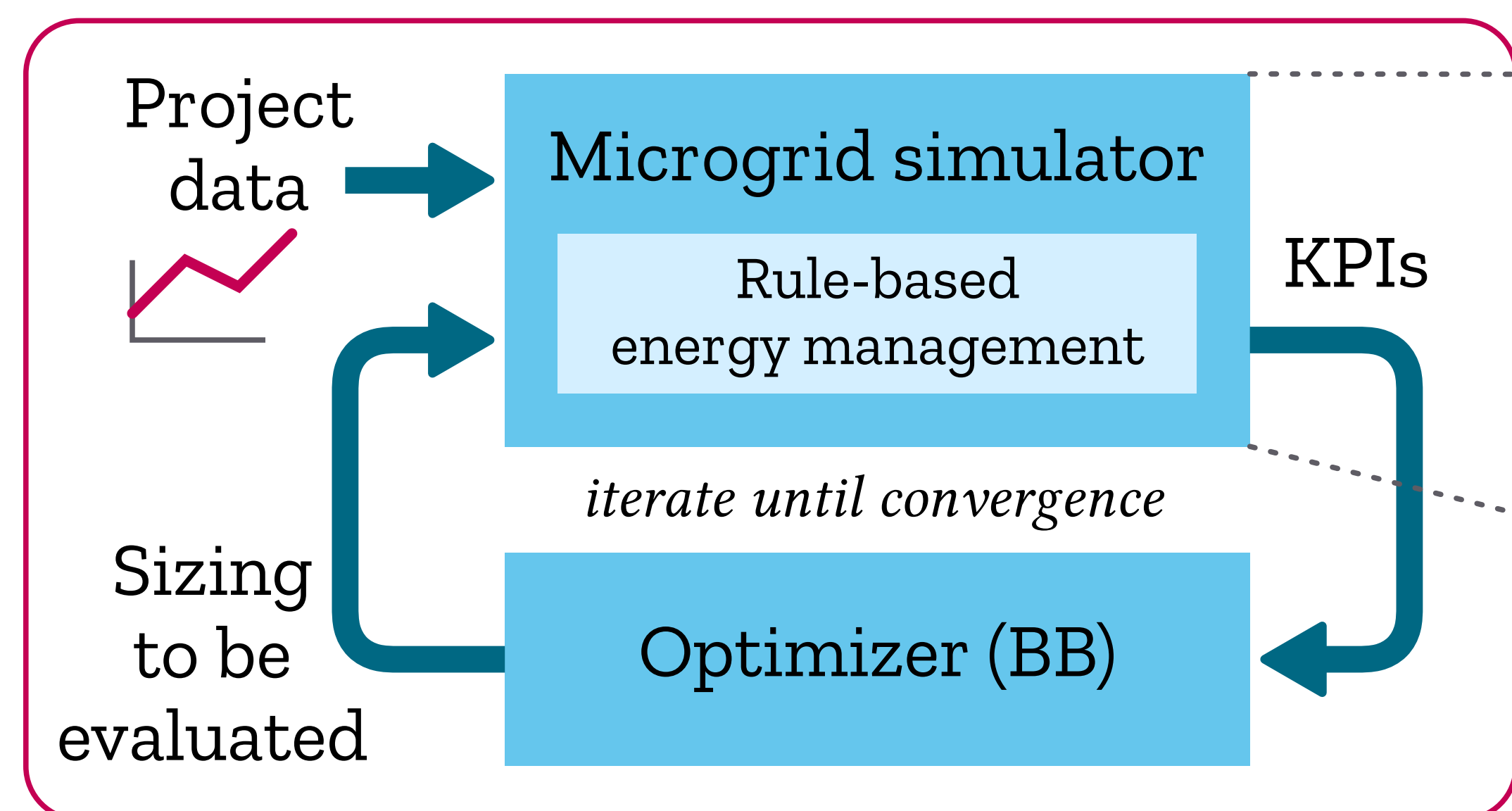
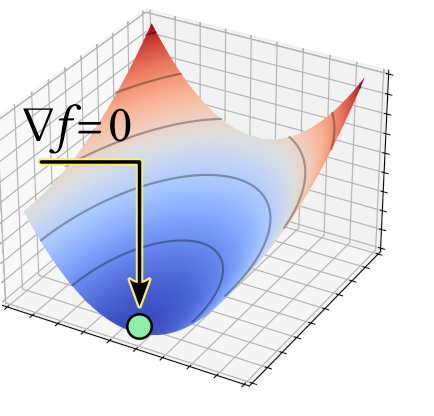
### 1b. Gradient-based

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



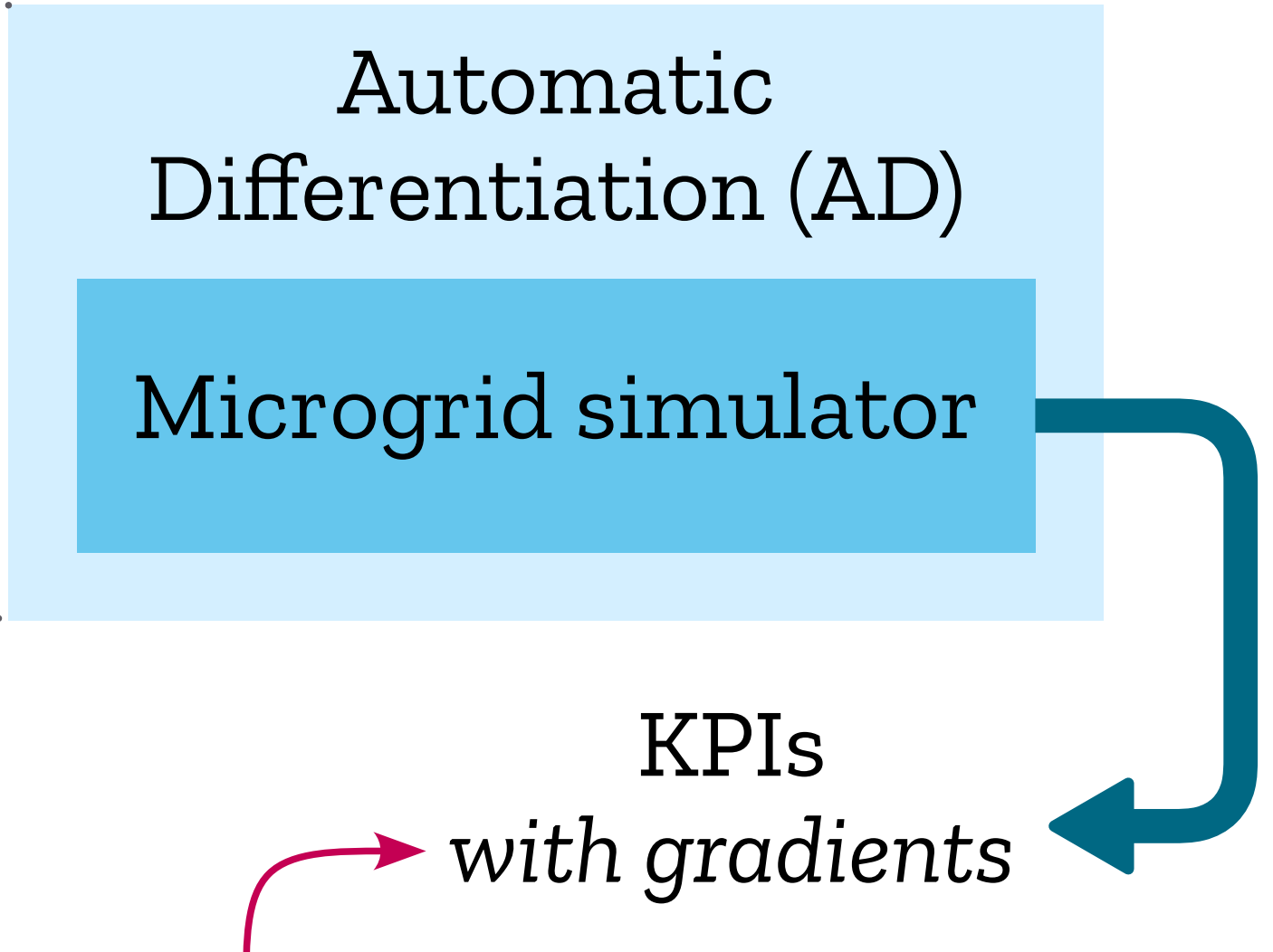
### 2. Algebraic

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...)

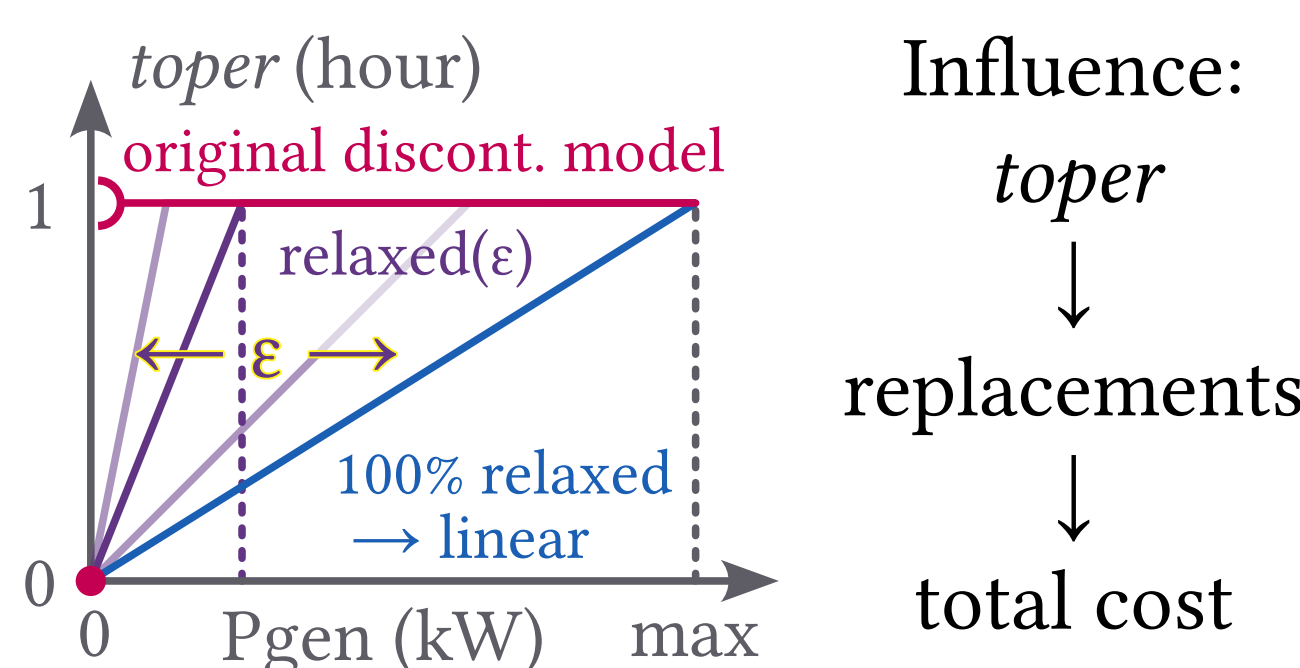


Q: **choice of optimizer?**  
 ○ Tools: NLOpt.jl library of optimization algorithms

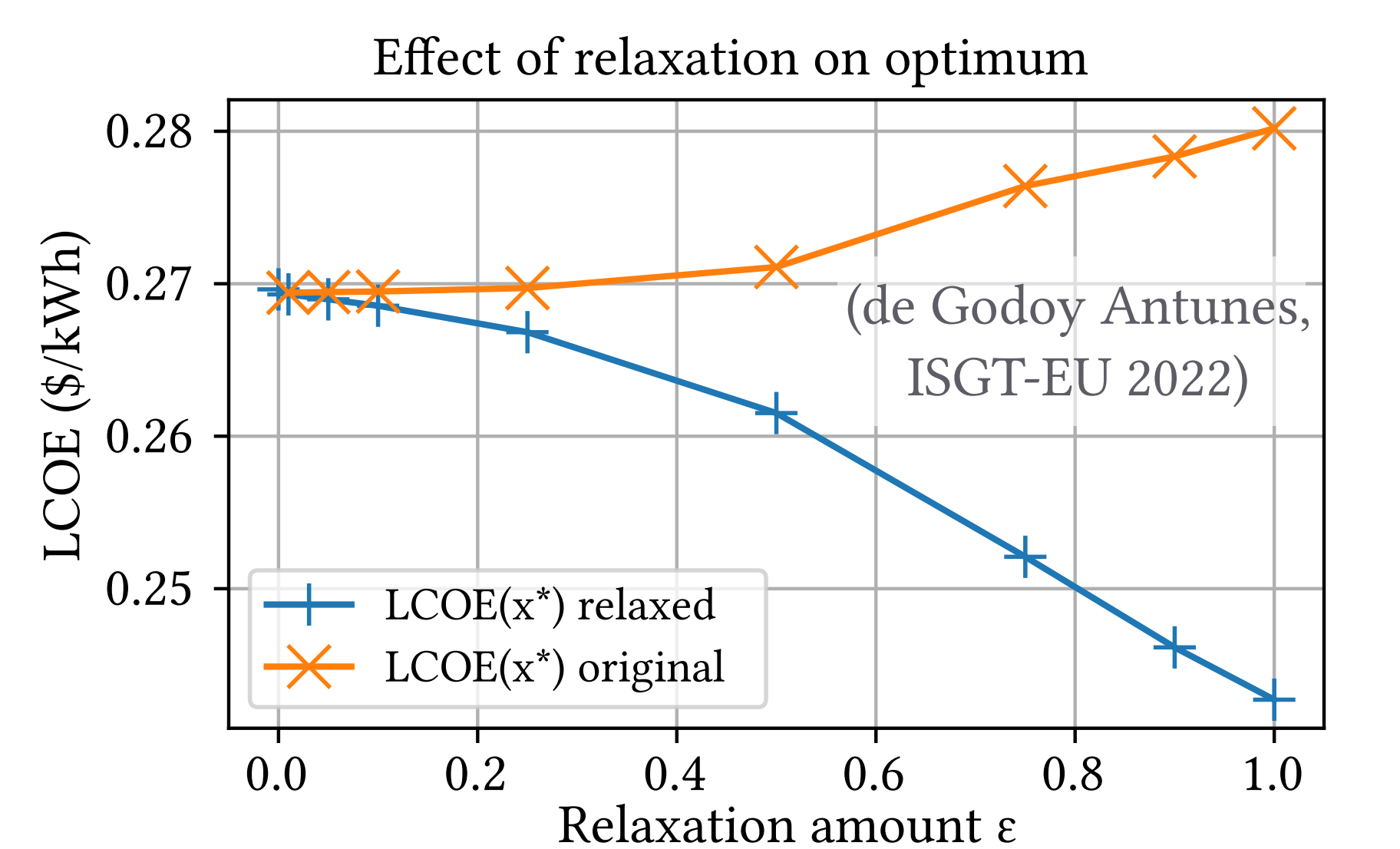
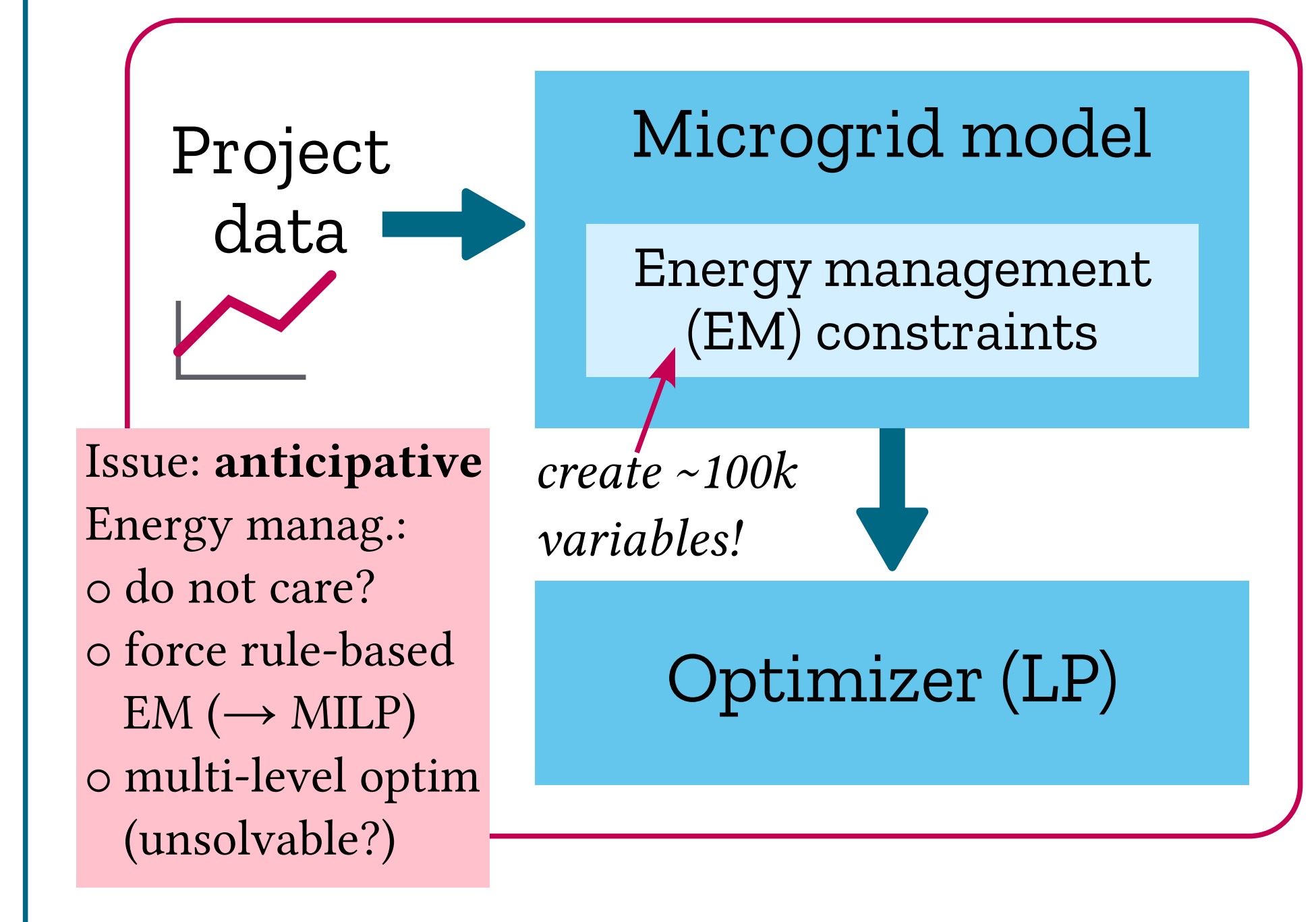
**Benchmark lessons:**  
 1. if small budget (~100 iter):  
 ● DIRECT best & fully reliable  
 2. if medium budget (~1k iter):  
 ● CRS2 best & pretty reliable  
 3. if local method (SBPLX●):  
 multistart is required



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



Q: **Tuning relaxation amount  $\epsilon$ ?** → **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	11 ms
	inside VM	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?