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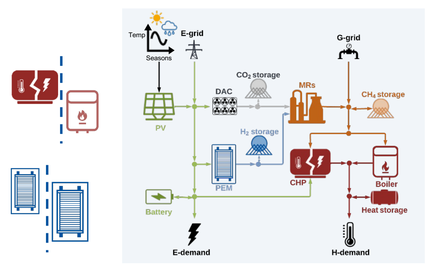


RiNSES⁴: Rigorous Nonlinear Synthesis of Energy Systems for Seasonal Energy Supply and Storage

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1. Challenge: The synthesis of energy systems poses a large-scale MINLP problem.

The synthesis problem of an energy system = Design + Operation decisions [1].



At the design level: The types and sizes of energy system components are determined.

At the operational level: Decisions are made regarding the on/off status and load allocations* for each time step.

Problem 1:

$$\min_{\dot{E}^{\mathrm{N}}_k, E^{\mathrm{N}}_k, \dot{E}^{\mathrm{buy}}_{e,t}, \dot{E}^{\mathrm{sell}}_{e,t}, \dot{E}^{\mathrm{in}}_{k,e,t}, \dot{E}^{\mathrm{out}}_{k,e,t}, E_{k,e,t}, \mathbf{y}, \mathbf{z}} \quad TAC = \frac{1}{\mathrm{APVF}} CAPEX + OPEX \tag{1a}$$

with

objective

$$CAPEX = \sum_{k\in\mathcal{K}} I_k = \sum_{k\in\mathcal{K}\setminus\mathcal{K}^{\mathrm{stor}}} I^{\mathrm{ref}}_k \left(\frac{\dot{E}^{\mathrm{N}}_k}{\dot{E}^{\mathrm{N,ref}}_k}\right)^{M_k} + \sum_{k\in\mathcal{K}^{\mathrm{stor}}} I^{\mathrm{ref}}_k \left(\frac{E^{\mathrm{N}}_k}{E^{\mathrm{N,ref}}_k}\right)^{M_k} \tag{1b}$$

$$OPEX = \sum_{k\in\mathcal{K}} c^m_k I_k + \sum_{t\in\mathcal{T}} \Delta t_t \sum_{e\in\mathcal{E}^{\mathrm{ext}}} \left(c^{\mathrm{buy}}_{e,t} \dot{E}^{\mathrm{buy}}_{e,t} - c^{\mathrm{sell}}_{e,t} \dot{E}^{\mathrm{sell}}_{e,t}\right) \tag{1c}$$

s.t.

energy balance

$$\sum_{k\in\mathcal{K}} \left(\dot{E}^{\mathrm{out}}_{k,e,t} - \dot{E}^{\mathrm{in}}_{k,e,t}\right) + \dot{E}^{\mathrm{buy}}_{e,t} - \dot{E}^{\mathrm{sell}}_{e,t} = \dot{E}^{\mathrm{D}}_{e,t} \qquad \forall e \in \mathcal{E}, \forall t \in \mathcal{T} \tag{1d}$$

storage balance

$$E_{k,e,t}\left(1 - \eta^{\mathrm{self}}_{k,e}\Delta t_t\right) + \Delta t_t \left(\eta^{\mathrm{in}}_{k,e} \dot{E}^{\mathrm{in}}_{k,e,t} - \frac{\dot{E}^{\mathrm{out}}_{k,e,t}}{\eta^{\mathrm{out}}_{k,e}}\right) = E_{k,e,t+1} \qquad \forall k \in \mathcal{K}^{\mathrm{sto}}, \forall t \in \mathcal{T} \tag{1e}$$

$$E_{k,e,t=1} = E_{k,e,t=|\mathcal{T}|+1} \qquad \forall k \in \mathcal{K}^{\mathrm{sto}} \tag{1f}$$

other constraints*

$$\mathbf{g}\left(\dot{E}^N_k, E^N_k, \mathbf{y}, \mathbf{z}\right) \le 0 \qquad \forall k \in \mathcal{K}, \forall e \in \mathcal{E} \tag{1g}$$

$$\mathbf{h}\left(\dot{E}^N_k, E^N_k, \dot{E}^{\mathrm{buy}}_{e,t}, \dot{E}^{\mathrm{sell}}_{e,t}, \dot{E}^{\mathrm{in}}_{k,e,t}, \dot{E}^{\mathrm{out}}_{k,e,t}, E_{k,e,t}, \mathbf{y}, \mathbf{z}\right) \le 0 \qquad \forall k \in \mathcal{K}, \forall e \in \mathcal{E}, \forall t \in \mathcal{T} \tag{1h}$$

decision variables

$$\dot{E}^N_k, E^N_k, \dot{E}^{\mathrm{buy}}_{e,t}, \dot{E}^{\mathrm{sell}}_{e,t}, \dot{E}^{\mathrm{in}}_{k,e,t}, \dot{E}^{\mathrm{out}}_{k,e,t}, E_{k,e,t} \in \mathbb{R}^+ \qquad \forall k \in \mathcal{K}, \forall e \in \mathcal{E}, \forall t \in \mathcal{T} \tag{1i}$$

$$\mathbf{y} \in R^{N_y}, \mathbf{z} \in \{0,1\}^{N_z} \qquad \forall k \in \mathcal{K}, \forall e \in \mathcal{E}, \forall t \in \mathcal{T} \tag{1j}$$

Solving Problem 1 is computationally challenging due to

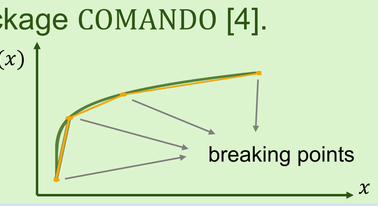
- temporal coupling constraints of full time series,
- large number of decision variables and constraints,
- and nonlinear behaviors.

[2][3] This work

2. RiNSES⁴ method

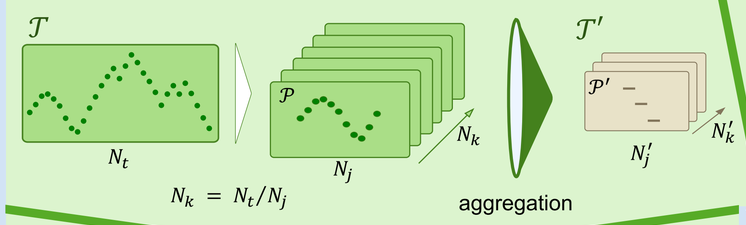
(a) Linearization [4][5]: 🎯 Eqs. (1b) (1g), and (1h)

- Simplify the nonlinear constraints.
- Apply the linearization approach from [5], which can be readily integrated using the python package COMANDO [4].



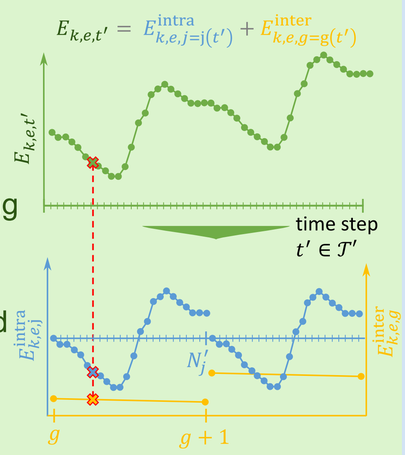
(b) Time-series aggregation [6][7]: 🎯 Eqs. (1d) and (1h)

- Reduce the size of exogenous inputs $\mathcal{T}$.
- Apply time-series aggregation approach based on [6] and the python package tsam [7].
- Replace $\mathcal{T}$ with $\mathcal{T}'$.



(c) Superposition storage modeling [8]: 🎯 Eqs. (1e) and (1f)

- Decouple the storage component modeling.
- Apply and extend the superposition modeling approach from [8].
- Replace Eqs. (1e) and (1f) with Eqs. (2a) to (2d).



$$\frac{E^{\mathrm{intra}}_{k,e,j+1} - E^{\mathrm{intra}}_{k,e,j}}{\Delta t_j} = -\eta^{\mathrm{self}}_{k,e} E^{\mathrm{intra}}_{k,e,j} + \left(\eta^{\mathrm{in}}_{k,e} \dot{E}^{\mathrm{in}}_{k,e,j} - \frac{\dot{E}^{\mathrm{out}}_{k,e,j}}{\eta^{\mathrm{out}}_{k,e}}\right) \tag{2a}$$

$$E^{\mathrm{inter}}_{k,e,g+1} = E^{\mathrm{inter}}_{k,e,g}\left(1 - \eta^{\mathrm{self}}_{k,e}\Delta t_t\right)^{N_j} + E^{\mathrm{intra}}_{k,e,N'_j+1} \tag{2b}$$

$$E^{\mathrm{inter}}_{k,e,1} = E^{\mathrm{inter}}_{k,e,N'_g+1} \tag{2c}$$

$$E_{k,e,t'} = E^{\mathrm{intra}}_{k,e,j=j(t')} + E^{\mathrm{inter}}_{k,e,g=g(t')} \tag{2d}$$

Solve Problem (2)

Fix design candidates

(d) Decomposition [9]: 🎯 Eqs. (1d) (1e), and (1h)

- Apply the option if the resulting operational optimization problem remains computationally challenging.
- Decompose Problem (2) to subproblems via the DeLoop method proposed by [9] & applied in [10].

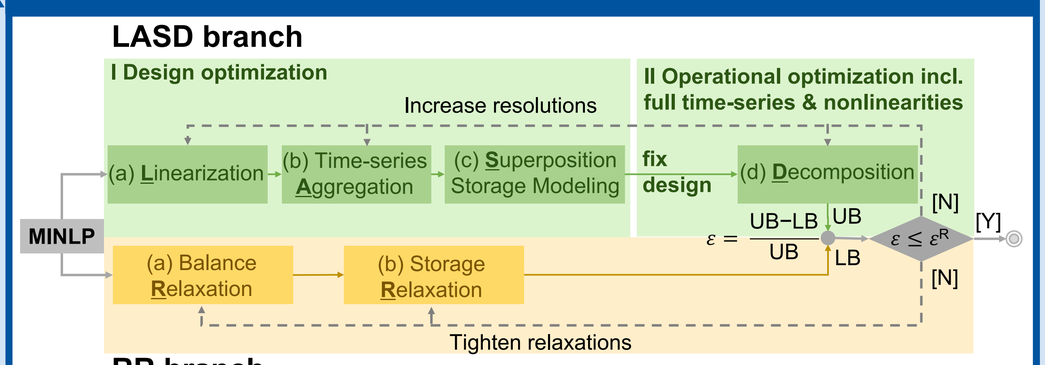
Solve Problem (3)

UB

Increase resolutions

LASD

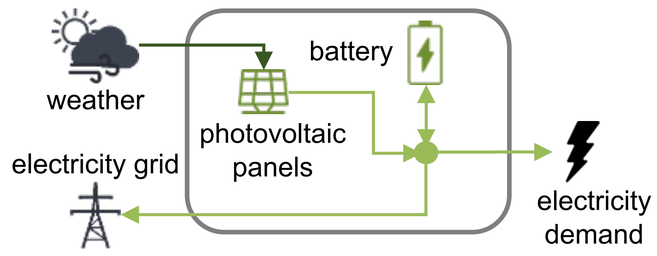
LASD branch



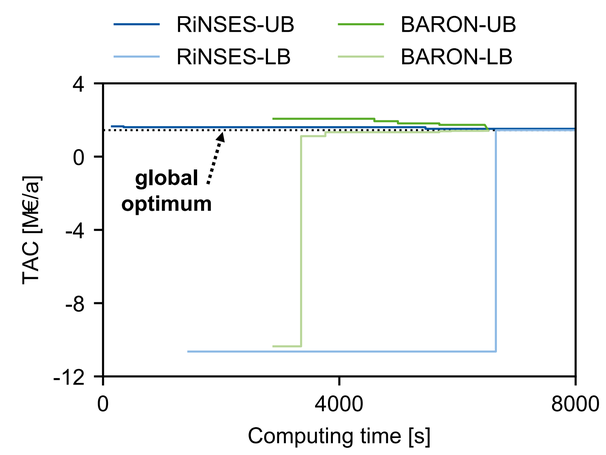
3. Case Study

Set-up: Design an energy system containing photovoltaic panels and a battery.

- The model parameters are sourced from the literature [10][11].
- The input time series is based on [10] and are modified to a 4-hour resolution.



Results: Method performance.



	RiNSES⁴		BARON	
	First solution	Optimal solution	First solution	Optimal solution
UB	150s	150s	2844s	6518s
LB	1444s	6649s	2844s	6518s

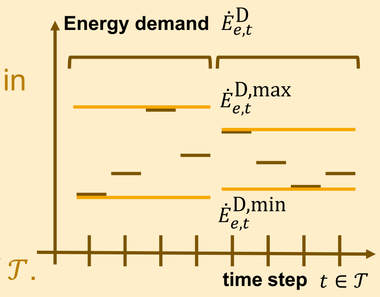
Tighten relaxations

LB

RR

(a) Balance Relaxation: 🎯 Eq. (1d)

- Apply the same time-series aggregation as in the LASD branch.
- Replace Eq. (1d) with Eqs. (3a) and (3b).
- Keep the initial size of $\mathcal{T}$.

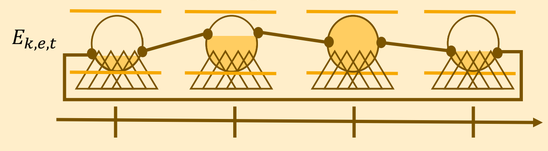


$$\sum_{k\in\mathcal{K}} \left(\dot{E}^{\mathrm{out}}_{k,e,t} - \dot{E}^{\mathrm{in}}_{k,e,t}\right) + \dot{E}^{\mathrm{buy}}_{e,t} - \dot{E}^{\mathrm{sell}}_{e,t} \le \dot{E}^{\mathrm{D,max}}_{e,t} \tag{3a}$$

$$\sum_{k\in\mathcal{K}} \left(\dot{E}^{\mathrm{out}}_{k,e,t} - \dot{E}^{\mathrm{in}}_{k,e,t}\right) + \dot{E}^{\mathrm{buy}}_{e,t} - \dot{E}^{\mathrm{sell}}_{e,t} \ge \dot{E}^{\mathrm{D,min}}_{e,t} \tag{3b}$$

(b) Storage Relaxation: 🎯 Eqs. (1e) and (1f)

- Address the storage components.



- Replace Eqs. (1e) and (1f) with Eqs. (4a) and (4b).

$$E_{k,e,t}\left(1 - \eta^{\mathrm{self}}_{k,e}\Delta t_t\right) + \Delta t_t \left(\eta^{in}_{k,e} \dot{E}^{\mathrm{in}}_{k,e,t} - \frac{\dot{E}^{\mathrm{out}}_{k,e,t}}{\eta^{out}_{k,e}}\right) \ge 0 \tag{4a}$$

$$E_{k,e,t}\left(1 - \eta^{\mathrm{self}}_{k,e}\Delta t_t\right) + \Delta t_t \left(\eta^{in}_{k,e} \dot{E}^{\mathrm{in}}_{k,e,t} - \frac{\dot{E}^{\mathrm{out}}_{k,e,t}}{\eta^{out}_{k,e}}\right) \le E^N_k \tag{4b}$$

Solve Problem (4)

4. Conclusion

- RiNSES⁴ is generally applicable to two-stage, time-dependent synthesis problems with coupled decision variables and constraints.
- The LASD branch for computing UB outperforms BARON.
- The RR branch for computing LB shows limitations.

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