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ENERGY SYSTEM OPTIMIZATION WORKSHOP

27 Nov 2025

Error-free model reduction with low-resolution precursor surrogates

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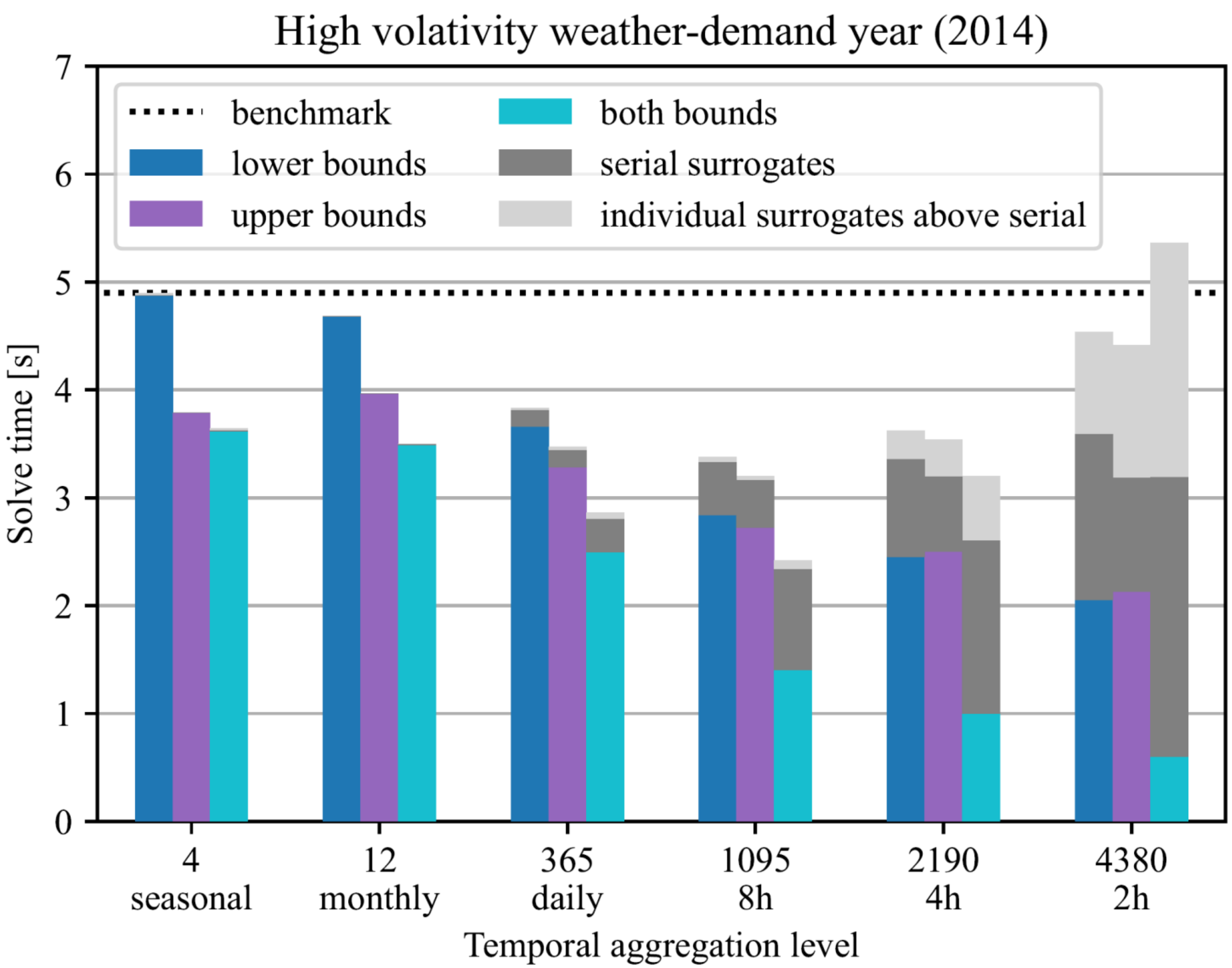
Overcoming the efficiency-accuracy trade-off

- There are “free lunches”, big lunches
- Why this is ground-breaking
- How, in short
- More on the way

Free, big lunch

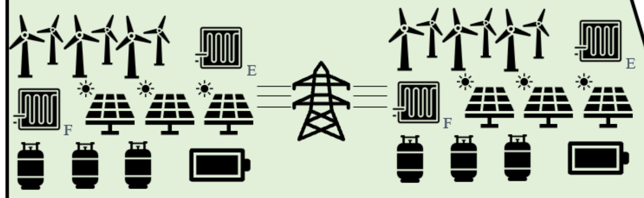
- 100% accuracy, no modeling error.
- Solve time down by 52%
- or 2.13x speedup



Model reduction comes at the expense of accuracy:
Most of the time, also shown in our previous work.

Energy system optimization

Optimization of: investment & operation of energy assets



Features

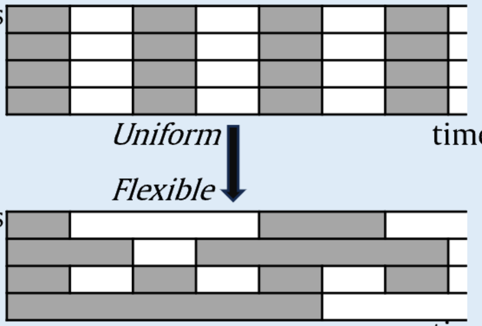
Spatial discretization

Temporal discretization

- Traditionally uniform across (part of) the time horizon and the assets, with hourly resolution
- Main source of model complexity

Fully flexible temporal resolution

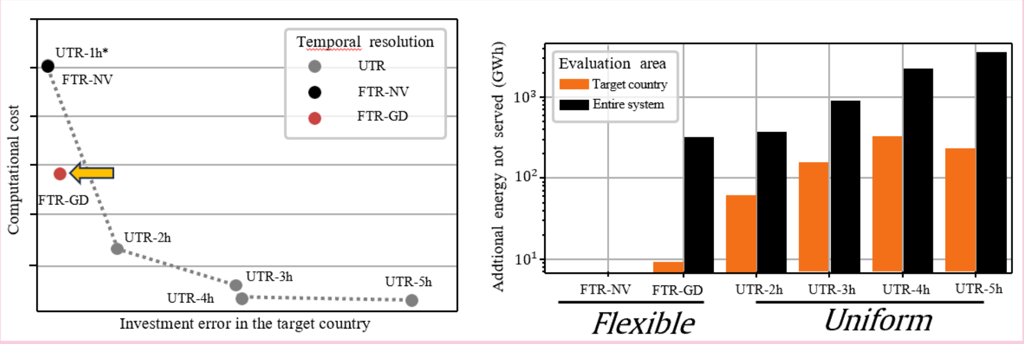
New temporal discretization:
Individual time blocks for each time-dependent
- decision variable (assigned from user input)
- constraint (automatically determined from decision variables)



Unlock opportunities to improve computational efficiency

Pushing the computation Pareto front: faster to solve with higher accuracy

Significant improvements in the operational feasibility



[1] Zhi Gao, Matteo Gazzani, Diego A. Tejada-Arango, Abel Soares Siqueira, Ni Wang, Madeleine Gibescu, Germán Morales-España, Fully flexible temporal resolution for energy system optimization, Applied Energy, Volume 396, 2025, 126267, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2025.126267 .

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Most of the time, and also shown in our previous work.

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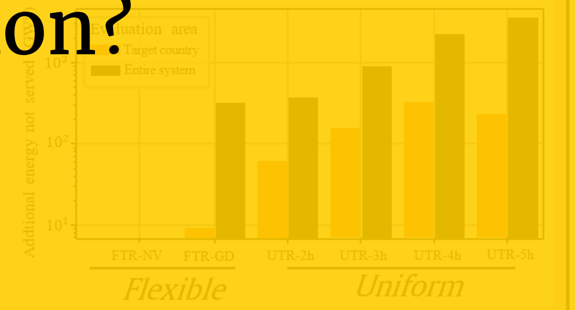
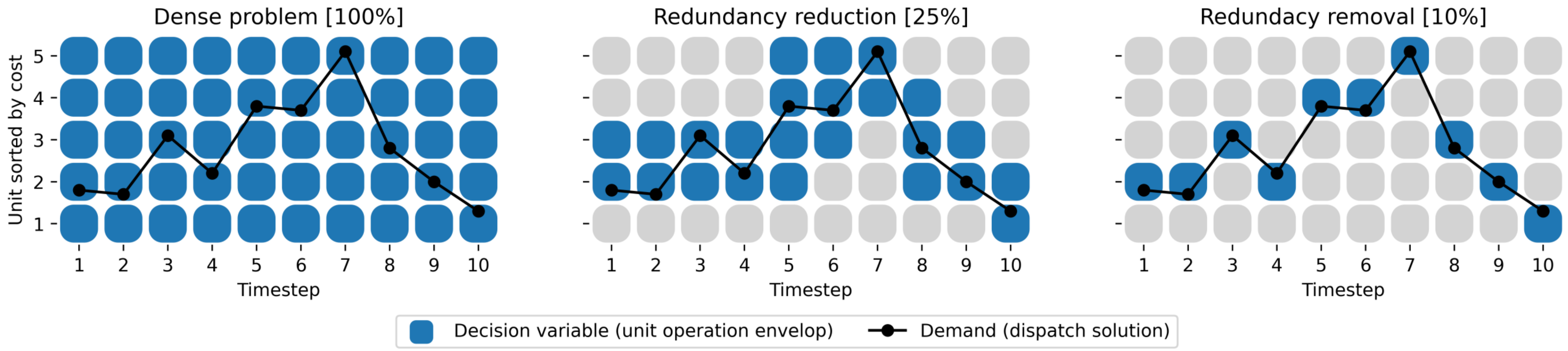


Is it possible to have error-free reduction?

[1] Zhi Gao, Matteo Gazzani, Diego A. Tejada-Arango, Abel Soares Siqueira, Ni Wang, Madeleine Gibescu, Germán Morales-España, Fully flexible temporal resolution for energy system optimization, Applied Energy, Volume 396, 2025, 126267, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2025.126267 .

Yes! If we can reduce “redundant” variables.

- Demonstration with a dispatch problem:
  5 production unit satisfying time-varying demand



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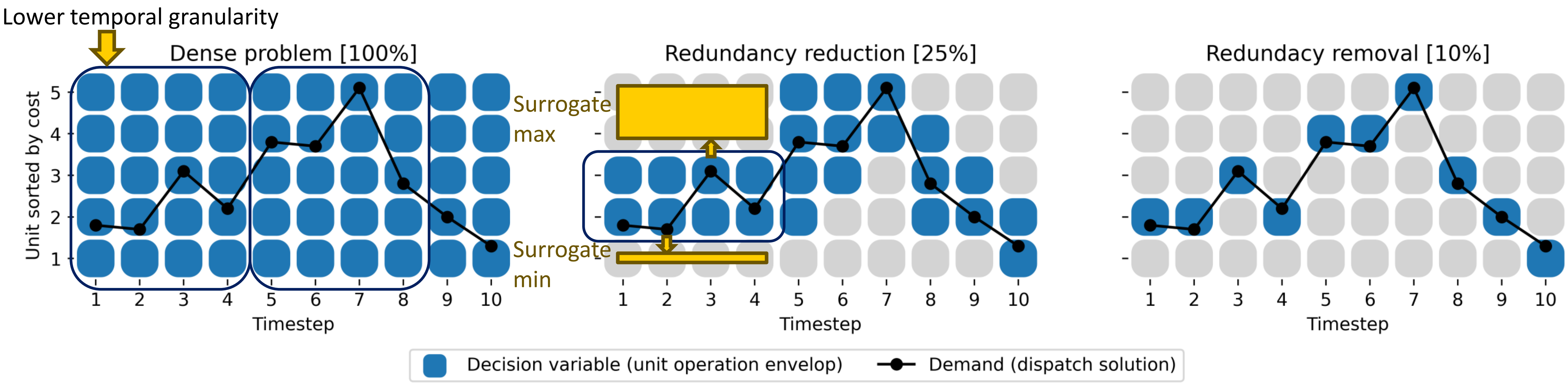
- Demonstration with a dispatch problem:
  5 production unit satisfying time-varying demand

- Low-resolution surrogates examine the best/worst scenario in each window.
  Variables outside of the boundaries can therefore be removed error-free.

- Similar logic when we have variable availability (like VREnewables).



Mathematical formulation

- Economic dispatch of national energy systems
- Surrogates are created in lower resolution, and min/max values of demand and capacity.

$$(P)(\mathbf{b}, \mathbf{e}, \mathcal{T}) : \min \sum_{t \in \mathcal{T}} \sum_{u \in \mathcal{U}} \sum_{n \in \mathcal{N}(u)} c_n x_{t,u,n} \tag{1a}$$

Total production cost

$$\text{s.t.} \quad \sum_{n \in \mathcal{N}(u)} x_{t,u,n} = b_{t,u} \quad \forall t \in \mathcal{T}, u \in \mathcal{U} \tag{1b}$$

Energy balance of country u

$$x_{t,u,n} \le e_{t,u,n} \quad \forall t \in \mathcal{T}, u \in \mathcal{U}, n \in \mathcal{N}(u) \tag{1c}$$

Capacity constraint of generator n

where $x_{t,u,n}, e_{t,u,n}, c_n \in \mathbb{R}_{\ge 0}, b_{t,u} \in \mathbb{R}_{\ge 0} \; \forall t \in \mathcal{T}$.

Preservation of accuracy (error-free)

- Mathematical proof led by Maaike Elgersma from TU Delft.

Theorem 1. *Consider the LP* $(P)(\mathbf{b}, \mathbf{e}, \mathcal{T})$ *as defined in* (1). *We also consider* $(\underline{P})(\underline{\mathbf{b}}, \overline{\mathbf{e}}, \mathcal{T})$ *and* $(\overline{P})(\overline{\mathbf{b}}, \underline{\mathbf{e}}, \mathcal{T})$*, where*

$$\overline{\mathbf{b}} \in [\mathbf{b}, \infty), \underline{\mathbf{b}} \in [0, \mathbf{b}], \overline{\mathbf{e}} \in [\mathbf{e}, \infty), \underline{\mathbf{e}} \in [0, \mathbf{e}]. \quad (4)$$

If $(P)(\mathbf{b}, \mathbf{e}, \mathcal{T}))$, $(\underline{P})(\underline{\mathbf{b}}, \overline{\mathbf{e}}, \mathcal{T})$ *and* $(\overline{P})(\overline{\mathbf{b}}, \underline{\mathbf{e}}, \mathcal{T})$ *are feasible, and* $c_i \neq c_j \ \forall i, j \in \mathcal{N}$ *where* $i \neq j$*, then for any optimal solutions* $\underline{\mathbf{x}}$ *and* $\overline{\mathbf{x}}$ *to* $(\underline{P})(\underline{\mathbf{b}}, \overline{\mathbf{e}}, \mathcal{T})$ *and* $(\overline{P})(\overline{\mathbf{b}}, \underline{\mathbf{e}}, \mathcal{T})$*, respectively, any optimal solution* $\mathbf{x}^*$ *to* $(P)(\mathbf{b}, \mathbf{e}, \mathcal{T}))$ *satisfies*

$$\min(\underline{x}_{t,u,n}, e_{t,u,n}) \leq x^*_{t,u,n} \quad \forall t \in \mathcal{T}, u \in \mathcal{U}, n \in \mathcal{N}(u) \quad (5)$$

and

$$\overline{x}_{t,u,n} < \underline{e}_{t,u,n} \Rightarrow x^*_{t,u,n} \leq \overline{x}_{t,u,n} \quad \forall t \in \mathcal{T}, u \in \mathcal{U}, n \in \mathcal{N}(u). \quad (6)$$

Proof. Suppose $(P)(\mathbf{b}, \mathbf{e}, \mathcal{T}))$, $(\underline{P})(\underline{\mathbf{b}}, \overline{\mathbf{e}}, \mathcal{T})$ and $(\overline{P})(\overline{\mathbf{b}}, \underline{\mathbf{e}}, \mathcal{T})$ are feasible. Let $\mathbf{x}^*$, $\underline{\mathbf{x}}$, and $\overline{\mathbf{x}}$ be optimal solutions to these problems, respectively. We show that x^* meets (5) and (6) ...

There must be optimal solutions within the surrogate bounds

Corollary 1. *Consider LP* $(P)(\mathbf{b}, \mathbf{e}, \mathcal{T})$ *as defined in* (1) *and the underestimation surrogate LP* $(\underline{S})(\underline{\mathbf{b}}, \overline{\mathbf{e}}, \mathcal{T}')$ *as defined in* (2) *with any subset* $\mathcal{T}'$ *of time steps* $\mathcal{T}$*, where*

$$\underline{b}_{k,u} = \min_{t \in \mathcal{S}_k}(b_{t,u}), \ \overline{e}_{k,u,n} = \max_{t \in \mathcal{S}_k}(e_{k,u,n}) \quad (10)$$

$\forall k \in \mathcal{T}', u \in \mathcal{U}, n \in \mathcal{N}(U)$. *Consider also the overestimation surrogate LP* $(\overline{S})(\overline{\mathbf{b}}, \underline{\mathbf{e}}, \mathcal{T}')$ *as defined in* (2)*, where*

$$\overline{b}_{k,u} = \max_{t \in \mathcal{S}_k}(b_{t,u}), \ \underline{e}_{k,u,n} = \min_{t \in \mathcal{S}_k}(e_{t,u,n}) \quad (11)$$

$\forall k \in \mathcal{T}', u \in \mathcal{U}, n \in \mathcal{N}(U)$.

If $(P)(\mathbf{b}, \mathbf{e}, \mathcal{T})$, $(\underline{S})(\underline{\mathbf{b}}, \overline{\mathbf{e}}, \mathcal{T}')$*, and* $(\overline{S})(\overline{\mathbf{b}}, \underline{\mathbf{e}}, \mathcal{T}')$ *are feasible, and* $c_i \neq c_j \ \forall i, j \in \mathcal{N}$ *where* $i \neq j$*, then for any optimal solutions* $\underline{\mathbf{x}}$ *and* $\overline{\mathbf{x}}$ *to* $(\underline{S})(\underline{\mathbf{b}}, \overline{\mathbf{e}}, \mathcal{T}')$ *and* $(\overline{S})(\overline{\mathbf{b}}, \underline{\mathbf{e}}, \mathcal{T}')$*, respectively, any optimal solution* $\mathbf{x}^*$ *to* $(P)(\mathbf{b}, \mathbf{e}, \mathcal{T})$ *satisfies*

$$\min(\underline{x}_{k,u,n}, e_{t,u,n}) \leq x^*_{t,u,n} \quad (12)$$

$\forall k \in \mathcal{T}', t \in \mathcal{S}_k, u \in \mathcal{U}, n \in \mathcal{N}(u)$ *and*

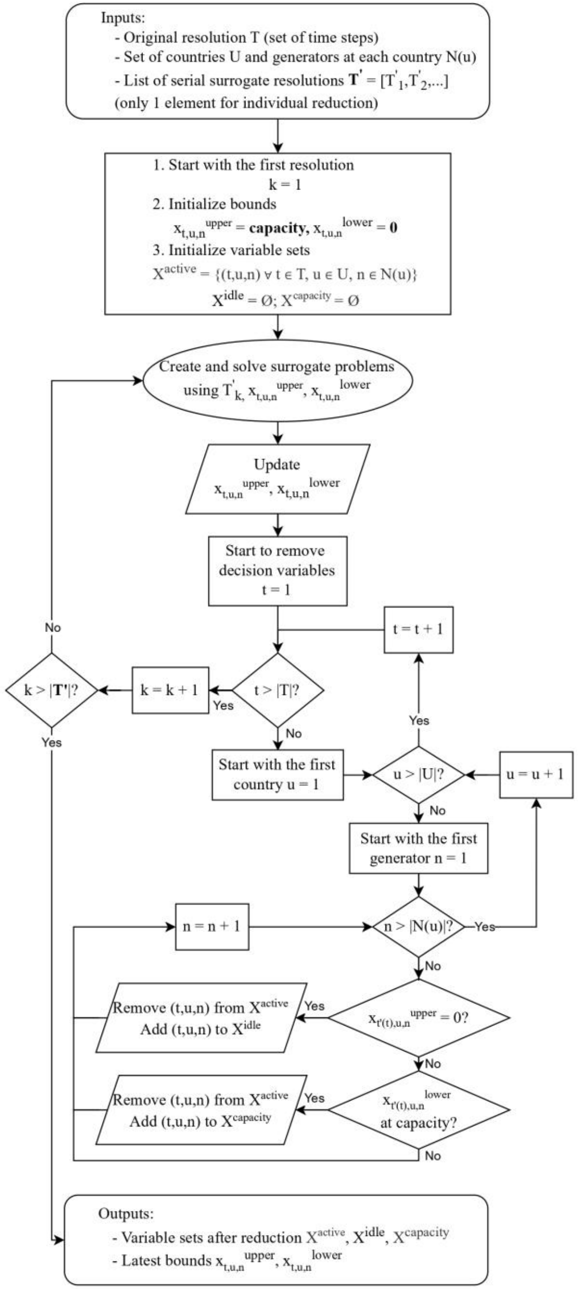
$$\overline{x}_{k,u,n} < \underline{e}_{k,u,n} \Rightarrow x^*_{t,u,n} \leq \overline{x}_{k,u,n}, \quad (13)$$

$\forall k \in \mathcal{T}', t \in \mathcal{S}_k, u \in \mathcal{U}, n \in \mathcal{N}(u)$.

Proof. Suppose $(P)(\mathbf{b}, \mathbf{e}, \mathcal{T})$, $(\underline{S})(\underline{\mathbf{b}}, \overline{\mathbf{e}}, \mathcal{T}')$, and $(\overline{S})(\overline{\mathbf{b}}, \underline{\mathbf{e}}, \mathcal{T}')$ are feasible. We first show that any optimal solutions to

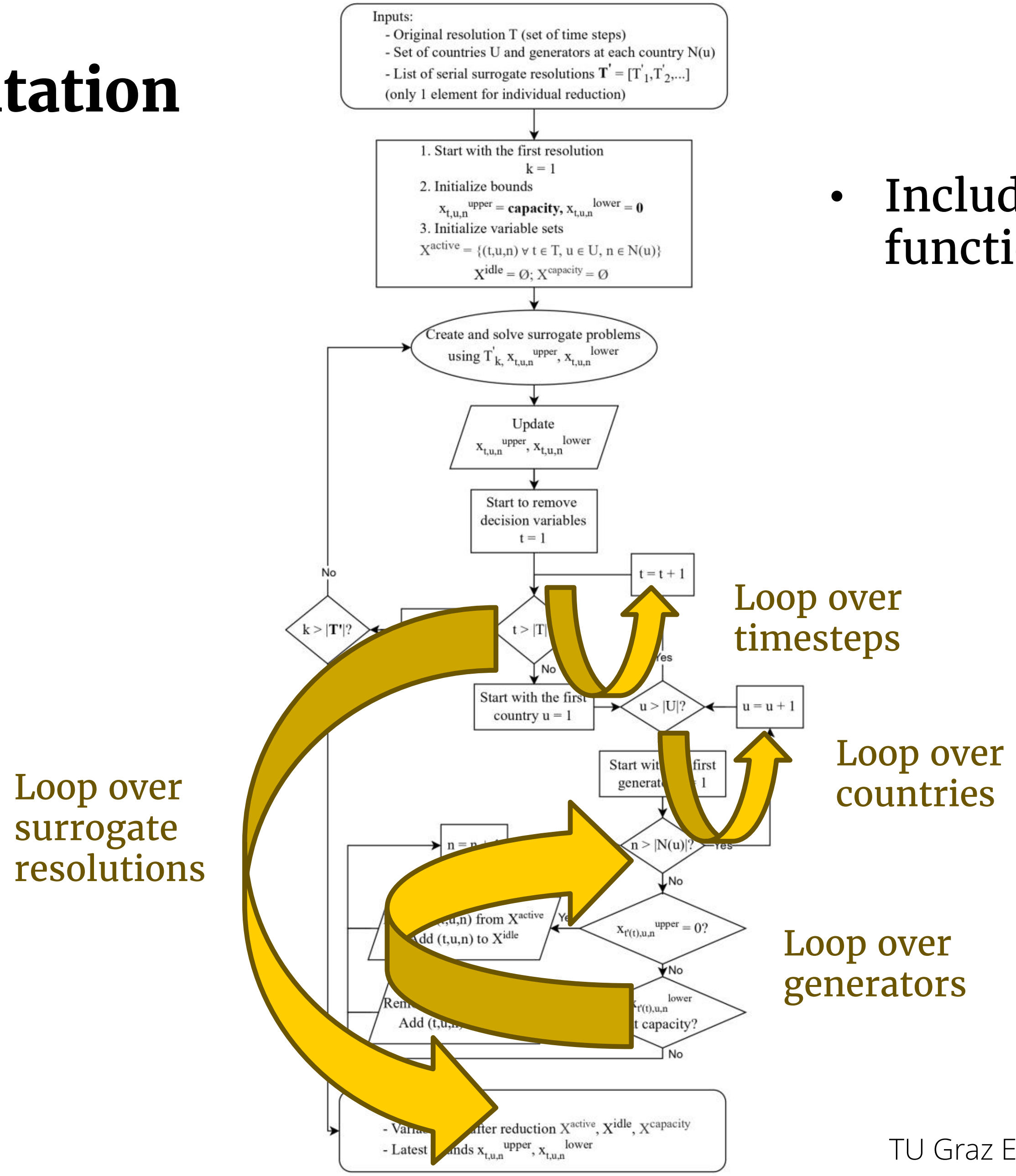
Low-resolution surrogates can be used for this.

Implementation



- Including individual & serial surrogate functions.

Implementation

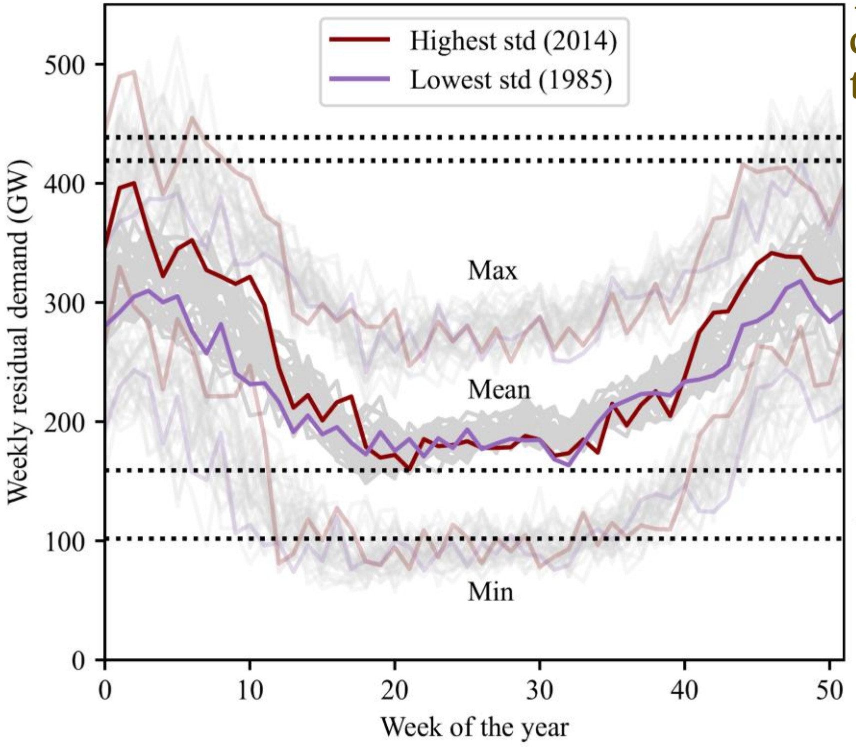


- Including individual & serial surrogate functions.

Case study (based on TYNDP 24)

- Economic dispatch of 35 national energy systems.
- Under the most stable and most fluctuating demand-weather years.

- Note: there is no energy storage, no transmission lines.



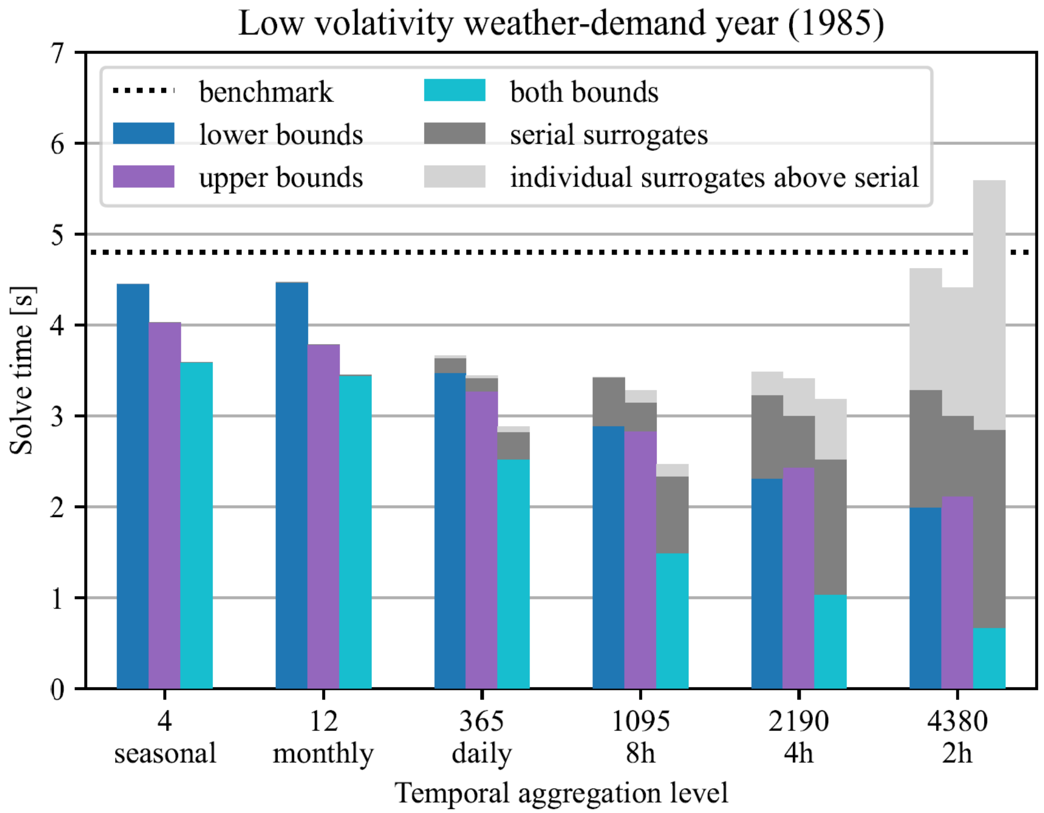
Total capacity by tech

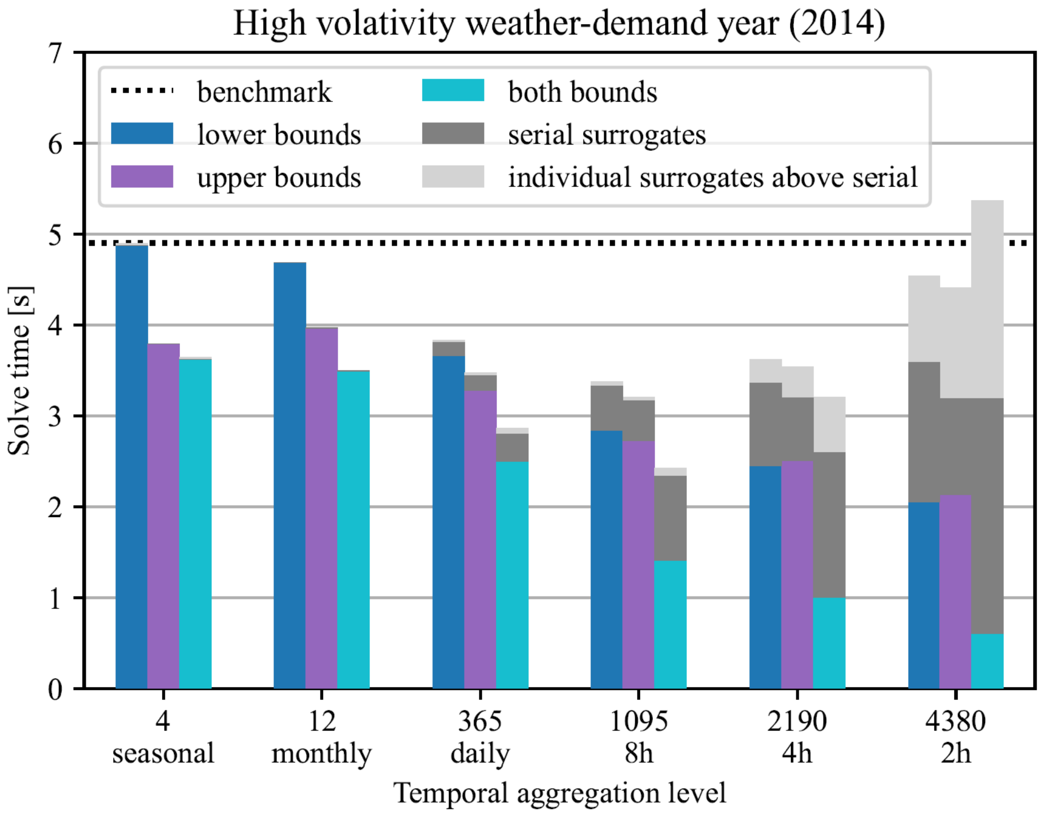
OCGT
CCGT
Coal
Nuclear

Case study (based on TYNDP 24)

- Significant gains in computational efficiency
- And memory usage (next slide)

- Note again: all instances error-free

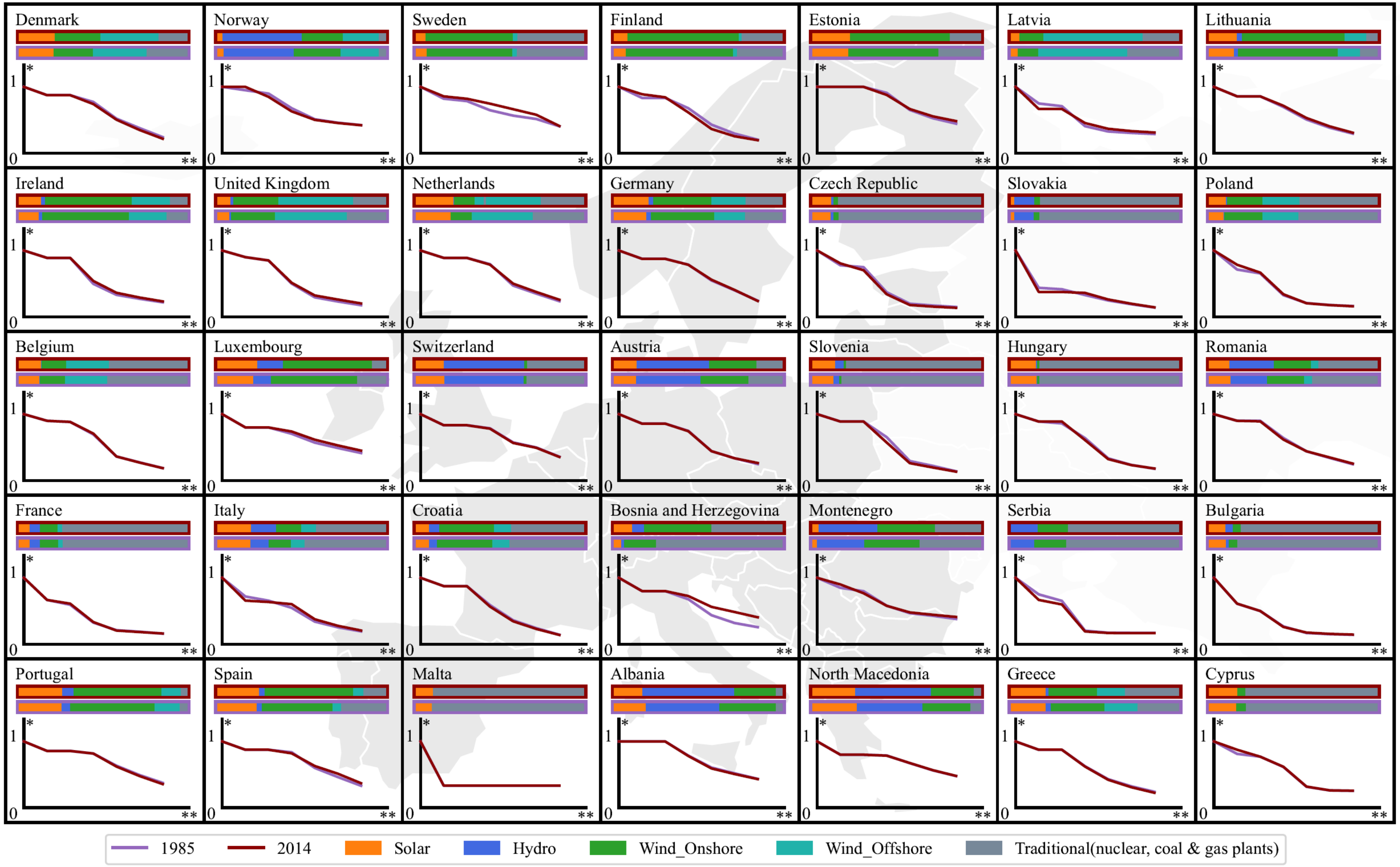




Reduction of decision variables

- Country-country comparison
  (Estonia & Czech top)
  (Spain & Malta below)

- Climate year comparison
  (Bosnia and Herzegovina)



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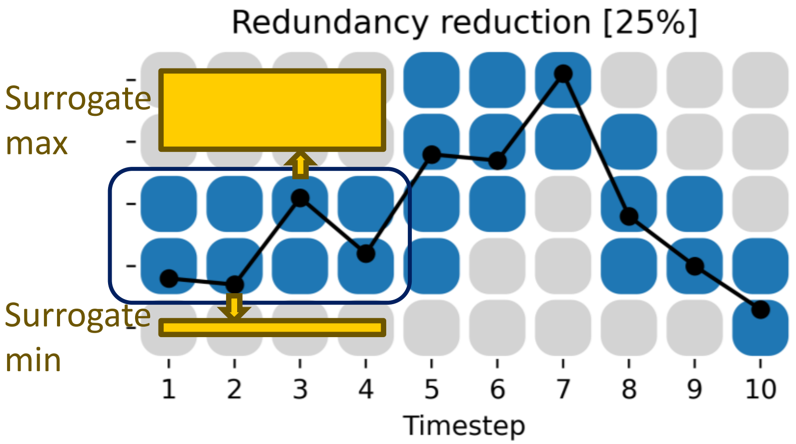

- More on the way
  - Extend to include more system features (storage, network etc.).
  - Re-think the use of computing power.

Let's keep in touch (Zhi will be open for PostDoc opportunities ☺)

Zhi Gao, Maaike Elgersma, Madeleine Gibescu, Germán Morales-España, Mathijs de Weerdt, Matteo Gazzani,
Error-free model reduction with low-resolution precursor surrogates for energy system optimization.
[submitted to PSCC 26]

Utrecht University

Sharing science,
shaping tomorrow