Identification of Infrastructure Pressure Points in a Decarbonized Grid across Climatic-technological Scenarios

PCHES

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I. Motivation: understanding vulnerabilities of decarbonized grids

- Decarbonization policies focusing on integration of renewable energies and electrification increasingly couple energy system with weather and climate.
- To understand vulnerabilities of decarbonized grids and potential interventions to improve reliability, we need to identify **infrastructure "pressure points"** constraining the ability of the renewable grid to meet demand under climate stressors.
- Complexity and interconnectedness of power grid can lead to disconnect between pressure points and where outages occur (Webster et al., 2022), so we **think about identifying pressure points as inferring effective network connections** that explain dynamics on the grid.

II. Case study: proposed zero-carbon NYS grid

Liu et al. (2023, preprint) develop a **simplified representation of proposed zero-carbon NYS grid** with expanded renewable generation, upgraded transmission, and additional electrified load.

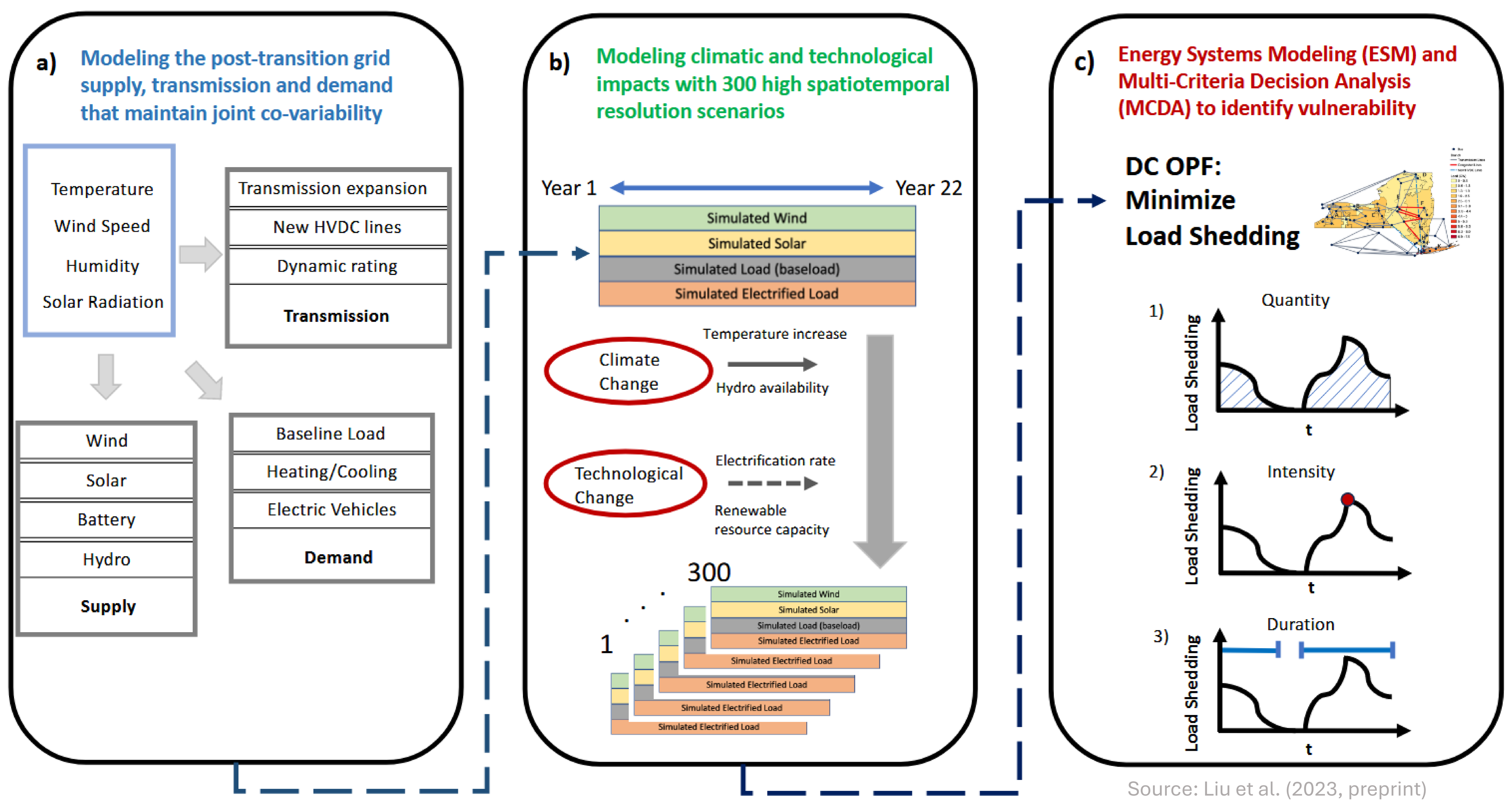
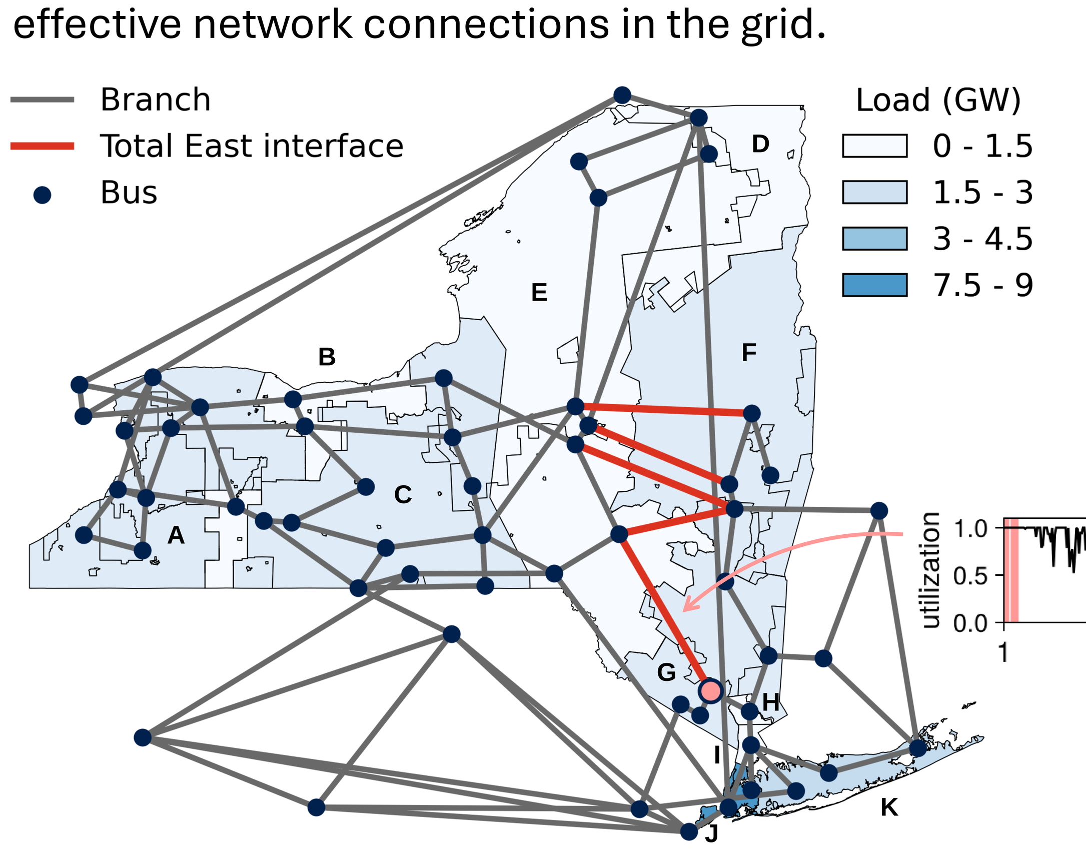


Figure 1. Overview of zero-carbon NYS grid model framework. Time series of relevant decision variables—*e.g.*, generation, curtailment, transmission, and load shedding—are used to infer effective network connections in the grid.



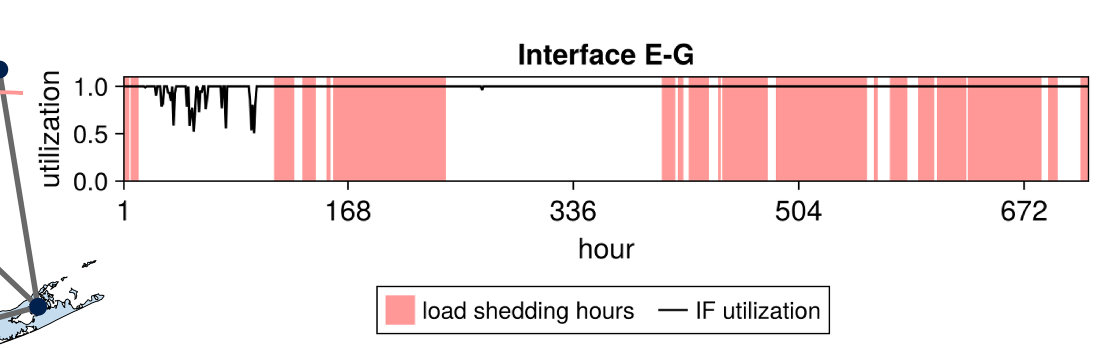


Figure 2. Spatial imbalance between renewable energy supply (upstate) and demand (downstate) leads to **significant transmission line congestion**, especially of the Total East interface. Previous analysis of bottlenecks in the grid focused on this congestion (Liu et al., 2023, preprint).

III. Methods: pairwise transfer entropy analysis for inferring network connections

Transfer entropy (Schreiber, 2000) lets us test for directed statistical relationships in time series data by casting **Wiener-Granger causality** in information-theoretic terms.

Transfer entropy (TE) from source process X to target process Y is given by

$$T_{X \to Y} = I(X^- : Y^+ \mid Y^-)$$

where

- Y^+ is the future RV of process Y,
- X^- and Y^- are past state variables of X and Y, respectively.

$T_{X \to Y} > 0$ means process X "causes" process Y: the history of X improves our prediction of the future of Y beyond what is predictable by the history of Y alone.

We will say that a piece of infrastructure is a **"pressure point"** if there is nonzero TE from its pattern of usage to the pattern of load shedding.

Key research questions:

1. What pressure points exist in the decarbonized NYS grid?
2. Is this definition of a pressure point useful for understanding vulnerabilities and potential interventions?

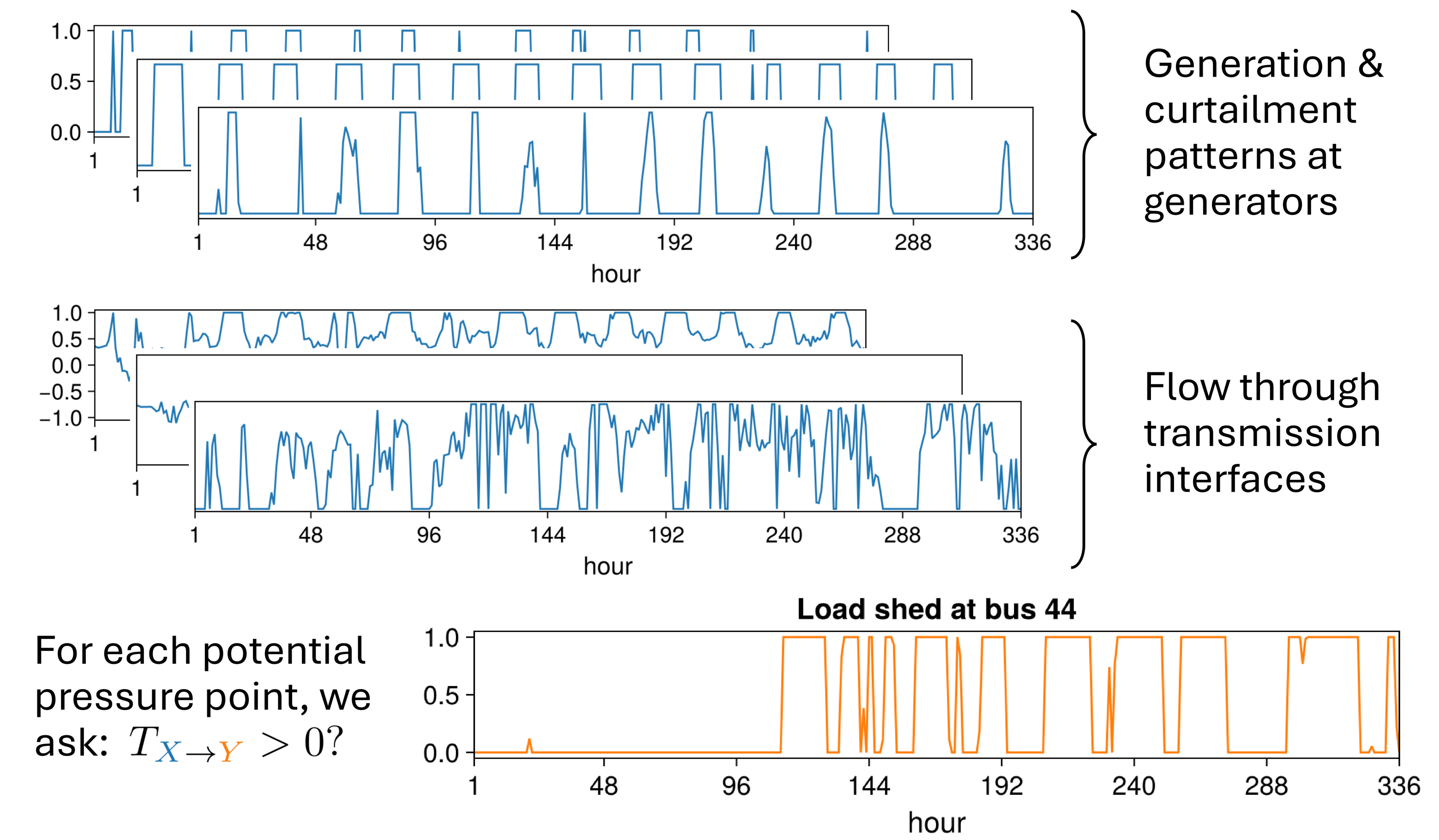
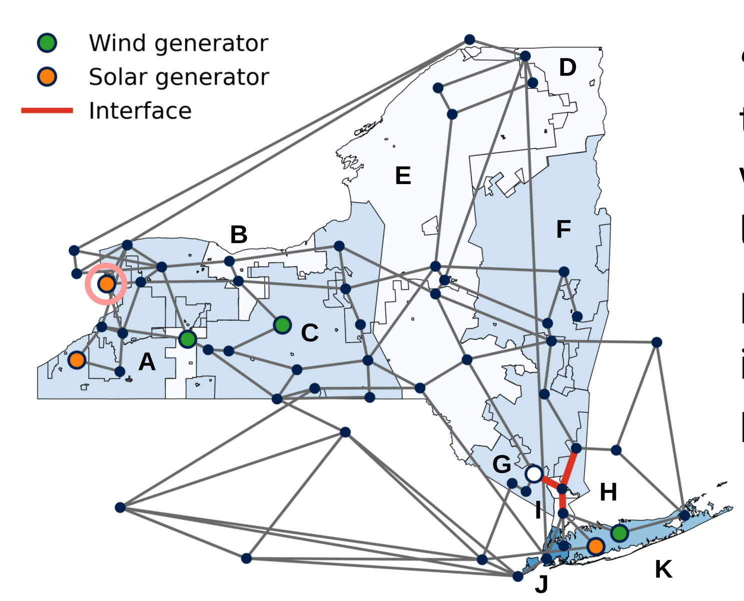


Figure 3. Workflow for pairwise TE analysis. Time series of generation, curtailment, and interface flow are realizations of source process; load shedding at bus of interest is realization of target process. Analysis involves (1) state space reconstruction for each process, (2) TE estimation, and (3) surrogate data generation and significance testing (Wibral et al., 2014).

IV. Results: pressure points beyond upstate-to-downstate transmission congestion



"Baseline" scenario: moderate temperature increase, overbuilt wind and solar capacity, relatively low levels of load shedding.

Figure 4. Generators and interfaces flagged as pressure points.

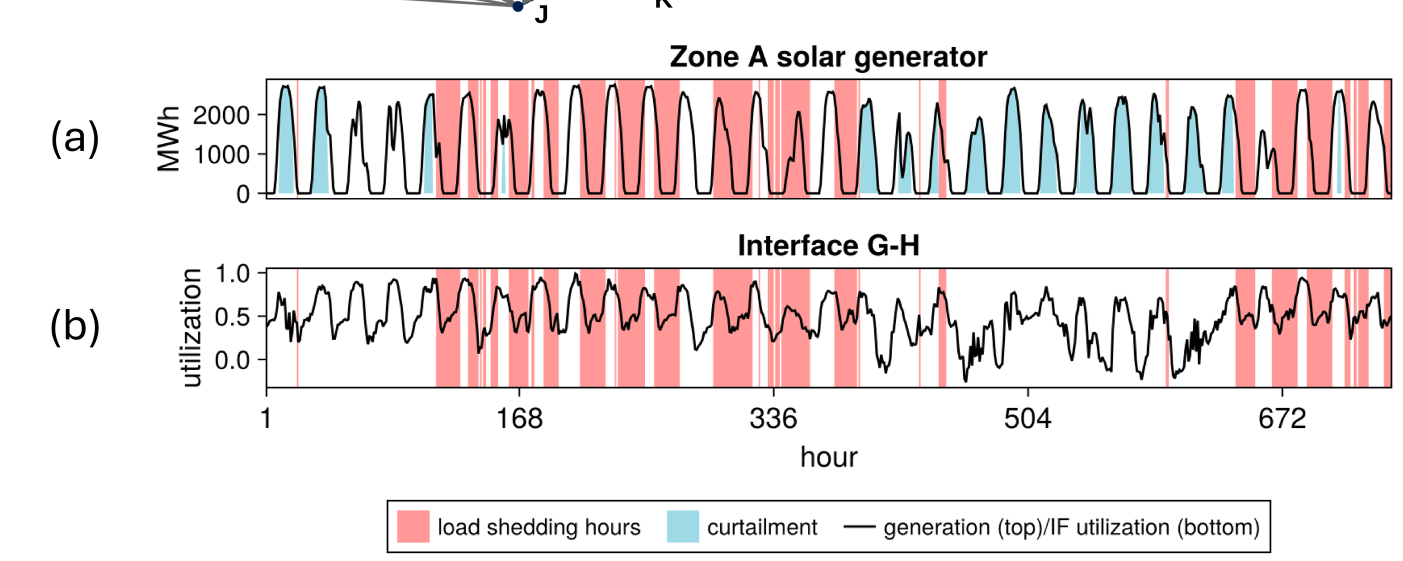
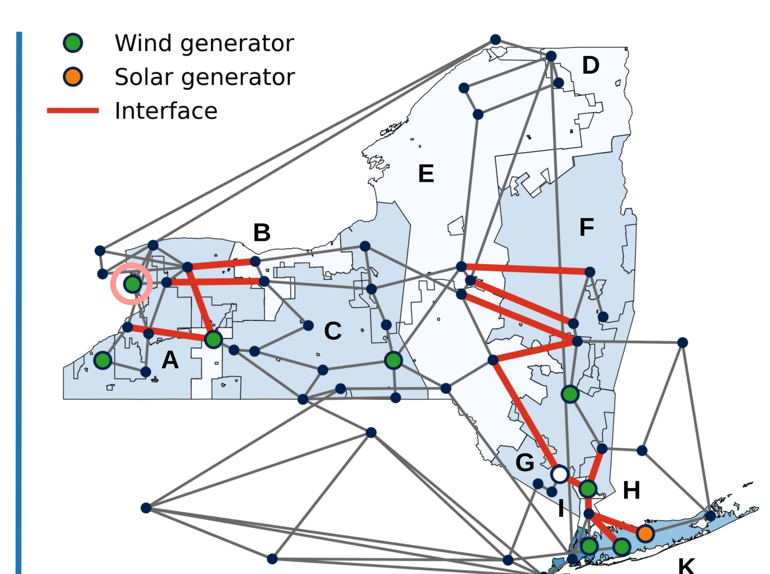


Figure 5. TE analysis picks up on predictive relationship between curtailment and load shedding. Load shedding occurs mainly at night, when solar energy supply is low (a). Load shedding tends to occur when IF G-H is underutilized due to low renewable supply upstate (b).

Takeaway from baseline scenario: **low renewable supply across the state is driving factor in load shedding**, but high curtailment suggests that long-duration batteries or flexible options such as hydrogen could improve reliability of the grid.

Next steps: (1) scenario discovery to map specific climate change and technological assumptions to appearance of various pressure points, **(2)** accounting for redundancy and synergy in identified pressure points.



A more extreme scenario: large temperature increase, underbuilt wind capacity, relatively high levels of load shedding.

Figure 6. Generators and interfaces flagged as pressure points.

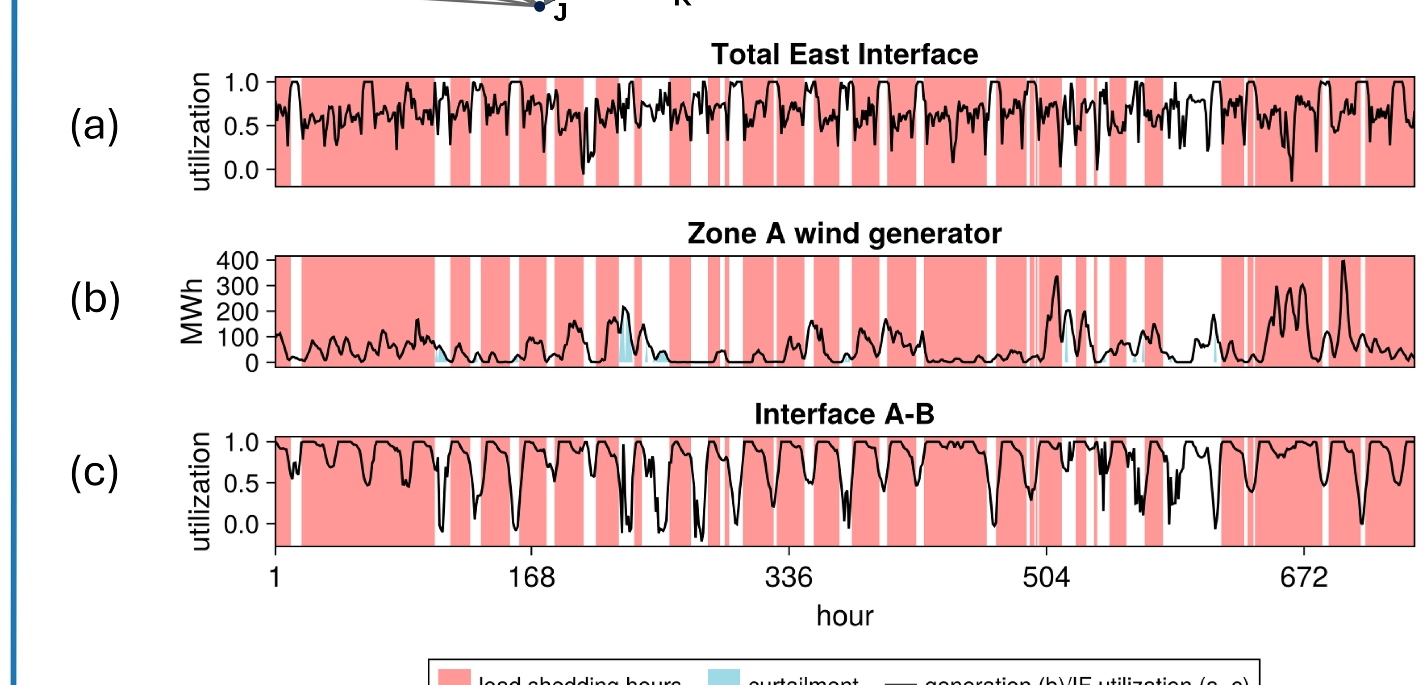


Figure 7. As in baseline scenario, load shedding tends to occur when Total East IF is underutilized due to low renewable supply upstate (a), but when demand overwhelms the system, we see load shedding even during hours with relatively high renewable capacity (b). Congestion in geographically distant IF A-B is also relevant in predicting load shedding downstate (c).

Takeaway from this extreme example: while low renewable supply is still a factor, **upstate congestion also plays a role** in predicting load shedding downstate.

References & acknowledgements

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