CETlab
The Clean Energy Transformation Lab

Resource Adequacy in Rapidly Expanding and Decarbonizing Electricity Systems

UC SANTA BARBARA

G. Terrén-Serrano[1,2], A. Sharma[1,2], R. Deshmukh[1,2,3], S. Prasad[2]

[1]Environmental Studies, [2]Environmental Markets Lab (emLab), [3]Bren School of Environmental Sciences & Management, University of California Santa Barbara

Motivation

- Electricity systems in emerging economies must expand and decarbonize simultaneously [1].
- As variable Renewable Energy (VRE) and electrification grow, supply and demand become weather-driven and correlated —planning reserve margin (PRM) alone no longer guarantees reliability [2].
- Long-term planning studies overlook reliability risks —leaving a gap between capacity expansion and resource adequacy.

Research Questions

- How **reliable** are cost-optimal expansion pathways for India's rapidly growing, decarbonizing grid?
- What PRM levels meet reliability standards, and **at what cost**?
- **When, and where** do loss-of-load events occur, and **how much** Expected Unserved Energy (EUE) do they cause?

Methods

Modeling Platform

- **GridPath-India** (MILP, Pyomo/Gurobi): open-source capacity expansion (CEM) + production cost model (PCM) [3].
- **35 load zones, interstate transmission, planning periods 2020–2050.**
- **CEM**: 2 representative days/month (peak + median); **PCM**: 8,760 h/yr, linearized unit commitment.
- **Solar/wind profiles (+1,300)**: NSRDB + ERA5, bias-corrected with Global Wind Atlas, validated against CEA generation.
- **Demand**: PIER v2.0 bottom-up state-level projections, that incliude agricultural sector solarization and climate change impacts.

Resource Adequacy Assessment

- Sequential Monte Carlo [4]: 18 weather years × 18 thermal outage years ($K = 324$ full-year simulations).
- Each weather year has weather-synchronized demand, VRE generation, and hydro inflows (machine learning).
- Each thermal outage year is drawn from a technology/ state/seassonal distribution (statistical inference).
- Capacity credits assigned via Top Net Load Hours, iteratively informing the CEM planning reserve margin.
- 12 monthly subproblems with circular horizons, solved in parallel.

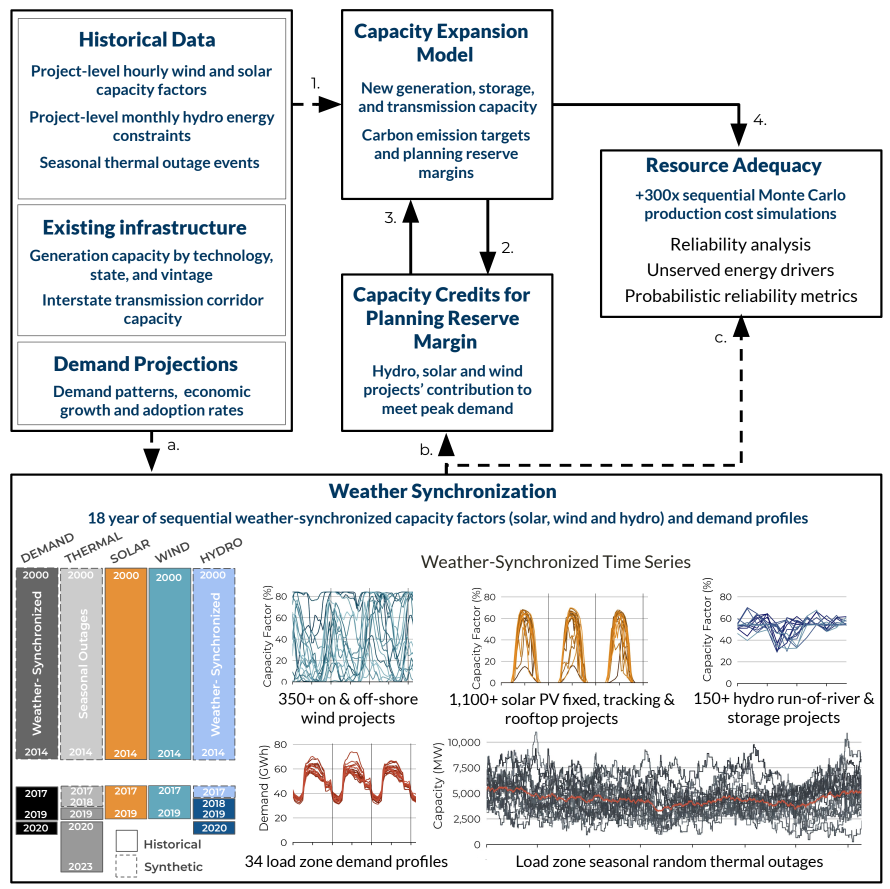

Figure 1. Proposed multi-model Integrated Resource Planning (IRP) framework.

Results

1. Lax reliability standards, not ambitious carbon targets, may cause productivity losses in emerging economies

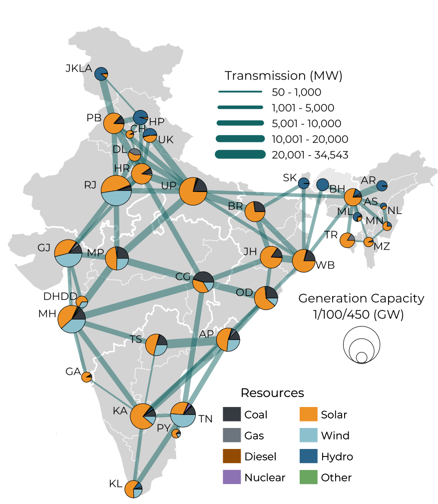

Figure 2. Partially decarbonized electricity system of India in 2040.

- Clean portfolios (VRE + storage) provide reliability at similar cost.
- A low PRM may comply with the local reliability standard (NENS$\leq$0.05%).
- Higher PRMs reduces EUE and social costs, but at rising marginal cost.

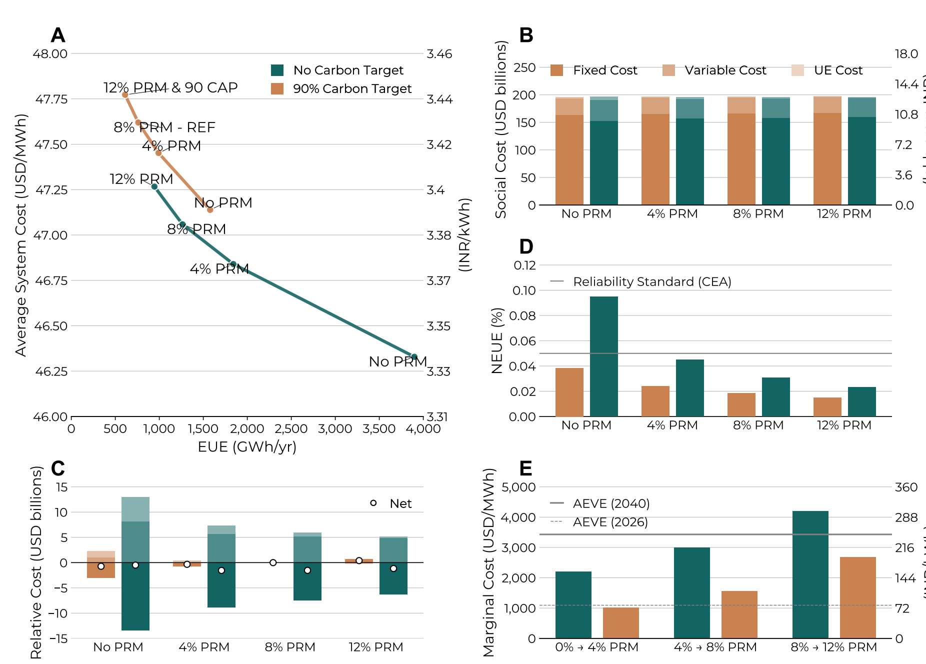

Figure 3. (A) Average cost of electricity, (B) total system cost, (C) system cost differences, (D) Normalized Expected Unserved Energy (NEUE) reliability standards, and (E) the marginal cost of reliability.

Results

2. Unserved energy events are dominated by short-duration outages in the post-monsoon season

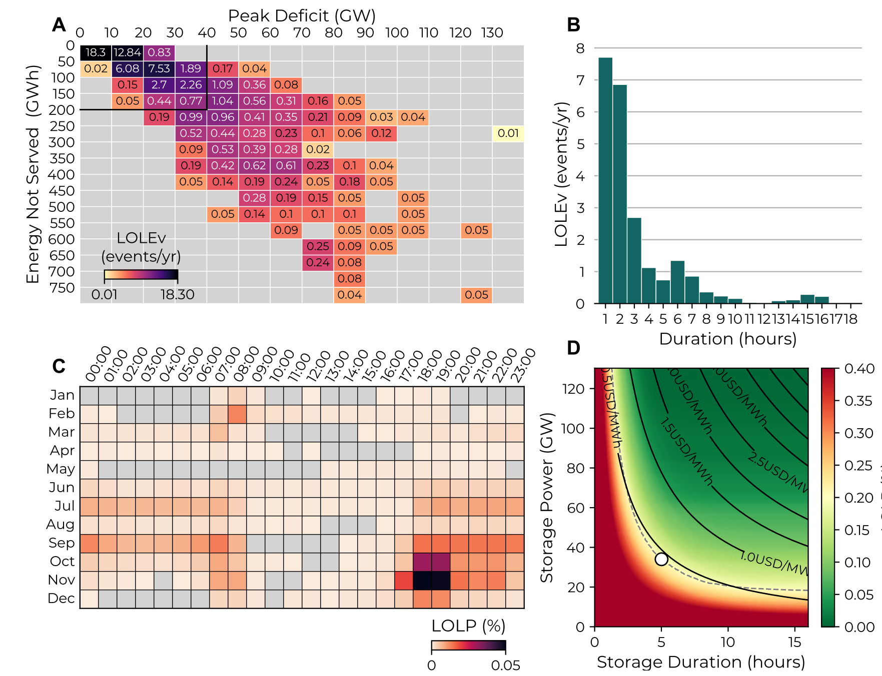

Figure 4. (A) Distribution of peak-unserved energy, (B) distribution of loss-of-load duration, (C) month-hours loss-of-load probability, and (D) reliability surface.

- Most loss-of-load events (LOLEv) are short (1–2 h), but some can last up to 18 h.
- The largest loss-of-load probability (LOLP) occurs in Oct–Nov between 5 and 7 pm.
- Loss-of-load risk is concentrated in the evening net-load peak, once solar generation ramps off while demand remains high.

Solution

- The **reliability surface** maps LOLP against storage power and duration, pricing reliability improvements in USD/MWh.
- Most LOLEv could be avoided by adding approximately **40 GW/200 GWh of energy storage** to the system.
- This solution would increase the average cost by **less than 0.5 USD/MWh**.
- This is equivalent to increasing the **PRM by 5%**.

3. Widespread events in the western grid drive loss-of-load in peripheral load zones

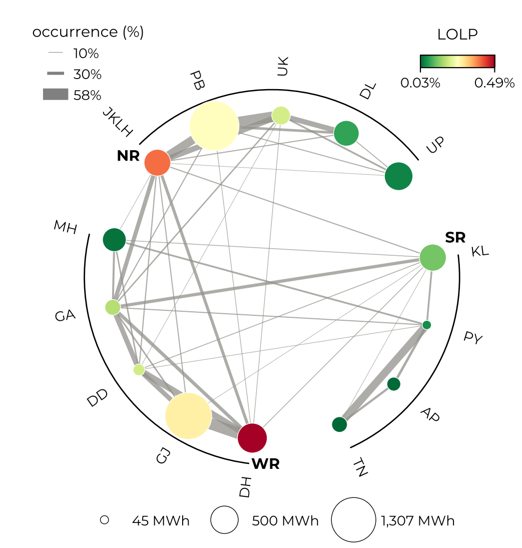

Figure 5. Loss-of-load hours simultaneity graph.

- Co-occurrence probability of loss-of-load is high (> 50%) among certain states in the NER, WR, and NR grids.
- LOLP and NENS are highest in peripheral load zones —Jammu, Kashmir & Ladakh (JKLH) and Dadra & Nagar Haveli.
- EUE is highest in Gujarat (GJ) and Punjab (PB).
- During outage events, transmission lines within the WR grid are congested, preventing available generation from being supplied.
- NR lines are not congested during outage events.
- Lines transferring electricity from the WR to the NR grids are likely to be congested during outage events.

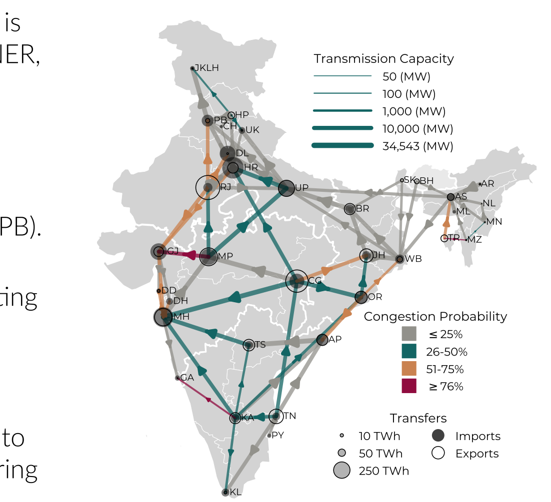

Figure 6. Transmission corridor congestion probability and imports/exports during loss-of-load.

Discussion

- Cost-optimal clean portfolios (VRE + storage) can meet India's reliability standards without raising average costs.
- PRMs alone are poor proxies for reliability in weather-driven systems —probabilistic resource adequacies are needed.
- Targeted short-duration storage additions eliminate most loss-of-load events at minimal cost.
- Reliability standards should weigh the social cost of unserved energy, not only average system cost.
- Weather-synchronized simulation of demand, VRE, and hydro is essential to capture correlated tail risks.

Limitations and Future Work

- **No intrastate transmission**: congestion is not represented, potentially overstating deliverability.
- **Perfect trading assumption**: market frictions (PPAs, liquidity, scheduling rules) are not modeled.
- Incorporate **climate change projections** to capture shifting demand patterns, extremes, and resource availability.
- **Validate weather-syncronized inputs** (outages, demand, VRE) against observed operations to quantify modeled-vs-actual accuracy.

Acknowledgement

G.T.S., A.S., and R.D. were partially supported by the World Resources Institute (WRI). Use was made of computational facilities purchased with funds from the National Science Foundation (CNS-1725797) and administered by the Center for Scientific Computing (CSC). The CSC is supported by the California NanoSystems Institute and the Materials Research Science and Engineering Center (MRSEC; NSF DMR 2308708) at UC Santa Barbara. The authors used the AI tool Claude to assist with coding, editing, and improving the clarity of the poster during the preparation of this work.

References

[1] IEA. Executive Summary. International Energy Agency; 2025. Available from: https://www.iea.org/reports/world-energy-outlook-2025/executive-summary.
[2] Sun Y, Frew B, Dalvi S, Dhulipala SC. Insights into methodologies and operational details of resource adequacy assessment: A case study with application to a broader flexibility framework. Applied Energy. 2022;328:120191.
[3] Terrén-Serrano G, Deshmukh R, Dukkipati S, Meng M, Prasad S, Mileva A, et al.. Affordable low-carbon electricity pathways for India under uncertainty; 2026. Available from: https://arxiv.org/abs/2607.10581.
[4] Hart E, Mileva A. Advancing resource adequacy analysis with the GridPath RA Toolkit: A case study of the Western US. GridLab; 2022. Available from: http://www.gridlab.org/publications.