OPERATIONAL RISK FINANCIALIZATION OF ELECTRICITY UNDER STOCHASTICITY

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INTRODUCTION

Modern **power grids** that incorporate **renewable sources** alongside traditional thermal generators, face the risks of **intermittency** which are inherently **stochastic**. Renewable energy such as solar and wind depend on exogenous factors, especially the **weather**. Thus, it is challenging to forecast renewables' power production ahead of time.

Grid operators must weigh the additional risk of increased renewable penetration, alongside **benefits** such as **reduced emissions**, and **no fuel costs.** However, grid operations models do not account for the costs of such risks.

Here, we introduce a **novel method** for **quantifying the risk** of renewables' generators penetration in the operation of a power grid. This method generates **grid simulations** and uses **Shapley values** to quantify individual asset reliability scores.

PROBLEM

Since 1962, a deterministic two-step procedure has been adopted by ISOs (or RTOs)

1. Day ahead: A deterministic mixed-integer program optimization problem determines the unit commitment for each hour of the next day.
   (a) Fossil fuel generators bid **prices p(q)** curves.
   (b) Renewables are assumed to produce forecasted quantities at zero cost.
   (c) Bids are aggregated into a **bid stack P(Q)**
   (d) Price is set where **forecasted demand** intersects the bid stack.

   UNCERTAINTY IN RENEWABLES IS IGNORED

2. Real time: The grid experiences *actual* demand. If there is a mismatch, i.e. **committed supply in the day ahead < actual demand**, ISO would call up peakers. This is **costly**, and **carbon intensive**.

ORFEUS APPROACH

Let X be random (intermittent production), a be decision variables from $\mathscr{A}$, which includes power flow and other constraints; and f_a represents cost.

Deterministic optimization — **Stochastic optimization**

$$\max_{a\in\mathscr{A}} f_a \mathbb{E}\{X\} \qquad \max_{a\in\mathscr{A}} \mathbb{E}\{f_a(X)\}$$

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X is reduced to its forecasted value $\mathbb{E}\{X\}$ — Full distribution information

OUR METHODOLOGY

Vatic: a **grid simulation engine** that implements the PJM schema and allows for **finer-grained manipulation of inputs** and for **greater flexibility in parallelized execution**.

Objective: isolate the risk that renewables' unpredictability contributes to a grid, comparing the conditional value at risk (CVaR) of differences in system costs across multiple scenarios.

METHODOLOGY

Step 1: Statistical model

Historical data: 185 renewable and 488 thermal generators located within *Texas-7k*, a simulated version of the ERCOT grid system currently deployed in Texas[1] .

Step 2: Monte Carlo scenario generation

Calibrated from step 1 to simulate real time daily scenarios. Captures renewables' under/over-production, stochastic demand, correlations[2].

Step 3: System Risk Computation

Objective is to reduce the right tail extreme risks. Let X be the excess cost due to renewables intermittency. The system risk $\rho(X)$ is defined as

$$\mathrm{CVaR}_\alpha(X) = \mathbb{E}\{X \mid X \geq \mathrm{VaR}_\alpha(X)\} \quad \text{where} \quad \mathrm{VaR}_q(X) = \inf\{x : F_X(x) \geq q\} \qquad (1)$$

where α represents the risk level.

Step 4: Risk Allocation

Distribute risk via **Shapley values**[4]. Let G be the set of N renewable assets, and pick a subset $H \subseteq G\backslash\{i\}$ **not** containing asset i. The cost attributable to generator $i \in G$ is

$$\phi_i = \sum_{H\subset G\backslash\{i\}} \frac{(|H|)!(N-|H|-1)!}{N!}\left(\nu(H) - \nu(H\cup\{i\})\right) \qquad \text{s.t.} \quad \sum_i \phi_i = \nu(\emptyset) - \nu(G) = X \qquad (2)$$

where $\nu(\cdot)$ are the costs of idealized assets. According to (1), the *fair* risk allocation is defined by $a_i = \mathbb{E}\{\phi_i(\nu) \mid X > \mathrm{VaR}_\alpha(X)\}$. Then,

$$\sum_i a_i = \mathbb{E}\left\{\phi_i(\nu) \mid X > \mathrm{VaR}_\alpha(X)\right\} = \rho(X).$$

We use a two-step approach:

(1) **Cohort-level Risk Allocation**: renewables are partitioned based on generator type (solar vs. wind);

(2) **Asset-level Risk Allocation**: cohort-level allocations are distributed among individual generators in proportion to their forecasted output.

Step 5: Reliability Cost Curves

Translate Risk Allocations into Reliability Cost Curves for renewables, i.e. the burden they impose on the grid. This probabilistic information is then incorporated into the day-ahead unit commitment, to re-inform steps 2 and 3 above and quantify the new excess system risk.

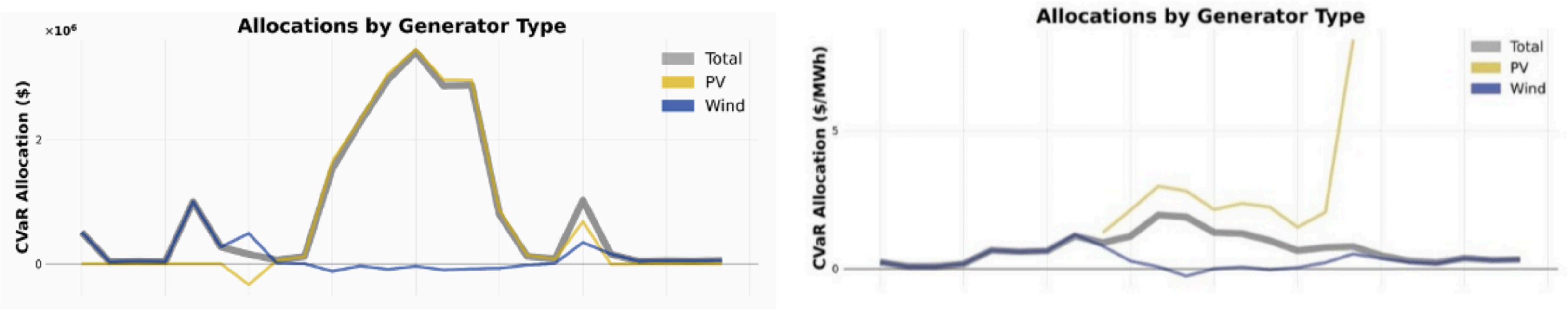


FIGURE 1: ***Cohort allocations*** for December 18, 2020 (left) and September 4, 2030 (right), Texas-7k Grid. The right figure shows the first-order Shapley asset-level allocations. Texas 7-k Grid comprises 673 and 977 total generators in 2020 and 2030, respectively.

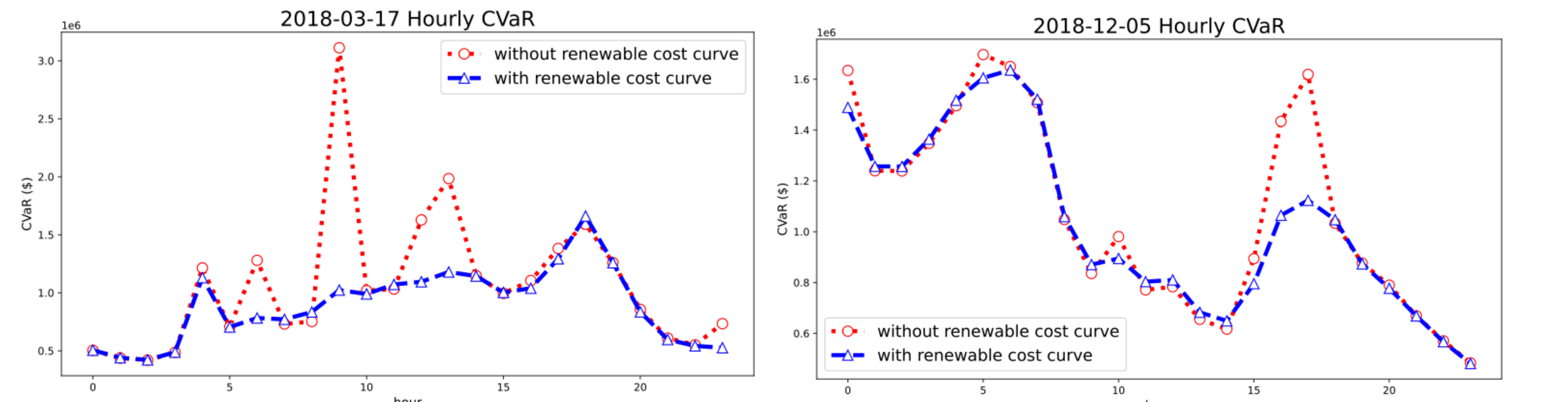


FIGURE 2: **System CVaRs** with and without cost curves, March 17 2030 (left) and December 5 2030 (right), Texas-7k Grid.

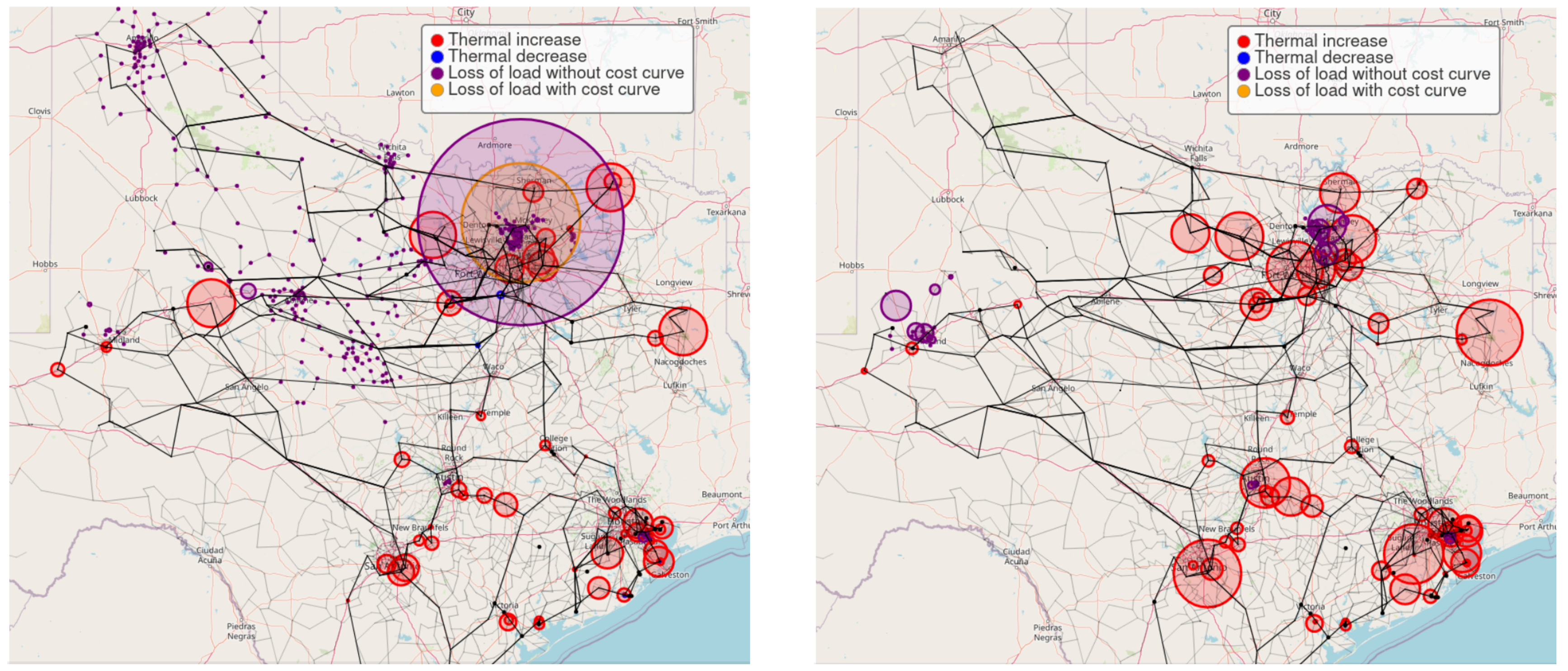


FIGURE 3: ***Redistribution of System CVaRs.*** Simulation through Vatic, on Texas 7-k grid during March 17th 2030. The left graph refers to 9am, while the right graph to 12pm. Texas 7-k Grid comprises 673 and 977 total generators in 2020 and 2030, respectively.

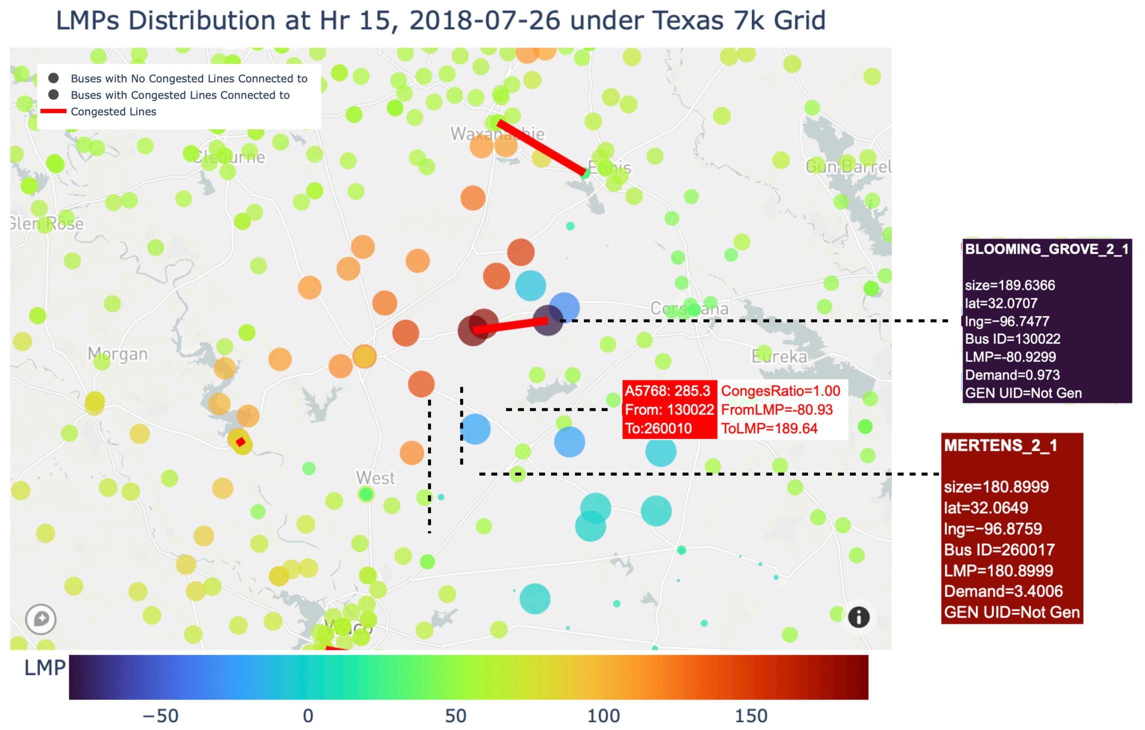
COMMERICAL APPLICATIONS

Our work is well suited to address grid uncertainty.

- **Storage revenue optimization** — grid **asset owners** can develop (i) **nodal distributions of locational marginal prices** and (ii) **risk indices** to structure **bids** that maximize profitability.
- **Calculation of Locational Marginal Emission Rates** — identify the production assets on the margin which determines the **marginal emission rate**. Renewable **portfolio owners** and **technology companies** building AI infrastructure rely on this information to guide **investment decisions.**
- **Bidding Strategies for portfolio owners of renewable assets** — owners of renewable assets can determine whether **taking a day-ahead position**, informed by risk indices on renewable production reliability, is preferable to being a passive price taker in the **real-time market**.
- **Bidding Strategies for Conventional resources** — with increased **volatility** in **Locational Marginal Prices** (LMPs), conventional asset owners will benefit from **day-ahead and real-time revenue projections** to refine their bidding strategies.
- **Stochastic tool for Grid Operators** — grid operators can leverage the to position the system for **reliably managing generation intermittency**.

TRY OUT OUR SOFTWARE!

VISUAL INTERACTIVE TOOL
https://orfeus.princeton.edu/data-visualization



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3. Princeton University, Vatic, https://github.com/PrincetonUniversity/Vatic/tree/main
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