



Risk Dashboard for Power Systems

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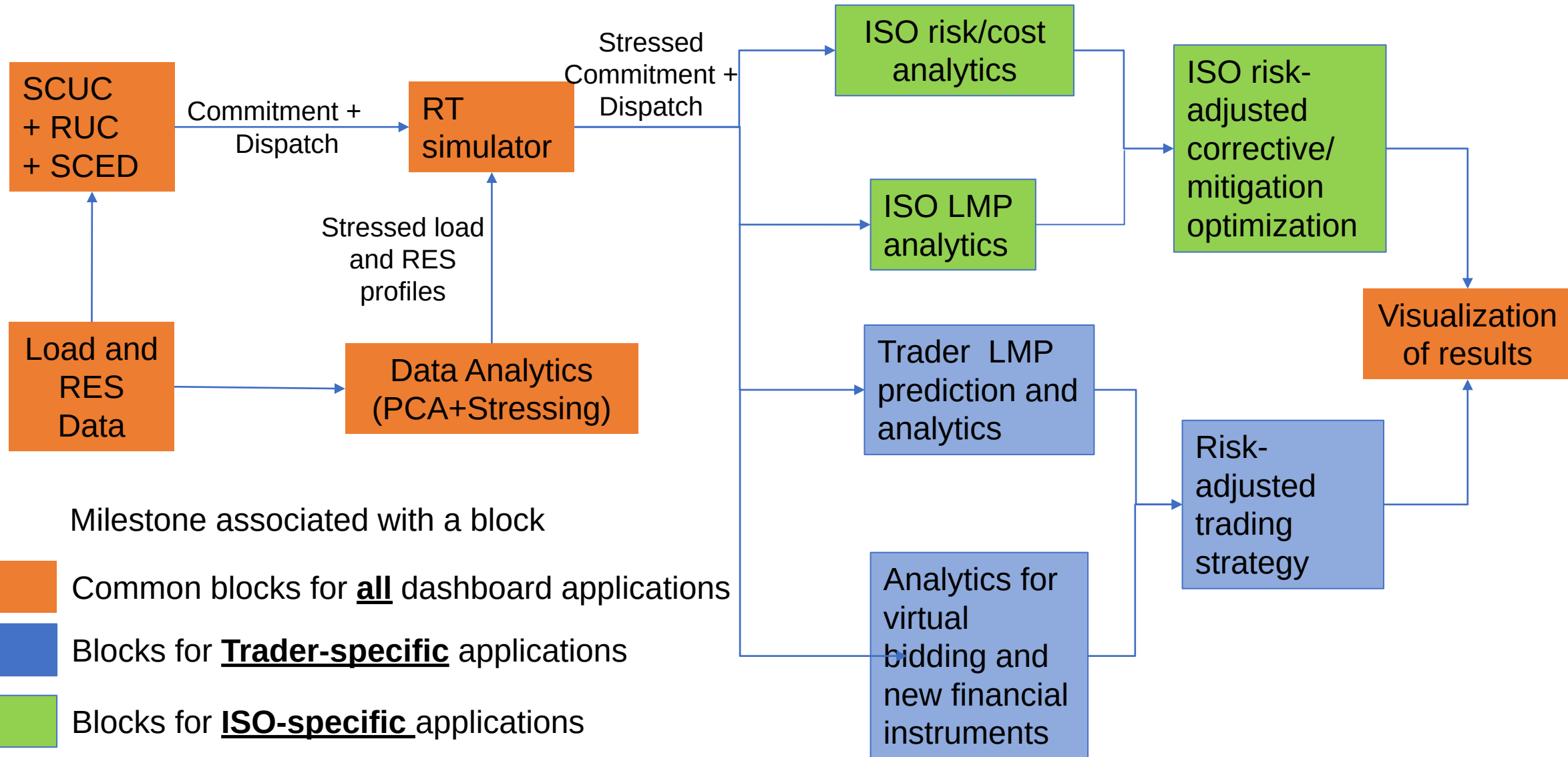
Heard at a recent PSERC meeting, from an ISO representative

Wind power can have large variability within a 5-minute window

"You can't make up 100 MW just like that"

- Our PERFORM team includes expertise in **power systems**, in **computational optimization**, in **financial engineering** and in **AI**.
- Goal of our program: help power systems participants make better **risk-aware decisions**.
- Our toolset is aggregated into a software product, a "**Risk Dashboard**".
- We are informed by our experience developing and selling software to the financial markets industry.
- Currently developing collaboration with NYISO and ISONE, and possibly other industry partners.

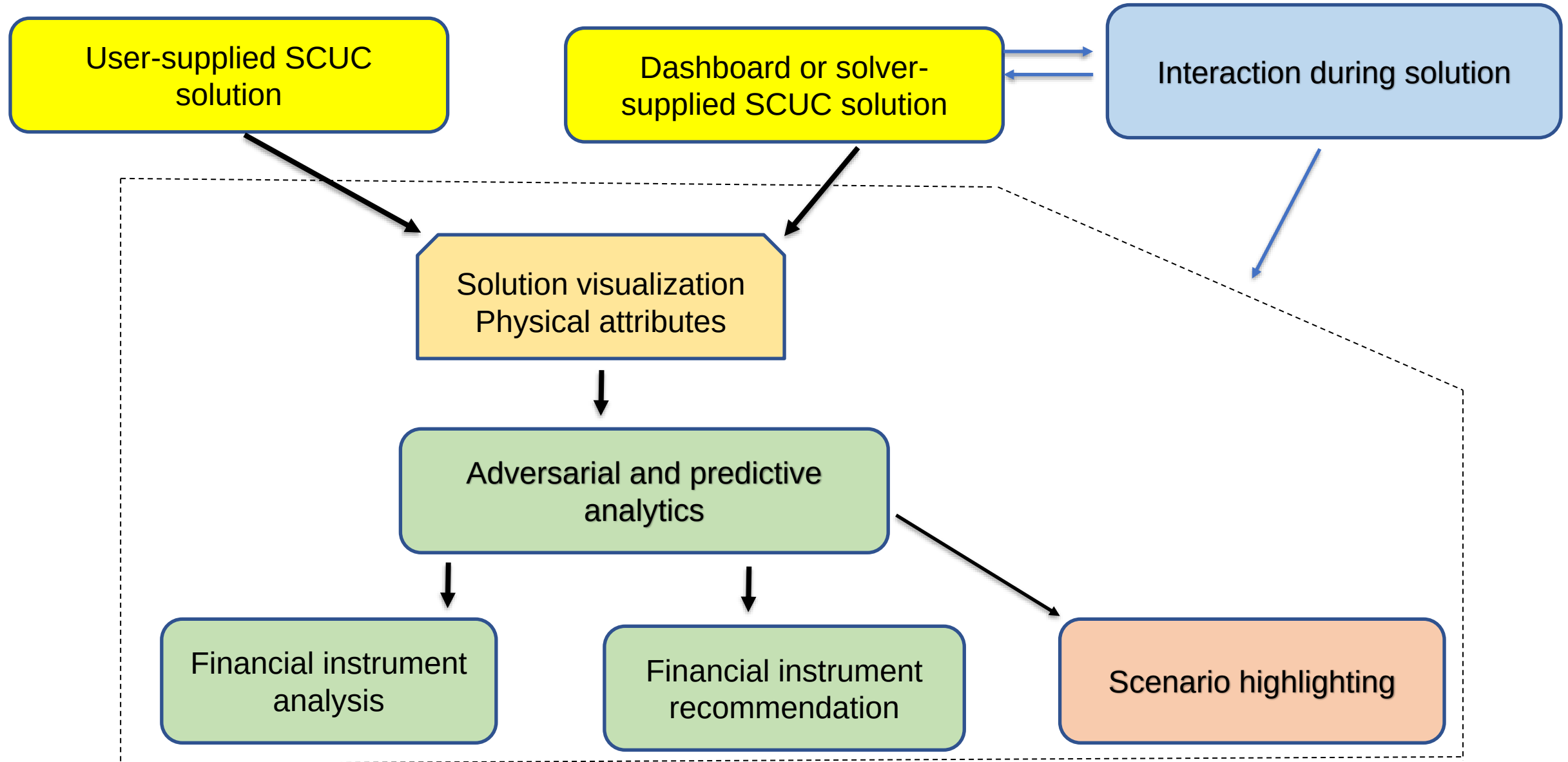
Outline of our Functionality



Scenario generation – essential component in risk assessment/control

- Basel Committee on Banking Supervision (2005): Scenarios (for risk analysis) should be **plausible** as well as **severe** as well as **suggestive of risk-reducing actions**.
- Currently, energy markets (SCUC) and real-time dispatch are not informed by plausible scenario-based risk considerations.
- Some might argue that dynamic reserves planning could incorporate such considerations.
- Our methodologies do not require a change in SCUC/RUC/RT, however will make it possible to perform rapid, counterfactual, scenario-based, data-driven risk analysis.
- We also (of course) are developing risk-aware versions of SCUC/RC/RT.
- **Factor stressing**: a key data-driven technique. **PCA analysis** of renewable/load **covariance matrices** shows latent low-rank structure (the “**factors**”).

Basic dashboard operation, V1



Algorithmic

- Scenario-enhanced SCUC and other forms of risk-aware SCUC
- Basic SCUC/RUC/SCED/RT dispatch
- Counterfactual evaluation of SCUC /RUC/SCED/RT dispatch solutions
- Computation of adversarial error-constrained scenarios
- **Risk-aware SCUC and real-time dispatch**
- High-volume (parallel/networked) rapid simulation/evaluation or RT behavior under volatile loads/renewables

ISO risk/cost
analytics

ISO LMP
analytics

ISO risk-
adjusted
corrective/
mitigation
optimization

Candidate solution exposed to adversary
Cuts then added to master formulation
Amounts to scenario generation on-the-fly
With a corresponding risk assessment

Wind/Load Power Stressing

**Obtain
forecast
weather data**

- Assume the forecast errors follow the historical distribution

**Stress wind
speed**

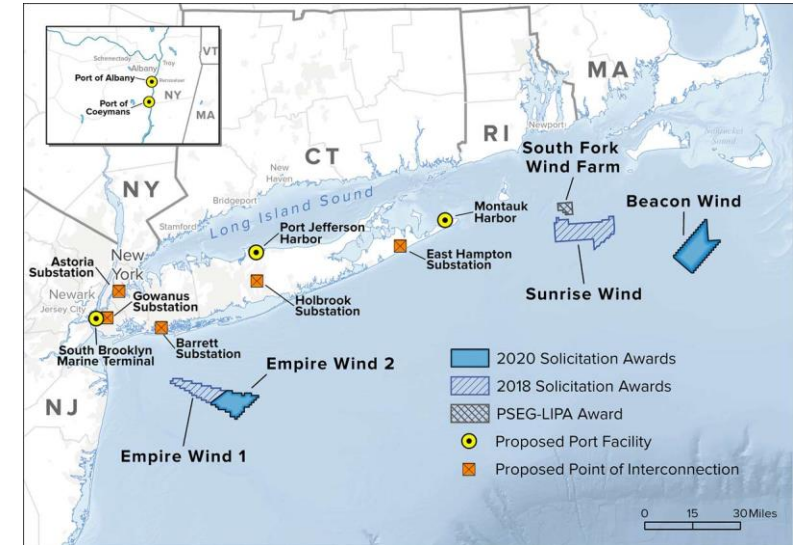
- Generate the forecast error in wind speed

**Stress other
weather data**

- Generate the forecast error in other weather features according to their correlations

**Generate
stressed wind
power**

- Calculate wind power based on the weather data with errors



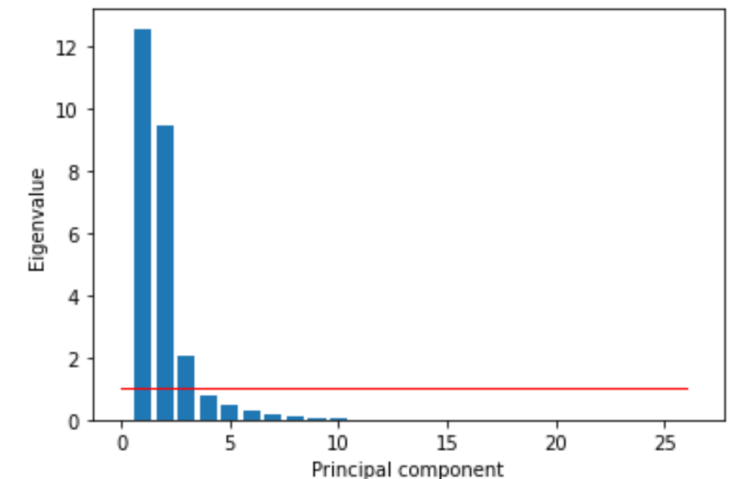
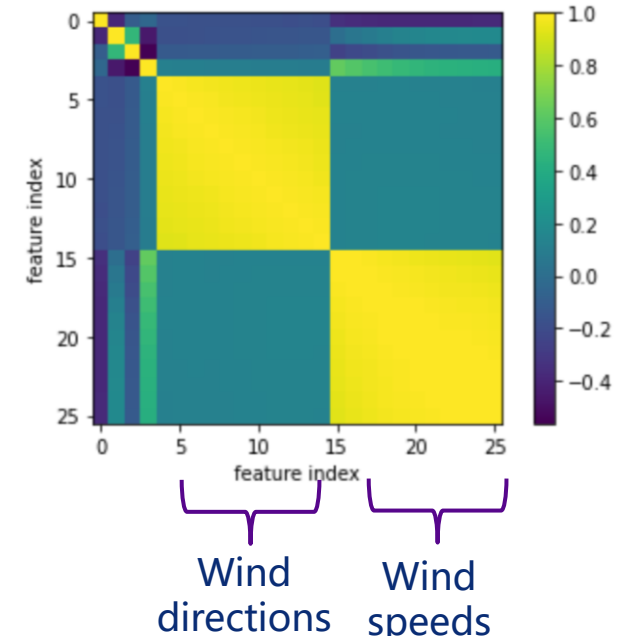
Wind/Load Power Stressing using PCA

Features used in wind power calculation

- | | |
|---|---------------------------------------|
| 1. surface air pressure (Pa) | } Used to calculate air density |
| 2. relative humidity at 2m (%) | |
| 3. air temperature at 2m (C) | |
| 4. turbulent kinetic energy at 120m (m2/s2) | Used to calculate turbulent intensity |
| 5. wind direction at 20m (deg) | 16. wind speed at 20m (m/s) |
| 6. wind direction at 40m (deg) | 17. wind speed at 40m (m/s) |
| 7. wind direction at 60m (deg) | 18. wind speed at 60m (m/s) |
| 8. wind direction at 80m (deg) | 19. wind speed at 80m (m/s) |
| 9. wind direction at 100m (deg) | 20. wind speed at 100m (m/s) |
| 10. wind direction at 120m (deg) | 21. wind speed at 120m (m/s) |
| 11. wind direction at 140m (deg) | 22. wind speed at 140m (m/s) |
| 12. wind direction at 160m (deg) | 23. wind speed at 160m (m/s) |
| 13. wind direction at 180m (deg) | 24. wind speed at 180m (m/s) |
| 14. wind direction at 200m (deg) | 25. wind speed at 200m (m/s) |
| 15. wind direction at 220m (deg) | 26. wind speed at 220m (m/s) |

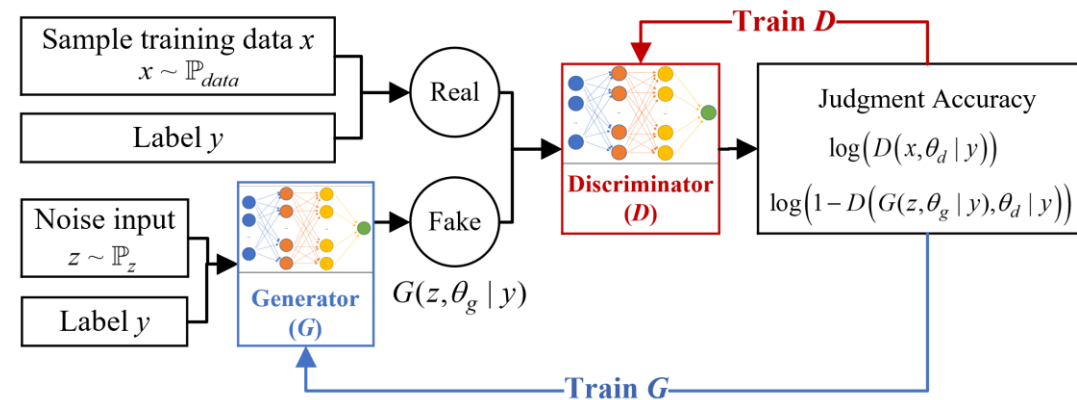
Only three principal components matter for stressing!

Correlated features



Wind/Load Power Stressing using GANs

GANs can be extended to a conditional model (**Conditional GANs, cGANs**) if both the generator and discriminator are conditioned on some **extra information y** .

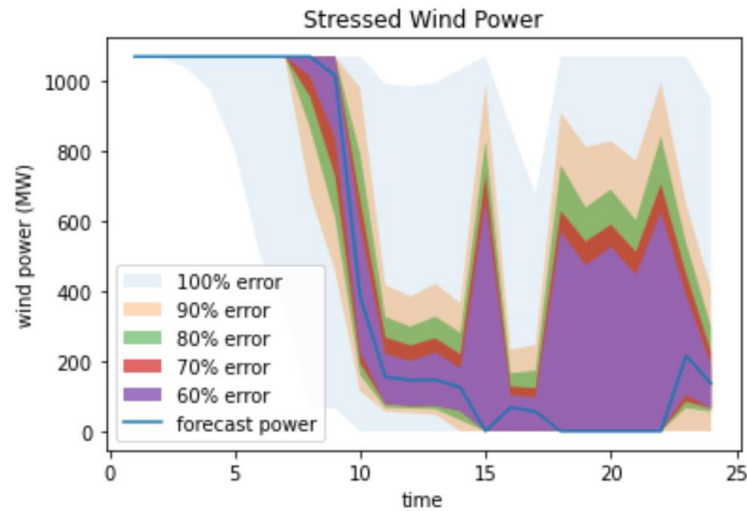


Conditional Generative Adversarial Network (cGAN)

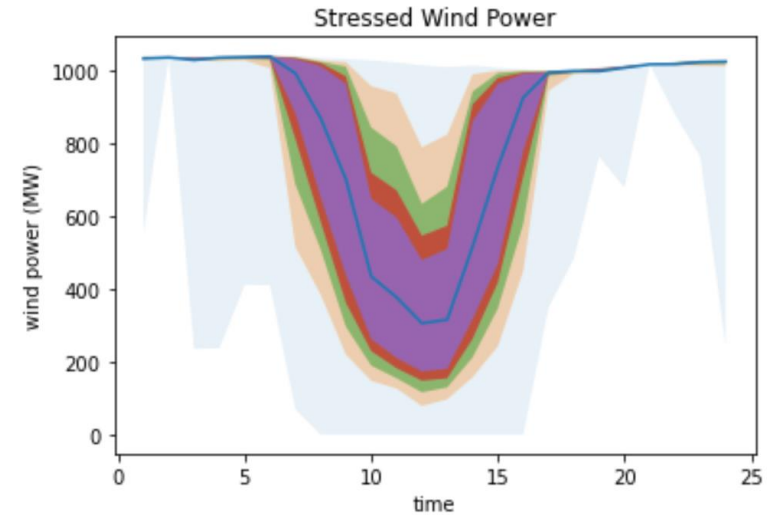
➤ **Objective of cGAN**
$$\min_{\theta_g} \max_{\theta_d} \mathbb{E}_{x \sim \mathbb{P}_{data}} [\log(D(x, \theta_d | y))] + \mathbb{E}_{z \sim \mathbb{P}_z} [\log(1 - D(G(z, \theta_g | y), \theta_d | y))]$$

Wind/Load Power Stressing using GANs

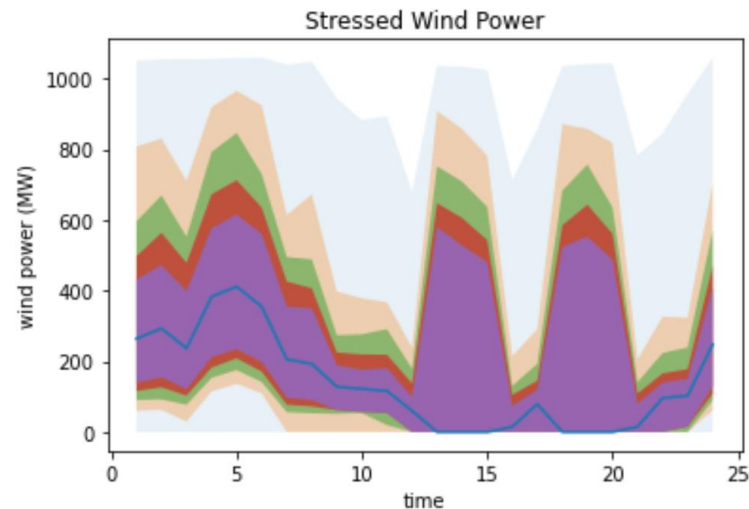
- **Case 1: January 1st**



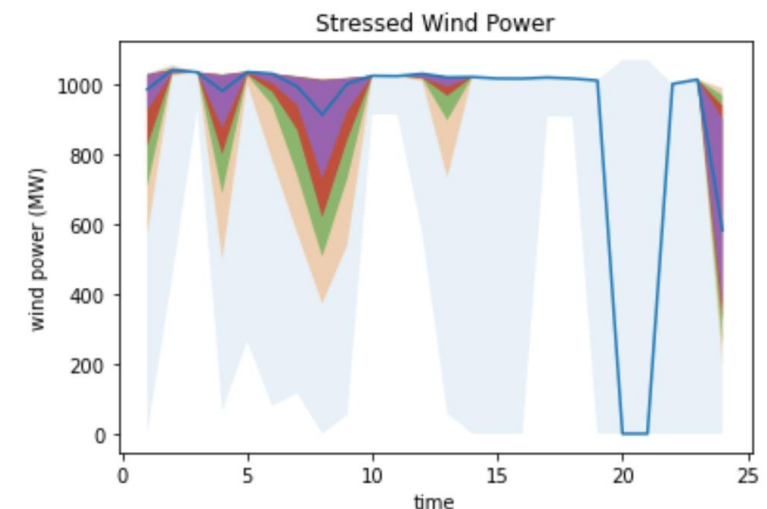
- **Case 2: March 14th**



- **Case 3: July 30th**

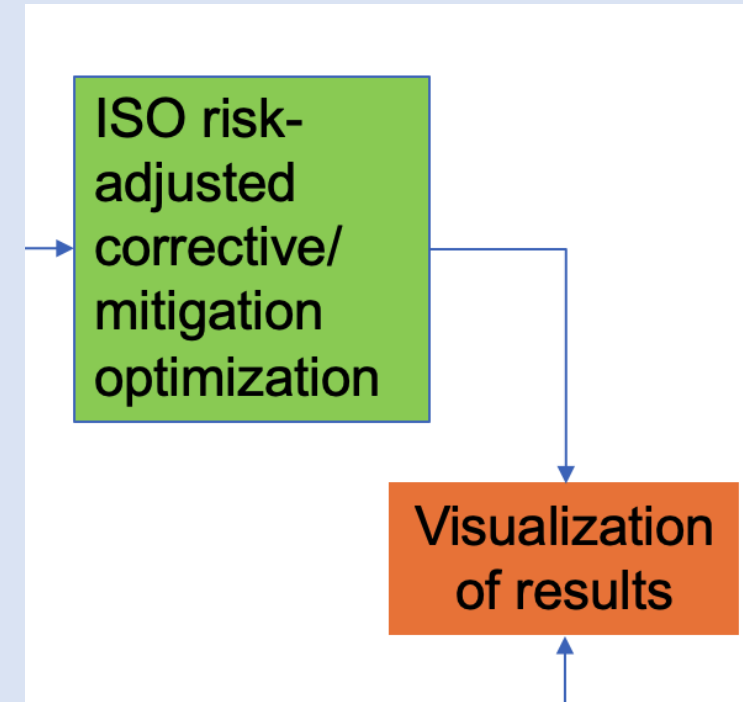


- **Case 4: October 29th**

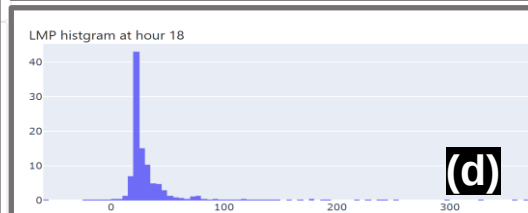
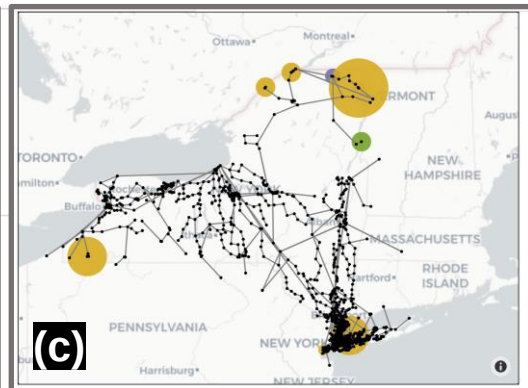
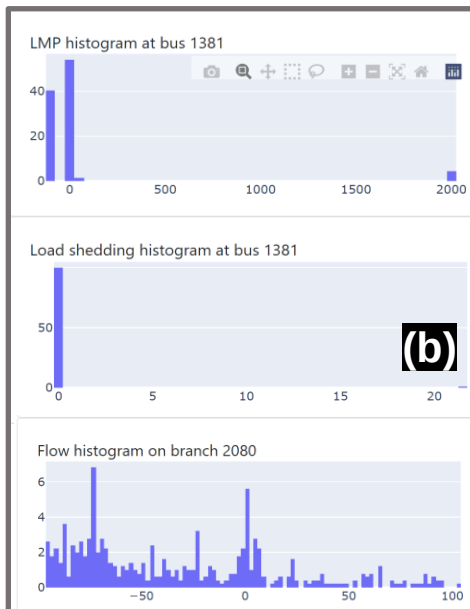
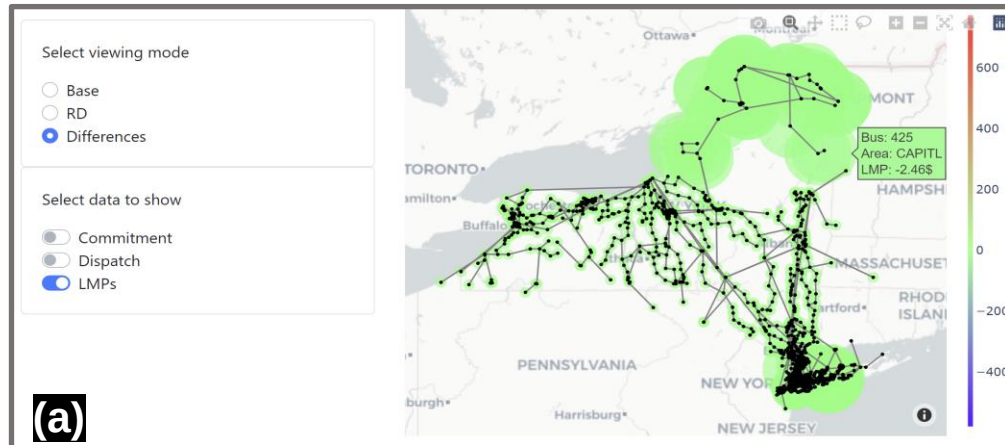


Visualization (partial list)

- Display of congestion, load shedding, wind spillage, LMPs, generation
- Display of financial statistics
- Display of risk map
- Displays interactive with solution procedure



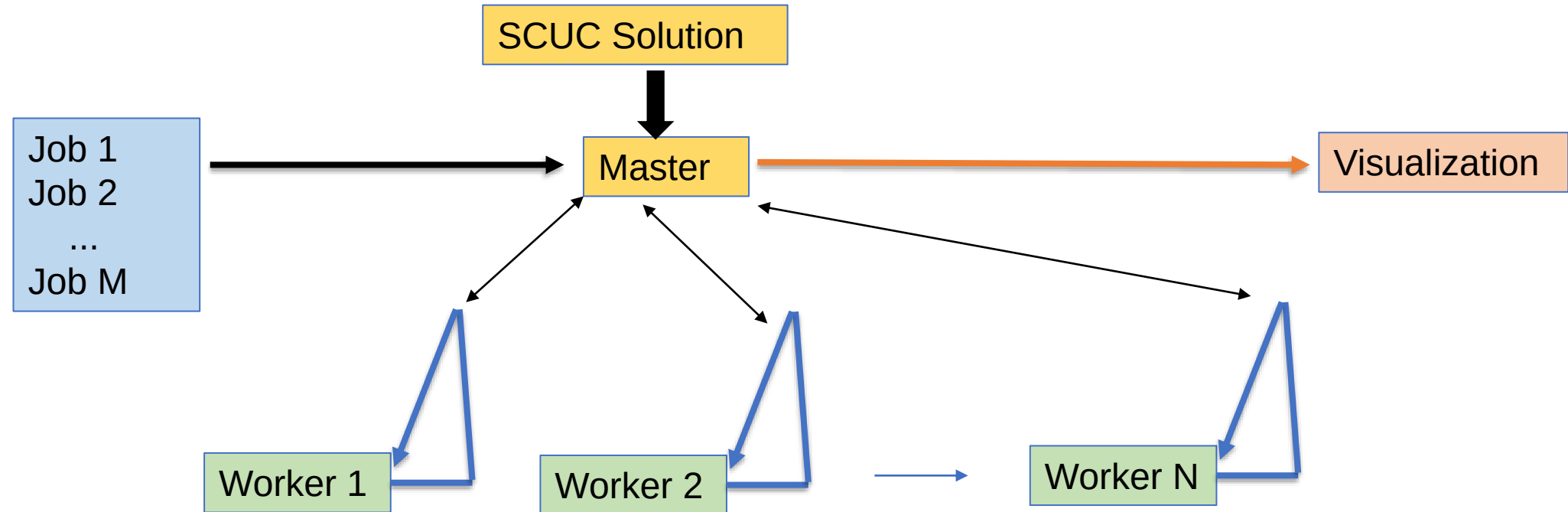
Visualization (partial list)



- (a) Visualization of the differences between the Risk-Driven (RD) and Baseline (BD)
- (b) Distribution of LMPs and load shedding and power flows across samples at a given node and edge
- (c) Display of nodal risks (measured as an expected power imbalance)
- (d) Distribution of LMP across samples for a given time interval

Master-Worker outline: Workhorse for our computations

Framework applicable to many uses. Today: simulation of RT outcomes of SCUC decisions



- Each worker implemented in a parallel process, runs a **sleep-wake-work-sleep cycle**
- ~ 100 % CPU efficiency across many cores
- On NYISO system RT dispatch framework attains throughput of ~1000 RT runs/second

Fintech

- Financial instrument design
- Financial instrument counterfactual analysis
- Financial instruments positioning as per SCUC
- Financial instrument portfolio computation

Trader LMP
prediction and
analytics

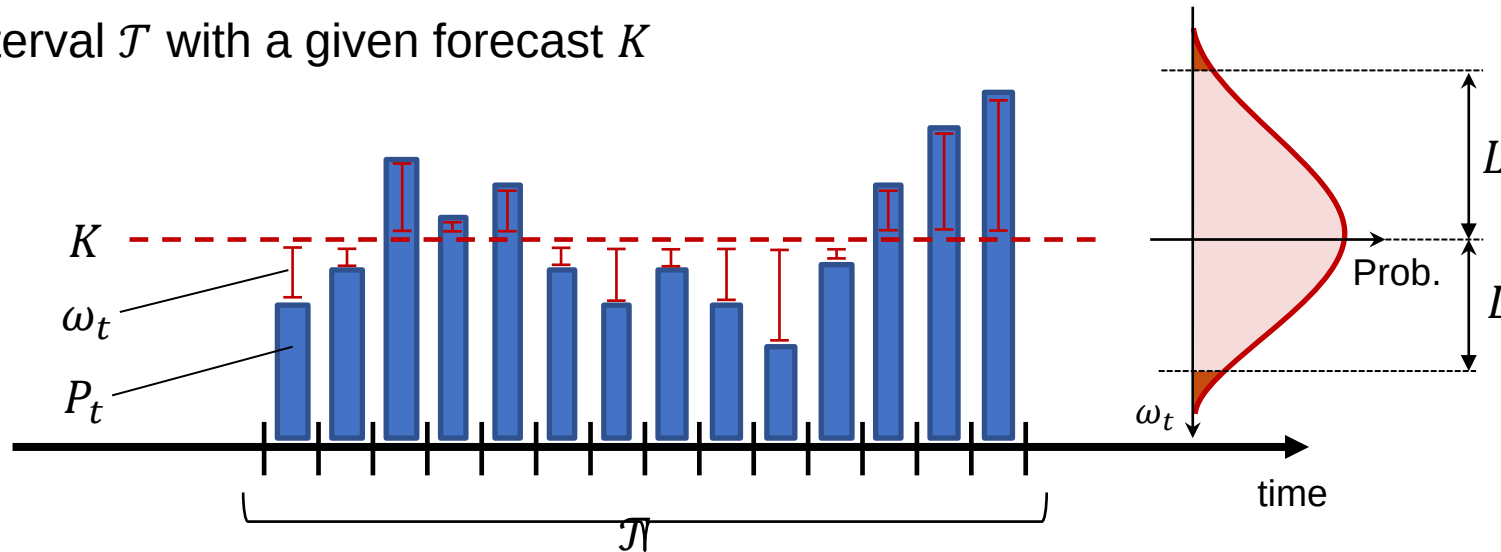
Analytics for
virtual
bidding and
new financial
instruments

Risk-
adjusted
**SCUC and
trading
strategy**

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graph LR; A[Trader LMP prediction and analytics] --> C[Risk-adjusted SCUC and trading strategy]; B[Analytics for virtual bidding and new financial instruments] --> C;
```

Fintech

- Define $\omega_t := K - P_t$ and assume $\omega_t \sim N(\mu, \sigma)$, where we call K_t **forecast** and ω_t **forecast error**
- Empirical studies suggest that a normal distribution is suitable to model wind power forecast error distributions
- Consider time interval $\mathcal{T}$ with a given forecast K



Reserve Provider

- Trades off between selling firm energy and reserving capacity for delivering flexible reserve
- Expected profit $\mathbb{E}[\sum_{t \in \mathcal{T}} \gamma \min(|\omega_t|, L)]$
- Opportunity cost of reserving L : $c_o(L)$

Wind producer

- Avoids over-/underproduction fees if $|\omega_t| \leq L$
- Expected fees for any $|\omega_t| > L$: $2\chi CVaR_{\alpha(L)}(\omega)$ where χ denotes fee for over/under generation (i.e., deviations from K) and CVaR is the expected value of ω_t under the condition that $\omega_t > L$

Effect of Fintech

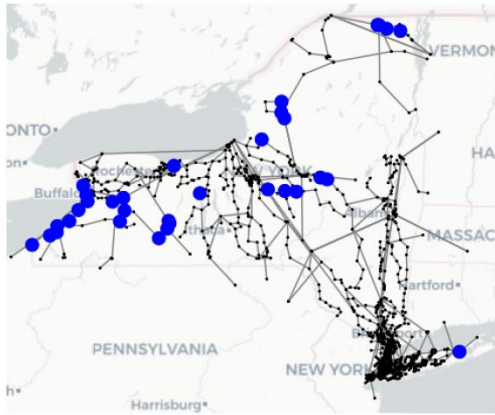
System performance with external financial instruments

	Aug. 28		Aug. 11		Aug. 3	
	BAU	RD	BAU	RD	BAU	RD
SCUC cost (base):	78.92 M\$	78.92 M\$	55.16 M\$	55.16 M\$	66.07 M\$	66.07 M\$
SCUC cost (RD):	–	82.76 M\$	–	56.59 M\$	–	67.05 M\$
RT cost (mean):	79.70 M\$	80.48 M\$	55.48 M\$	55.65 M\$	66.42 M\$	66.70 M\$
RT cost (90%-CVaR):	79.70 M\$	81.63 M\$	54.44 M\$	55.38 M\$	65.12 M\$	66.24 M\$
EENS:	283.88 MW	15.70 MW	55.81 MW	0.05 MW	79.65 MW	15.60 MW
Generator cost stdv.	0.20 M\$	1.21 M\$	0.16 M\$	0.45 M\$	0.20 M\$	0.46 M\$
Loss-of-load cost stdv.*	1.03 M\$	0.15 M\$	0.26 M\$	0.00 M\$	0.26 M\$	0.08 M\$

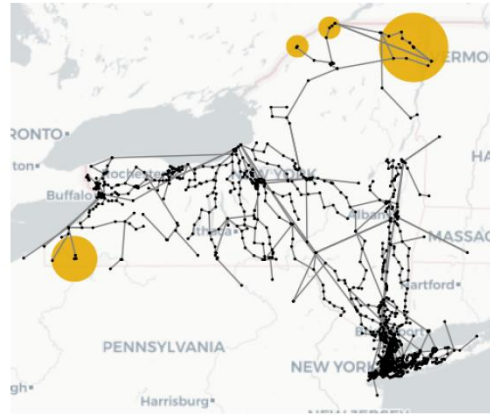
- RD leads to a systematically more expensive DA SCUC cost (up to 4.9%) and robustness of the cost solution
- However, RT costs (which are the ones that matter) are almost as cheap as BAU costs (up to a 1.2% in mean)
- RD leads to greater robustness: up to 1000x time reduction in EENS

Effect of Fintech

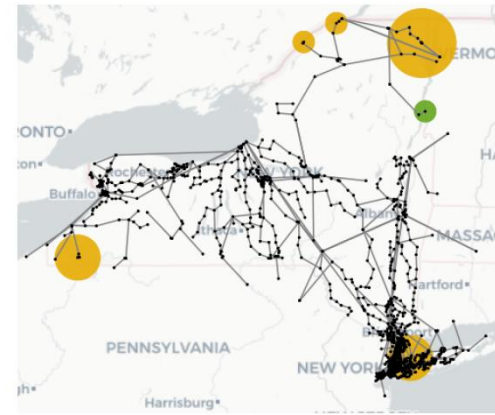
We also observe that the agent behavior differs (especially on stressed days, e.g. Aug 28)



(a) Wind sites



(b) Commitment changes BAU to RD at hour 16.

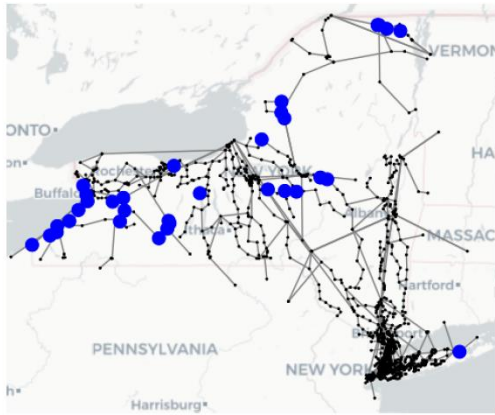


(c) Commitment changes BAU to RD at hour 18.

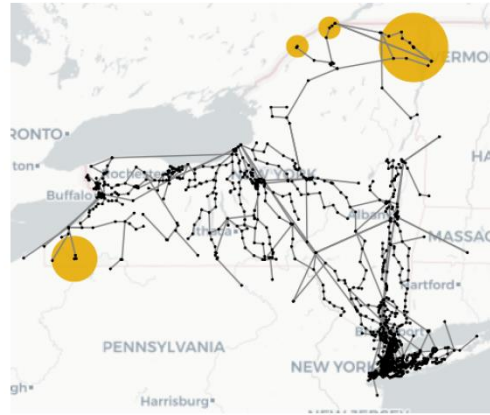
Changes affect not only gas units (e.g. additional commitments) but also other renewables (e.g. biofuels).

Effect of Fintech

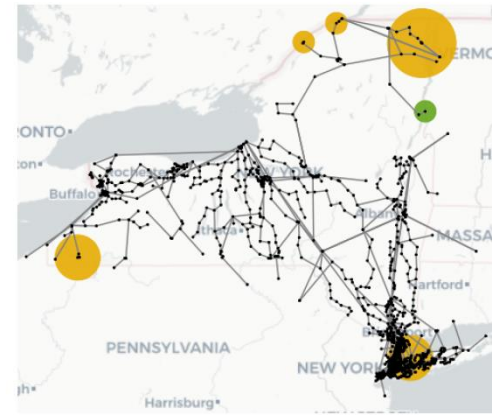
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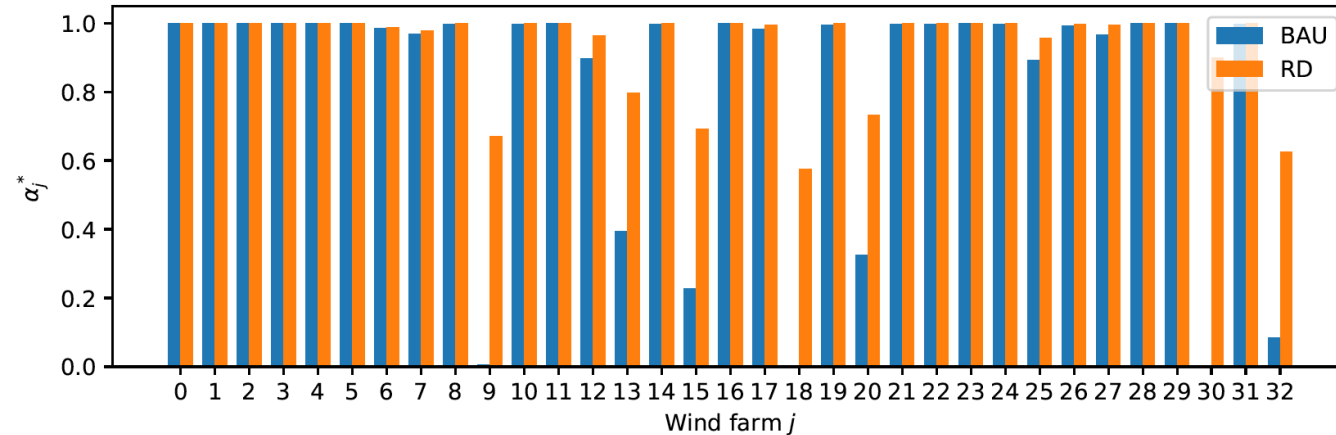
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Effect of Fintech

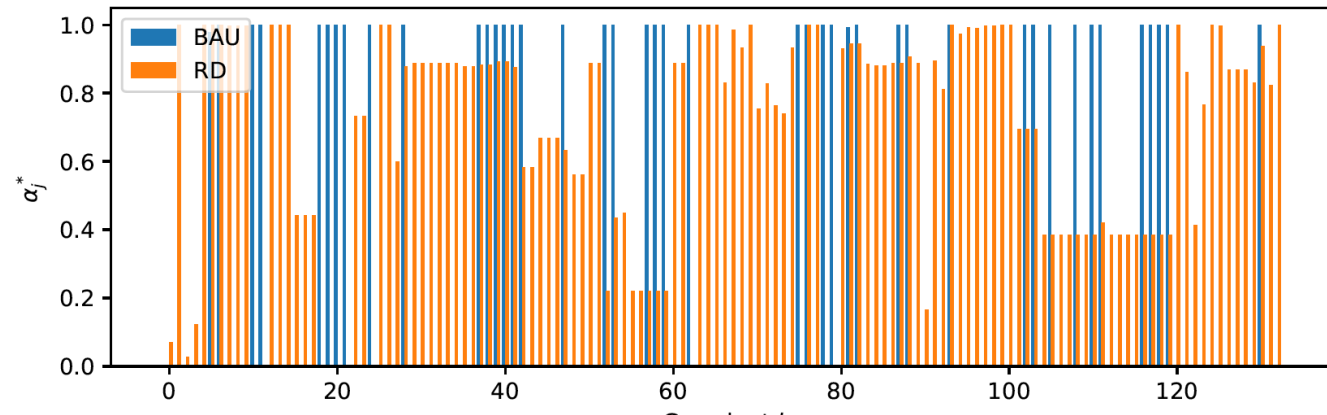
What are the effects of Fin Instruments on dispatch?

Wind
Producers



Averaging
 α_j favors RD

Natural Gas
Generators



	BAU	RD
Wind farms	0.809	0.935
Gas plants	0.323	0.675

Conclusion

- Risk management scales to realistically large networks
 - And we can improve our performance further
- Data stressing helps robustify the optimal dispatch using data-inspired but physically meaningful stressors
- Financial instruments help reduce the cost of the robust dispatch and provide extra compensation for flexible producers
- Visualization enhances situational and decision awareness