SOLAR ENERGY
TECHNOLOGIES OFFICE
U.S. Department Of Energy

Solar Uncertainty Management and Mitigation for Exceptional Reliability in Grid Operations (SUMMER-GO)

Solar Forecasting II: Annual Review and Workshop

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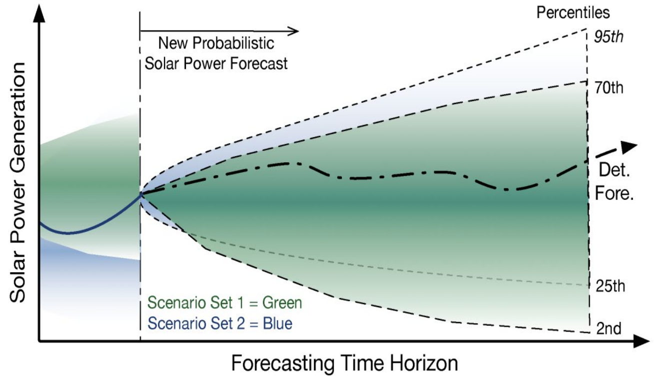
Project Objectives

SUMMER-GO will bring probabilistic solar forecasts into ERCOT's real-time operation environment through automated reserve and dispatch tools that increase economic efficiency and improve system reliability.

- Develop accurate, calibrated, and sharp probabilistic solar power forecasts at multiple time-scales & spatial resolutions
- Develop and validate risk-parity economic dispatch for ***5-minute dispatch period*** through ***novel application*** of financial planning techniques
- Develop and validate adaptive reserves algorithm to ***reduce flexibility and regulation reserves by >25%*** and ***deploy in ERCOT'S iTest system***
- Produce situational awareness tool, SolarView, to present relevant, timely information and allow for ***better decision making***



Project Progress to Date

Budget Period 1 Focuses:

1. Develop Probabilistic Solar Power Forecasts
2. Develop Adaptive Reserve Algorithms
3. Develop Risk-Parity Dispatch
4. Develop Situational Awareness Tool, SolarView

Focus 1: Probabilistic Forecasting

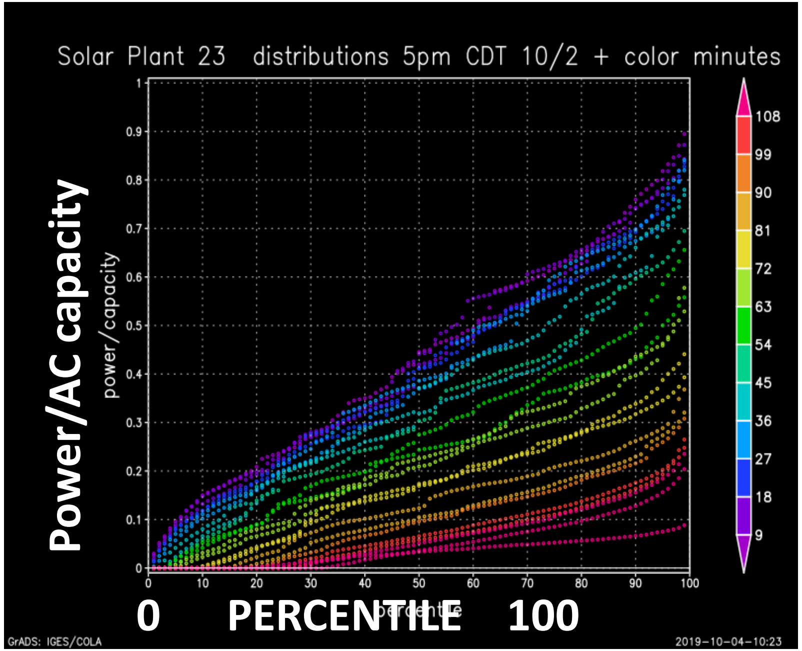
Large ensemble development

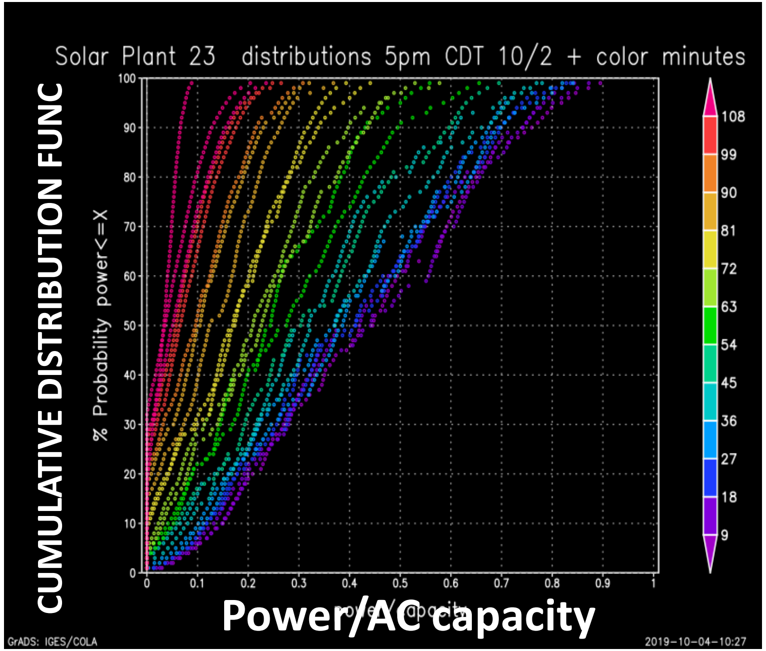
- Expanding from typical ensemble size to very large, ~130-member ensemble
- Combination of time-lagged members and perturbed ensemble sets
- NWP model GHI passed through Maxar solar power forecast system → power for each member

Model	Output grid	Output maximum lead time	Output interval	Forecast updates	Time lag members in dataset	Number of members per run
ECMWF High-res	0.125°	240 h	1 h	6 h	3	1
NOAA GFS	0.25°	384 h	1 h	6 h	3	1
NOAA NAM nest	3 km	60 h	1 h	6 h	3	1
NOAA HRRR	3 km	18 h	15 min	1 h	15	1
ECMWF ensembles	1°	360 h	6 h	12 h	1	51
NOAA GFS ensembles	0.5°	384 h	3 h	6 h	1	21
NOAA Rapid Refresh	13 km	18 h	1 h	1 h	15	1
NOAA Short-Range Ens	16 km	87 h	3 h	6 h	1	13
Canadian Global	0.24°	384 h	3 h	12 h	2	1
Canadian Regional	10 km	48 h	1 h	6 h	3	1

Example Forecasts From Large Ensemble

- Real-time example: Issued at 5:00 pm on October 2nd for 6:00 pm
- Late in the day with variable clouds





Probabilistic Forecast Post-Processing

Challenges of raw NWP ensemble:

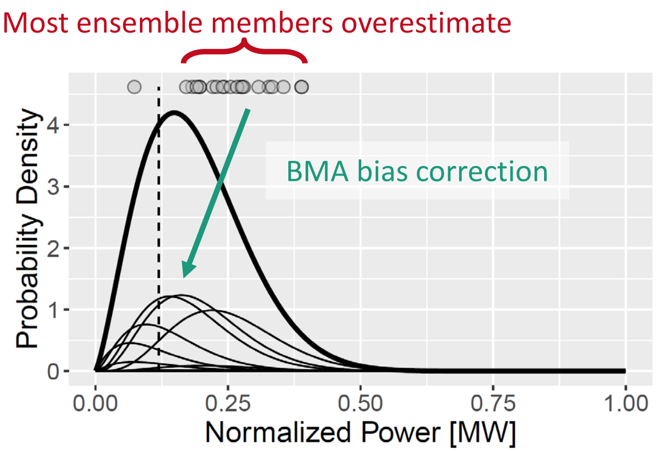
- Under-dispersion, bias, and coarseness
- Inverter clipping

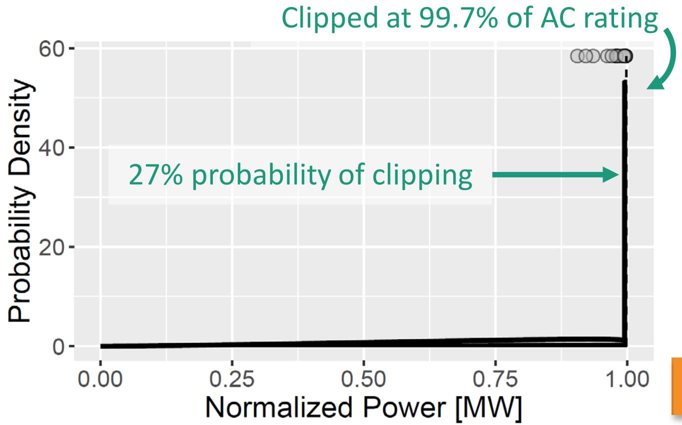
Bayesian model averaging (BMA) post-processing:

- Member-by-member correction
- Members weighted based on historical performance
- Overall probability is a mixture:

$$p(y|f_1, \dots, f_K) = \sum_{k=1}^{K} w_k h_k(y|f_k)$$

- Each ensemble member is dressed with a two-part model, $h_k(y|f_k)$:
    1. Beta kernel
    2. Estimate of probability of clipping





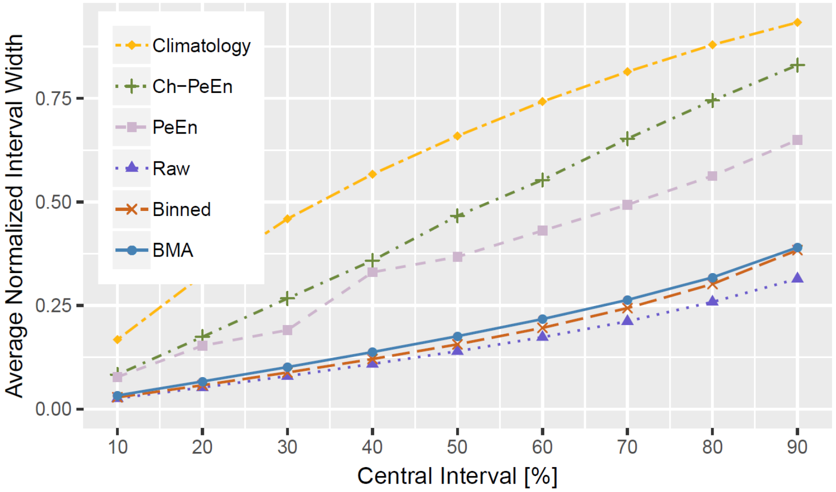
Forecast Benchmarking

Case study for probabilistic metric evaluation:

- Rolling 4-hour ahead, hourly resolution forecast over 2018
- 11 sites in Texas

Compare 4 methods:

1. (Benchmark 1) “PeEn”: Persistence Ensemble
   - Empirical CDF of last 20 measurements at same hour of the day
2. (Benchmark 2) “Raw”: Empirical CDF of raw NWP ensemble
3. “SLI”: 72-hour Sliding Window BMA forecast
   - Trained with forecasts and observations from the last n hours
4. “TOD”: 60-day Time-of-Day BMA forecast
   - Trained with forecasts and observations from the last n days, plus a $(2n+1)$-day window centered at the same date in the previous year



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Probabilistic Metrics

- Evaluate average sharpness of central $(1 - \rho) \times 100\%$ interval:

$$\frac{1}{T}\sum_{t=1}^{T} F_t^{-1}\left(1-\frac{\rho}{2}\right) - F_t^{-1}\left(\frac{\rho}{2}\right)$$

- Continuous Ranked Probability Score (CRPS) captures sharpness and reliability

$$\overline{\text{CRPS}} = \int_0^1 \frac{1}{T}\sum_{t=1}^{T} \text{QS}_\phi(F_t^{-1}(\phi), y_t)\,d\phi$$

  - where the quantile score is:

$$\text{QS}_\phi = 2(\mathbf{1}\{y_t \le F_t^{-1}(\phi)\} - \phi)(F_t^{-1}(\phi) - y_t)$$

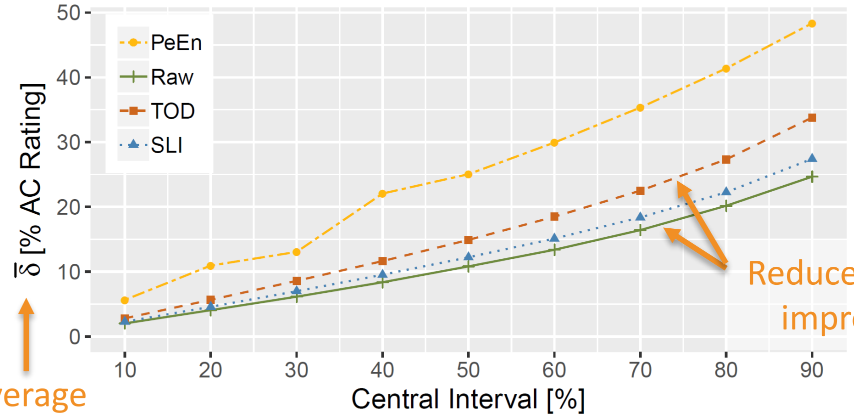
  - Can be substituted with weighted quantile score:

$$\text{wQS}_\phi = w(\phi)\text{QS}_\phi, \text{ where } w(\phi) = \begin{cases} (1-\phi)^2, & \text{left-weighted} \\ \phi(1-\phi), & \text{center-weighted} \\ \phi^2\,, & \text{right-weighted} \end{cases}$$

- Compare improvement over a reference forecast through CRPS skill score:

$$\text{SS} = \frac{\overline{\text{CRPS}} - \overline{\text{CRPS}}_{ref}}{\overline{\text{CRPS}}_{ideal} - \overline{\text{CRPS}}_{ref}} = 1 - \frac{\overline{\text{CRPS}}}{\overline{\text{CRPS}}_{ref}}$$

Methods Comparison for a Single Site

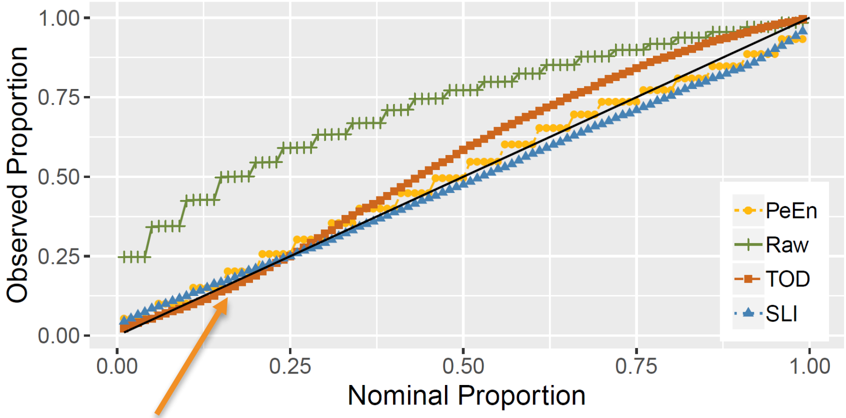


Average interval width

Sharpness

Reduce sharpness, but improve reliability

Reliability



Better calibration, particularly at lower tail

11-Site Case Study Results

- PeEn forecast is coarsely calibrated but broad.
- Raw ensemble is very sharp, but unreliable.
- BMA has CRPS skill scores of **27—50%** over PeEn.
- Raw NWP ensemble has CRPS skill scores of **14—45%** over PeEn.
- BMA has CRPS skill scores of **3—36%** over raw ensemble.
- Most sites improve with either BMA approach
    - A few are better with SLI but worse with TOD.
- SLI errs towards under-dispersion; TOD errs towards over-dispersion.

$\overline{\text{CRPS}}$ & SS OF ROLLING 4-HOUR AHEAD FORECASTS OVER 2018 FOR REMAINING 9 PV PLANTS. SS_{PeEn} IS SS WITH PEEN AS THE REFERENCE FORECAST; SS_{RAW} IS REFERENCED TO THE RAW ENSEMBLE.

Site	$\overline{\text{CRPS}}$ (%$\mathcal{P}$) PeEn	Raw	SLI	TOD	SS_{PeEn} (%) SLI	TOD	SS_{raw} (%) SLI	TOD
C	9.74	8.40	6.00	**5.65**	41.2	**44.7**	28.5	**32.7**
D	10.2	6.74	**6.46**	7.35	**36.8**	28.1	**4.13**	-9.03
E	13.5	7.53	7.37	**7.04**	27.8	**31.1**	2.11	**6.54**
F	9.86	6.93	**6.09**	6.10	**40.4**	40.2	**12.2**	11.9
G	11.9	10.0	**6.39**	8.46	**37.5**	17.2	**36.3**	15.6
H	11.0	8.17	**6.96**	**6.96**	31.8	**31.9**	**14.8**	**14.8**
I	10.8	8.07	6.90	**6.89**	32.4	**32.5**	14.4	**14.5**
J	12.3	7.72	**7.47**	7.48	**26.9**	26.8	**3.17**	3.09
K	12.6	6.91	**6.44**	7.09	**37.0**	30.6	**6.89**	-2.53

BMA Forecast Performance

Performance across multiple lead-times

- Analysis re-run at 1-, 12-, and 24-hour lead-times
- Ensemble size reduces from 21 members to 14 (12-hour ahead) or 9 (24-hour ahead)
- CRPS skill score improvements maintained or increased

Performance of Distribution Tails

- Under-estimation of tail risk concerning to utilities
  - High cost, high reliability impacts
- Weighted CRPS skill scores compared to raw ensemble show left tail has the highest improvement (**6-47%**)
  - Right tail improves for most sites as well, with skill scores up to **22%**

	SLI				TOD			
Site	$w = 1$	w_l	w_c	w_r	$w = 1$	w_l	w_c	w_r
A	7.87	11.4	8.35	3.25	5.61	8.64	5.20	2.74
B	12.7	16.2	12.0	9.73	13.1	16.4	12.4	10.4
C	28.5	38.7	27.6	16.2	32.7	42.0	31.6	21.9
D	4.13	8.37	3.39	-0.37	-9.03	-6.23	-11.2	-9.54
E	2.11	5.70	1.92	-1.56	6.54	8.52	6.11	4.94
F	12.1	20.7	11.9	1.01	11.9	16.5	10.2	8.26
G	36.3	47.0	34.6	21.8	15.6	28.0	10.9	3.28
H	14.8	19.6	15.6	8.21	14.8	20.5	14.2	9.23
I	14.4	21.2	15.5	4.83	14.5	20.5	13.9	8.30
J	3.17	8.30	2.47	-2.37	3.09	8.96	1.47	-2.05
K	6.89	11.0	7.13	1.46	-2.53	-3.28	-2.37	-1.84

Focus 2: Adaptive Reserve Algorithm (ARA)

Step 1: ERCOT Non-Spinning reserve baseline

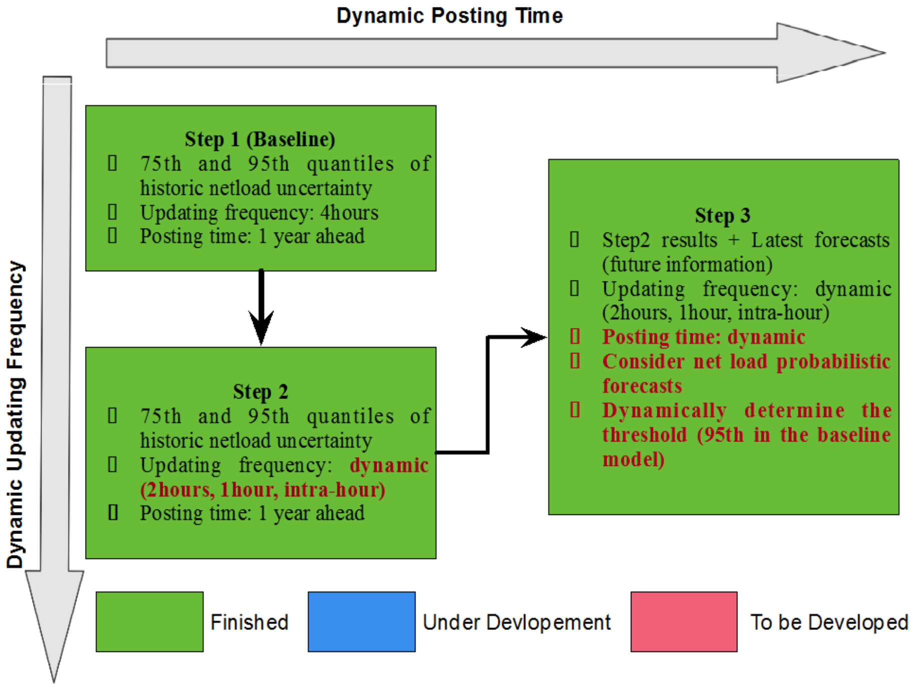
- Four-hour block
- $70^{th}/95^{th}$ netload uncertainty of the same month in previous three years
- Post 1-year before

Step 2: Dynamic updating frequency

- Change Non-Spin profile resolution based on data resolution (1-hour)
- Testing 1-hour and 2-hour updating frequency

Step 3: Dynamic posting time

- Probabilistic netload forecasts
- Update with the forecast's timeline
- Dynamic threshold based on forecasting uncertainty



Flowchart of the developed adaptive Non-Spin reserve algorithm

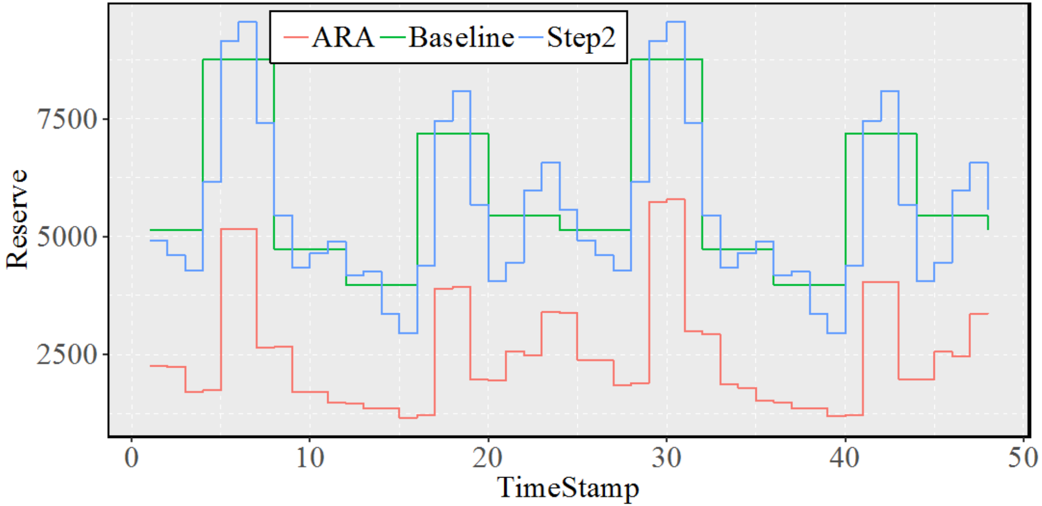
Adaptive Reserves Results

Results from dynamic updating frequency ("Step 2"):

- ✓ More flexible updating frequency
- ✓ 2-hour updating: **5.3%** reduction
- ✓ 1-hour updating: **7.5%** reduction

Results from adding dynamic posting time ("ARA"):

- ✓ Flexible daily profile
- ✓ Adaptive based on the future net load uncertainty
- ✓ Up to **45%** reduction, given case study forecast at 95% confidence level
- ✓ The reserve reduction can be modified based on different confidence levels



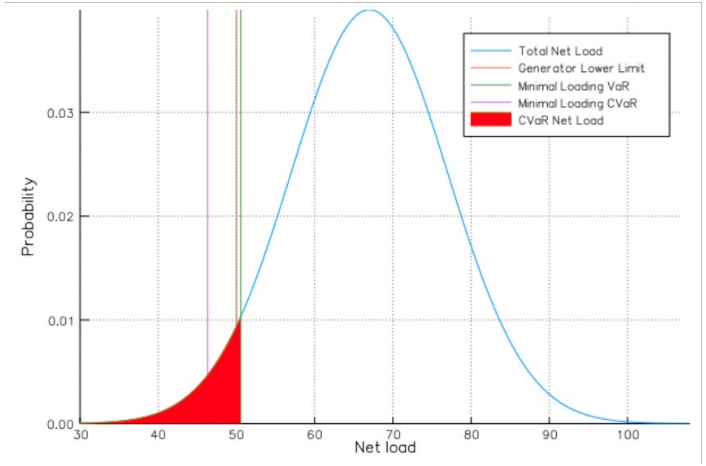
Two day Non-spin profiles of determined by different steps

Focus 3: Risk-Parity Economic Dispatch

Objective: *Minimize risk in economic dispatch internalizing Conditional Value at Risk (CVaR)*

- Two values need be incorporated:
  - **curtailment risk**
  - **load shedding risk**

- Model CVaR using the 100 percentiles of the probabilistic forecast



$$
\begin{aligned}
\min_{\mathbf{P},\,\delta}\quad & \sum_{i\in\mathcal{T}} f_i(p_{th,i}) + (C_{li}\delta_{li} - C_{rc}\delta_{rc})^2 \\
\text{s.t.}\quad & -\left(\sum_{i\in\mathcal{T}} p_{th,i} + \sum_{k=1}^{M} u_{li}^k P_{re}^k - \sum_{i\in\mathcal{L}} p_{l,i}\right) \geq \delta_{li}, \\
& \sum_{k=1}^{M} u_{li}^k = 1, \\
& 0 \leq u_{li}^k \leq \frac{1}{\varepsilon} p^k \quad \forall k = 1, \ldots, M, \\
& \left(\sum_{i\in\mathcal{T}} p_{th,i} + \sum_{k=1}^{M} u_{li}^k P_{re}^k - \sum_{i\in\mathcal{L}} p_{l,i}\right) \geq \delta_{rc}, \\
& \sum_{k=1}^{M} u_{rc}^k = 1, \\
& 0 \leq u_{rc}^k \leq \frac{1}{\varepsilon} p^k \quad \forall k = 1, \ldots, M, \\
& p_{th,i} \in \mathcal{X}_{th,i}, \\
& \delta_{li} \geq 0, \quad \delta_{rc} \geq 0
\end{aligned}
$$

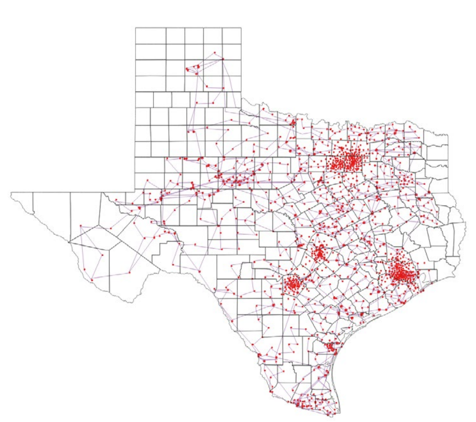
Load Shedding Risk

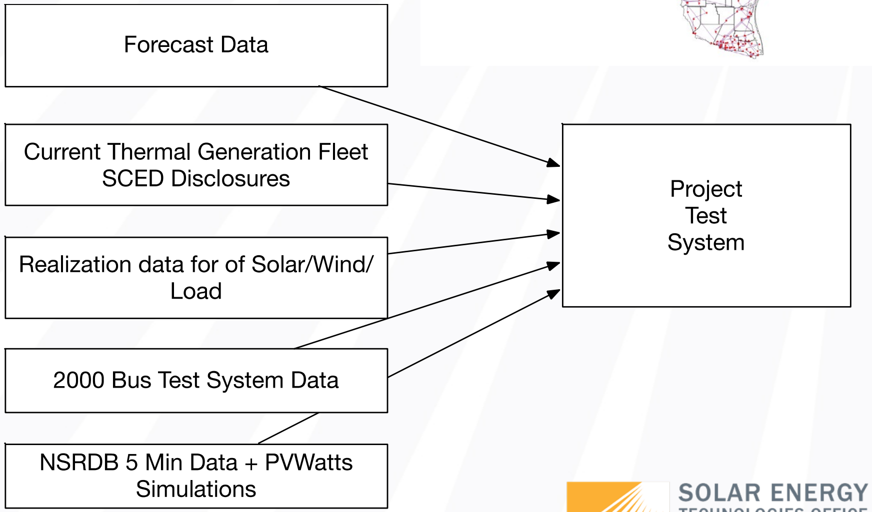
Renewables Curtail Risk

Detailed ERCOT Test Model

- SCED Disclosure data has been analyzed to develop a comprehensive thermal fleet data set for ERCOT.
- 2 years of realization data for Wind/Solar/Load has been parsed and assigned to the zones.
- The thermal fleet has been assigned to buses in the 2000 Bus System
- New solar plants locations have been identified

ACTIVSg2000 synthetic ERCOT system

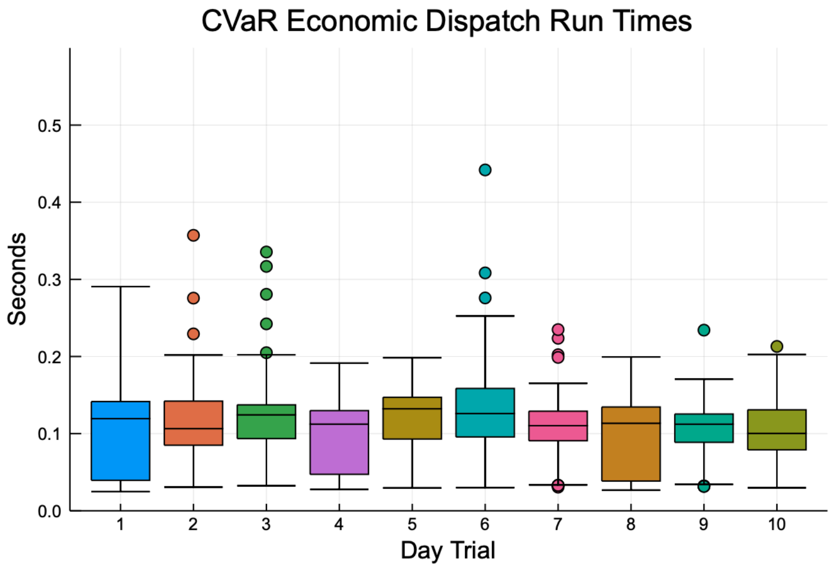


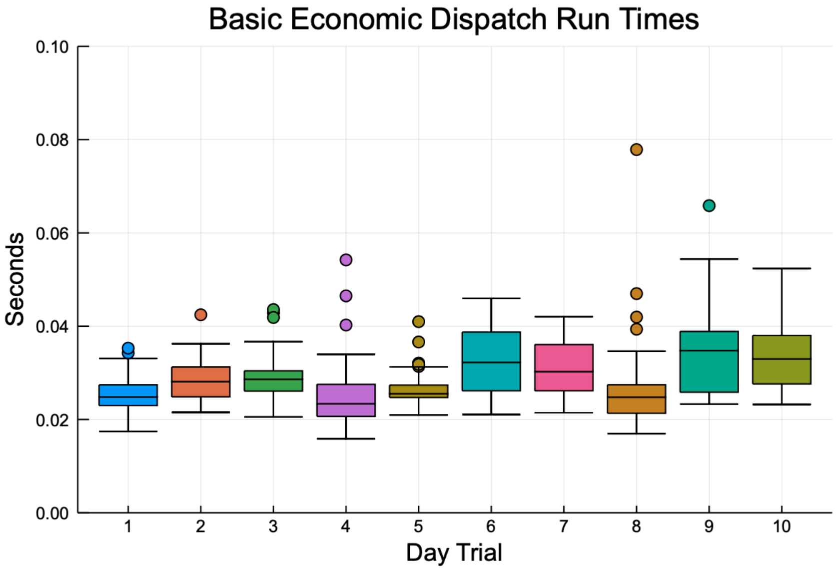


Computational Environment

- The resulting problem is an LQ problem.
  - Language: Julia 1.2.0
  - AML: JuMP v0.20.0
  - Solver: Gurobi 8.11 (Barrier Method)
- Hardware:
  - Processor: 3.1 GHz Intel Core i7
  - Memory: 16 GB 2133 MHz LPDDR3
- Simulation and Data Model:
  - `PowerSimulations.jl`
  - `PowerSystems.jl`

Computational Times CVaR Economic Dispatch

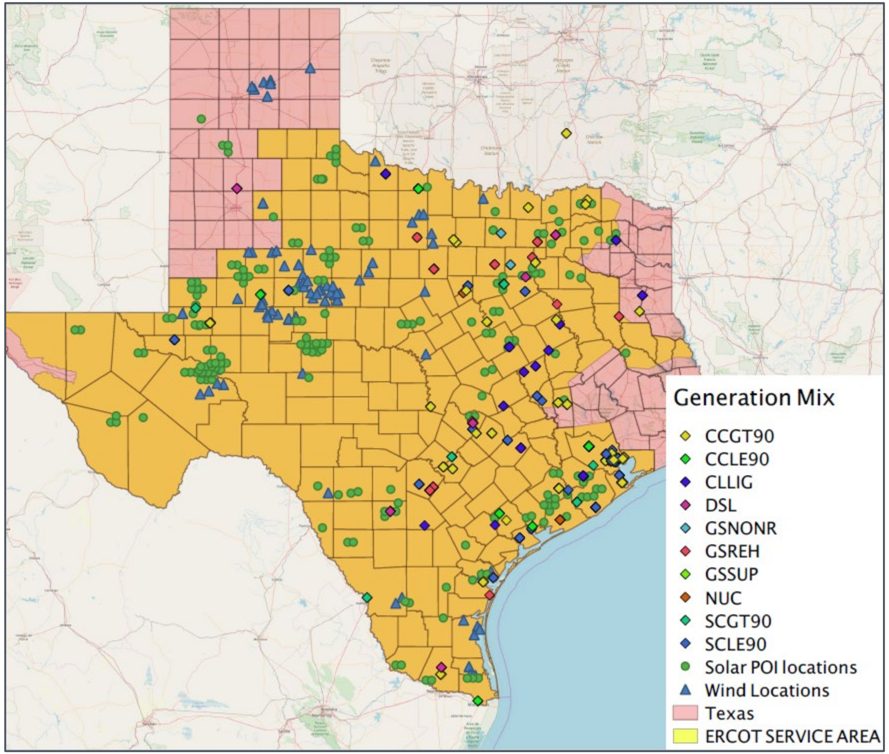


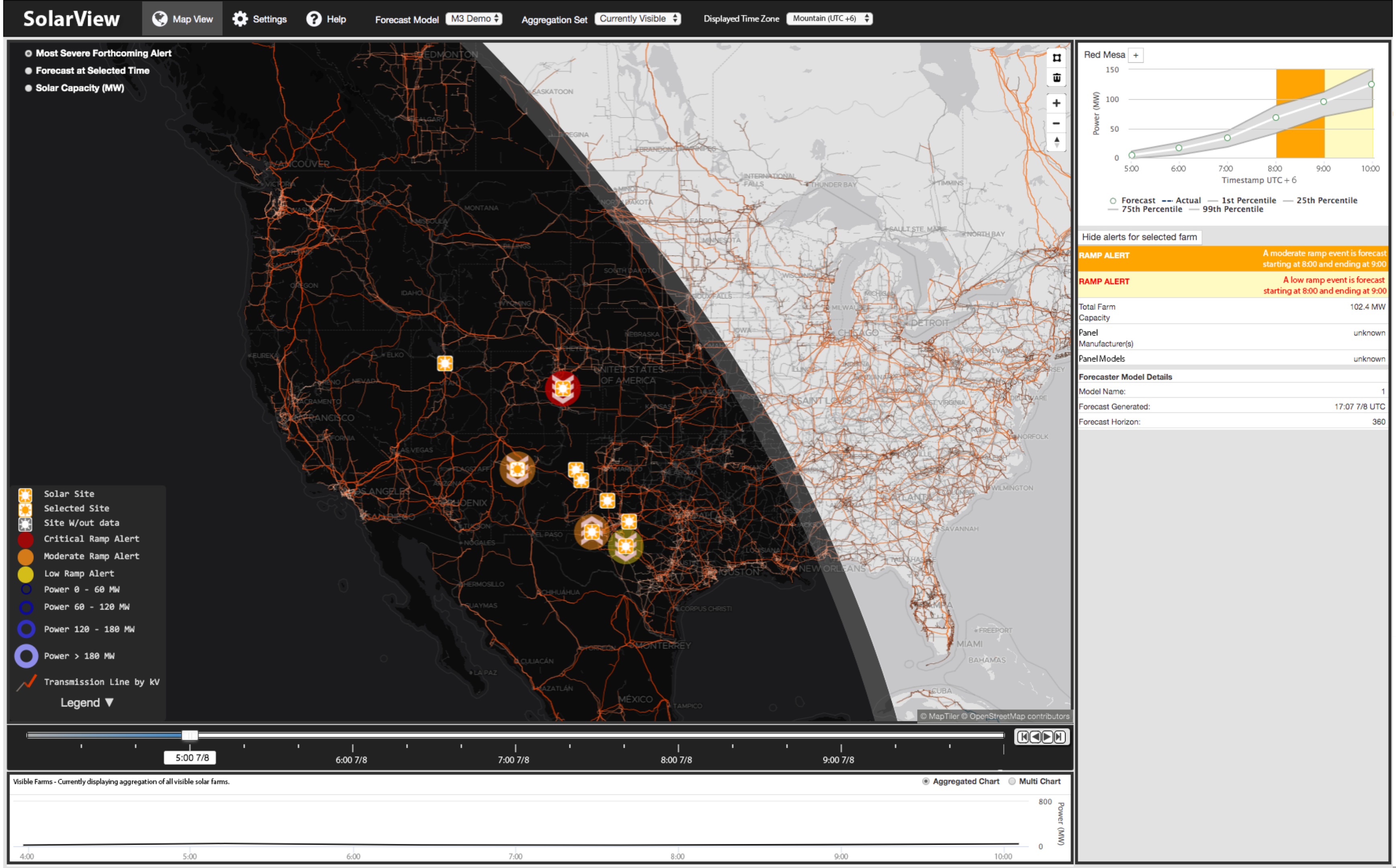


- Preliminary evaluation of 10 representative days of operations: 5-minute resolution, 15-minute update
- CVaR-ED model shows slower solution times given the addition of the probability simplex and the CvAR estimation.
- The solution times are still reasonable to be used for Economic Dispatch operations.

High-Solar Future Scenario: In Progress

- Simulating **39 GW** solar from **204** new plants
  - From ERCOT's Interconnection Queue (May 2019) with completed Full Interconnection Study
- **~30%** expected annual solar penetration
  - Keeping load, thermal generators, and wind capacity constant
- Ballpark instantaneous solar penetration (pre-curtailment): **>55-90%**

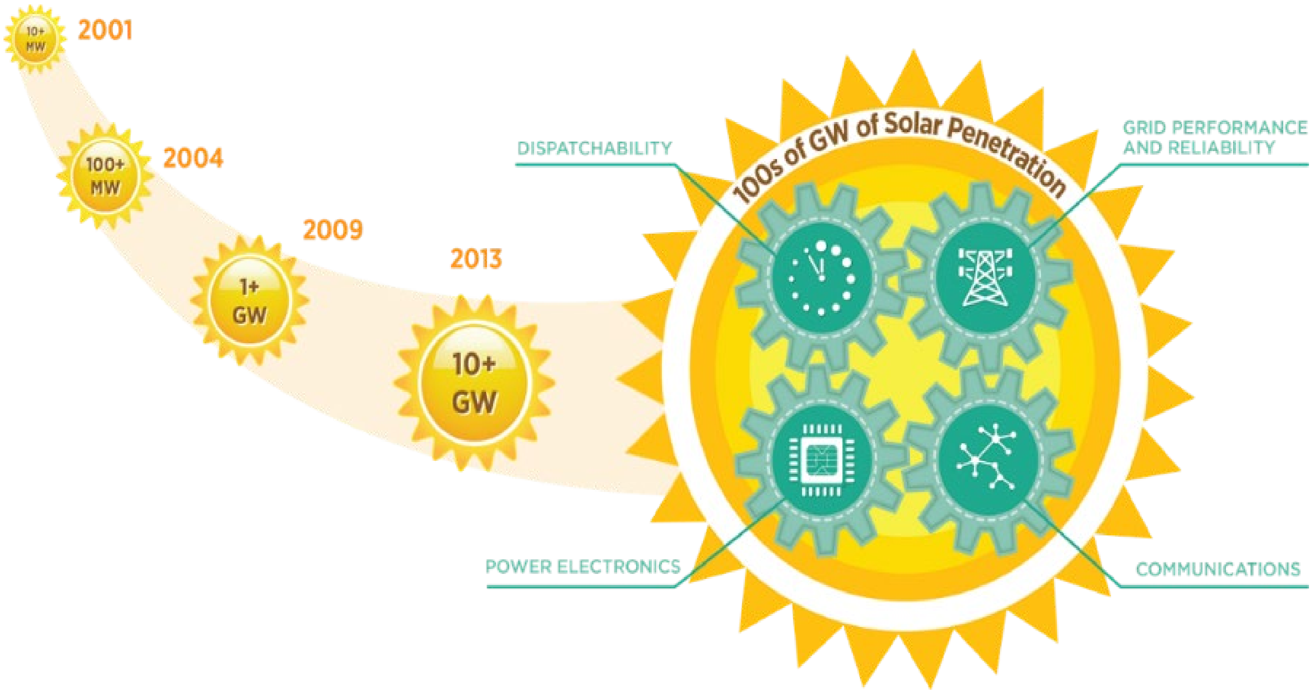



SolarView
Map View
Settings
Help
Forecast Model
M3 Demo
Aggregation Set
Currently Visible
Displayed Time Zone
Mountain (UTC +6)
Most Severe Forthcoming Alert
Forecast at Selected Time
Solar Capacity (MW)
Solar Site
Selected Site
Site W/out data
Critical Ramp Alert
Moderate Ramp Alert
Low Ramp Alert
Power 0 - 60 MW
Power 60 - 120 MW
Power 120 - 180 MW
Power > 180 MW
Transmission Line by kV
Legend ▼
© MapTiler © OpenStreetMap contributors
5:00 7/8
6:00 7/8
7:00 7/8
8:00 7/8
9:00 7/8
Red Mesa +
Power (MW)
150
100
50
0
5:00
6:00
7:00
8:00
9:00
10:00
Timestamp UTC + 6
Forecast
Actual
1st Percentile
25th Percentile
75th Percentile
99th Percentile
Hide alerts for selected farm
RAMP ALERT
A moderate ramp event is forecast starting at 8:00 and ending at 9:00
RAMP ALERT
A low ramp event is forecast starting at 8:00 and ending at 9:00
Total Farm Capacity
102.4 MW
Panel Manufacturer(s)
unknown
Panel Models
unknown
Forecaster Model Details
Model Name:
1
Forecast Generated:
17:07 7/8 UTC
Forecast Horizon:
360
Visible Farms - Currently displaying aggregation of all visible solar farms.
Aggregated Chart
Multi Chart
800
0
Power (MW)
4:00
5:00
6:00
7:00
8:00
9:00
10:00

Patents and Publications

Conference Presentations and Journal Articles				
Full Author List	Paper Title	Conference or Journal	Location	Date
Stephen Jascourt, Christopher Cassidy, Eric Wertz and Travis Hartman	Probabilistic 5-minute Solar Farm Power Forecasts for the SUMMER-GO Project (poster)	American Geophysical Union Fall Meeting	Washington, DC	December 10-14, 2018
Stephen Jascourt, Christopher Cassidy, Eric Wertz and Travis Hartman	Probabilistic Solar Power Using a Large Ensemble	American Meteorological Society 10th Conference on Weather, Climate and the New Energy Economy	Phoenix, AZ	January 7-10, 2019
Bri-Mathias Hodge	Solar Uncertainty Management and Mitigation for Exceptional Reliability in Grid Operations	2019 ESIG Meteorology & Market Design for Grid Services Workshop	Denver, CO	June 4-6, 2019
Kate Doubleday, José Daniel Lara, William Kleiber, and Bri-Mathias Hodge	Regional Solar Power Forecasting with Vine Copulas for Power System Applications	Vine Copulas and Their Applications Workshop	Munich, Germany	July 8-9, 2019
Kate Doubleday, William Kleiber, and Bri-Mathias Hodge	Probabilistic Solar Power Forecasting Using Bayesian Model Averaging (student poster)	IEEE Power and Energy Society General Meeting	Atlanta, GA	August 4-8, 2019
Kate Doubleday, William Kleiber, and Bri-Mathias Hodge	Probabilistic Solar Power Forecasting Using Bayesian Model Averaging	IEEE Transactions on Sustainable Energy		*Submitted* September 2019

Questions?



10+ MW
2001
100+ MW
2004
1+ GW
2009
10+ GW
2013
100s of GW of Solar Penetration
DISPATCHABILITY
GRID PERFORMANCE AND RELIABILITY
POWER ELECTRONICS
COMMUNICATIONS