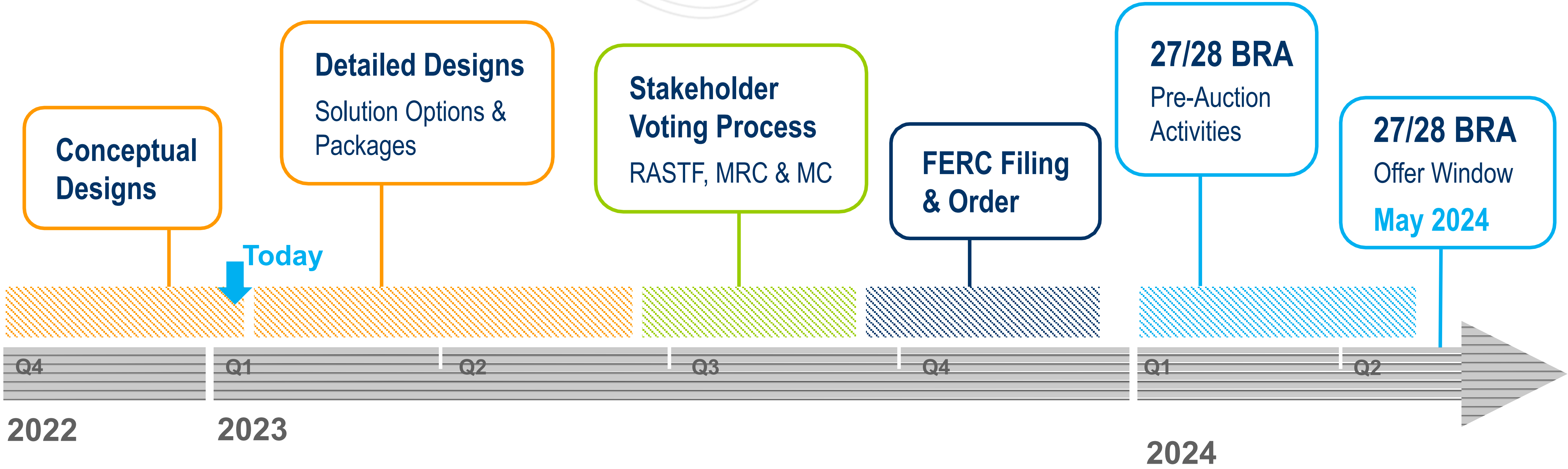
PJM: Update on Conceptual Design for Capacity Market Reforms

RASTF

January 18, 2023

RASTF Work Plan Timeline for 27/28 BRA Implementation



Today’s Presentation

- Update on PJM’s conceptual design for capacity market reforms
  - Initial perspectives on high-level design presented at the August 31, 2022 RASTF meeting (slides)

Note on Winter Storm Elliot:

- In the early stages of analyzing the recent events and performance during the winter storm, which is and will be an important consideration in our discussions on market design at the RASTF

Key Market Design Objectives

Reliability: Supports procurement of sufficient capacity to meet our resource adequacy targets

Efficiency: Embraces competitive principles, and provides transparent price signals for efficient entry and exit of resources

- Facilitates competitive, least-cost procurement of resources

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Conceptual design focused on enhancements to better achieve these two primary objectives

PJM's conceptual design retains focus of the capacity market and product on resource adequacy & ensuring sufficient resources to meet loss-of-load criteria

Product Definition:

- A **commitment to perform** when needed by PJM, particularly **during times of stressed system conditions** (times of resource adequacy need or load shed risk), subject to penalties for non-performance or bonus credits for over-performance
- Must be **physical** (existing or meeting criteria for a planned resource) and **deliverable** to load
- Measured and **accredited in UCAP MW**, which captures a resource's expected performance during times of load shed risk and its incremental contribution to resource adequacy on the system (relative to that of a perfect generator)
- **Substitutable**, where 1 MW of UCAP can be exchanged for any other MW of UCAP on the margin while maintaining equivalent resource adequacy for a given metric, including across resource types with disparate operating characteristics and limitations

Reliability Risk Modeling

Reliability Risks in the Capacity Market

Improve how we **capture** reliability risks in our modeling, and how we **allocate** risks in the market

Enhance our reliability risk modeling, especially that of winter risks:

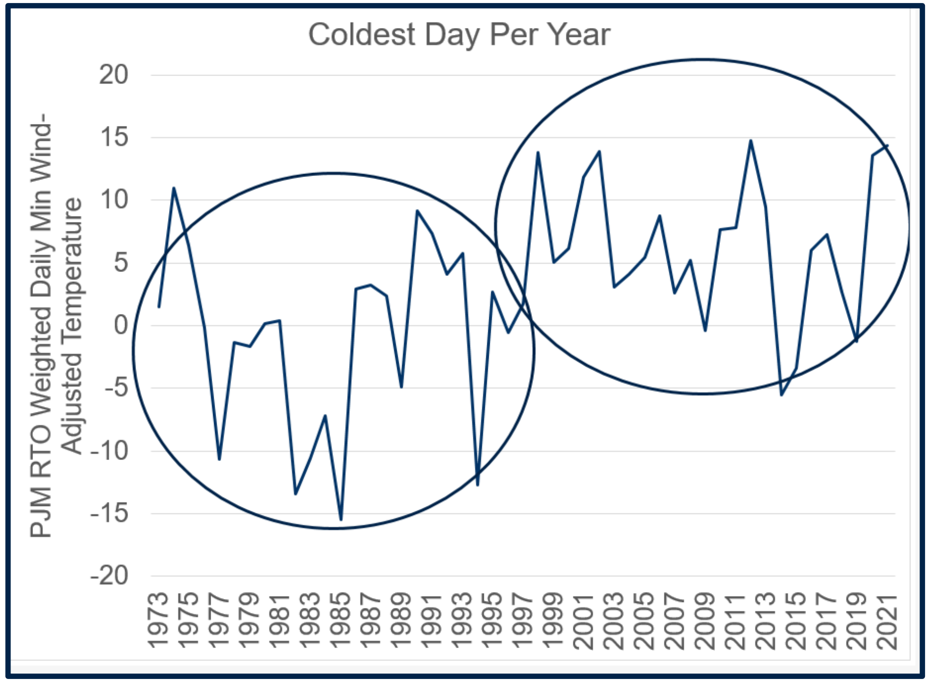
- Enhance risk modeling by explicitly modeling how forced outage rates vary with temperature (increasing in extreme cold)
- Expand weather history in reliability modeling to more years (e.g. 50 years) than we do today to capture more extreme summer and winter weather distribution “tails” in history
- Both enhancements result in models that better captures extreme event risk, so they receive higher importance in setting procurement target and in accreditation

Other model enhancements:

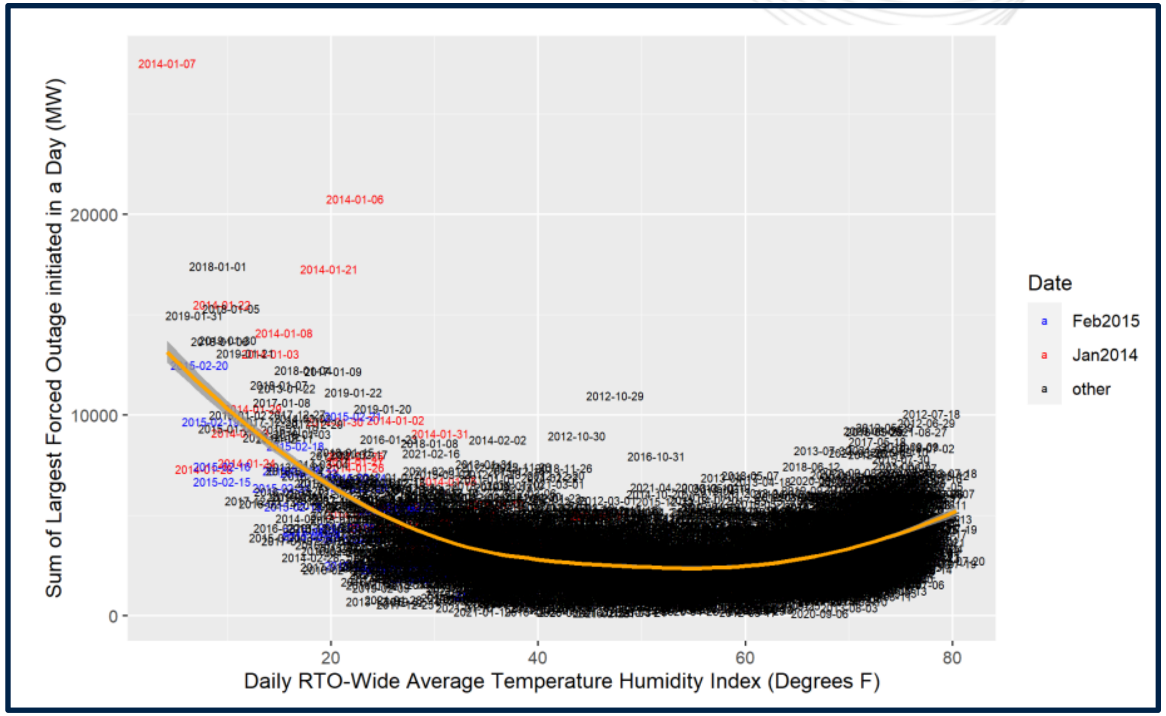
- Load forecast improvements, including move to hourly forecast
- Move to hourly models for RTO and LDA reserve studies (improve modeling of locational needs)

Reliability Risks - Data / Analyses

Historical Coldest Days Per Year in PJM (up through 2021)



Thermal forced outages in period 2012-2021 (excluding retired units)

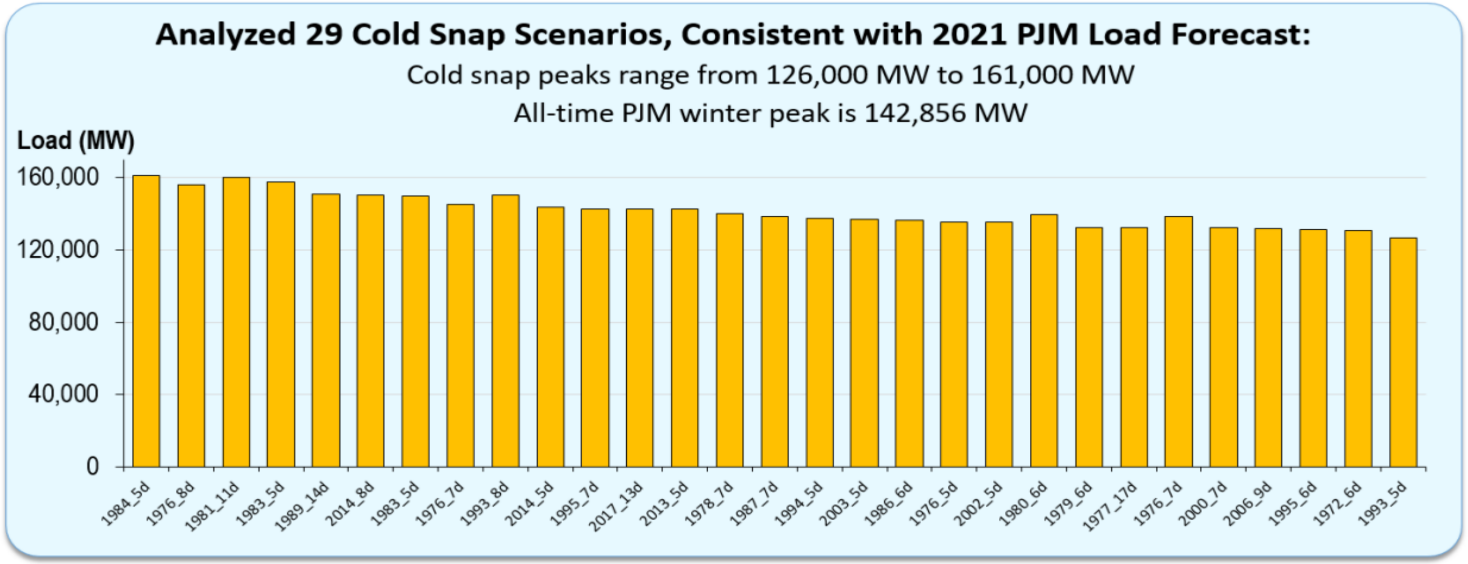


Fuel Security Analysis at "1 in 10" UCAP Reserves (RASTF presentation)

Simulated the performance of a portfolio that just meets the 1 in 10 LOLE criterion under extreme cold weather conditions.

- Resource unavailability in analysis was based on weather (incl. fuel) related forced outages for thermal units and wind/solar hourly profiles seen in recent cold snaps

Historical Cold Snaps (many falling in 70s / 80s)

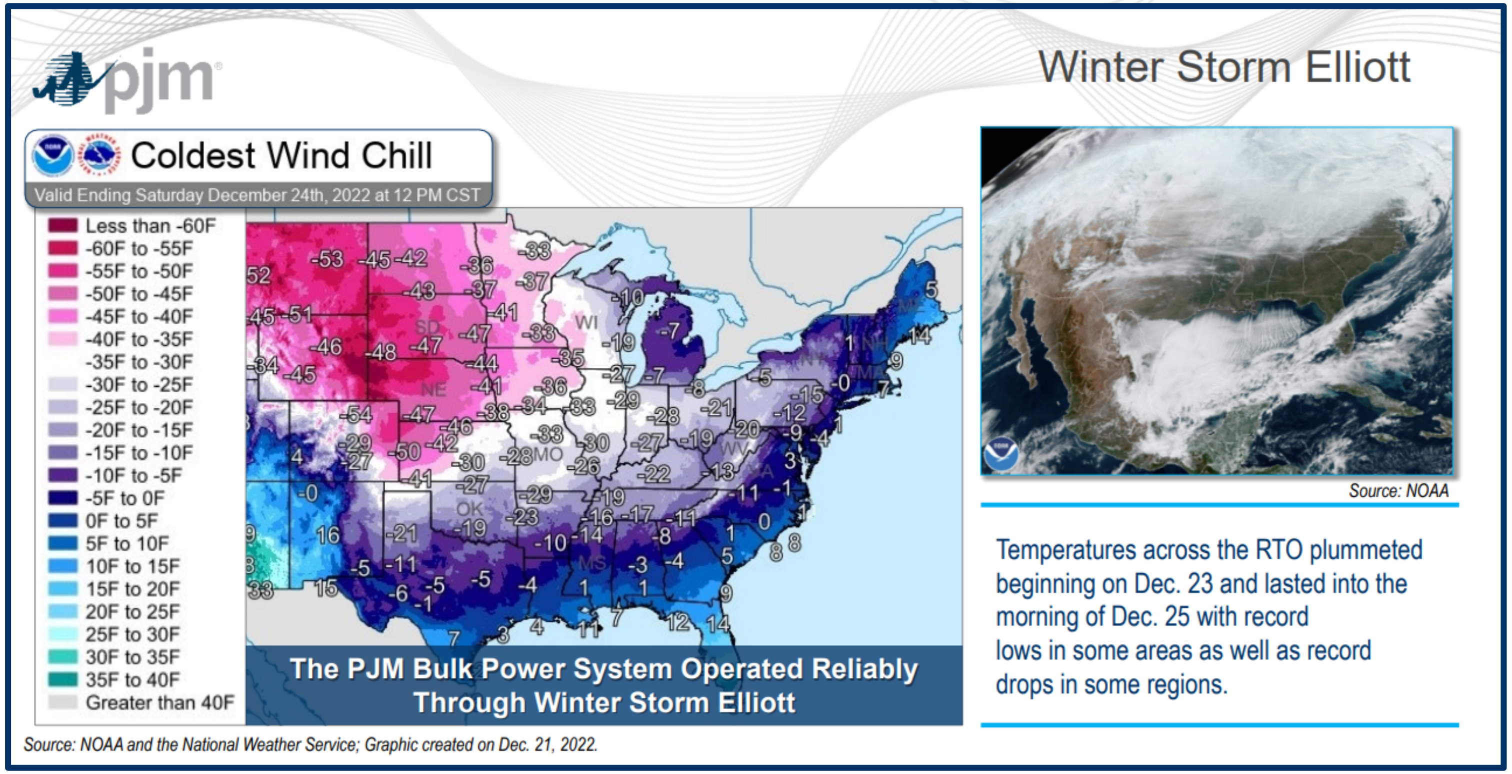


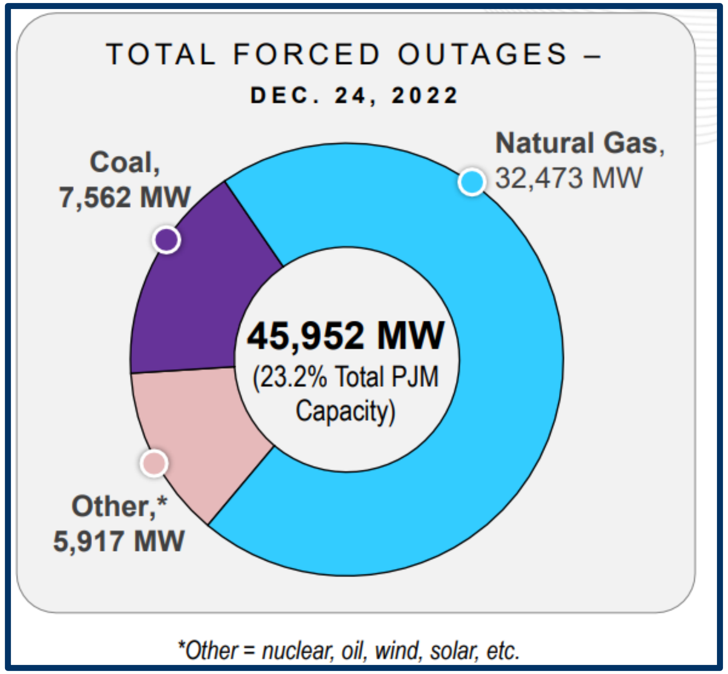
Key Results

- 7 cold snaps show *Conditional LOLE* > 0
- Cold snaps with most risk:
  - Winter 84/85:
    Conditional LOLE 1.81 days/winter,
    Conditional LOLH 8.6 hours/winter,
    Conditional EUE: 41,228 MWh/winter
  - Winter 81/82:
    Conditional LOLE 1.26 days/winter,
    Conditional LOLH 5.5 hours/winter,
    Conditional EUE: 19,298 MWh/winter

Reliability Risks - Data / Analyses (cont'd)

Winter Storm Elliot (MIC presentation)





Accounting/Allocation of Reliability Risks

- Under status quo design, certain generation-based reliability risk drivers are accounted for by increasing amount of capacity procured
- This yields equivalent reliability but does not align risk causation with risk allocation, misaligning compensation and incentives

- We propose to instead de-rate those supply classes or resources introducing the risks

Status quo accounting of generator reliability risks:

Risks	Source	Accounting of Risk
Load Uncertainty	Demand	Demand-side (FPR)
Random Thermal Forced Outages	Supply (thermals)	Accreditation (EFORd)
Variable Resource Risks	Supply (e.g. wind/solar)	Accreditation (ELCC)
Limited Duration Resource Risks	Supply (e.g. battery)	Accreditation (ELCC)
Thermal Winter Correlated Outages	Supply (thermals)	Demand-side (FPR)
Variability in Independent Thermal Forced Outages	Supply (thermals)	Demand-side (FPR)
Ambient De-rates (Summer)	Supply (thermals)	Demand-side (FPR)
Thermal Planned & Maint. Outages	Supply (thermals)	Demand-side (FPR)

Reliability Metric

EUE as Primary Reliability Metric

Move to **Expected Unserved Energy (EUE)** as primary reliability metric to better align with experienced reliability, increasing weight placed on extreme (long & deep) load shed

- Set RTO target based on the “equivalent” EUE seen in our models today when at a 1-in-10 LOLE

- **Better captures severity of events** and relative importance or weighting across different tail-end event types & drives
- Since the relative weighting of different event types changes, using an EUE metric in accreditation better captures true contribution to reliability across events
  - For example, a certain resource type may be able to help avoid most (short & shallow) load shed events but have limited value during the most extreme events where most unserved energy is observed; such a resource would receive relatively high LOLE-based accredited value but lower EUE-based accredited value

Example of differences in loss-of-load metrics:

Event Characteristic	Metric Affected	California Aug 2020	Texas Feb 2021	Difference
Number of Events	LOLEv	2 events	1 event	-50%
Number of Days	LOLE	2 days	3 days	+50%
Number of Hours	LOLH	6 hours	71 hours	+1,083%
Unserved Energy	EUE	2,700 MWh	990,000 MWh	+36,567%
Max Shortfall	-	1,072	20,000+	+1,766%

Qualification and Accreditation

Winter Qualification Requirements

- NERC standards on winterization for generators are currently under review at the FERC (project link: EOP-012-1)

- The ISO/RTO Council ("IRC"), of which PJM is a member, has filed comments in the proceeding: IRC comments
  – Requesting the Commission (i) approve the standards as drafted, while simultaneously (ii) directing NERC to go back and enhance the EOP-012-1 standard to address noted weaknesses, including the manner in which the "extreme cold weather temperature" of a unit is determined

- Beyond pending NERC standards, the proposed design focuses on capturing correlated outage risks of generators due to reasons like failure to winterize, lack of firm fuel, etc. in the capacity accreditation process

Accreditation: ELCC for All

Improve accreditation to capture additional risk drivers and more accurately and equitably determine resources' relative contributions to resource adequacy

- Consistently account for all supply-side availability risks for all resource types
- Accredit thermal using ELCC model
  - Incorporate temperature-dependent forced outage rates
  - Account for differences in performance of fuel secure vs. insecure resources
  - Under this framework, can incrementally improve model to better capture other thermal limitations that impact relative value (e.g., run hour limitations)
- Accredit DR using ELCC model
  - Account for availability limitations coinciding with periods of risk
- Accredit based on marginal contribution to resource adequacy (i.e. marginal impact on the reliability metric – EUE – relative to a perfect generator)

Incorporating weather in ELCC Model

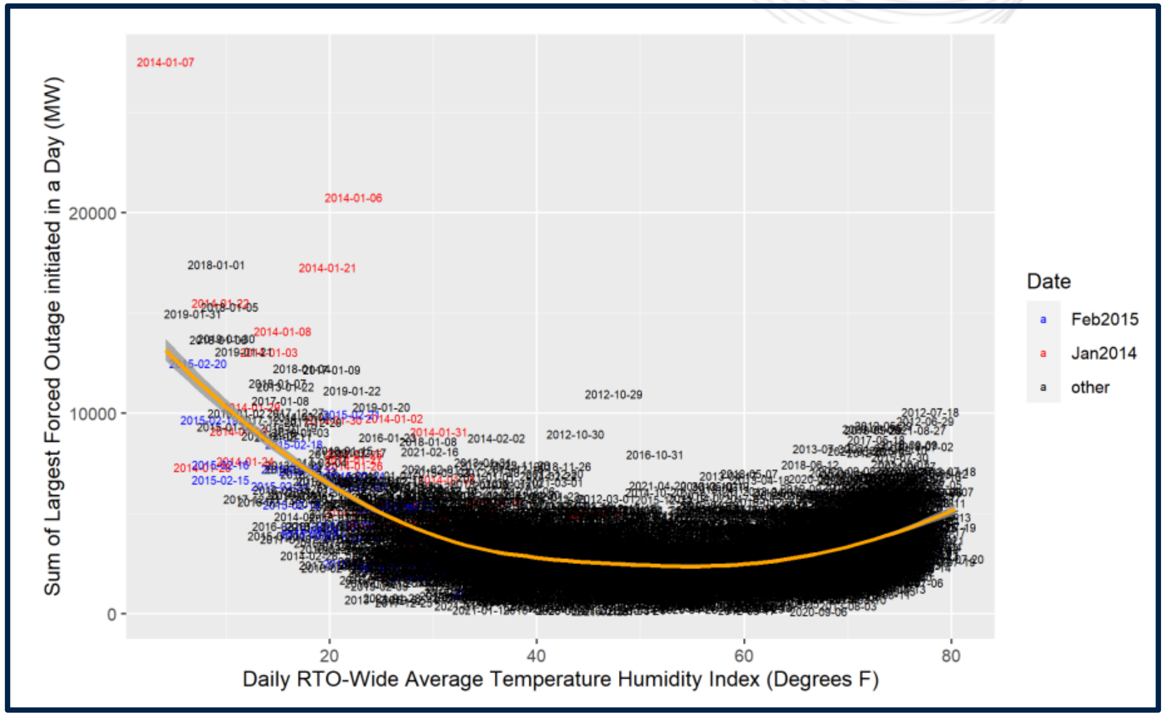
- Currently, the ELCC model does not directly use weather data
  - Load scenarios are derived using a normal distribution based on PJM Load Forecast
  - Thermal forced outages for all weeks, except winter peak week, are not weather-dependent
- Using weather from an adequate set of historical years (e.g. 50 years) would allow us to directly derive:
  - Load scenarios (via PJM Load Forecast regression model)
  - Variable resource performance (via backcast provided by vendor)
  - Thermal resource performance (via a new temperature-dependent forced outage model)

New temperature-dependent forced outage model

- Historical performance of thermal resources for last 50 years not available
- If a given temperature has occurred multiple times in the last 5 years, a resource may have performed in some of those instances while in others it may have failed to perform
  - Enhanced availability models can reflect the probability that a unit experiences a forced outage as a function of temperature based on actual historical data
- After estimating that model, for a given temperature pattern, multiple ELCC performance scenarios for a unit can be derived
  - In some of those scenarios the unit will perform while in others it will experience a forced outage

Temperature Dependent Forced Outage Model

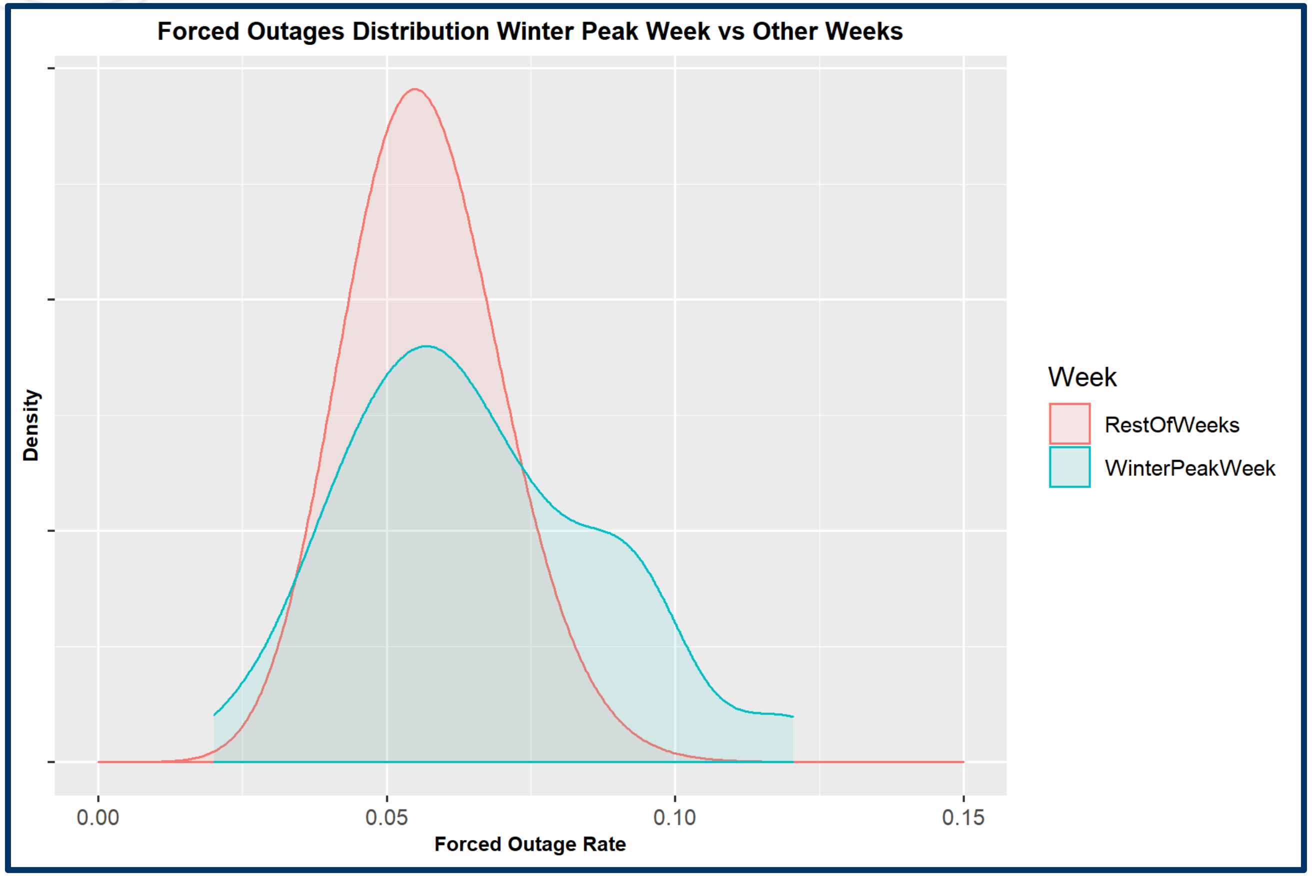
- At previous RASTF meetings, PJM has presented data showing a correlation between temperature and the occurrence of forced outages



Graph presented at 10/11/22 RASTF meeting

- PJM currently models winter peak week forced outages differently than for the rest of the year

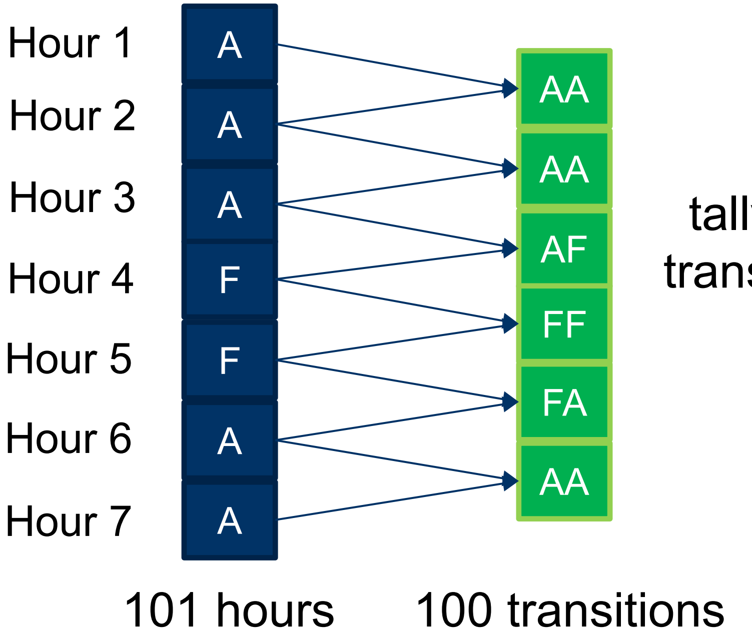
Graph is built with data from the 2022 RRS for delivery year 2026/27



Opportunities

- The Winter Peak Week distribution shown in the previous slide was built with data from winter peak weeks in period delivery year (DY) 07/08 through delivery year 21/22 (excluding DY 13/14 and replacing it with DY 14/15)
  - The maximum and minimum RTO-wide forced outage values in the winter peak week distribution are 12% and 2.2%, respectively
  - The minimum RTO-wide forced outage value occurred on the winter peak week of delivery year 19/20, which was a rather mild winter week.
- In the RRS and ELCC models, the minimum forced outage value above (2.2%) has the same chance of occurring than the maximum forced outage value (12%) on winter days with 90/10 or 95/5 simulated peak loads.
  - It is worth exploring other methodologies to determine if the above practice is acceptable or if refinements are needed.

- Assume we have a unit with 101 on-demand hours of data. In 77 of those hours the unit is fully available while in 24 is fully on a forced outage. The EFORd of the unit is ~ 24%
- If we label an available hour with an A and each outage hour with an F (of any size) we get:



tallying all transitions T

T	Count
AA	73
AF	3
FF	21
FA	3

	A	F
A	73 / 76	3 / 76
F	3 / 24	21 / 24

calculating the transition probabilities (e.g. when unit is in A, what is the probability that it remains in A)

Markov Chain Transition Matrix

	A	F
A	0.961	0.039
F	0.125	0.875

- For a Markov Chain Transition Matrix, we can calculate the Steady State behavior, which is the long-term probability that the unit will be in each state

Markov Chain Transition Matrix

	A	F
A	0.961	0.039
F	0.125	0.875

Steady State

	Prob
A	0.76
F	0.24

We are back at the EFORd of the unit

- In an LOLE model, using Monte Carlo, we can create multiple scenarios (Sc) from the Markov Chain Transition Matrix

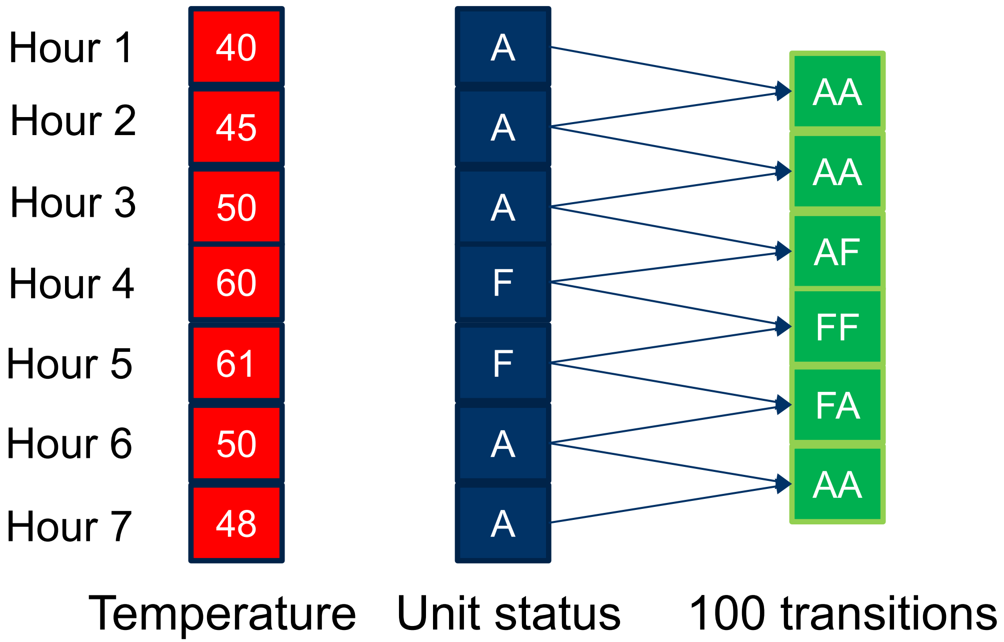
	Sc 1	Sc 2	Sc 3	Sc 4	Sc 5	……	Sc N
Hour 1	A	A	F	A	A		A
Hour 2	A	F	F	A	A		A
Hour 3	A	F	A	A	A		A
Hour 4	F	F	A	A	A		A
Hour 5	F	A	A	A	A		A
Hour 6	A	A	A	A	F		F
Hour 7	A	A	A	F	F		F
…	…	…	…	…	…		…
Hour X	A	F	A	F	A		A

If N is large enough

Hour 1	In ~24% of scenarios unit is forced out in H1
Hour 2	In ~24% of scenarios unit is forced out in H2
Hour 3	In ~24% of scenarios unit is forced out in H3
Hour 4	In ~24% of scenarios unit is forced out in H4
Hour 5	In ~24% of scenarios unit is forced out in H5
Hour 6	In ~24% of scenarios unit is forced out in H6
Hour 7	In ~24% of scenarios unit is forced out in H7
…	
Hour X	In ~24% of scenarios unit is forced out in HX

Incorporating weather into the Forced Outage Modeling

- To examine if the transition probabilities (AA, AF, FF, FA) are impacted by weather variables such as temperature, we can use the approach described in the 2019 paper by Murphy et al
- Using our previous example



We now have a temperature value associated with each transition.

In the previous basic example, to derive the transition matrix (and the transition probabilities), we just simply tallied the transitions and performed some basic math. For instance, to determine the AA transition probability, we divided 73 (the number of AA transitions) by 76 (the number of times the first state in any transition was A)

To analyze if temperature impact the transition probabilities we need to change the modeling.

Transition Probabilities as a function of temperature

- To assess if a unit's transition probabilities in the transition matrix are impacted by temperature, we will use logistic regression

	A	F
A	P_{AA} (T)	P_{AF} (T)
F	P_{FA} (T)	P_{FF} (T)

For P_{AA} (T) and P_{AF} (T), we will compile all hourly AA and AF transitions and the associated temperatures. Then, we will start by fit the following model:

$$\text{OddsRatio}_{AA}(T) = \beta_1 * constant_{hot} + \beta_2 * constant_{cool} + \beta_3 * degrees_{hot} + \beta_4 * degrees_{hot}^2 + \beta_5 * degrees_{cool} + \beta_6 * degrees_{cool}^2$$

where

$$degrees_{hot} = \max(temperature - 18.3℃, 0)$$
$$degrees_{cool} = \max(18.3℃ - temperature, 0)$$
$$constant_{hot} = 1\ if\ degrees_{hot} > 0$$
$$constant_{cool} = 1\ if\ degrees_{cool} > 0$$

Transition Probabilities as a function of temperature

	A	F
A	P_{AA} (T)	P_{AF} (T)
F	P_{FA} (T)	P_{FF} (T)

Then, we apply step-wise backward regression, to gradually eliminate variables from the regression model to find a reduced model that best explains the data. The selected model is the one with the lowest Akaike Information Criterion (AIC)

Note that for a unit whose forced outages are not impacted by temperature at all, the selected model will be

$$\text{OddsRatio}_{AA}(T) = \beta_1 * constant_{hot} + \beta_2 * constant_{cool}$$

with $\beta_1 = \beta_2$

The OddsRatio value is then used to derive P_{AA} (T), while P_{AF} (T) = 1 - P_{AA} (T)

The same procedure is then run to calculate P_{FA} (T) and P_{FF} (T)

Using the temperature-dependent transition probabilities in an LOLE model

As an example, let's consider a unit that tends to experience more forced outages as the temperature decreases. The scenarios in the LOLE model may look like below:

There will be different transition matrices based on temperature

As it gets colder, a larger share of the N scenarios will show the unit forced out

Temperature		Sc 1	Sc 2	Sc 3	Sc 4	……	Sc N
65	Hour 1	A	A	F	A		A
70	Hour 2	A	F	A	A		A
64	Hour 3	F	A	A	A		A
54	Hour 4	F	F	A	A		A
44	Hour 5	F	A	F	A		A
34	Hour 6	F	F	A	A		F
24	Hour 7	A	F	F	F		F
…	…	…	…	…	…		…
14	Hour X	F	F	F	F		F

- Hour 1: In ~24% of scenarios unit is forced out in H1
- Hour 2: In ~24% of scenarios unit is forced out in H2
- Hour 3: In ~24% of scenarios unit is forced out in H3
- Hour 4: In ~34% of scenarios unit is forced out in H4
- Hour 5: In ~34% of scenarios unit is forced out in H5
- Hour 6: In ~44% of scenarios unit is forced out in H6
- Hour 7: In ~54% of scenarios unit is forced out in H7
- …
- Hour X: In ~64% of scenarios unit is forced out in HX

Using the temperature-dependent transition probabilities in an LOLE model

As an example, let's consider a unit that **DOES NOT** tend to experience more forced outages as the temperature decreases. The scenarios in the LOLE model may look like below:

Transition matrices don't change based on temperature

As it gets colder, the same share of the N scenarios will show the unit forced out

Temperature		Sc 1	Sc 2	Sc 3	Sc 4	……	Sc N		
65	Hour 1	A	A	F	A		A	Hour 1	In ~24% of scenarios unit is forced out in H1
70	Hour 2	A	F	A	A		A	Hour 2	In ~24% of scenarios unit is forced out in H2
64	Hour 3	F	A	A	A		A	Hour 3	In ~24% of scenarios unit is forced out in H3
54	Hour 4	F	F	A	A		A	Hour 4	In ~24% of scenarios unit is forced out in H4
44	Hour 5	F	A	F	A		A	Hour 5	In ~24% of scenarios unit is forced out in H5
34	Hour 6	F	F	A	A		F	Hour 6	In ~24% of scenarios unit is forced out in H6
24	Hour 7	A	F	F	F		F	Hour 7	In ~24% of scenarios unit is forced out in H7
…	…	…	…	…	…		…	…	
14	Hour X	F	F	F	F		F	Hour X	In ~24% of scenarios unit is forced out in HX

Outage size in the temp. dependent forced outage model

- As shown in previous slides, the temperature dependent forced outage model is a two-state model: the unit is either available (A) or on a forced outage (F)
- In the LOLE model, what outage size should we consider when a unit is in the forced outage state?
  – Currently, we are considering two approaches to estimate the outage size:
    - Single duration-weighted outage size to be used during entire year
    - Summer duration-weighted outage size and winter duration-weighted outage size

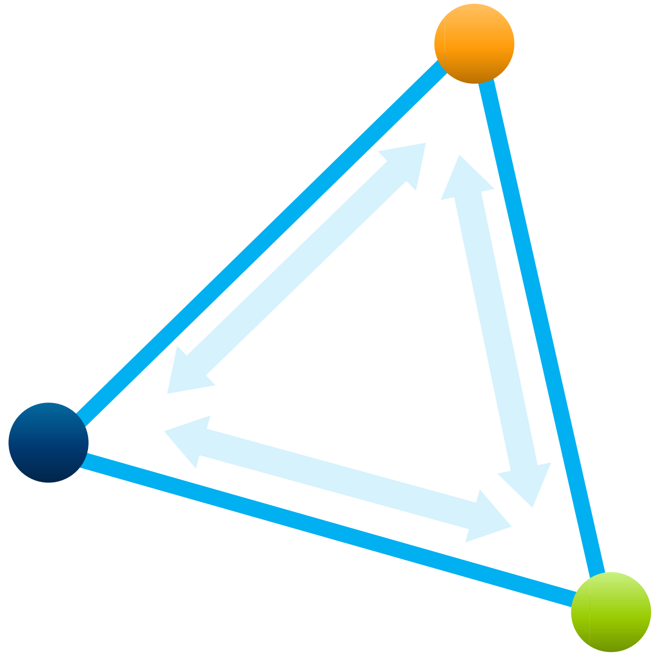
Performance Assessments

Performance Assessments

There exists a tension across at three natural design criteria for performance assessments, requiring compromise across them.

Importance of sufficiently strong/frequent assessments

Timing of assessments focused on hours of risk



Limiting risk of atypical underperformance

Timing of Performance Assessment Intervals

Spectrum of Options for PAI Triggers

Only during loss of load hours	Only during reserve shortages	Only based on emergency actions	Based on emergency and pre-emergency actions	Locationally when nodal LMP exceeds a threshold value (e.g., $850/MWh) that is indicative of scarcity, plus stressed system or local conditions as at left	During "stress" conditions at left, supplemented with additional intervals to meet a certain number (e.g., 30) of PAIs every year, based on ex-post (end of delivery year) hours with tightest supply cushion	During many (e.g., several hundred) predetermined hours	During all hours

Performance Assessment Design

Maintain current conceptual framework for performance assessments, with changes to certain design elements for enhanced clarity and transparency

- **Assessment Periods** focused on times of system stress
- **Performance Penalty Rate** at status quo levels or higher, to better align forward capacity market with real-time performance assessments
- For determining the **Expected Performance** of generation during PAIs, considering:
  a) A static baseline (status quo), where expected performance is based on a single committed UCAP value and the PAI balancing ratio in all hours, or
  b) A variable baseline, where expected performance may vary hour-to-hour consistent with the risk-weighted hourly availability assumed in the accreditation
- Improve clarity and simplify **Excusals**

Multi-Component Penalty Structure

Consider enhancements to multi-component incentive structure that values performance during risk hours, capability testing, and compliance with obligations

One option under consideration is to take the maximum penalty across:

1. PAI penalties
2. Testing penalties
   - All dispatchable resources subject to testing with assessed penalties for inability to demonstrate capability at or above committed capacity value
   - Resources that have demonstrated capabilities through normal course of operation would not be required to undergo additional testing
3. Daily capacity deficiency and obligation non-compliance penalties
   - Clawback of capacity revenues proportionally for days / periods of deficiency / non-compliance

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