Extreme Weather Impacts on Resource Adequacy: Intermittent Renewable Resource Modeling

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NYISO Resource Adequacy

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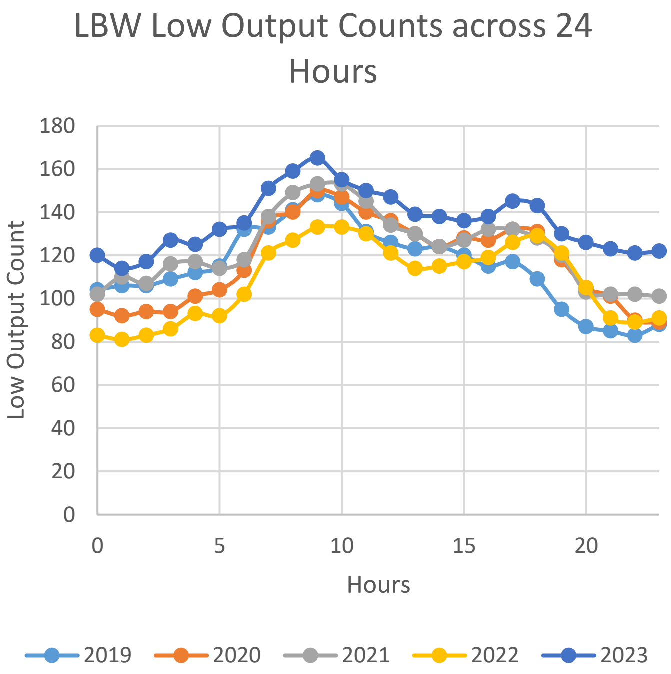
Considerations

- Intermittent renewable resources can exhibit high volatility in their production due to weather patterns
  - Examples of intermittent renewable resource types include land-based wind (LBW), offshore wind (OSW), and photovoltaic solar (PV or "solar")
- Currently, the installed reserve margin (IRM) study model uses the previous 5 years of production data to establish intermittent renewable resource production profiles
- The prior 5 years of data may not fully capture the potential variability of intermittent renewable resource production
- Including more data, especially the data that represents varying weather patterns, could improve the modeling of intermittent renewable resources
- Examining additional historical data will aid in developing potential intermittent renewable resource modeling enhancements
  - The Installed Capacity Subcommittee (ICS) has identified intermittent renewable resource modeling enhancements as an area for further exploration/research

What is an extreme weather year?

- **The extreme weather year may be defined in several ways:**
  - Low total intermittent renewable resource energy output
  - Low peak intermittent renewable resource production
  - Low production by intermittent renewable resources during peak load times
  - Low "output counts" for intermittent renewable resources
  - Low "renewable output hour counts"
    - For example, a single hour summation of all renewable resource outputs that is below 10% net capacity factor
    - The use of a 10% capacity factor threshold is intended solely for this effort and was selected as a proxy metric based on the previous work conducted in the NYISO's 2023-2042 System & Resource Outlook and assessments as part of the Extreme Weather Working Group (EWWG) efforts
  - Low renewable output hour counts during peak load hours or the Peak Load Window
    - Low renewable output within a time frame of peak load hours may contribute to increased chances of a loss of load event
    - However, this may unnecessarily constrain the time periods considered and, thus requires careful consideration to help ensure accurate capturing of potential intermittent renewable resource production risks
- **Regardless of method chosen, the weather year for all units should be consistent in the IRM study modeling**
  - Zonal metrics will show varying extreme weather years, but the year simulated needs to stay consistent across the entire fleet of intermittent renewable resources
    - The modeling should not use different years that vary by resource types and/or location
      - For example, using a 2005 production profile shape for Load Zone K solar, a 2006 production profile shape for OSW, and a 2007 production profile shape for LBW in Load Zone D
      - A common year production profile should apply to all intermittent renewable resource types in all locations



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Assessment of Low Output Counts

- **As part of this assessment, the NYISO compared simulated profiles (developed by DNV for the NYISO) and historical production data**
- **When comparing the simulated data to production data, there is a 1:1 mapping of the simulated data sites to the production sites**
  - The DNV simulated data often has shapes for the installed units, but the geographically closest DNV site is used if there is no data for a specific installed unit
  - The DNV simulated site data capacity factors are calculated using the site's Installed Capacity (ICAP)
  - The DNV simulated data is based on the following sample sets: 571.4 MW of solar (~18% of total ICAP), 2,430.2 MW of LBW (~78% of total ICAP), and 136 MW of OSW (~4% of total ICAP)
- **For both the DNV simulated data and historical production data, the hourly energy is calculated by multiplying the hourly capacity factor by the unit's ICAP:**
  - $Site\ Hourly\ Energy\ Output = Site\ Hourly\ Capacity\ Factor \times Site\ ICAP$
- **Then the sites are summed to a total fleet hourly energy for each individual resource type:**
  - $Resource\ Type\ Hourly\ Energy\ Output = \sum Site\ Hourly\ Energy\ Output$
- **From there, the resource types are calculated and analyzed as follows:**
  - $All\ Resource\ Types\ Hourly\ Energy\ Output = Solar\ Hourly\ Output + LBW\ Hourly\ Output + OSW\ Hourly\ Output$
  - $Capacity\ Factor = \frac{All\ Resource\ Types\ Hourly\ Energy\ Output}{Total\ ICAP\ of\ All\ Resource\ Types}$
  - $Total\ ICAP\ of\ All\ Resource\ Types = 3{,}137.6\ MW$
- **The low renewable output count is identified when the capacity factor across all intermittent renewable resources is <0.1 (less than 10%)**

Eastern Standard Time	Solar (MW)	LBW (MW)	OSW (MW)	Total (MW)	Capacity Factor	Is <0.1?
7/18/2017 16:00	405.930	78.924	13.342	498.196	0.159	FALSE
7/18/2017 17:00	305.668	67.493	14.838	387.998	0.124	FALSE
7/18/2017 18:00	172.358	64.563	15.137	252.058	0.080	TRUE
7/18/2017 19:00	4.918	76.747	16.130	97.795	0.031	TRUE
7/18/2017 20:00	0.000	105.311	18.972	124.283	0.040	TRUE
7/18/2017 21:00	0.000	139.943	18.020	157.963	0.050	TRUE

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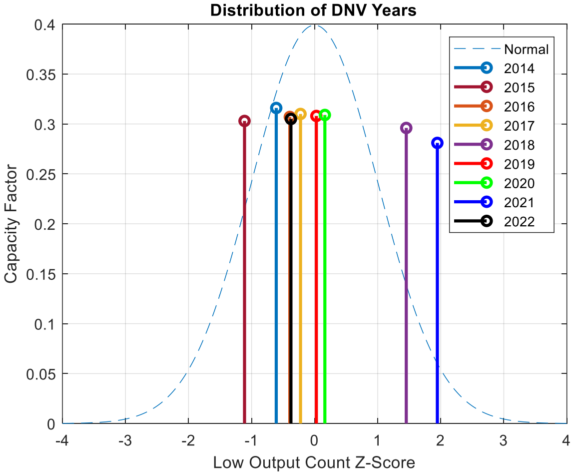
Analysis of Simulated Profiles

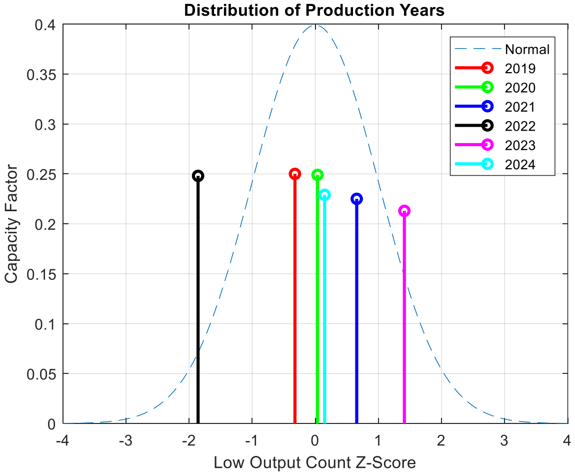
- $Z = \frac{x-\bar{x}}{\sigma},\ where\ x = low\ output\ counts,\ \bar{x} = average\ low\ output\ counts,\ \sigma = standard\ deviation\ of\ low\ output\ counts$
    - The Z-Score displays the number of standard deviations that a year's aggregate low output count is above or below the average annual low output count
- **Simulated data can be used to show which years have overall lower capacity factors and more low output hours**
- **Observations for more recent years (past 5 years):**
    - 2021 has a low overall capacity factor and is almost 2 standard deviations above the average annual low output count
    - 2019, 2020, and 2022 have overall average low output counts and are within 1 standard deviation of the average annual capacity factor for the intermittent renewable resource fleet
- **Observations over a longer historical lookback period (back to 2014):**
    - 2018 (similar to 2021) is another year with a high low output count and below average annual capacity factor for the intermittent renewable resource fleet
    - 2014, 2016, and 2017 have overall average low output counts and are within 1 standard deviation of the average annual capacity factor for the intermittent renewable resource fleet
    - 2015 reflects higher intermittent renewable production with an average annual capacity factor for the intermittent renewable resource fleet but 1 standard deviation below the average annual low output count

DNV Simulated Data Summary						
Years	Solar CF	LBW CF	OSW CF	CF	Low Output Count	Z Score
2006	0.215	0.326	0.484	0.312	869	-1.919
2001	0.226	0.307	0.441	0.298	924	-1.425
2010	0.217	0.310	0.497	0.301	939	-1.291
2013	0.220	0.314	0.482	0.304	953	-1.165
2002	0.217	0.337	0.481	0.321	958	-1.120
2015	0.230	0.312	0.446	0.303	959	-1.112
2014	0.221	0.331	0.446	0.316	1015	-0.609
2016	0.234	0.314	0.471	0.307	1039	-0.394
2022	0.227	0.314	0.457	0.305	1041	-0.376
2017	0.218	0.321	0.484	0.310	1058	-0.224
2019	0.217	0.321	0.458	0.308	1086	0.027
2020	0.227	0.320	0.462	0.309	1101	0.162
2000	0.210	0.310	0.473	0.299	1108	0.225
2007	0.229	0.312	0.481	0.304	1110	0.242
2011	0.209	0.300	0.451	0.290	1134	0.458
2009	0.216	0.294	0.473	0.288	1145	0.556
2008	0.222	0.303	0.448	0.295	1152	0.619
2003	0.206	0.309	0.478	0.297	1161	0.700
2004	0.210	0.309	0.470	0.298	1182	0.888
2012	0.224	0.298	0.421	0.290	1196	1.014
2005	0.226	0.282	0.462	0.279	1233	1.345
2018	0.207	0.306	0.469	0.295	1245	1.453
2021	0.214	0.287	0.453	0.281	1300	1.946

Current Production Data Representation

- **Currently, according to the DNV simulated data and production data analysis:**
  - 2018, 2021, and 2023 are “bad weather years” that represent lower intermittent renewable resource production
    - The simulated data analysis suggests that 2018 and 2021 are almost 2 standard deviations above the mean for low output counts, and production shows that 2023 is worse than 2021
  - 2014, 2016, 2017, 2019, 2020, and 2024 are “average weather years” that represent average intermittent renewable resource production
    - Both the DNV simulated data and production data indicate that 2019 and 2020 are overall average weather years
  - 2022 is a “good weather year” according to production data that represents higher intermittent renewable resource production





Low Output Count Methodology

- **While other metrics exist for identifying an “extreme weather year,” the “low output count” methodology (see Slides 4-5) can provide a more comprehensive and independent data review**
  - Total energy and peak production review one aspect of the data and ignore the characteristics of the entire profile
  - Using peak load times, peak load windows, and summer season analysis introduces the dependency on load profile or modeled load profiles
  - Using the low output count methodology can successfully identify “bad weather years,” consistently between the DNV simulated data and production data
- **Despite the potential impact from changing parameters used in the data review, the low output count methodology can produce potentially meaningful inputs for the probabilistic reliability model**
  - The 10% net capacity factor threshold was selected solely for this analysis and can be changed to a different value; however, any such changes are not expected to materially impact the data review outcomes
  - More granular data review beyond the fleet level (e.g., zonal) can yield different outcomes, but may reduce the level of weather correlation across the New York Control Area
  - Extending the timeframe of historical data (e.g., beyond 10 years) can also yield different outcomes. However, actual production data is very limited beyond the most recent 10 years
- **Modeling identified “bad weather year” data can impact the IRM based on the interaction between the modeled intermittent renewable resource production profiles and the load profiles**

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Modeling 10 Years of Data in MARS

- **A potential modeling approach of using 10 years of historical intermittent renewable production profiles was previously discussed at the ICS**
  - The potential IRM impacts of such alternative approach, as previously reviewed with ICS, are summarized below
- **The additional 5 years of data for solar, LBW, and OSW were created using the DNV simulated data on top of the current modeling**
  - By including the additional data, the "bad weather years" identified previously would be captured in the model
- **To assess the potential IRM impacts of using 10 years of historical data, the NYISO ran GE MARS cases at 4,250 replications using the 2024-2025 IRM Final Base Case (FBC)**
  - Reached standard error requirement by 3,500 replications
  - No noticeable increase in run-time was observed
- **The assessment identified a 0.17% increase to IRM from the 2024-2025 FBC**
  - IRM increased from 24.4% to 24.57%

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LOLE Impacts from Test Cases

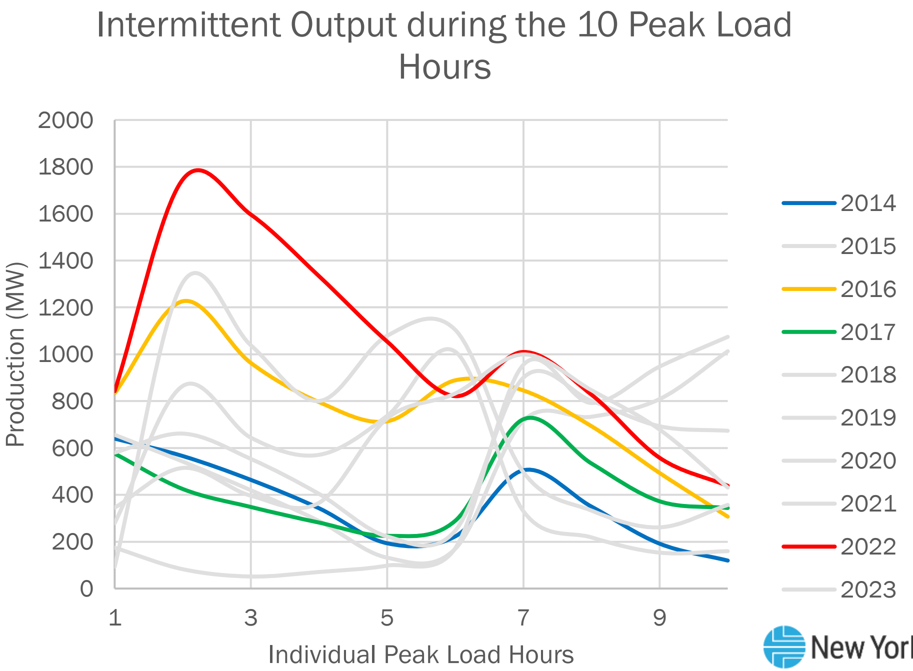
- **The NYISO ran test cases that used a single year's shape for all replications which produced different results than the prior analysis discussed on the previous slide**
  - 2014 through 2018 shapes were created using the DNV simulated data
    - These shapes were created from zonal averages like a MARS simulation
  - 2019 through 2023 shapes are the production data for the 2024-2025 FBC
  - Note: all years' ICAP are normalized within the MARS model to the modeled capacity of the 2024-2025 IRM study
    - 571.4 MW of solar, 2,430.2 MW of LBW, and 136 MW of OSW
- **Observations:**
  - The impact on the loss of load expectation (LOLE) for the 2024-2025 FBC is heavily influenced by the 10 highest peak load hours in the year (see next slide for additional information)
    - If a specific year has a lower intermittent renewables output during those hours compared to the output modeled for the 2024-2025 FBC, a loss of load event generally occurs, and that shape file will have a greater LOLE impact
  - Both in the case of a full year and peak load hours analyses, the simulated data analysis examines a wider time frame than the hours that are most impactful in MARS
    - The peak load hour analyses observed 186 hours across hour beginning (HB) 16 to 21 in July, 372 hours across HB16 to 21 in July and August, and 620 hours across HB12 to 21 in July and August
    - These have different results because the scopes of time frames are much larger than the approximate 10 hours that primarily drive the LOLE increases in MARS for the 2024-2025 FBC

Intermittent Shapes Modeled	LOLE	Delta
2019-2023	0.100	0.000
2014-2023	0.104	+0.004
2014	0.113	+0.013
2015	0.106	+0.006
2016	0.093	-0.007
2017	0.112	+0.012
2018	0.103	+0.003
2019	0.107	+0.007
2020	0.104	+0.004
2021	0.103	+0.003
2022	0.086	-0.014
2023	0.101	+0.001

LOLE driven by 10 Peak Load Hours

- Correlation Coefficient of -0.954 between LOLE delta and average output delta during the peak 10 hours of load

Intermittent Shapes Modeled	LOLE	Delta	Average Output (MW) during 10 Peak Load Hours	Delta from 2024-2025 FBC
2019-2023	0.100	0.000	652	0
2014-2023	0.104	+0.004	593	-59
2014	0.113	+0.013	359	-293
2015	0.106	+0.006	548	-104
2016	0.093	-0.007	776	+124
2017	0.112	+0.012	412	-241
2018	0.103	+0.003	574	-79
2019	0.107	+0.007	442	-210
2020	0.104	+0.004	687	+34
2021	0.103	+0.003	497	-156
2022	0.086	-0.014	1023	+370
2023	0.101	+0.001	614	-39



Observations from the Test Cases

- **The LOLE and IRM impacts are mainly driven by the production of intermittent renewable resources during the highest 10 peak load hours**
  - The MARS model is heavily driven on an hourly basis so if a specific renewables shape is underperforming during the peak load hours (compared to the production modeling of the 2024-2025 FBC), a loss of load event arises
  - Seeking to conclude that any year may represent an "extreme weather year" based on these specific simulated peak load hours may not be accurate because there is no guarantee that HB16 to 21 on July 17th, 18th, and 19th will be driving the LOLE every year
- **Assessing low average capacity factors and high low output counts are more reasonable metrics to help identify an "extreme weather year"**
  - Better captures potential changes in the peak load hours given various model changes
  - A year that reflects lower overall intermittent renewable resource production is more likely to reflect lowered production across a broader range of peak load hours
  - Identifying years with the lowest annual capacity factor for the intermittent renewable resource fleet provides a more objective and sustainable measure that is independent of the specific peak load hours

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Key Observations

- **DNV's simulated data shows similar trends to production data**
- **There are many potential ways to determine an "extreme weather year"**
  - The metrics used significantly influence classification of a particular year
- **The LOLE impacts in the test cases are heavily influenced by intermittent renewable resource output during the top 10 peak load hours**
  - These specific 10 hours will change with modeling updates from year-to-year and may expand to include a broader range of hours as modeled conditions change over time
  - Examining intermittent renewable resource production "underperformance" from a broader perspective can better account for such changes

Next Steps

- Continue discussions at Extreme Weather Working Group based on feedback
- Share research and findings at ICS

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Questions?

Our Mission and Vision

Mission

Ensure power system reliability and competitive markets for New York in a clean energy future

Vision

Working together with stakeholders to build the cleanest, most reliable electric system in the nation

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