First Draft Methodology Appendix of PJM Effective Load Carrying Capability Model

July, 2020

ELCC Methodology Appendix

Load Modeling Methodology

Context: The Reserve Requirement Study includes load uncertainty consistent with the PJM Load Forecast. The PJM Load Forecast provides expected 50/50 load values as well as probabilistic distributions around peaks derived from around 300 weather scenarios.

Load Modeling for ELCC has 3 components:

1. Hourly Load Shapes (HLS) based on historical weather years
2. Weight for each Hourly Load Shape (HLS)
3. Load Uncertainty for each Hourly Load Shape (HLS)

Component 1 - Hourly Load Shapes are derived consistent with a) the actual weather experienced during the historical years and b) the most recent PJM Load Forecast Model for the future target delivery year. Specifically, the actual weather during the historical years will be input into the PJM Load Forecast Model to derive hourly load shapes for the future target delivery year.

Component 2 - Weight for each Hourly Load Shape: The derivation of the weights for each Hourly Load Shape includes 3 steps. The weights are intended to represent the frequency with which each historical weather year occurs. The 3 steps are listed below

a) Calculate the summer and winter peaks for each of the 300 weather scenarios in the PJM Load Forecast, then use cluster analysis to group the weather scenarios represented by pairs (summer peak, winter peak) into a limited set of clusters. This step provides information such as: there are X% of the 300 weather scenarios in the cluster that is representative of Extreme Summer peaks and Extreme Winter peaks.

Cluster	Description	Number of Scenarios	% of Scenarios
Cluster 1	Extreme Summer – Extreme Winter	X1	Y1%
Cluster 2	Extreme Summer – Mild Winter	X2	Y2%
…		…	…
Cluster n	Mild Summer – Mild Winter	Xn	Yn%

b) Determine the summer and winter peaks in the Hourly Load Shapes (Component 1). For instance, if there are 7 load shapes, there will be 7 pairs (summer peak, winter peak)

c) For each of the pairs in Step 2, determine the most representative Cluster based on the summer and winter peak values. For instance, if Year 1 in Step 2 has an Extreme Summer and an Extreme Winter, then the Year 1 Hourly Load Shape is representative of Cluster 1; the weight assigned to Year 1 is Y1% which is the share of scenarios that result in an Extreme Summer peak and Extreme Winter peak.

Component 3 – The determination of the load uncertainty for each of the Hourly Load Shapes is based on the weather scenarios included in the representative cluster. For instance, if the Year 1 Hourly Load Shape is representative of Cluster 1, then the X1 scenarios in Cluster 1 are used to derive the load uncertainty for the Year 1 HLS. The procedure to derive the load uncertainty is as follows:

- Identify the monthly peaks from the weather scenarios in the Cluster that the HLS is representative of. For instance, for Year 1, identify the 12 monthly peak values in each of the X1 weather scenarios in Cluster 1.
- Using the 12 monthly peak values from the representative cluster's weather scenarios, determine the parameters of a multivariate normal distribution. A multivariate normal distribution is used instead of a normal distribution to account for correlations between monthly peaks.
- Using Monte Carlo and the multivariate normal distribution, derive 1,000 load scenarios for each of the HLS.

Resource Modeling

Thermal Generation

Context: The Reserve Requirement Study includes thermal generation performance uncertainty via EEFORd and Planned Outage Factor based on historical GADS data from the most recent 5 year period.

Thermal Generation performance modeling in the ELCC model also requires the Planned Outage Factor for each unit as well as two additional metrics related to EEFORd: the Mean Time to Failure (MTTF) and the Mean Time to Repair (MTTR). These metrics are derived for each unit based on historical GADS data from the most recent 5 year period.

Derivation of MTTF and MTTR for each unit from GADS data:

- Calculate Total Hours, where Total Hours is equal to Service Hours plus Full Forced Outage Hours
- Calculate Effective Available Hours, where Effective Available Hours is equal to Total Hours times (1 – EEFORd)
- Calculate Effective Forced Outage Hours, where Effective Forced Outage Hours is equal to Total Hours times EEFORd
- Calculate MTTF, where MTTF is equal to Effective Available Hours divided by Number of Full Forced Outages
- Calculate MTTR, where MTTR is equal to Effective Forced Outage Hours divided by Number of Full Forced Outages

The MTTF and MTTR values above are needed in the ELCC model because Monte Carlo simulation will be used to derive a pattern of availability and unavailability for each thermal unit in the system. This pattern captures full availability and full unavailability. Partial outages are not explicitly modeled by the Monte Carlo. However, the calculation of the MTTF and MTTR above is adjusted so that partial outages are accounted for. The adjustment is performed in the second and third steps above where the Effective Available Hours and the Effective Forced Outage Hours are calculated by using EEFORd. EEFORd is a metric that includes full and partial forced outages.

Monte Carlo Modeling of Forced Outages

The objective of using Monte Carlo to model forced outages is to derive multiple and variable patterns of availability and unavailability for each unit to capture the random nature of forced outages.

Standard assumptions in reliability models are:

- The Time a Unit is not on a Random (Forced) Outage is a random variable that follows an exponential distribution.
- The Time a Unit is on a Random (Forced) Outage is a random variable that follows an exponential distribution.

The exponential distribution requires one parameter, the mean. For the ELCC model, the parameter for the first exponential distribution is the Mean Time To Failure (MTTF) while the parameter in the second distribution is the Mean Time To Repair (MTTR).

Given a random number R (with $0 < R < 1$),

$$T\_Online = -1 \times \ln(R) \times MTTF$$

$$T\_Offline = -1 \times \ln(R) \times MTTR$$

where T_Online stands for time a unit is not on a random (forced) outage and T_Offline stands for time a unit is on a random (forced) outage.

Algorithm to develop 1,000 scenarios

1. Determine the initial State of each thermal unit by drawing a random number R0 and then comparing it to each unit's EEFORd
   a. If R0 <= EEFORd, unit starts in the Offline State
   b. If R0 > EEFORd, unit starts in the Online State
2. Determine how long (in hours) a unit will be in each state by using the formulas for T_Online and T_Offline above. The formulas are dependent on random numbers R (R1, R2,…,Rn). Note that every time a unit enters a new State, a new random number should be used. Also, the sets of random numbers should be different for each generator.
3. Repeat the calculations in Step 2 until a pattern of Offline-Online states has been determined for each unit covering the 8,760 hours in a year.
4. Repeat Steps 1-3 for each of the remaining 999 scenarios.

Planned Outages

The scheduling of planned outages for each thermal unit resembles closely the approach taken in the Reserve Requirement Study. For each thermal unit in the system, a Planned Outage Factor in weeks is determined based on historical GADS data from the most recent 5 year period.

The principle underlying the planned outage schedule is that PJM will have the ability to avoid having a large number of units on a planned outage during high load conditions. The outcome of using that principle is that no units will be scheduled to have a planned outage during the summer peak season. A similar outcome results for the winter peak season, though a few units may end up getting scheduled on a planned outage during such period.

A planned outage schedule that seeks to levelize available reserves throughout the year achieves the objectives of the principle outlined above. In essence, an algorithm that levelizes available reserves places the majority of the planned outages during periods where load tends to be low. By placing the planned outages during these periods, the available reserve levels throughout the year become more homogeneous (i.e. they are levelized).

A different planned outage schedule is derived for each of the load scenarios in each of the Hourly Load Shapes according to the following procedure:

- Determine the total MW Week Planned Outage Requirement for each unit by multiplying the Planned Outage Factor times the ICAP value.
- Sort the units based on the MW Week Planned Outage Requirement from highest to lowest.
- Before scheduling any planned outage, calculate the weekly percent available reserve by dividing the ICAP value by each of the 52 weekly peaks (summer peak week will end up with about 15% reserves while shoulder period weeks may end up with 50% reserves or more).
- Calculate the Total Reserve Deviation (TRD):
  - $TRD = \sum_{i=1}^{52} (R_i - \min(R_i))^2$

  where Ri is the weekly percent available reserve of week i. Ri can be mathematically defined as:

  - $R_i = \frac{(ICAP - PlannedOutages_i - WeeklyPeak_i)}{WeeklyPeak_i}$
- For each unit in the sorted list of units, identify all the periods in which each unit could be scheduled on a planned outage. For instance, if a unit has a planned outage requirement of 10 weeks, there are 43 periods in which the unit can be scheduled on a planned outage: Week 1 -Week 10, Week 2 – Week 11, Week 3 – Week 12, …, Week 43 – Week 52.
  - Calculate TRD for each of the alternative periods in which the planned outage can occur. For instance, in the example mentioned earlier, there will be 43 TRD values.
  - Select the period that produces the smallest TRD value. This is the period in which the planned outage is scheduled to occur. This decision is consistent with the concept of levelizing reserves.
  - Once a planned outage period has been selected for a given unit, this selection impacts the Ri values calculated at the time of scheduling the planned outage of subsequent units.