


Accrediting Resource Adequacy Value to Thermal Generation

Report

03/30/2022

PREPARED FOR

Advanced Energy Economy (AEE)

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ABBREVIATIONS USED IN REPORT

ADJ _{Var}	EFOR Variability Adjustment Factor
ADJ _{Corr}	EFOR Correlation Adjustment Factor
ADJ _{Fuel}	EFOR Fuel Availability Adjustment Factor
ADJ _{WDO}	EFOR Weather Dependent Outage Adjustment Factor
AESO	Alberta Electric System Operator
BESS	Battery Energy Storage Systems
CAISO	California Independent System Operator
CC	Combined Cycle
CT	Combustion Turbine
DS	Diesel Generator
ECAP	Equivalent Capacity
EFOR	Equivalent Forced Outage Rate
EFORD	Equivalent Forced Outage Rate Demand
EIA	U.S. Energy Information Administration
ELCC	Effective Load Carrying Capability
ERCOT	Electric Reliability Council of Texas
EUE	Expected Unserved Energy
FERC	Federal Energy Regulatory Commission
GW	Gigawatts
ICAP	Installed Capacity
INC _{Fuel}	Incremental Fuel Availability Adjustment Factor
INC _{WDO}	Incremental Weather Dependent Adjustment Factor
IRM	Installed Reserve Margin
IRM _{FUEL}	IRM calculated using the fuel and weather dependent outage rates
IRM _{ICAP}	Installed Reserve Margin calculated using the traditional ICAP methodology
IRM _{UCAP}	Installed Reserve Margin calculated using the UCAP methodology
IRM _{WDO}	IRM calculated using the weather dependent outages
LOLE	Loss of Load Expectation
MISO	Midcontinent Independent System Operator
MW	Megawatts
MW _{EFOR}	Sum of ICAP values for all resources for which EFOR is applied
MW _{Fuel}	Sum of ICAP values for all resources subject to the potential fuel unavailability
MW _{WDO}	Sum of ICAP values for all resources for which WDO are modeled
NREL	National Renewable Energy Laboratory
NSRDB	National Solar Radiation Database
OFO	Operational Flow Orders
PJM	PJM Interconnection
Pk Load	System Peak Load
PSH	Pumped Storage Hydro
PV	Photovoltaic
SAM	System Advisor Model
SERVM	Strategic Energy & Risk Valuation Model

SPP	Southwest Power Pool
ST	Steam Turbine
UCAP	Unforced Capacity
WDO	Weather Dependent Outage

EXECUTIVE SUMMARY

Quantifying the comprehensive resource adequacy contribution of renewable and energy-limited resources has been explored in rigorous detail by many resource planners over recent decades through the evaluation of Effective Load Carrying Capability (ELCC). However, the accreditation of conventional thermal generators has not been explored as robustly. A common assumption is that the Equivalent Forced Outage Rate Demand (EFORd) is a reasonable proxy for the impact that these generators will have on the need for reserves. A system with homogeneous resources with EFORd of 10% would presumably need to carry reserves of 10% to compensate for that level of performance. However, that is only true if the system has perfect outage characteristics of 10% of the fleet offline in all hours of need. Random forced outages will lead to some hours having many more megawatts offline and some hours with less. Reserves of 10% would not protect reliability in hours with more outages. Generally reserve margin studies account for this, but the impact does not get assessed to the thermal fleet directly; it gets socialized by load on the demand side. Other performance effects of conventional units including correlated outages due to weather or common equipment failures are often not considered at all. This paper explores the potential impacts of thorough quantitative consideration of outage modeling on accreditation methods, particularly in structured capacity markets.

While the implications of this consideration will vary from system to system, the results of this analysis suggest that the capacity accreditation of conventional resources is often overstated. For the test system considered, the impact on accreditation ranges up to 20% as shown in the table below. It should be understood, however, that not all systems may see that level of impact, depending upon the specific nature of the system and the mix of resources on that system.

Table ES1. Correlated Outage Impacts

		Winter Accreditation Impact	Winter Capacity Credit ¹	Summer Accreditation Impact	Summer Capacity Credit
Standard Accounting Practice	Forced Outage Rate	5.0%	95.0%	5.0%	95.0%
	Outage Variability	2.7%	92.3%	4.6%	90.4%
Proposed Additional Considerations	Outage Correlation	2.3%	90.0%		
	Weather Dependent Outages	10.0%	82.3% ²	5.6%	84.7%
	Fuel Supply Outages ³	6.2%	76.1% ⁴		

Current practice within the industry is to calculate the ELCC for non-dispatchable resources such as solar and wind resources and energy limited resources such as Battery Energy Storage Systems (BESS). The ELCC of such generating resources is often calculated by determining how much additional load can be served by the resource without negatively impacting key reliability metrics, such as Loss of Load Expectation (LOLE). The ELCC is expressed as a fraction of the nameplate of the resource being evaluated. Since these resources have energy limits or cannot be dispatched, their reliability

¹ Values shown in the Winter Capacity Credit and Summer Capacity Credit column are cumulative.

² Impact calculated incremental to Outage Variability

³ As studied in this analysis, Fuel Supply Outages are only applicable to natural gas units that do not have a backup supply source such as on on-site alternate fuel.

⁴ Impact calculated incremental to Weather Dependent Outages

contribution is generally less than 100%. Representative ELCCs are shown in Table 1 below. The ELCC of renewable resources can range from 0-80% and the ELCC of BESS can range from 10% to 100%.

Table ES2. Published Regional ELCC Values

	PJM ⁵	CAISO ⁶	MISO ⁷	SPP ⁸	ERCOT ⁹
Onshore Wind	15.0%	16.3%	16.6%	16.8%	21.0%
Off-Shore Wind	40.0%	N/A	N/A	N/A	31.0%
Solar Fixed	38.0%	8.7%	50.0%	85.1%	74.0%
Solar Tracking	54.0%	11.0%	50.0%	85.1%	74.0%
4-Hr Battery	83.0%	90.6%	100.0% ¹⁰	N/A	N/A

Many factors including the technology penetration, technology characteristics, and system characteristics can affect the ELCC of these resources. In addition to the impact of energy limitations and non-dispatchability, the impact of outages or availability are typically embedded in the analysis and will affect the ELCC. For example, the output profiles of wind and solar resources reflect periods of forced or maintenance outages. In other words, outages from wind, solar and energy storage are reflected on the supply-side under most ELCC models. This report explores the implications of assessing ELCC and Thermal resource uncertainty both on the supply side.

ELCCs have not typically been quantified for thermal resources since they are dispatchable and theoretically do not have energy constraints. The only reduction in the reliability contribution of these resources would be due to unplanned outages. Accrediting capacity for thermal resources is typically done by quantifying the difference in nameplate or Installed Capacity (ICAP) and Unforced Capacity (UCAP). UCAP is generally calculated as a function of both its ICAP and its EFORD as follows:

$$UCAP = ICAP * (1 - EFORD).$$

However, the development of EFORD and its application in traditional resource adequacy modeling, even when applied as part of a UCAP formulation, is not sufficient to identify the true load carrying capability of such resources. While EFORD is an appropriate calculation for the determination of the expectations of a particular unit’s availability when considered on an independent basis, its application in traditional resource adequacy modeling does not take into consideration of the distribution of

⁵ PJM. “PJM ELCC Class Average Ratings for 2023/2024 BRA” July 2021. Accessed from <https://www.pjm.com/-/media/planning/res-adeq/elcc/elcc-class-ratings-for-2023-2024-bra.ashx>

⁶ Astrapé. “2021 Joint CA IOU ELCC Study” June 2021, pp. 3-4. Accessed from <https://www.astrape.com/publications/>

⁷ MISO. “MISO Planning Year 2020-2021 Wind & Solar Capacity Credit” December 2019, pp. 3-4. Accessed from <https://cdn.misoenergy.org/2020%20Wind%20&%20Solar%20Capacity%20Credit%20Report408144.pdf>

⁸ SPP. “2020 ELCC Wind and Solar Study Report” July 2021, pp. 2-3. Accessed from <https://spp.org/documents/65169/2020%20elcc%20wind%20and%20solar%20study%20report.pdf>

⁹ Astrapé. “2020 ERCOT Reserve Margin Study” January 2021, Appendix 2, p. 35. Accessed from <https://www.astrape.com/publications/>

¹⁰ MISO. “Resource Adequacy Business Practice Manual BPM-0110r24” December 2020, p. 70. Accessed from <https://cdn.misoenergy.org//BPM%20011%20-%20Resource%20Adequacy110405.zip>

system outages or the potential correlations in outages across a generation fleet that may impact the overall ability of the fleet to serve load.

The Federal Energy Regulatory Commission (FERC), PJM¹¹, and other RTOs are actively considering how to address uncertainty of performance of resources in resource adequacy planning and the implications for capacity accreditation. Questions addressed in this paper include:

1. Should some supply-side uncertainties currently being socialized to demand-side of the resource adequacy construct (i.e., load) be addressed on the supply-side instead?
2. Should the status quo modeling/quantification of these uncertainties be modified?
3. What uncertainties are not accounted for today but can be reasonably quantified?"

Overall, directly evaluating resource uncertainty on the supply-side delivers a more accurate accreditation of the reliability contributions from each resource type. Today, a portion of the thermal resource uncertainty is not being directly accounted for in its capacity accreditation, and therefore that uncertainty is being socialized to load. Accounting for the uncertainty categories in this report creates a more consistent approach for determining capacity accreditation between resources currently assessed via ELCC (wind, solar, storage) and thermal resources.

This report examines the potential impacts of a full and complete supply side accounting for such uncertainties, including forced outages, correlated outages, weather dependent outages, and fuel unavailability of traditional thermal resources, thus determining the potential impact of those categories their ability to serve load. While the report itself is not intended to address the impacts on total capacity needs that consideration of such correlated outages may cause, it is intended to address the technology capacity accreditations associated with considering those outages.

From a markets perspective, applying outage uncertainties to capacity accreditation further creates differentiation between types of traditional, thermal units that did not previously exist. Furthermore, it impacts the ranking of thermal and storage units in the bid stack. As highlighted in Tables 16 -17, such differences in valuation could impact the results of a given capacity auction.

Each of the four categories and their resulting impact on capacity accreditation are described below.

OUTAGE VARIABILITY

A key component of reliability planning is accounting for generator performance uncertainty. Intuitively, a system with a 5% forced outage rate would need to carry about 5% more capacity to account for the outages. However, this would only work if the system always had exactly 5% of its generators on outages. In reality, the variability of outages means that some hours can have 7% of the

¹¹ E.g. <https://www.pjm.com/-/media/committees-groups/task-forces/rastf/2021/20211217/20211217-item-04-education-reliability-risks-and-drivers-post-meeting.ashx>

system unavailable while others might have 2% of the system unavailable. Typical outage variability is shown in Figure ES1.

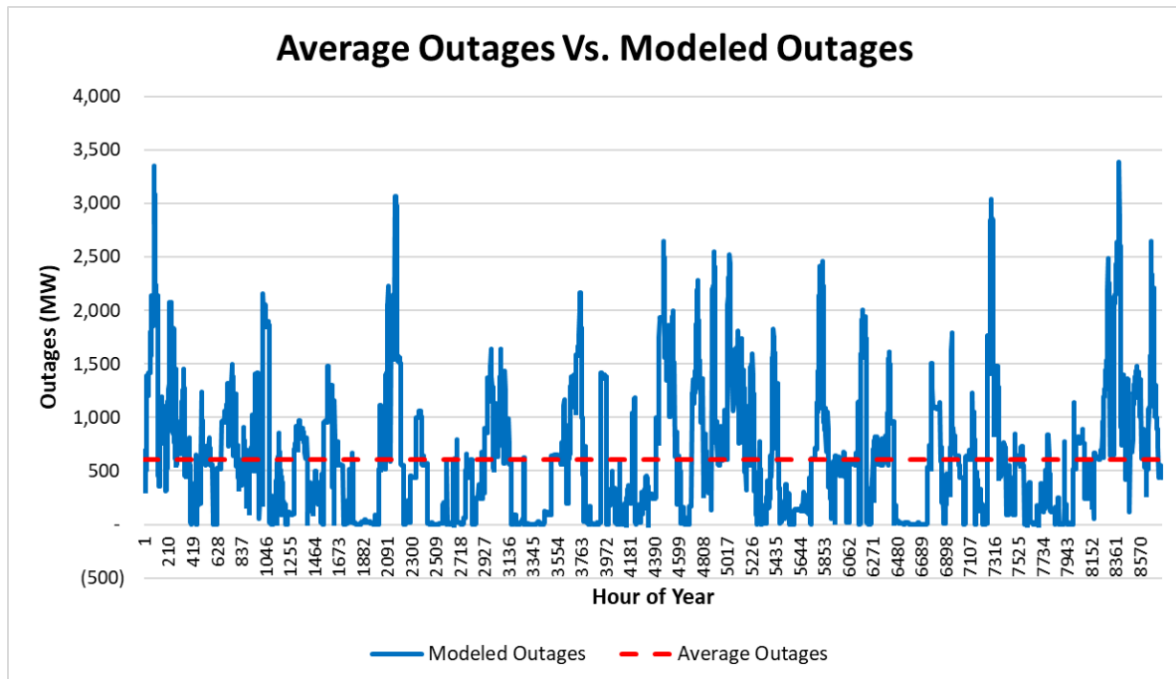


Figure ES1. Average Versus Modeled Outages

Resource adequacy modeling quantifies the impact of this variability. To maintain 0.1 LOLE, the system wouldn't need reserves equal to the largest possible outage condition though, because many hours have outages below the average. After weighing the results of thousands of simulated years of outages, the typical resource adequacy analysis will demonstrate that a system with a 5% forced outage rate would need to carry perhaps 7% reserves to account for generator performance uncertainty. Thus, this variability in cumulative outages results in a higher reserve margin requirement than what might otherwise be implied by a simple equivalent forced outage rate (EFOR)/UCAP application.

Since most resource adequacy standards are set via simulations with random forced outages, this risk is generally fully captured in the reserve margin requirements set by ISOs and utilities. However, since accreditation is performed using EFOR statistics only, the reliability risk due to variability is effectively being socialized across all load. In our example above, the generators would receive 95% accreditation on average even though they only supply 93% reliability value due to the variability of outages.

To properly assign these costs, a change to the accreditation process is needed. This variability can be reflected directly in the capacity accreditation of thermal resources by calculating an effective load carrying capability for those resources. This thermal ELCC can be determined by making an adjustment to the EFORd currently used in the UCAP calculation as follows:

$$ELCC = (1 - EFORd - ADJ_{VAR}),$$

where ADJ_{VAR} represents this variability adjustment to the EFOR. In the hypothetical example above, this adjustment factor would be 2%, the increase in IRM impact associated with the variable nature of the outage modeling. The equivalent capacity (ECAP) of the resource would then be:

$$ECAP = ICAP * ELCC.$$

On a non-hypothetical system, this variability adjustment can be determined by first calculating the IRM for a specific system using traditional EFOR modeling, adding or removing capacity as necessary until a reliability of 0.1 LOLE is achieved. Second, IRM is calculated again, but instead of traditional EFOR modeling, outage modeling is turned off so that all units are perfect capacity, but every unit is then derated to its UCAP value. This has the effect of modeling an average outage rate every hour. Because of the cumulative outage variability, the total capacity requirements of the traditional IRM calculation will be greater than the total capacity requirements of the UCAP approach. The difference between the total capacity requirements of the two calculated IRMs, calculated on a percentage basis, is the outage variability impact.

Astrapé performed such an analysis on the test system assuming both a winter peaking load configuration as well as a summer peaking load configuration. The test system was the PJM South region evaluated on an islanded basis as described in the Study Approach section below. Seasonal peak load adjustments were made to effectuate the winter and summer peaking conditions as required.

As demonstrated in the table below, the result of the winter peaking load configuration showed that for the 20 gigawatt (GW) test system (19.8 GW of impacted EFOR-based generation), the outage variability between UCAP and ICAP caused an additional 536 MW of needed capacity, resulting in an outage variability adjustment of 2.7%.

Table ES3. Winter EFOR Adjustment Factor Calculation

Component	Value	Reference
Perfect Outage Capacity Requirements	23,540 MW	[A]
Variable Outage Capacity Requirements	24,076 MW	[B]
Variability Impact	536 MW	[C]=[B]-[A]
Impacted Capacity	19,780 MW	[D]
Variability Adjustment	2.7%	[E] = [C]/[D]

The Perfect Outage Capacity Requirements represents the capacity needed to achieve Installed Reserve Margin (IRM) requirements for a system modeled with units derated to their UCAP value assuming no other outages.¹² The Variable Outage Capacity Requirement represents the capacity needed for a system modeled with units at their ICAP capacity and traditional EFOR outage modeling. The difference between these, therefore, represents the impact of outage variability on the reliability of the system. This factor can be applied to all resources for which EFORd is calculated (i.e., the Impacted Capacity).

The table below shows the same calculations for the summer peaking load configuration, resulting in a variability adjustment of 4.6%.

¹² For this analysis, IRM requirements were established as the amount of capacity necessary to maintain an LOLE of 0.1 days/year.

Table ES4. Summer EFOR Adjustment Factor Calculation

Component	Value	Reference
Perfect Outage Capacity Requirements	21,729 MW	[A]
Variable Outage Capacity Requirements	22,587 MW	[B]
Variability Impact	858 MW	$[C]=[B]-[A]$
Impacted Capacity	18,489 MW	[D]
Variability Adjustment	4.6%	$[E] = [C]/[D]$

Since the current methodologies for the ELCC calculations of BESS and renewable resources such as wind and solar already incorporate this variability, no adjustment is necessary for those resources. The Study Approach section of this report describes this calculation process in more detail.

The difference between summer and winter adjustment factors is an issue that warrants further investigation. However, likely factors are the differences in the nature of summer reliability events (long duration events impacted by outages) versus winter reliability events (shorter duration events involving significant load variability and uncertainty).

The Study Approach section of this report describes this calculation process in more detail.

OUTAGE CORRELATION

The concept of the outage variability adjustment above can be extended to also consider correlation of outages. Both the EFORd calculation methodology and most resource modeling techniques assume outages are independent, meaning the outage of one resource does not impact the expectation of the outage of other resources. By contrast, outages can be correlated, meaning that the outage of one resource may, in fact, be related to the availability of other resources. For example, consider a generating facility with two generators tied to the grid by a common generator step-up transformer. In the event the generator step-up transformer were to fail, both generators would be forced offline simultaneously and the event would affect their subsequent EFOR calculations. Future simulations of the system assuming traditional, independent outage modeling might result in the modeled outage of one generator at one time and the other generator at a separate time. In reality, the common-mode failure of the generator step-up transformer causes both generators to fail at the same time. These types of correlated outages are not accounted for in traditional resource adequacy modeling techniques. If some portion of the system's overall outages are indeed correlated, the distribution of system outages will be even more uneven with periods of significant outages and periods of minimal outages. The figure below shows an example of a simulated system with independent outages and assuming a randomly distributed level of correlation.

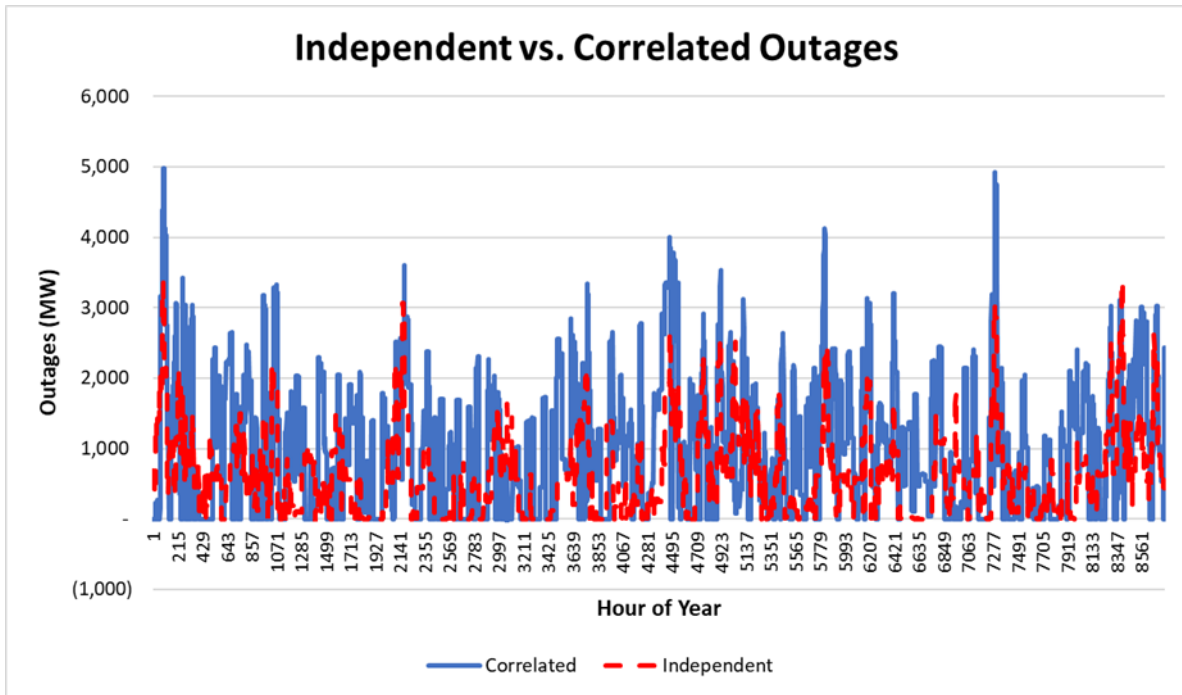


Figure ES2. Comparison of Independent Versus Correlated Outages

When such correlation occurs at times of high demand, it can contribute to reliability events. Identifying the precise level of correlation can be difficult and was not done as part of this analysis. However, Astrapé performed analysis on the winter peaking load configuration of the test system assuming a varying correlation that ranged from +/-10% of system capacity and calculated the ELCC impact to the traditional, thermal resources. NERC GADS data and cumulative outage tables can inform the level of actual correlation inherent in system outages, but since this project used publicly available data, that was not possible. Further, there are some outages that are clearly correlated such as switchyard failures, shared environmental control failures, and transmission line failures versus weather-related outages that may show only partial correlation. Deciphering this correlation, however, is not critical as long as the resource adequacy simulations replicate the system outage patterns, the effects of correlation can be deduced. The correlation effect can be isolated in the same way that the outage variability effect can be isolated via simulating with static outages and comparing to realistic random outages. As shown in the table below, the result of that analysis showed an EFOR Correlation Adjustment Factor (ADJ_{Corr}) of 5.0%.

Table ES5. Winter EFOR Correlation Adjustment Factor Calculation

Component	Value	Reference
Perfect Outage Capacity Requirements	23,540 MW	[A]
Variable Correlated Outage Capacity Requirements	24,526 MW	[B]
Correlated Impact	986 MW	[C]=[B]-[A]
Impacted Capacity	19,780 MW	[D]
Correlation Adjustment	5.0%	[E] = [C]/[D]

This value would be used in the thermal resource ELCC calculation in lieu of the ADJ_{Var} factor as follows:

$$ELCC = (1 - EFOR_d - ADJ_{Corr}),$$

As with the ADJ_{var} factor, this adjustment would be applicable to all resources for which EFORD is applied, but not those intermittent and energy limited resources that utilize a more traditional ELCC calculation. No such correlation analysis was performed for the summer peaking load configuration of the test system.

The Study Approach section of this report describes this calculation process in more detail.

WEATHER DEPENDENT OUTAGES

One of the ways in which correlated outages can be more specifically quantified is outages correlated to severe weather events. As temperatures become more extreme, the combination of increased demand on the resources and the effects of temperature on the equipment itself creates a higher overall risk of failure. This is especially true during extreme cold weather events, as has been demonstrated during many of the extreme weather events over the last decade. While specifics are not available due to confidentiality, a number of utilities have explicitly modeled the impacts of correlated outages as a function of weather. For example, Georgia Power Company included the impacts of cold weather outages in its 2018 Reserve Margin Study included as part of its 2019 Integrated Resource Plan.¹³

Astrapé incorporated the incremental forced outage rates as a function of temperature displayed in Figure 1 based on research performed at Carnegie Mellon University (referred to herein as the Sinnott Murphy report).¹⁴ These incremental forced outage rates were applied to the test system for both cold weather and hot weather and their impacts on the ability of the affected thermal resources to serve load were quantified. Although the NERC GADS data used to construct the relationships between weather and forced outage rates includes outages related to fuel supply, Dr. Murphy recognizes that the non-linearity of fuel unavailability with temperature means that the published model doesn't fully reflect the true risk of fuel concerns in the extreme scenarios that affect resource adequacy.¹⁵ The figure below is an example of the cold weather outages for Combined Cycle (CC) resources as reported on page 9 of the Sinnott Murphy report.

¹³ State of Georgia Public Service Commission Docket #42310.

¹⁴ Murphy, Sinnott, et. Al. "A time-dependent model of generator failures and recoveries captures correlated events and quantifies temperature dependence." November 2019. Available from <https://www.sciencedirect.com/science/article/pii/S0306261919311870>.

¹⁵ Murphy. "The largest instances of under-prediction by our model occurred during two known events in which significant generator outages were due to causes not included as covariates: the 2014 Polar Vortex (due to fuel unavailability events, which increase non-linearly in cold weather) and Hurricane Sandy (an extreme weather event but not with regard to temperature)."

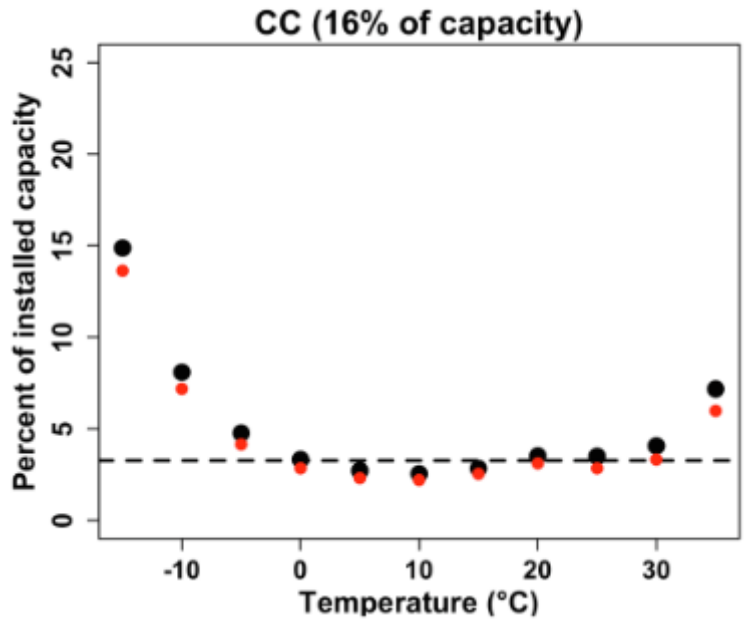


Figure 1. CC Outage Profile from Sinnott Murphy Report

The report contained similar graphs for several unit categories. Astrapé used the values from these graphs as inputs to the Strategic Energy & Risk Valuation Model (SERVM).¹⁶ The two figures below respectively show the incremental outage impact due to cold weather outages and hot weather outages as determined from the Sinnott Murphy report and modeled in this study.

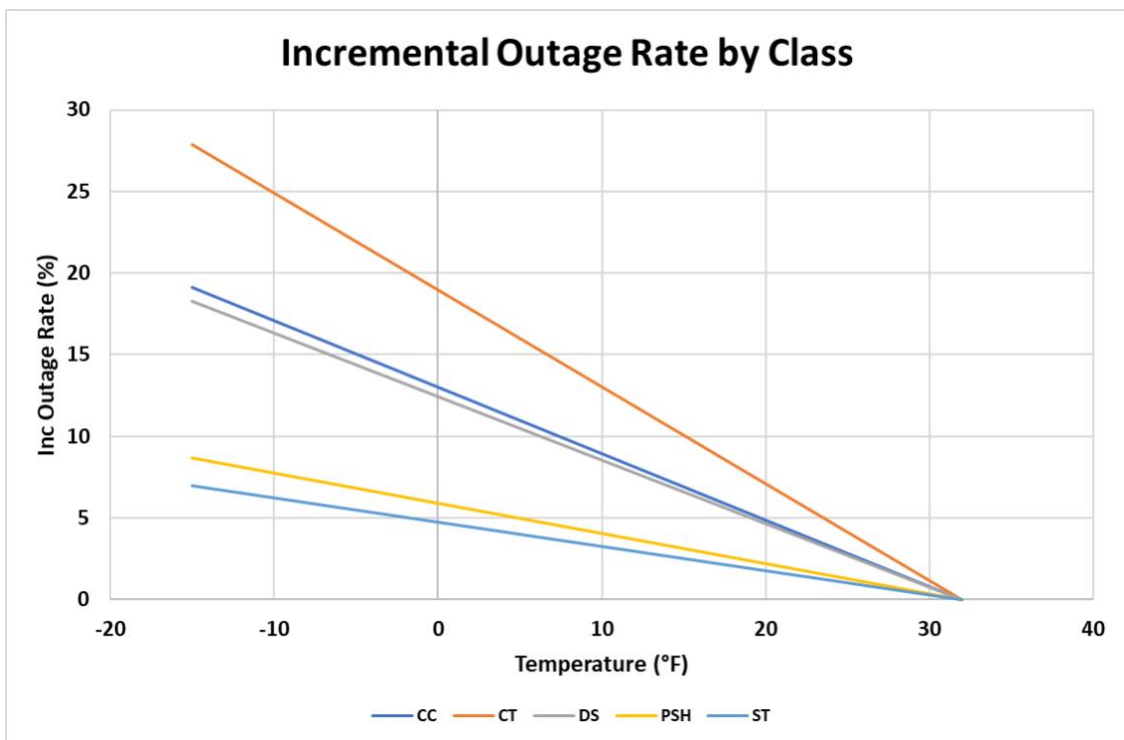


Figure ES3. Cold Weather Outage Assumptions

¹⁶ While the incremental outage rates are quantified according to exponential relationship in the Sinnott Murphy paper, the values modeled in SERVM were fit to linear curves to reflect a conservative impact of weather on outage rates.

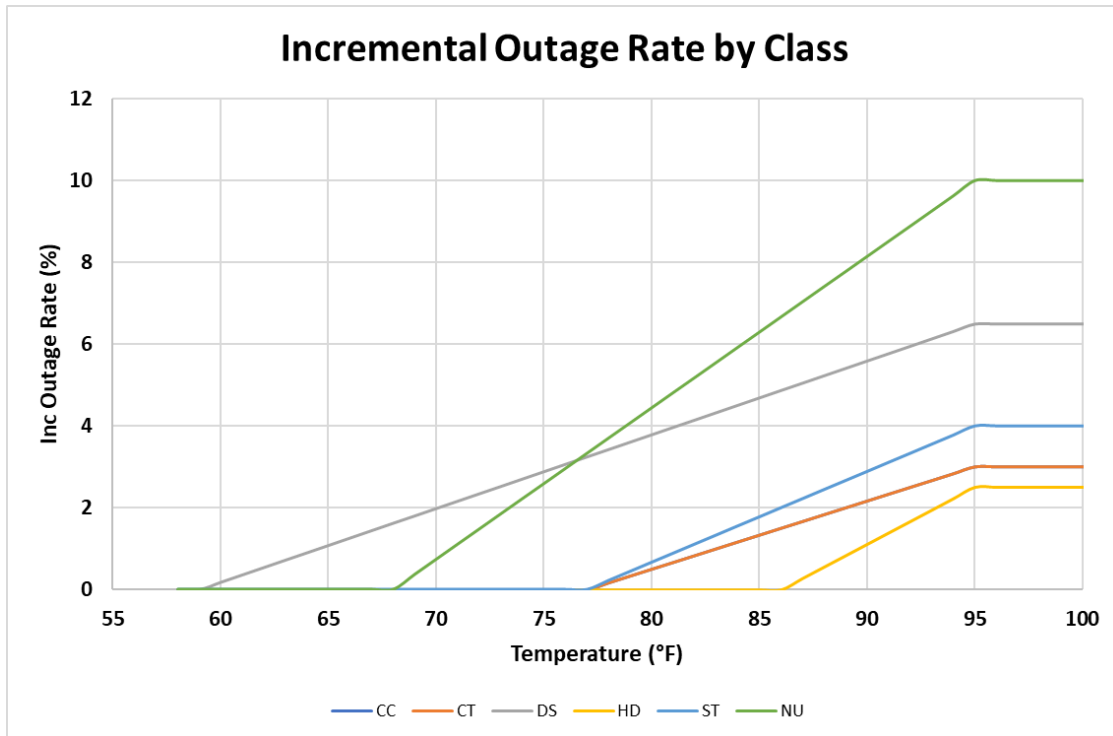


Figure ES4. Hot Weather Outage Assumptions

The cold weather outage analysis was performed on the winter peaking load configuration and produced a Weather Dependent Outage (WDO) EFOR Adjustment Factor (ADJ_{WDO}) of 12.7% as calculated in the table below.

Table ES6. Winter WDO Adjustment Factor Calculation

Component	Value	Reference
Variable Outage Capacity Requirements	24,076 MW	[A]
WDO Capacity Requirements	26,033 MW	[B]
WDO Impact	1,957 MW	[C]=[B]-[A]
Impacted Capacity	19,576 MW	[D]
Incremental WDO Adjustment	10.0%	[E] = [C]/[D]
Variability Adjustment	2.7%	[F]
Total Adjustment	12.7%	[G] = [E]+[F]

As the table demonstrates, the WDO Impact is calculated incrementally to the ICAP reliability requirements and represents the incremental impact weather dependent outages have on system reliability. This incremental adjustment can then be added to the Variability adjustment to obtain the WDO Adjustment Factor. This factor would be used in the thermal resource ELCC calculation in lieu of the ADJ_{Var} factor as follows:

$$ELCC = (1 - EFOR_d - ADJ_{WDO}).$$

Astrapé recognizes that not all generators within a respective class will exhibit weather dependence on outages, so the application of this adjustment should reflect individual unit performance.

Hot weather outage analysis was performed on the summer peaking load configuration and produced an ADJ_{WDO} of 10.3% as shown in the table below.

Table ES7. Summer WDO Adjustment Factor Calculation

Component	Value	Reference
Variable Outage Capacity Requirements	22,587 MW	[A]
WDO Capacity Requirements	23,612 MW	[B]
WDO Impact	1,025 MW	[C]=[B]-[A]
Impacted Capacity	18,272 MW	[D]
Incremental WDO Adjustment	5.6%	[E] = [C]/[D]
Variability Adjustment	4.6%	[F]
Total Adjustment	10.3% ¹⁷	[G] = [E]+[F]

The hot and cold weather outage adjustment factors must be applied independently depending upon whether the system is primarily summer peaking or winter peaking.

The difference between the summer adjustment impact and the winter adjustment impact are due directly to the lower incremental outage rate for extreme summer temperatures as compared to those for extreme winter temperatures.

It should also be noted that for purposes of this analysis, the ADJ_{WDO} was calculated as a single value for all affected resource classes. However, given that the incremental outage rate varies by resource class, future analysis may be warranted to calculate the adjustment factor by class.

The summer and winter ADJ_{WDO} values above were calculated inclusive of the ADJ_{Var} factor and not the ADJ_{Corr} factor, although similar factors can be calculated relative to the ADJ_{Corr} . Only those resources subject to weather dependent outages would use the ADJ_{WDO} . All other resources would only use the ADJ_{Var} (or ADJ_{Corr}) factor. Resources such as renewable or BESS resources that already utilize the ELCC methodology would have no adjustment.

The data suggests certain thermal generation technology types perform significantly below their capacity accreditation during extreme weather conditions, just when the system needs them most. To put ELCC resources and Thermal resources on the same footing, grid planners should account for this weather dependent performance in capacity accreditation.

The Study Approach section of this report describes this calculation process in more detail.

FUEL AVAILABILITY

While the Sinnott Murphy report appears to only consider outage correlations with temperature, there is an additional impact during extreme cold weather events on the availability of fuel itself, particularly the availability of natural gas. While it was not possible from the available empirical data to create a direct correlation between temperature and fuel availability, anecdotal evidence from a variety of sources suggest that by the time temperatures reach 0°F, as much as 10% of the natural gas supply

¹⁷ Individual component results reflect rounding impacts not reflected in the Total Adjustment.

could become unavailable.¹⁸ To be clear, this component of our analysis is intended to capture physical availability of fuel that reflects that during very cold periods even gas generators with firm fuel supply contracts can be affected. Critically, our analysis assumes that scheduling procedures are optimized for reliability in that all fuel backup opportunities are utilized and gas is efficiently scheduled to maximize energy production. This means that proposed accreditation adjustments are isolating the reliability impact of fuel supply concerns and are not conflating availability impacts driven by economic scheduling practices. However, given the paucity of fuel supply data available for this analysis, further effort is warranted to accurately quantify a heuristic for gas availability as a function of temperature.

Astrapé modeled this outage probability on the winter peaking load configuration of the test system and applied this additional probability to all natural gas resources. The result was an EFOR Fuel Availability Adjustment Factor (ADJ_{Fuel}) of 18.9% as calculated in the table below.

Table ES8. EFOR Fuel Availability Adjustment Factor Calculation

Component	Value	Reference
WDO Capacity Requirements	26,033 MW	[A]
Fuel Capacity Requirements	26,638 MW	[B]
Fuel Impact	605 MW	[C]=[B]-[A]
Impacted Capacity	9,739 MW	[D]
Incremental Fuel Adjustment	6.2%	[E] = [C]/[D]
WDO Adjustment	12.7%	[F]
Total Adjustment	18.9%	[G] = [E]+[F]

This adjustment factor would be used in the thermal resource ELCC calculation in lieu of other adjustment factors as follows:

$$ELCC = (1 - EFORd - ADJ_{Fuel}).$$

This adjustment factor would only be applied in the circumstance in which natural gas unavailability can be explicitly modeled in the development of the IRM, and base line EFORd value derived from historical data excluded fuel related outage events in calculating its average availability. Furthermore, it would only be applied to those natural gas resources subject to such fuel unavailability. For example, any resource with on-site replacement fuel - such as a dual-fueled Combustion Turbine (CT) with onsite oil reserves or a gas steam unit with a secondary coal supply – would not be subject to this adjustment.

The ADJ_{Fuel} factor above was calculated inclusive of both the ADJ_{Var} factor and the ADJ_{WDO} factor. Non natural gas resources that are subject to weather dependent outages would still be subject to the ADJ_{WDO} factor and any EFOR resource not subject to either ADJ_{WDO} or ADJ_{Fuel} would still be subject to the ADJ_{Var} factor. As with the ADJ_{WDO} , the ADJ_{Fuel} could be calculated relative to the ADJ_{Corr} rather than the ADJ_{Var} .

The Study Approach section of this report describes this calculation process in more detail.

¹⁸ See Appendix A for a list of references used in making this determination.

SUMMARY OF RESULTS

The following table summarizes the results of the analyses discussed above for cold weather events as performed on the winter peaking load configuration of the test system. For reporting purposes, the weather dependent outages and fuel availability outages were combined with correlated outages results to create a set of adjustment factors with and without correlation included.

Table ES9. Summary of Winter Simulations

Adjustment Factor	Adjustment %	Affected Resources
EFOR Variability	2.7%	All resources with EFOR
EFOR Weather Dependent Outages	12.7%	All resources subject to WDO
EFOR Fuel Availability	18.9%	All natural gas resources subject to WDO and without fuel backup
EFOR Correlation	5.0%	All resources with EFOR
EFOR WDO with Correlation	15.0%	All resources subject to WDO
EFOR Fuel with Correlation	21.2%	All resources subject to WDO and without fuel backup

All values in the table reflect cumulative impact (e.g., EFOR Fuel Availability encompasses the combined impacts of variability, WDO, and fuel availability).

The table below summarizes results of the analyses discussed above for hot weather events as performed on the summer peaking load configuration of the test system.

Table ES10. Summary of Summer Simulations

Adjustment Factor	Adjustment %	Affected Resources
EFOR Variability	4.6%	All resources with EFOR
EFOR Weather Dependent Outages	10.3%	All resources subject to WDO

As mentioned above, the application of summer and winter adjustment factors are independent of one another. For systems that have predominantly winter reliability risk, the winter adjustment factors should be utilized. Likewise, for systems that have predominantly summer reliability risk, the summer adjustment factor should be utilized. Systems that have more balanced reliability risks should be evaluating that risk on a seasonal rather than annual basis, in which case the summer adjustment factors would be used in the summer and the winter adjustment factors would be used in the winter.

It is important to note that not all resource types are impacted by every category of adjustment. For example, according to the Sinnott Murphy report, nuclear resources are not going to be subject to winter WDO adjustments, but are likely to be subject to summer WDO adjustments. Likewise, coal units would not be subject to adjustments for gas unavailability, but would likely be subject to WDO adjustments. Gas units, both combustion turbine and combined cycle, are likely to be subject to both WDO and fuel availability adjustments, except in the case where on site backup fuel is available – in which case they would only be subject to WDO adjustments.

It is also important to recognize that the use of these adjustment factors is tied directly to the modeling and consideration of their effects in the determination of the system reserve margin. The EFOR Variability Adjustment Factor (with or without correlation) could be considered applicable in all systems based on the most common resource adequacy study practices. However, the other adjustment factors should only be applied if those considerations (i.e., incremental cold weather outages or fuel unavailability) have been incorporated into the reserve margin analysis. Nevertheless, it should be expected that while incorporating these effects into the ICAP IRM determination will result in a higher ICAP IRM, the offsetting reductions in the capacity accreditation is such that the UCAP-based IRM should not be affected.

Furthermore, it is important to remember that some of these outages, such as weather dependent outages, may already be embedded to some degree in existing EFOR rates. However, unless they are broken out and explicitly modeled explicitly as temperature dependent outages, the impacts of these outages are spread out across all hours of the period rather than concentrated across the specific temperature ranges. Even with seasonal EFORs, the impact is still spread across all hours of the season. Thus, when considering and modeling weather dependent outages, it is important that the underlying EFOR is properly adjusted to exclude the effects of these weather dependent outages.

Finally, it should be understood that this analysis was performed as an indication of the potential need for such adjustments to thermal capacity values to be considered. Therefore, while the analysis was performed on an actual system (PJM South), it is intended primarily to be representative of the nature and potential magnitude of the adjustments needed. So while these adjustment factors should be reasonably characteristic of many systems, some systems may have sufficiently different characteristics such that adjustment factors would be significantly different. As such, careful consideration should be given as to whether more system-specific factors should be generated on a case by case basis.

POTENTIAL FURTHER EXPLORATION

The analysis performed in this study was an initial examination of the impacts of outages on the ability of traditional, thermal resources to carry load. There are a number of areas in which further analysis and exploration is warranted. These are described below.

1. Combined results of summer and winter events.

The analyses performed in this study for cold weather events and hot weather events were performed independently. Cold weather events were evaluated on a winter peaking test system with no hot weather outage events modeled. Likewise, hot weather events were evaluated on a summer peaking test system with no cold weather outage events modeled. Aggregating summer and winter events and associated outage probabilities may produce different results than those indicated in this report.

2. **ADJ_{WDO} by unit class.**

While the analyses performed in this study did model differences in performance by unit class, it did not specifically calculate the weather dependent outage adjustment factors by unit class. More detailed analysis would provide this additional level of granularity.

3. **Variability or correlation adjustments by size or age of units.**

While the analyses performed in this study did model differences in performance by unit class, it did not differentiate performance of units by either size or age of units. Further research may indicate that units with different sizes or ages may perform differently, justifying a more detailed evaluation of their ELCC.

4. **Further research quantifying outage correlation.**

Further research quantifying outage correlation could create greater support for the heuristic used in this study.

5. **Impacts of oil fluidity on outage rates.**

For purposes of this analysis, it was presumed that the Sinnott Murphy report did not incorporate fuel availability outages. However, the analysis itself only researched natural gas availability. During extreme cold weather events, oil fluidity can also create outages due to fuel unavailability issues. It is unclear whether the Sinnott Murphy report included such outages in its research. If it did not, it may be beneficial to research this issue further.

6. **Impacts of coal pile freeze-ups.**

As with oil fluidity, it is unclear whether the Sinnott Murphy report included the effects of coal pile freeze ups in its research. If it did not, it may be beneficial to research this issue further.

INTRODUCTION

The purpose of this report is to identify and quantify potential impacts that various outage conditions may have on the ability of a thermal generating resources to carry load. It is also intended to assess the general efficacy of the metrics used to measure that ability of resources to carry load. Astrapé used a model of the PJM South region as a test system to simulate these various conditions as described below.

Current practice within the industry is to calculate the Effective Load Carrying Capability (ELCC) for non-dispatchable resources such as solar and wind resources and energy limited resources such as Battery Energy Storage Systems (BESS). The ELCC of such generating resources is often calculated by determining how much additional load can be served by the resource without negatively impacting key reliability metrics, such as Loss of Load Expectation (LOLE). No such equivalent practice exists for more traditional thermal generation. This report explores the need for and possible implemental of a thermal unit equivalent to the ELCC calculations currently used for renewables and other energy limited resources.

While many regions express the capability of its traditional thermal generation in terms of its nameplate or Installed Capacity (ICAP), some regions express the capability of traditional thermal generation in terms of its Unforced Capacity (UCAP). UCAP is generally calculated as a function of both its ICAP and its Equivalent Forced Outage Rate Demand (EFORd) as follows:

$$UCAP = ICAP * (1 - EFORd).$$

The development of EFORd and its application in traditional resource adequacy modeling, even when applied as part of a UCAP formulation, is not sufficient to identify the true load carrying capability of such resources. While EFORd is an appropriate calculation for the determination of the expectations of a particular unit's availability when considered on an independent basis, its application in traditional resource adequacy modeling does not always take into consideration potential correlations in outages across a generation fleet that may impact the overall ability of the fleet to serve load. This report examines four such categories of correlation and examines their potential impact on a traditional resource's ability to serve load. Those categories include:

1. Outage Variability Due to Variability
2. Outage Correlation
3. Weather Dependent Outages
4. Outages Due to Fuel Unavailability

The Study Approach section below describes each of these in detail.

MODEL DEVELOPMENT

The Strategic Energy & Risk Valuation Model (SERVM) utilized for this study was based upon load and resource profiles of the PJM South region, developed mainly with publicly available information. Astrapé chose the PJM South region for several reasons. First, the idea of this analysis was to model a representative system that might translate to other regions. Since PJM South is the smallest of the PJM regions, simulation time would be relatively fast but would produce results that could translate to other regions. Second the PJM South region is naturally winter peaking. This was important as the bulk of the analysis focused on cold weather events.

The data development and study framework used in the analysis were similar to those by Astrapé for systems such as ERCOT, MISO, SPP, AESO, as well for electric utilities such as Tennessee Valley Authority, Southern Company, Duke Energy, and Pacific Gas and Electric. For examples of how such studies are developed and performed, reference is made to the list of publicly available studies on the Astrapé website at <https://www.astrape.com/publications/>.

STUDY YEAR

The study year for the analysis was 2022.

PEAK DEMAND FORECAST

The winter peak demand forecast for 2022 was set at 19,708 MW, which represents the median of the 38 load shapes modeled (see Load Modeling below).

LOAD MODELING

Load volatility associated with variances in weather patterns were modeled via historical weather year simulations. Loads were modeled as 38 hourly load shapes representing expected weather conditions for the years 1980 thru 2017 applied to load forecasts for the study year. The peak load volatility resulting from these load shapes is shown in Appendix B.

ECONOMIC FORECAST ERROR

The set of Load Forecast Errors (LFE) in the table below, and their associated probability of occurrence, were applied to each load shape.

Table 1. LFE Model

LFE	Probability
-4%	6%
-2%	24.2%
0%	39.5%
2%	24.2%
4%	6%

CONVENTIONAL RESOURCE MODELING

Due to the confidential nature of the pertinent information, conventional resources were modeled using publicly available information. In some cases, detailed public information was limited and certain assumptions were subsequently made. As such, the list of resources and their associated capacities to be modeled were determined from information found in the Federal Energy Regulatory Commission (FERC) Form U.S. Energy Information Administration (EIA) 860. These units were then modeled with class average heat rates at maximum capacity. Outage data was developed so that resources conformed to class average EFORs, and a generic planned outage rate of 5% which is a typical system average was applied to all resources.

SOLAR PROFILE DEVELOPMENT

Irradiance data for two locations in the PJM South region were downloaded from the National Renewable Energy Laboratory (NREL) National Solar Radiation Database (NSRDB) Data Viewer for the years 1998 to 2017.¹⁹ The data obtained from the NSRDB Data Viewer was input into NREL's System Advisor Model (SAM) for each year and location to generate the hourly solar profiles based on the solar weather data for fixed and tracking solar photovoltaic (PV) plants.²⁰ Solar profiles for 1980 to 1998 were selected by using the daily solar profiles from the day that most closely matched the peak load for the aggregate MISO load out of all the days +/- 2 days of the source day for the 1998 to 2017 interval. The profiles for the remaining years 1998 to 2017 came directly from the normalized raw data.

HYDRO RESOURCE MODELING

Available hydro data from 1980 to 2017 was collected from the EIA Form 923.²¹ The appropriate hydro projects were assigned to PJM South for all 38 weather years. Using the aggregate actual hourly data provided on the PJM website from 2016 to 2018, inputs were developed to be used by the proportional load following algorithm for the proper PJM zones. The average daily minimum and maximum dispatch levels, the total monthly energy, as well as the monthly maximum dispatch levels were identified from the historical hourly data for PJM. Curve fit equations were applied to historical data from the monthly energies calculated in the EIA form. The daily maximum and minimum dispatch and monthly maximum dispatch in conjunction with the total monthly energy are parameters that go into the determination of the hourly hydro schedule. The daily minimum hydro dispatch is scheduled at the minimum load hour of the day, and the daily maximum hydro is scheduled at the maximum load hour of the day. The monthly maximum hydro is scheduled at the max load hour of the month.

¹⁹ <https://maps.nrel.gov/nsrdb-viewer/>

²⁰ <https://sam.nrel.gov/>

²¹ <https://www.eia.gov/electricity/data/eia923/>

RESOURCE MIX

The model of the system described above resulted in a system with the mix of resources shown in the figure below.

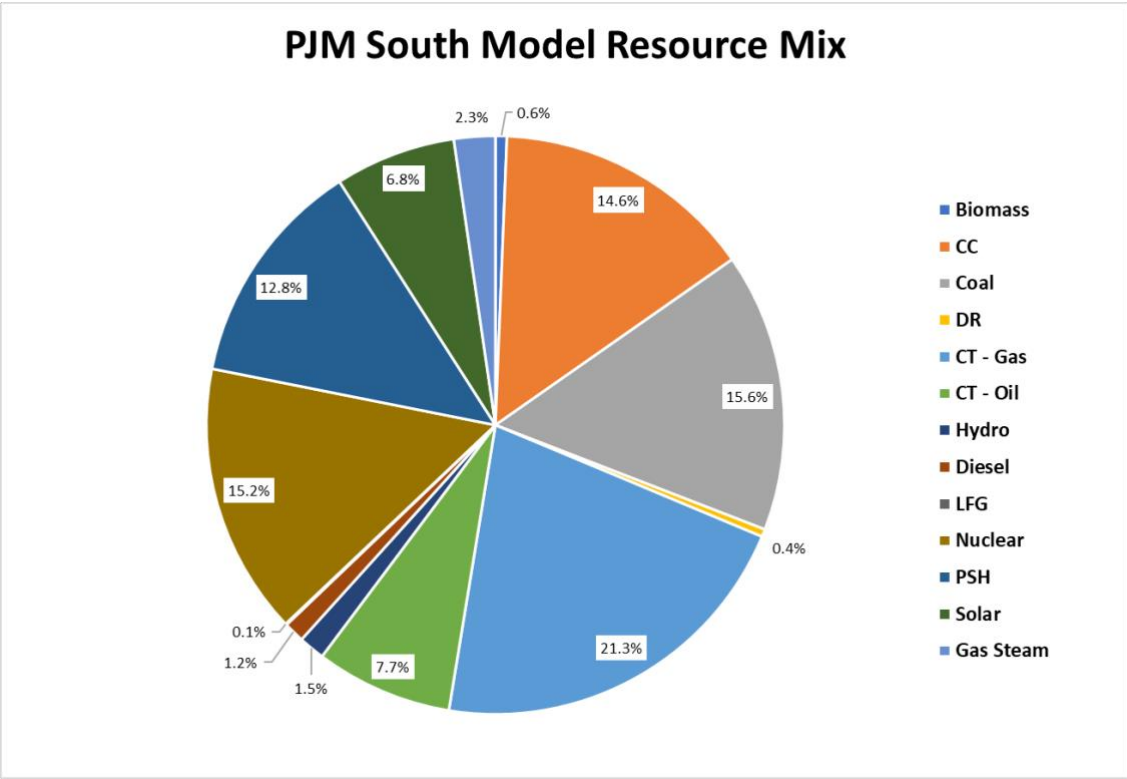


Figure 2. PJM South System Mix²²

²² Based on information provided in the FERC Form EIA 860.

STUDY APPROACH

The goal of this analysis was to determine the impact of unit outages on the ability of traditional, EFOR-based units to serve load and to translate this impact into an ELCC equivalent for these resources. To calculate this impact, Astrapé sought to determine the impact of such correlated outages on the IRM of a system calibrated to an LOLE of 0.1 days/year. Astrapé examined four classifications of outages:

1. The variability of outages as compared to UCAP which assumes a static level of outages,
2. The correlation of outages between resources as compared to independently modeled outages,
3. The increase in outages associated with extreme temperatures, and
4. Outages associated with loss of fuel source during extreme weather events.

The following describes how Astrapé determined the Installed Reserve Margin (IRM) impacts for each of these classifications to quantify those impacts into an ELCC equivalent.

IRM DEVELOPMENT METHODOLOGY

As indicated above, Astrapé chose the PJM South region to calculate the IRM impacts. As demonstrated in the figure below, PJM South is naturally winter peaking.²³ Thus, all cold weather events would be evaluated on a test system with winter peaking load conditions.

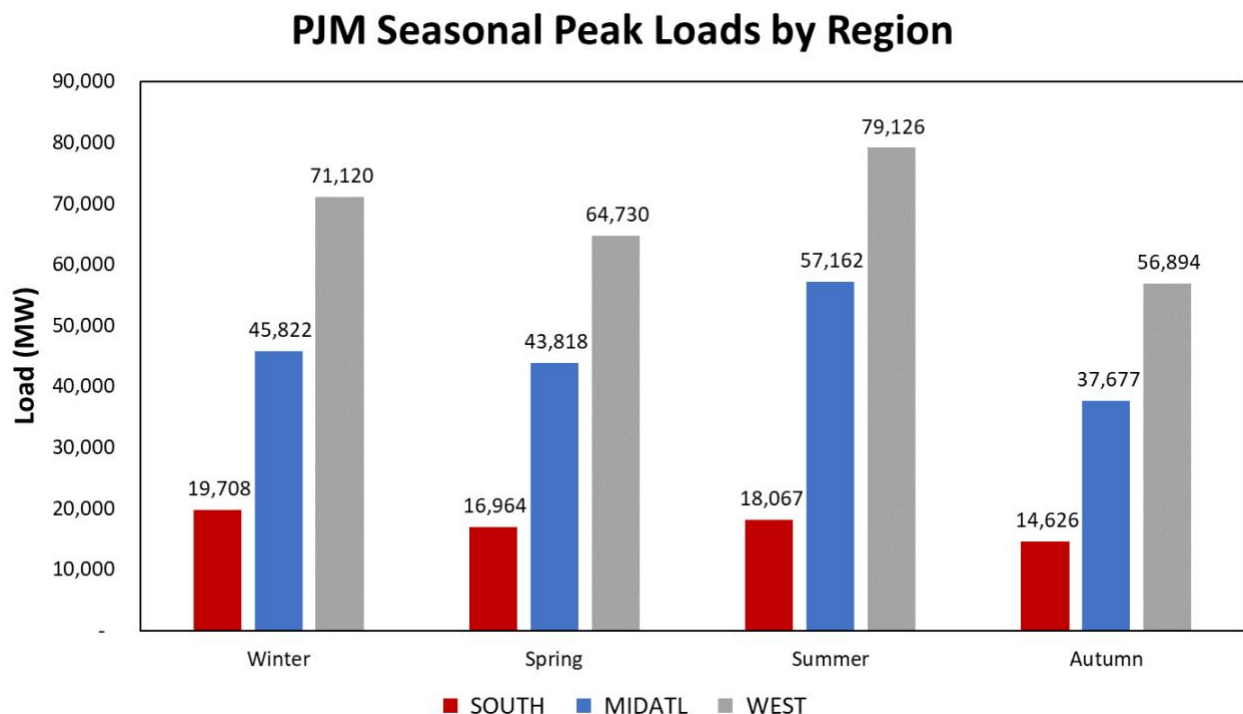


Figure 3. PJM Seasonal Peak Loads

²³ The PJM load shapes and peak demand forecasts modeled in this study were developed based on publicly available information and thus may not perfectly reflect current expectations of the seasonal peak loads for these regions.

To minimize execution time of the model, the test system was modeled on an islanded basis. Because there is reliability benefit associated with being interconnected system due to market interactions during times of reliability need, modeling an islanded system would otherwise result in a very high IRM. Therefore, to simulate the benefit associated with an interconnected system while still modeling an islanded system, a 10% market benefit was assumed in the IRM calculations to account for market interactions (i.e., IRMs were lowered by 10%).²⁴

Because the seasonal peak loads for the PJM South region are so close to one another and to ensure winter dominance, two further adjustments were made to the regional model. First, the spring and fall peak loads were adjusted downward to reflect the per unit spring and fall peak loads for the PJM Mid-Atlantic region. This was done to ensure that SERVM would schedule all planned maintenance in the spring and fall. The resulting PJM South seasonal peak loads are reflected in the figure on the following page.

Second, to further ensure that most, if not all, Expected Unserved Energy (EUE) occurred in the winter, 2,500 MW of summer only curtailable load was added to the system.

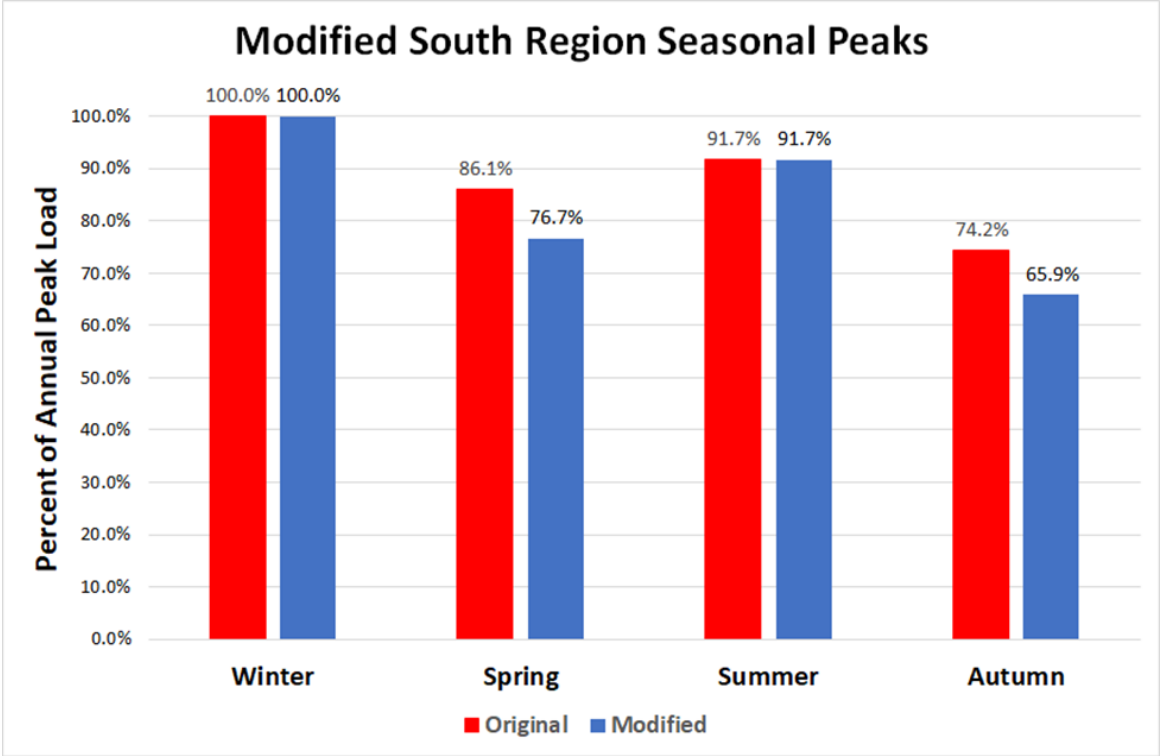


Figure 4. Modified PJM South Seasonal Peak Loads

In the scenarios requiring summer dominance, a test system with summer peaking load conditions was desired. Therefore, similar adjustments to the seasonal peak loads of the test system were made to

²⁴ Thus, if the IRM for a given scenario was calculated to be 30%, the IRM for that scenario was deemed to be 20% instead.

simulate the summer peaking load profile of the PJM Mid-Atlantic region. This resulted in seasonal peak demands on a per unit basis as shown in the following figure.

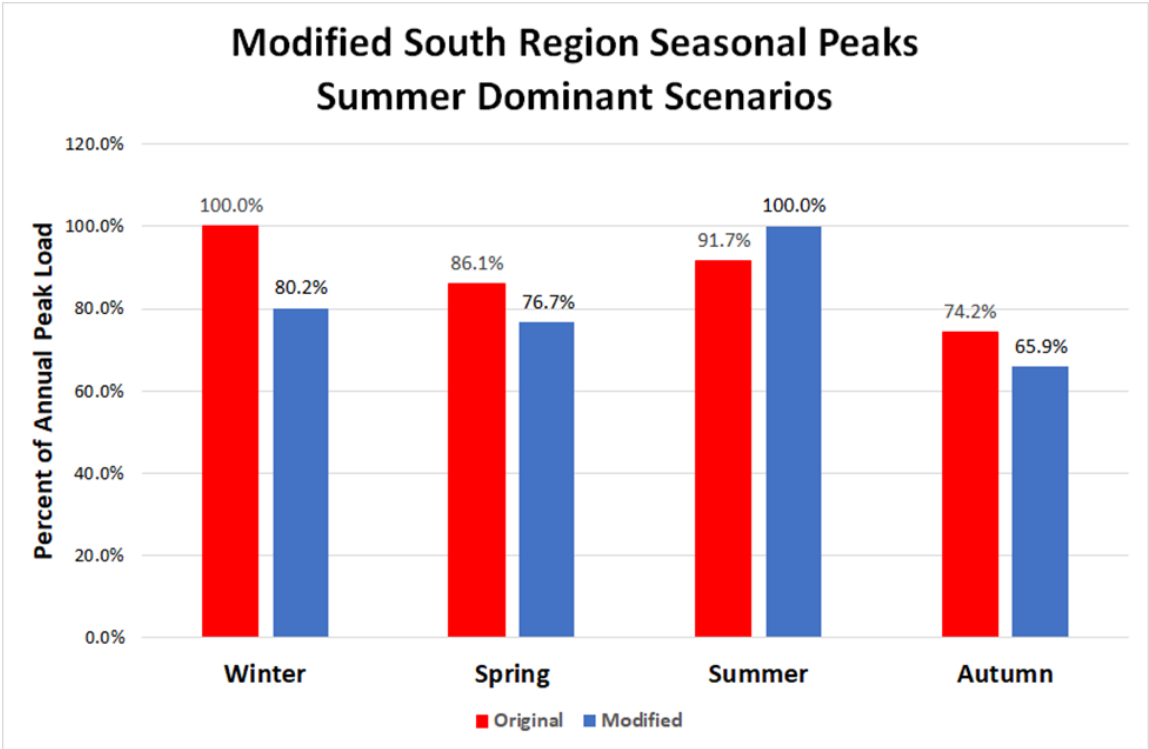


Figure 5. Modified PJM South Seasonal Peaks for Summer Dominant Scenarios

As with the winter dominant test system, 2,500 MW of winter only curtailable load was added to the test system to ensure that all (or virtually all) of the EUE occurred in the summer.

To make the analysis between summer and winter comparable, both the summer peaking system and the winter peaking system were set to the same peak load.

The actual IRM for each scenario was then developed by iteratively modeling the system with incremental positive or negative perfect MW adjustments as necessary until the simulated system reached an LOLE of 0.1 days/year.

OUTAGE VARIABILITY

While almost all entities within the industry use some form of ELCC calculation to determine the capacity value of renewable and BESS resources, the capacity value of more traditional resources are determined either through their installed capacity (ICAP) value or their unforced capacity value (UCAP) determined by the equation

$$UCAP = ICAP * (1 - EFORD).$$

However, since EFORD is an average expectation of outage rate for the resource, UCAP necessarily assumes this same outage rate across all hours. Thus, UCAP does not fully consider the variances in outage rates that can materialize in any given simulation of the system as described below.

At the resource level, the EFORd of a given resource is calculated based on the historical outage profile of that particular resource, and thus represents future expectations for outages at that facility. Because of how it is calculated, however, EFORd represents the average outage rate for the facility. By contrast, outages occur somewhat randomly, such that there are numerous potential future outcomes for not only the single resource, but the system made up of a multitude of such resources. In theory, one would expect the average outcome of all future outcomes to converge to the historical EFORd not only for the resource, but also for the system-weighted outage rate. The figure below demonstrates how the system-weighted outage rate of a simulated system may vary over 30 iterations (i.e., 30 potential future outcomes) and the extent to which they are distributed about the average system-weighted outage rate (i.e., the expected reliability of the system).

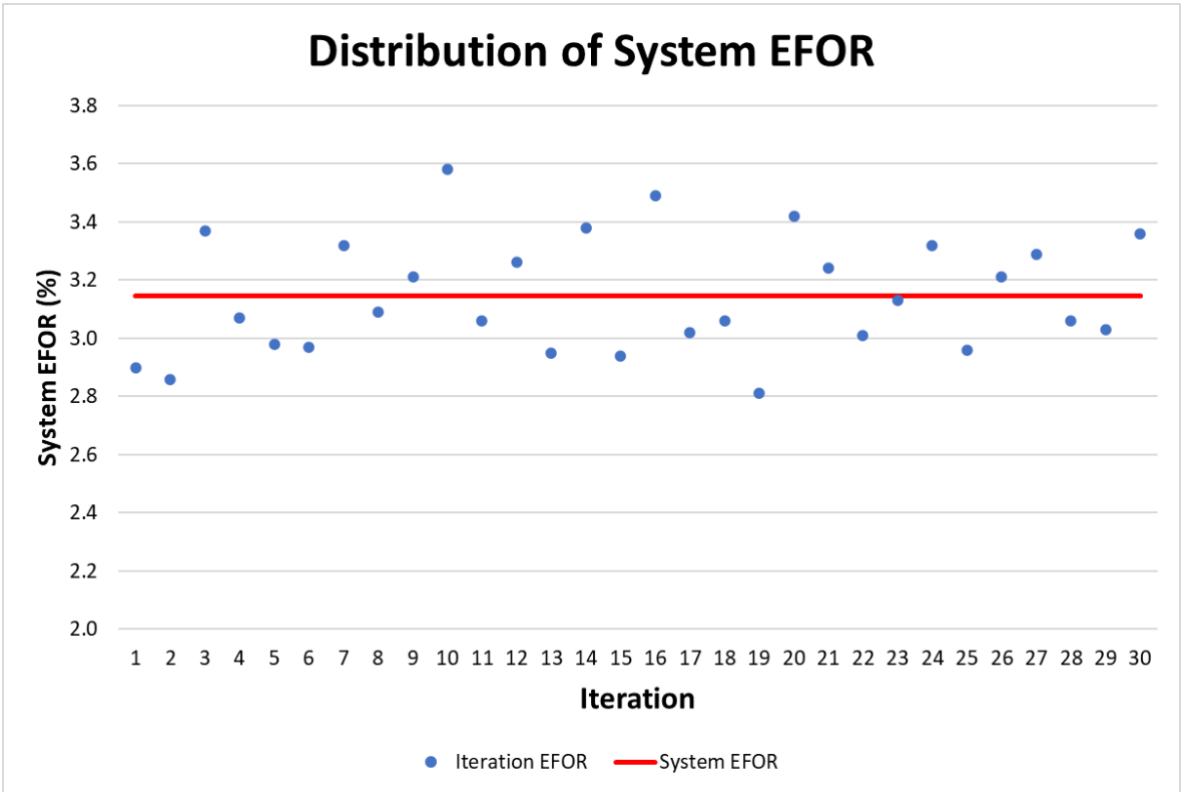


Figure 6. Example of EFOR Distribution

As shown, in any given simulated outcome, the reliability of the system may be higher or lower than the expected value. Similarly, because of the random nature of the outages, total outages on the system will vary throughout the year, with some hours higher than the system-weighted outage rate and other hours lower as demonstrated in the figure below.

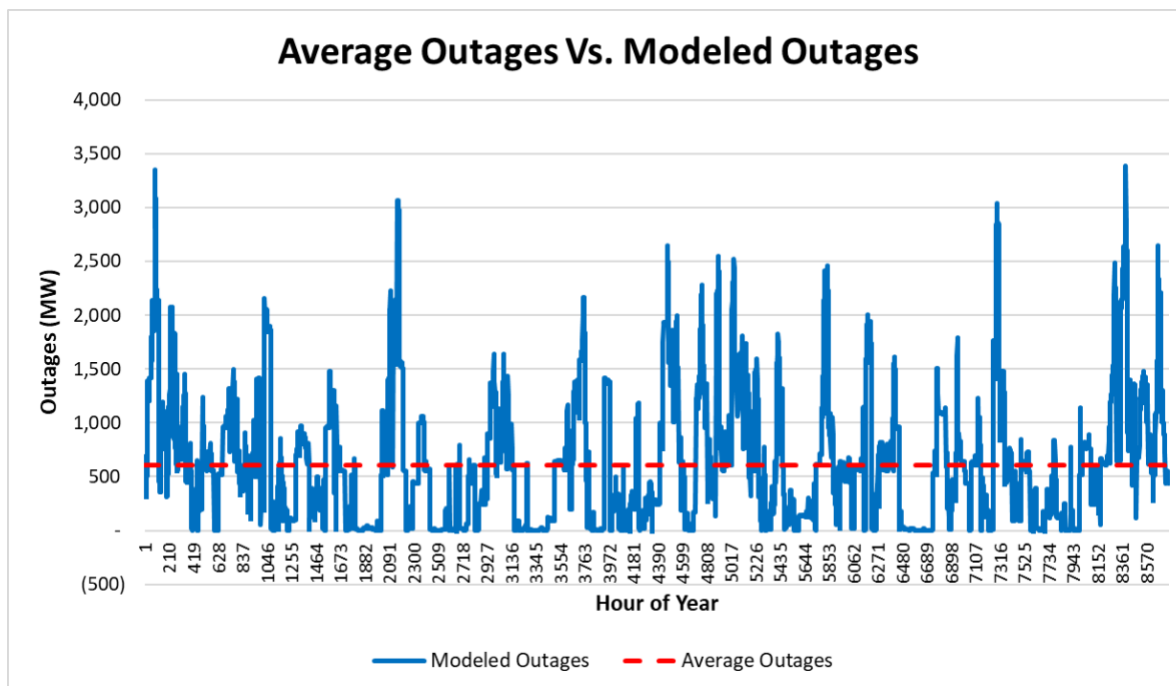


Figure 7. Demonstration of Outage Variability

The figure demonstrates that there are numerous hours with significantly higher cumulative outages than the average (i.e., EFORD). This will create a need for more reserves than would be otherwise implied by capacity values based on UCAP, which are based on the average outage rate presumed in the EFORD of the unit.

To isolate the impact of this variability, Astrapé calculated a base-level IRM that would reflect only the load variability of the system and the average outage rate of the system represented by EFORD. This impact was accomplished by modeling all resources as being derated to their UCAP capacity value and then simulating the system without any other outage values. This would result in a IRM that is lower than that which would be determined by the more traditional method of modeling the resources at their ICAP value and simulating the unit outages. The difference in these IRM values could then be translated into an adjustment factor that can be applied to the UCAP value to create an equivalent ELCC for these resources. The adjustment factor would be calculated as follows:

$$\text{Equation (1): } ADJ_{\text{Var}} = (\text{IRM}_{\text{ICAP}} - \text{IRM}_{\text{UCAP}}) * \text{Pk Load} / \text{MW}_{\text{EFOR}}$$

Where

ADJ_{Var} = the adjustment factor due to outage variability

IRM_{ICAP} = the IRM (in per unit) calculated using the traditional ICAP methodology

IRM_{UCAP} = the IRM (in per unit) calculated using the UCAP method described above

Pk Load = the system peak load (in MW)

MW_{EFOR} = the sum of the ICAP values for all resources for which EFOR is applied (in MW).²⁵

²⁵ For purposes of this analysis, all IRM values were determined using a perfect MW adjustment (i.e., a 100% load factor resource without any outages). Thus, this perfect MW capacity adjustment, along with any renewable, BESS, or other resources without outage rates, would be excluded from the MW_{EFOR} calculation.

An equivalent ELCC can then be calculated using the equation

$$\text{Equation (2): } ELCC = (1 - EFOR_d - ADJ_{Var}).$$

This ELCC value can then be multiplied by the ICAP of the resource to determine its equivalent capacity (ECAP) as follows:

$$\text{Equation (3): } ECAP = ICAP * ELCC.$$

All resources for which EFOR is applied (and therefore included in the determination of MW_{EFOR} above) would have a capacity value established by the ELCC equivalent using the EFOR of that specific resource.

OUTAGE CORRELATION

The concept of outage variability still presumes that outages are independent of one another. However, the outage of one resource can have an impact on the subsequent availability of other resources. Since historical outage data was not available for this system, statistical tests of outage correlation could not be performed. Nevertheless, assuming a potential correlation range of +/- 10% that varies randomly within this range across the year, Astrapé was able to develop a heuristic that simulated this varying level of correlation. The heuristic calculated a random value every hour that ranged from -2,000 MW to 2,000 MW (approximately +/- 10% of the system). This value resulted in an adjustment to the total outages in that hour so that some hours showed less outages than would be assumed without correlation and other hours showed more outages than would be assumed without correlation. The heuristic was then tuned such that the average outages across the year for both the correlated outage set and the independent outage set were the same (i.e., the correlation heuristic did not increase the overall system outage rate). The figure below shows an example of the impact such a heuristic would have on the outage profile of a single annual simulation.

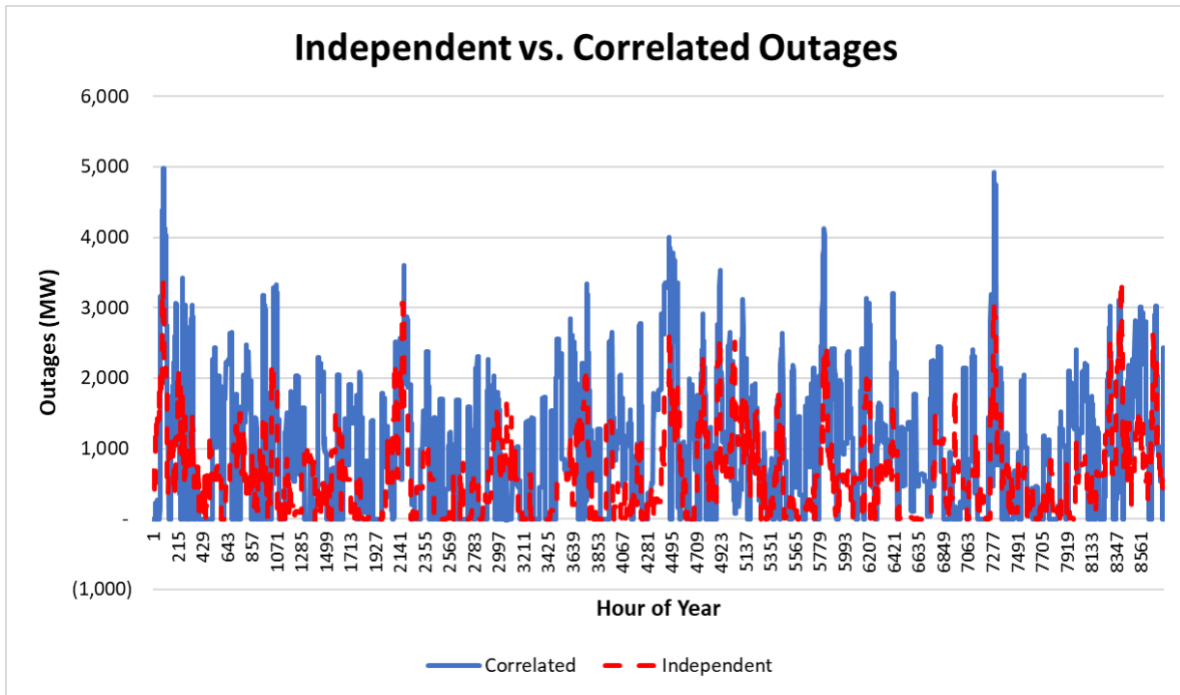


Figure 8. Example of Correlated Outage Impacts

This heuristic may also be expressed in terms of its impact on total available generation. The figure below shows a duration curve of total available generation for the same simulation as above for both the independent case and the correlated case.

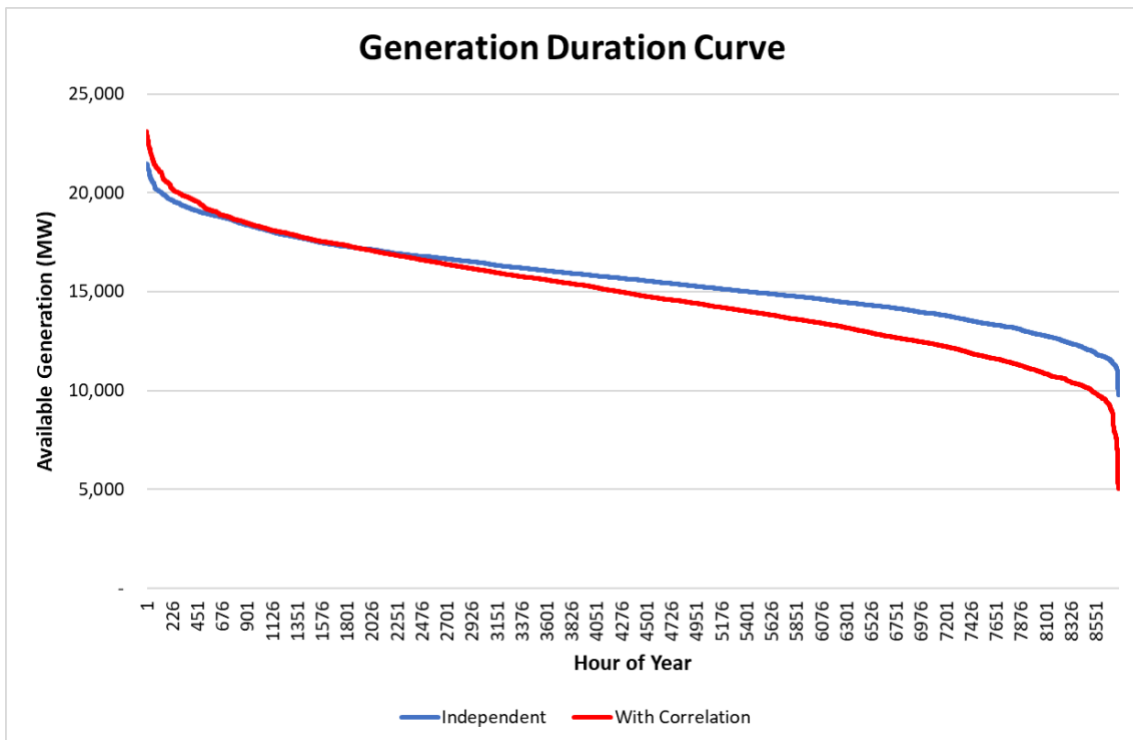


Figure 9. Available Generation Duration Curve with and without Outage Correlation

While this heuristic does not necessarily represent the actual expectations for correlated outages, it would be anecdotally representative of the level of correlation that would be present. Modeling this

heuristic would result in a IRM that would be higher than the traditional IRM_{ICAP}. Comparing this correlated IRM (IRM_{Corr}) back to the IRM_{UCAP} in a manner similar to that which was done above with outage variability would result in an adjustment factor that takes into account not only the variability, but also the impact of outage correlation. That adjustment factor would be determined as follows:

$$\text{Equation (4): } ADJ_{Corr} = (IRM_{Corr} - IRM_{UCAP}) * Pk \text{ Load} / MW_{EFOR}$$

where

ADJ_{Corr} = the adjustment factor due to outage correlation

IRM_{Corr} = the IRM (in per unit) calculated using the outage correlation heuristic.

IRM_{UCAP} = the IRM (in per unit) calculated using the UCAP method described above

Pk Load = the system peak load (in MW)

MW_{EFOR} = the sum of the ICAP values for all resources for which EFOR is applied.

An equivalent ELCC can then be calculated using the equation:

$$\text{Equation (5): } ELCC = (1 - EFORD - ADJ_{Corr}).$$

All resources for which EFOR is applied (and therefore included in the determination of MW_{EFOR} above) would have an ECAP value established by the ELCC equivalent using the EFORD of that specific resource and applied per Equation (3). It should be noted that this value would be in lieu of the ADJ_{Var} value and not in addition to it.

WEATHER DEPENDENT OUTAGES

One aspect of outage correlation that can be more precisely determined is the correlation that outages have with temperature. As temperatures become more extreme, the combination of increased demand on the resources and the effects of temperature on the equipment itself create a higher overall risk of failure. This is especially true during extreme cold weather events, as has been demonstrated during many of the extreme weather events over the last decade. Based on research performed at the Carnegie Mellon University (referred to herein as the Sinnott Murphy report),²⁶ Astrapé was able to model the weather dependent correlation identified in that report. Astrapé pulled the values from the temperature dependent outage graphs from page 9 of that report, subtracted off the “baseline” outages indicated in those graphs to get incremental outage correlations, and then converted those incremental outage correlations from the report into incremental temperature dependent outage rates within SERVIM. This was done for both cold weather outages and hot weather outages.

The figure below illustrates the modeled incremental outage probability for various resource classes as a function of temperature for cold weather outages.

²⁶ Murphy, Sinnott, et. Al. “A time-dependent model of generator failures and recoveries captures correlated events and quantifies temperature dependence.” November 2019. Available from <https://www.sciencedirect.com/science/article/pii/S0306261919311870>.

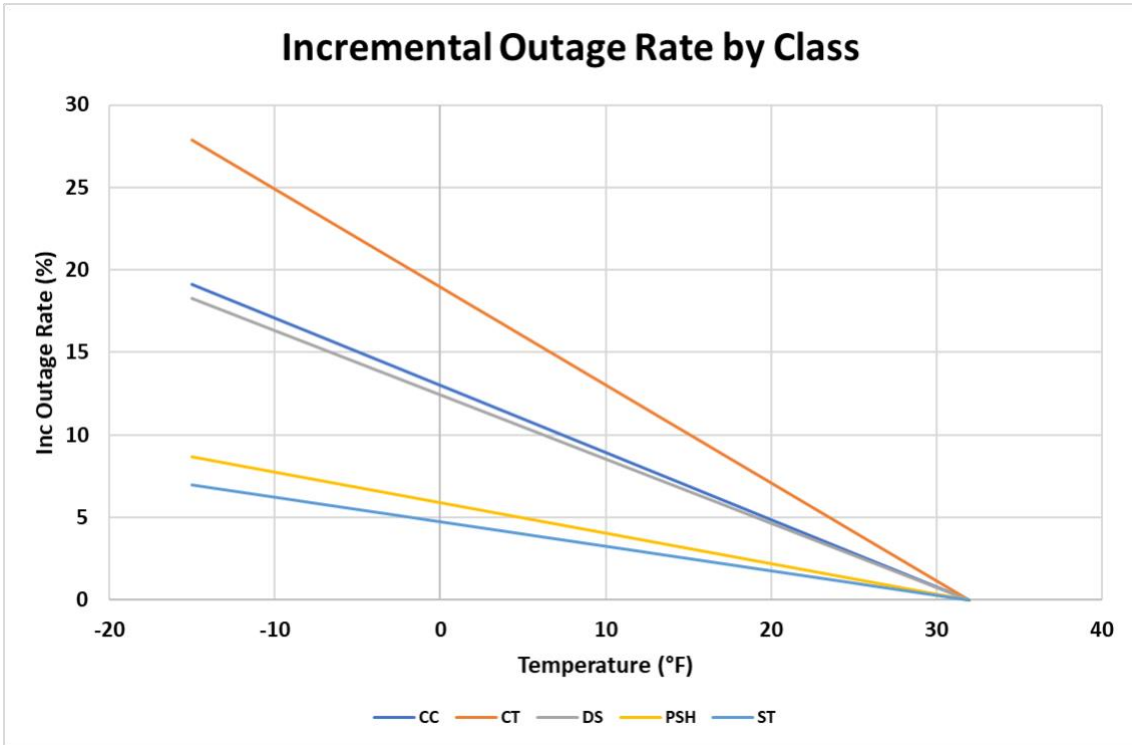


Figure 10. Cold Weather Outage Rates

The figure below illustrates the modeled incremental outage probability for various resource classes as a function of temperature for hot weather outages.

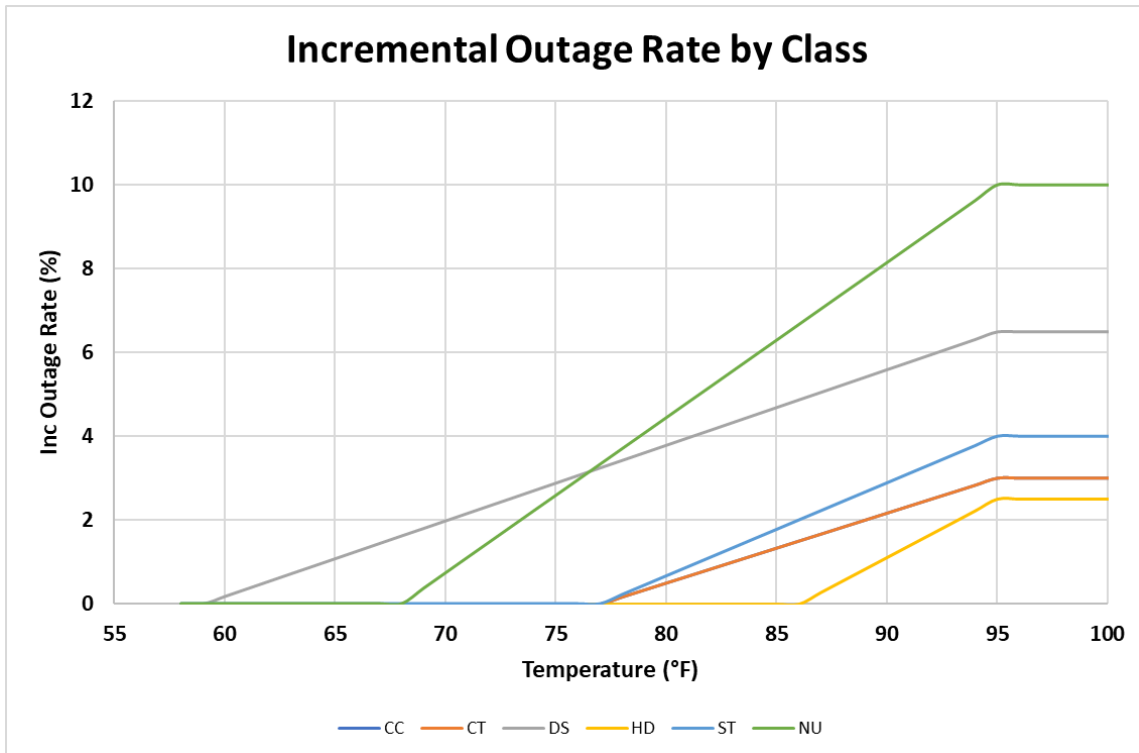


Figure 11. Hot Weather Outage Rates

These incremental outage rates have an upward pressure on IRM. However, not all resources that are impacted by the ADJ_{Var} factor are affected by cold weather outages. Therefore, it is not possible to

compare the IRM calculated using these rates (IRM_{WDO}) to the IRM_{UCAP} to get an all-inclusive adjustment factor. Rather, the IRM_{WDO} must be compared back to the IRM_{ICAP} to get an incremental weather dependent adjustment factor as follows:

$$\text{Equation (6): } INC_{WDO} = (IRM_{WDO} - IRM_{ICAP}) * Pk \text{ Load} / MW_{WDO},$$

where

INC_{WDO} = the incremental weather dependent adjustment factor

IRM_{WDO} = the IRM (in per unit) calculated using the weather dependent outages

IRM_{ICAP} = the traditional, ICAP-based IRM (in per unit)

Pk Load = the system peak load (in MW)

MW_{WDO} = the sum of the ICAP values for all resources for which WDO are modeled

The INC_{WDO} can then be added to the ADJ_{Var} (or alternatively the ADJ_{Corr}) to get the final weather dependent outage adjustment factor as follows:

$$\text{Equation (7): } ADJ_{WDO} = ADJ_{Var} + INC_{WDO}$$

or

$$\text{Equation (7a): } ADJ_{WDO} = ADJ_{Corr} + INC_{WDO}.$$

This value must be determined and applied independently for cold weather outages and hot weather outages.

An equivalent ELCC can then be calculated using the equation:

$$\text{Equation (8): } ELCC = (1 - EFORD - ADJ_{WDO}).$$

The ECAP value can then be determined by applying this ELCC to Equation (3). This ADJ_{WDO} adjustment factor would only be applied in the circumstance in which the weather dependent outages were properly modeled and taken into consideration in the development of the system IRM. Furthermore, it would only be applied to those resources subject to weather dependent outages. Other resources would calculate their ELCC based on the ADJ_{Var} or ADJ_{Corr} as appropriate. For example, based on the research in the Sinnott Murphy report, nuclear resources are not generally susceptible to incremental outage rates during extreme cold weather events.

FUEL AVAILABILITY

The weather dependent outages identified in the Sinnott Murphy report appears to only be identifying outage correlations with extreme hot and cold temperatures. However, during extreme cold weather events, there is an additional impact on the availability of fuel itself, particularly the availability of natural gas. While it was not possible from the available empirical data to create a direct correlation between temperature and fuel availability, numerous industry reports (see full list of sources in Appendix A) provided anecdotal evidence suggesting that by the time temperatures reach 0°F, as much

as 10% of the natural gas supply could become unavailable. For example, in the NERC report on the 2011 Southwest extreme winter event, there was a 9.4% reduction in the daily natural gas supply.²⁷ Similarly, the NERC 2014 Polar Vortex Review indicated that the Reliability First region lost 10,700 MW of approximately 102 GW of oil and gas generation, which is roughly 10% of generation.²⁸ Finally, the April 2021 report on the 2021 extreme cold weather event in ERCOT identified 5 GW (out of roughly 50 GW or 10%) of natural gas generation out due to fuel unavailability.²⁹ While the impacts of these events may be lesser at higher temperatures and be limited primarily to those resources without firm natural gas transportation due to Operational Flow Orders (OFO), the impacts at colder temperatures will affect even firm transportation holders as suppliers and pipeline operators alike declare Force Majeure events.

To simulate this impact on the test system, Astrapé developed a simple linear heuristic that began with zero incremental outage probability at 20°F and increased to 10% outage probability at 0°F. This heuristic was then combined with the cold weather outage rates previously developed to create the incremental outage rate profiles in the figure below.

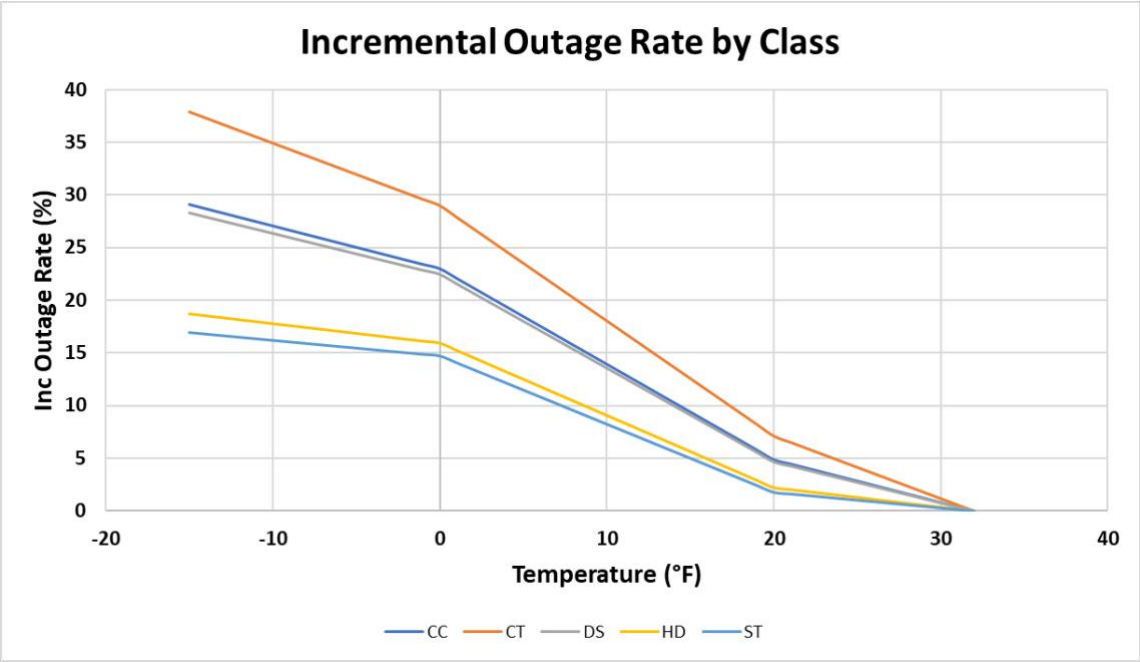


Figure 12. Incremental Outage Rate Including Fuel Risk

²⁷ FERC and NERC. “Report on Outages and Curtailments During the Southwest Cold Weather Event of February 11-5, 2011.” August 2011, p. 113. Available from: <https://www.ferc.gov/sites/default/files/2020-04/08-16-11-report.pdf>

²⁸ NERC. “Polar Vortex Review.” September 2014, p. 9. Available from: https://www.nerc.com/pa/rrm/January%202014%20Polar%20Vortex%20Review/Polar_Vortex_Review_29_Sept_2014_Final.pdf

²⁹ ERCOT. “Update to April 6, 2021 Preliminary Report on Causes of Generator Outages and Derates During the February 2021 Extreme Cold Weather Event.” April 2021, p. 18. Available from: http://www.ercot.com/content/wcm/lists/226521/ERCOT_Winter_Storm_Generator_Outages_By_Cause_Updated_Report_4.27.21.pdf

Applying this heuristic would result in a IRM that is higher even than the IRM_{WDO} . Since the impacts are applicable to an even smaller subset of resources, this fuel outage IRM (IRM_{FUEL}) can be compared back to the IRM_{WDO} to create an incremental fuel availability adjustment factor as follows:

$$\text{Equation (9): } INC_{Fuel} = (IRM_{Fuel} - IRM_{WDO}) * Pk \text{ Load} / MW_{Fuel}$$

Where

INC_{Fuel} = the incremental fuel availability adjustment factor

IRM_{Fuel} = the IRM (in per unit) calculated using the fuel and weather dependent outage rates

IRM_{WDO} = the IRM (in per unit) calculated using only the weather dependent outage rates

Pk Load = the system peak load (in MW)

MW_{Fuel} = the sum of the ICAP values for all resources subject to the potential fuel unavailability (in MW)

The INC_{Fuel} can then be added to the ADJ_{WDO} to get the final fuel availability outage adjustment factor as follows:

$$\text{Equation (10): } ADJ_{Fuel} = ADJ_{WDO} + INC_{Fuel}$$

This ADJ_{Fuel} would be used in the thermal resource ELCC calculation in lieu of other adjustment factors as follows:

$$\text{Equation (11): } ELCC = (1 - EFORd - ADJ_{Fuel}).$$

The ECAP value could then be determined by applying this ELCC to Equation (3). This ADJ_{Fuel} adjustment factor would only be applied in the circumstance in which natural gas unavailability can be properly modeled and taken into consideration in the development of the system IRM. Furthermore, it would only be applied to those natural gas resources subject to such fuel unavailability. For example, any resource with on-site replacement fuel - such as a dual-fueled Combustion Turbine (CT) with onsite oil reserves or a gas steam unit with a secondary coal supply – would not be subject to this adjustment.

As described above, the ADJ_{Fuel} factor is being calculated inclusive of both the ADJ_{Var} factor (not the ADJ_{Corr} factor) and the ADJ_{WDO} factor. Non natural gas resources that are subject to weather dependent outages would still be subject to the ADJ_{WDO} factor and any EFOR resource not subject to either ADJ_{WDO} or ADJ_{Fuel} would still be subject to the ADJ_{Var} factor. As with the ADJ_{WDO} , the ADJ_{FUEL} could be calculated relative to the ADJ_{Corr} rather than the ADJ_{Var} .

STUDY RESULTS

Astrapé evaluated each of the four outage classifications and calculated the ELCC impact as described below.

OUTAGE VARIABILITY

As described in the Study Approach section above, Astrapé modeled the PJM South test system on an islanded basis using a typical ICAP approach as well as the UCAP approach described above. This was performed on the winter peaking load condition test system as well as the summer peaking load condition test system.

The table below shows the IRM calculations for the winter peaking load conditions.

Table 2. ICAP/UCAP IRM Calculations for Winter Peaking System

	UCAP	ICAP	
Load	19,708	19,708	[A]
Existing Generation	23,252 ³⁰	23,252	[B]
Market Benefit³¹	1,971	1,971	[C]
MW Adjustment	2,259	2,795	[D]
Final Capacity ((B)-[C]+[D])	23,540	24,076	[E]
IRM ([E]/[A]-1)	19.4%	22.2%	

From these, the ADJ_{Var} factor was calculated in accordance with Equation (1) above as shown in the table below.

Table 3. EFOR Variability Adjustment Factor Calculation for Winter Peaking System

	UCAP ³²
Pk Load	19,708
IRM_{ICAP}	22.2%
IRM_{UCAP}	19.4%
MW_{EFOR}	19,780
ADJ_{Var}	2.7%

As an example of how this would be applied to a resource, the 2.7% ADJ_{Var} factor can be applied to the Hopewell CC, which has a 3.1% EFORd. Using Equation (2), the ELCC can be calculated as follows:

³⁰ While the modeled capacity of this case was technically, 22,417MW reflecting UCAP capacity, this was merely a modeling technique to simulate an average outage expectation across all hours. To establish the IRM intended, however, requires use of the original ICAP capacity.

³¹ Market benefit assumed at 10% of peak load.

³² In determining the IRM using a perfect MW adjustment, this calculation can simplify as follows:

$$\text{Equation (1')} = ADJ_{Var} = (MW_{Adjustment_{ICAP}} - MW_{Adjustment_{UCAP}}) / MW_{EFOR}$$

$$\text{Hopewell CC ELCC} = (1 - \text{EFOR} - \text{ADJ}_{\text{Var}}) = (1 - .031 - .027) = 94.2\%.$$

With an ICAP of 344.6 MW, this translates to an ECAP value of 324.6 MW using Equation (3) as compared to a typical UCAP value of 334 MW.

The same analysis was performed for the summer peaking system. The two tables below show the IRM and ADJ_{Var} calculations, respectively.

Table 4. ICAP/UCAP IRM Calculations for Summer Peaking System

	UCAP	ICAP	
Load	19,708 ³³	19,708	[A]
Existing Generation	22,761 ³⁴	22,761	[B]
Market Benefit³⁵	1,971	1,971	[C]
MW Adjustment	939	1,797	[D]
Final Capacity ([B]-[C]+[D])	21,729	22,587	[E]
IRM ([E]/[A]-1)	10.3%	14.6%	

Table 5. EFOR Variability Adjustment Factor Calculation for Summer Peaking System

	UCAP
Pk Load	19,708
IRM_{ICAP}	14.6%
IRM_{UCAP}	10.3%
MW_{EFOR}	18,489
ADJ_{Var}	4.6%

The differences between summer and winter adjustment factors is an issue that warrants further investigation to definitively establish causation. However, likely factors may be the differences in the nature of summer reliability events (long duration events impacted by outages) versus winter reliability events (shorter duration events involving significant load variability and uncertainty).

CORRELATED OUTAGES

As described in the Study Approach section above, Astrapé incorporated correlated outages in the winter peaking system and recalculated the ICAP IRM values. The table below shows the IRM calculations.

Table 6. Correlated IRM Calculations

	UCAP	Correlated ICAP	
Load	19,708	19,708	[A]
Existing Generation	23,252	23,252	[B]
Market Benefit³⁶	1,971	1,971	[C]

³³ For purposes of this analysis, the summer peak load was set to equal the winter peak load.

³⁴ The lower capacity as compared to the winter calculation reflects the difference in summer and winter ratings due temperature corrected output values.

³⁵ Market benefit assumed at 10% of peak load.

³⁶ Market benefit assumed at 10% of peak load.

MW Adjustment	2,259	3,245	[D]
Final Capacity ([B]+[C]+[D])	23,540	24,526	[E]
IRM ([E]/[A]-1)	19.4%	24.4%	

From these, the ADJ_{Corr} factor was calculated in accordance with Equation (4) above as shown in the table below.

Table 7. EFOR Correlated Adjustment Factor Calculation

Component	Value
Pk Load	19,708
IRM_{Corr}	24.4%
IRM_{UCAP}	19.4%
MW_{EFOR}	19,780
ADJ_{Corr}	5.0%

As an example of how this would be applied to a resource, the 5.0% ADJ_{Corr} factor can be applied to the Hopewell CC as described before. Using Equation (5), the ELCC can be calculated as follows:

$$\text{Hopewell CC ELCC} = (1 - \text{EFOR} - \text{ADJ}_{Corr}) = (1 - .031 - .05) = 91.9\%.$$

With an ICAP of 344.6 MW, this translates to an ECAP value of 316.7 MW using Equation (3) as compared to a typical UCAP value of 334 MW.

A correlated outage analysis was not performed on the summer peaking system.

WEATHER DEPENDENT OUTAGES

As described in the Study Approach section above, Astrapé incorporated the cold weather outage profiles and calculated associated IRM values for the winter peaking system. The table below shows the IRM_{WDO} calculations.

Table 8. Cold Weather Dependent Outage IRM Calculations

Component	Value
Load	19,708 [A]
Existing Generation	23,252 [B]
Market Benefit³⁷	1,971 [C]
MW Adjustment	4,752 [D]
Final Capacity ([B]+[C]+[D])	26,033 [E]
IRM ([E]/[A]-1)	32.1%

This IRM was compared against the IRM_{ICAP} value to calculate the INC_{WDO} factor in accordance with Equation (6) above as shown in the table below.

³⁷ Market benefit assumed at 10% of peak load.

Table 9. EFOR Weather Dependent Adjustment Factor Calculation for Cold Weather Outages

Component	Value
Pk Load	19,708
IRM_{WDO}	32.1%
IRM_{ICAP}	22.2%
MW_{WDO}	19,576
INC_{WDO}	10.0%

Using Equation (7), the ADJ_{WDO} can then be calculated as

$$ADJ_{WDO} = 2.7\% + 10.0\% = 12.7\%.$$

As an example of how this would be applied to a resource, the 12.7% ADJ_{WDO} factor can be applied to the Hopewell CC as described before. Using Equation (8), the ELCC can be calculated as follows:

$$\text{Hopewell CC ELCC} = (1 - \text{EFOR} - \text{ADJ}_{WDO}) = (1 - 0.031 - 0.127) = 84.2\%.$$

With an ICAP of 344.6 MW, this translates to an ECAP value of 290.2 MW using Equation (3) as compared to a typical UCAP value of 334 MW.

If applied incrementally to the correlated adjustment factor (ADJ_{Corr}) rather than the uncorrelated one (ADJ_{Var}) per Equation (7a), then the ADJ_{WDO} would be

$$ADJ_{WDO} = 5.0\% + 10.0\% = 15.0\%.$$

Astrapé likewise incorporated the hot weather outage profiles and calculated associated IRM values for the winter peaking system. The tables below show the IRM_{WDO} and ADJ_{WDO} calculations, respectively.

Table 10. Hot Weather Dependent Outages IRM Calculations

Component	Value
Load	19,708 [A]
Existing Generation	22,761 [B]
Market Benefit³⁸	1,971 [C]
MW Adjustment	2,822 [D]
Final Capacity ([B]+[C]+[D])	23,612 [E]
IRM ([E]/[A]-1)	19.8%

Table 11. EFOR Weather Dependent Adjustment Factor Calculation for Hot Weather Outages

Component	Value
Pk Load	19,708
IRM_{WDO}	19.8%
IRM_{ICAP}	14.6%
MW_{WDO}	18,273
INC_{WDO}	5.6%

³⁸ Market benefit assumed at 10% of peak load.

Using Equation (7), the hot weather ADJ_{WDO} can then be calculated as

$$ADJ_{WDO} = 4.6\% + 5.6\% = 10.3\%^{39}$$

As with the variability adjustment factor, the greater duration and frequency of hot weather events is such that the relative impact of weather dependent outages is greater in the summer than in the winter.

FUEL AVAILABILITY

As described in the Study Approach section above, Astrapé incorporated the fuel availability outage profiles in the winter peaking system and calculated associated IRM values. The table below shows the IRM_{Fuel} calculations.

Table 12. Fuel Availability IRM Calculations

Component	Value
Load	19,708 [A]
Existing Generation	23,252 [B]
Market Benefit ⁴⁰	1,971 [C]
MW Adjustment	5,357 [D]
Final Capacity ([B]+[C]+[D])	26,638 [E]
IRM ([E]/[A]-1)	35.2%

This IRM was compared against the IRM_{WDO} value to calculate the INC_{Fuel} factor in accordance with Equation (9) above as shown in the table below.

Table 13. EFOR Correlated Adjustment Factor Calculation

Component	Value
Pk Load	19,708
IRM_{Fuel}	35.6%
IRM_{WDO}	32.1%
MW_{Fuel}	9,739
INC_{Fuel}	6.2%

Using Equation (10), the ADJ_{Fuel} can then be calculated as

$$ADJ_{Fuel} = 12.7\% + 6.2\% = 18.9\%.$$

This value assumes a ADJ_{WDO} value calculated incrementally to the ADJ_{Var} rather than the ADJ_{Corr} . Using the correlated adjustment factor (ADJ_{Corr}) as an alternative starting point, the ADJ_{Fuel} would be:

$$ADJ_{Fuel} = 15.0\% + 6.2\% = 21.2\%.$$

As an example of how this would be applied to a resource, the 18.9% ADJ_{Fuel} factor can be applied to the Hopewell CC as described before. Using Equation (2), the ELCC can be calculated as follows:

³⁹ Actual calculations account for precision not shown in the rounded table values.

⁴⁰ Market benefit assumed at 10% of peak load.

$$\text{Hopewell CC ELCC} = (1 - \text{EFOR} - \text{ADJ}_{\text{WDO}}) = (1 - .031 - .189) = 78.0\%.$$

With an ICAP of 344.6 MW, this translates to an ECAP value of 268.3 MW using Equation (3) as compared to a typical UCAP value of 334 MW.

SUMMARY OF RESULTS

The following two tables summarize the results of the ELCC adjustment factor calculations for winter and summer. For reporting purposes, the weather dependent outages and fuel availability outages were combined with correlated outages results to create a set of adjustment factors with and without correlation included.

The following table summarizes the results of the ELCC adjustment factor calculations for cold weather events.

Table 14. Summary of Winter Results

Adjustment Factor	Adjustment %	Affected Resources	
Outage Variability (ADJ_{Var})	2.7%	All resources with EFOR	[A]
Incremental WDO Adjustment	10.0%	All resources subject to WDO	[B]
Incremental Fuel Availability Adjustment	6.2%	All natural gas resources without on site alternate fuel	[C]
Total Adjustment with WDO (ADJ_{WDO})⁴¹	12.7%	All resources subject to WDO	[D] = [A] + [B]
Total Adjustment with Fuel Availability (ADJ_{Fuel})	18.9%	All natural gas resources without on site alternate fuel	[E] = [D] + [C]

The following table summarizes the results of the ELCC adjustment factor calculations for hot weather events.

Table 15. Summary of Results for Hot Weather Events

Adjustment Factor	Adjustment %	Affected Resources
Outage Variability (ADJ_{Var})	4.6%	All resources with EFOR
Incremental WDO Adjustment	5.6%	
Weather Dependent Outages (ADJ_{WDO})	10.3%	All resources subject to WDO

⁴¹ Assuming additional correlation among generator outages raises each of the total adjustment results by 2.3%

CONCLUSIONS AND FURTHER EXPLORATION

GENERAL CONCLUSIONS

The analyses performed in this study were an initial examination of the impacts of outages on the ability of traditional, thermal resources to carry load. The results demonstrate that the equivalent load carrying capability of thermal resources is influenced by more than just EFOR and, as such, a simple UCAP capacity accreditation may not accurately reflect the true reliability contribution of these thermal resources.

As it relates to outage variability, this impact is already being accounted for in the resource adequacy analyses for most regions (i.e., the impact is already included in the system wide IRM calculation). However, it is not being taken into account in the capacity accreditation of these thermal resources, even in those regions where UCAP accounting is being applied.

For the other categories (correlated outages, weather dependent outages, and fuel availability), the impact may or may not be incorporated into IRM calculations, depending upon the resource adequacy modeling assumptions of the region. As such, it would only be appropriate to include such additional ELCC adjustments in those areas where the impact is being modeled.

Failure to incorporate these adjustments could potentially create a disparity in the relative treatment between traditional resources and renewable and BESS resources. As demonstrated in these analyses, EFOR alone falls short as a metric to use for establishing capacity accreditation for thermal generation. With current accreditation practices that only account for EFOR, thermal resources have a higher value than they otherwise would if these uncertainties had been properly assigned to the resources contributing to them. This, in turn, can lead to an inequity in the bid evaluation process since capacity accreditations for thermal and non-thermal resources are not on the same footing. To demonstrate, consider the example below in which four units of identical size each bid into a capacity auction at the same price.

Table 16. Example Bid Evaluation using UCAP

Resource	Type	ICAP MW	Bid Price (\$)	EFOR (%)	ELCC/ UCAP %	Eq MW	Eval Price (\$)
Unit 1	BESS	100	100.0		85%	85	117.6
Unit 2	EFOR Only	100	100.0	5%	95%	95	105.3
Unit 3	EFOR + WDO	100	100.0	5%	95%	95	105.3
Unit 4	EFOR + WDO + Fuel	100	100.0	5%	95%	95	105.3

Each of the four resources are subject to a different category of outage impacts. Unit 1 is a BESS resource that gets typical ELCC treatment. Units 2-4 are traditional resources that get UCAP treatment. However, Unit 2 is not affected by weather dependent outages. Unit 3, while subject to WDO, is not subject to fuel unavailability outages. Unit 4 is subject to both. In this example, Units 2-3 all have an equivalent evaluation price based on their UCAP calculation. In this evaluation, the BESS unit would have the lowest ranking (i.e., the highest evaluation price).

Now consider the same example incorporating the equivalent (cold weather) adjustment factors calculated in this study. The table below shows the results.

Table 17. Example Bid Evaluation Using Equivalent ELCC

	Type	ICAP MW	Bid Price (\$)	EFOR (%)	Adjust (%)	ELCC (%)	Equiv MW	Eval Price (\$)
Unit 1	BESS	100	100.0			85.0%	85	117.6
Unit 2	EFOR Only	100	100.0	5%	1.4%	93.6%	93.6	106.8
Unit 3	EFOR + WDO	100	100.0	5%	8.90%	86.1%	86.1	116.1
Unit 4	EFOR + WDO + Fuel	100	100.0	5%	15.80%	79.2%	79.2	126.3

As the table demonstrates, the revised calculation creates a differentiation between the three traditional, thermal units that did not previously exist. Furthermore, it moves the ranking of the BESS unit up from last place to third place. Such differences in valuation could impact the results of a given capacity auction.

SUMMER VS. WINTER RESULTS

With respect to summer peaking results vs. winter peaking results, the study shows that summer impacts are generally higher than winter impacts for outage variability but not for weather dependent outages. The differences for outage variability are due primarily to the greater duration and frequency of summer events as compared to winter events. The differences for weather dependent outages are driven by the differences in incremental outage rates for winter extreme temperatures versus summer extreme temperatures.

RESERVE MARGIN IMPLICATIONS

It is important to recognize that the use of these adjustment factors are tied directly to the modeling and consideration of their effects in the determination of the system reserve margin. The EFOR Variability Adjustment Factor (with or without correlation) could be considered applicable in all systems based on the most common resource adequacy study practices. However, the other adjustment factors should only be applied if those considerations (i.e., incremental cold weather outages or fuel unavailability) have been incorporated into the reserve margin analysis. Nevertheless, it should be expected that while incorporating these affects into the ICAP IRM determination will result in a higher ICAP IRM, the offsetting reductions in the capacity accreditation is such that the UCAP-based IRM should not be affected.

UNDERLYING EFOR

The analyses performed in this study calculated incremental weather dependent outages incrementally to the baseline EFOR values identified in the report. It then modeled those outages incrementally to the generic EFOR rates in the model. Thus, the analysis assumes that the modeled EFOR values in the test system excluded the weather dependent impacts. This was appropriate for this

study since the goal was merely to identify this incremental impact. However, careful examination of the Sinnott Murphy report shows that report identified a “baseline” level of EFOR that excluded the extreme hot and cold temperature-related outages. Current methods of calculating EFOR do not separate these events from other events. As such, when implementing both weather dependent outages and fuel unavailability outages in a resource adequacy analysis, it is important to make sure that the baseline EFOR rates modeled for the traditional, thermal resources have been appropriately modified to exclude these impacts. Modeling the incremental weather dependent outages in addition to traditionally calculated EFOR rates would result in greater levels of outage than would be rightly anticipated.

In summary, this study has demonstrated that the impact of some uncertainties affecting the ability of thermal resources to reliably serve load are not being assigned to the resources causing them in the capacity accreditation process. Further, there are some uncertainties that are not being considered at all, even in the IRM determination. Whereas ELCC takes into account the limitations and unavailability associated with the non-dispatchable and/or energy limited nature of renewable and storage resources, EFOR does not fully take into account the ability of thermal resources to reliably serve load. Thus, establishing capacity accreditation on UCAP overstates their ability to serve load and may potentially create disparities between thermal and non-thermal resources in the capacity selection process.

FURTHER EXPLORATION

There are a number of areas in which further analysis and exploration is warranted. These are described below.

Combined results of summer and winter events. The analyses performed in this study for cold weather events and hot weather events were performed independently one from another. Cold weather events were evaluated on a winter peaking test system with no hot weather outage events modeled. Likewise, hot weather events were evaluated on a summer peaking test system with no cold weather outage events modeled. Aggregating summer and winter events and associated outage probabilities may produce different results than those indicated in this report.

ADJ_{WDO} by unit class. While the analyses performed in this study did model differences in performance by unit class, it did not specifically calculate the weather dependent outage adjustment factors by unit class. More detailed analysis could make such a differentiation.

Variability or correlation adjustments by size or age of units. While the analyses performed in this study did model differences in performance by unit class, it did not differentiate performance of units by either size or age of units. Further research may indicate that units with different sizes or ages may perform differently, justifying a more detailed evaluation of their ELCC.

Further research quantifying outage correlation. Further research quantifying outage correlation could create greater support for the heuristic used in this study.

APPENDIX A – REFERENCE SOURCES

ERCOT. "Update to April 6, 2021 Preliminary Report on Causes of Generator Outages and Derates During the February 2021 Extreme Cold Weather Event." April 2021. Available from: http://www.ercot.com/content/wcm/lists/226521/ERCOT_Winter_Storm_Generator_Outages_By_Cause_Updated_Report_4.27.21.pdf

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APPENDIX B – TEST SYSTEM LOAD VOLATILITY

The figure below shows the weather-driven load volatility of the modeled PJM South test system.

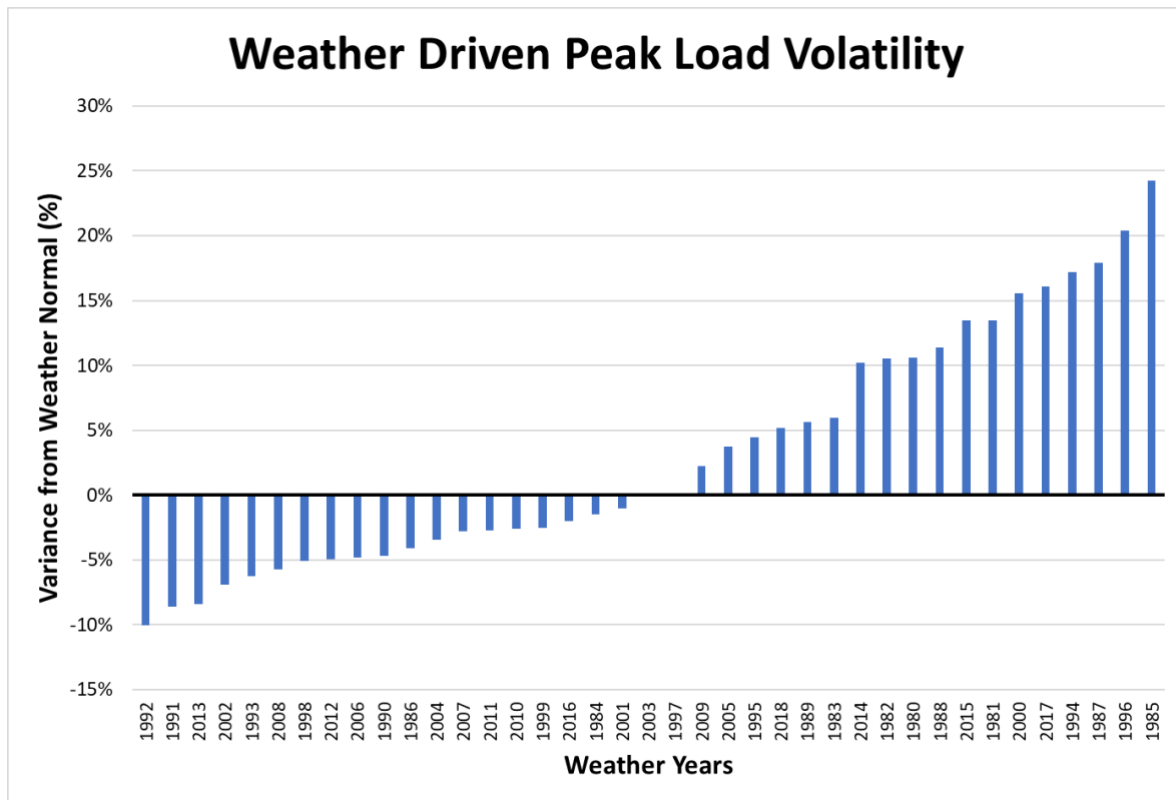


Figure 13. As Modeled Load Volatility