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A Simple Model of Effective Load Carry Capability

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ABSTRACT

Measuring the contribution of variable and supply-limited resources to grid reliability is becoming increasingly important as such resources expand their role in the electricity grid. Several large system operators have recently adopted Effective Load Carrying Capability (ELCC) as an approach to measuring these contributions. ELCC measures a resource's contribution to reliability based on the incremental quantity of load that can be satisfied by adding the resource to the grid.

ELCC represents an important advance in calculating resource adequacy, as it better reflects the realities of how supply resources contribute to system reliability compared to previous methods. Computing ELCC, however, generally involves sophisticated and complex Monte Carlo modeling to account for the numerous factors that affect system reliability. Embedded in this modeling are many judgments that affect the results. The complexity of the modeling creates a 'black box' that makes the embedded judgments and their implications difficult to assess.

In this paper, we provide a simple model that avoids much of the complexity of the full Monte Carlo model while preserving the core essence of the ELCC calculation. While it does not generate precise estimates of ELCC, the model illustrates the basic factors that affect ELCC calculations and illuminates some core results. Results from the model show the following:

- Different ELCC methods, and in particular whether to measure ELCC based on marginal or average values, significantly affect how much particular resources are credited for their capacity.
- The marginal ELCC for solar and wind resources declines quickly as their share of total power production increases in the grid, implying that increases in these variable renewable resources will increase the benefits of complementary resources such as electricity storage facilities. The effect is especially strong for solar power, apparently because output from solar resources is inherently limited to certain hours of the day. This prevents solar from contributing to reliability at other hours when it is not available. In contrast, storage, which has no such limitation, does not have similar declines in marginal ELCC.
- Using any type of ELCC averaging approach creates choices about ELCC resource classification that can have large impacts on derivate ELCC ratings.

I. Introduction

As variable renewable energy resources continue to penetrate electricity grids, there has been increasing interest in how to measure the contribution of these resources to system reliability. Measuring a resource's contributions to reliability is important not only for grid operators who are concerned about preventing blackouts, but also for the owners of resources, whose capacity market payments depend on how their contributions are measured.

Traditionally, system operators such as Regional Transmission Organizations (RTOs) have determined how much capacity a resource may offer based on the resource's average availability during periods of peak usage, using fixed factors like a forced outage rate (Aagaard and Kleit 2022, 144-46). These traditional methods assume that all accredited capacity in the system contributes equally to reliability and that each resource's performance is independent of the performance of other resources. As developments in the grid have called these assumptions into question, more sophisticated methods of evaluating capacity that examine the incremental effects of adding a particular resource to the grid on the overall reliability of the system have arisen.

Several RTOs have adopted a measurement method for reliability contributions known as "Effective Load Carrying Capability" (ELCC). ELCC measures the incremental additional demand for power that can be satisfied due to the addition of a resource to the system. This incorporates the coincidence of an additional new resource's output with peak demand and with output from other existing resources. ELCC creates a percentage term that measures the amount of load a particular generator can support as a percent of the relevant generator's capacity.

ELCC represents an important advance in calculating resource adequacy that better reflects the realities of how supply resources contribute to system reliability. Computing ELCC, however, generally involves sophisticated and complex Monte Carlo modeling to account for the numerous factors that affect system reliability. Embedded in this modeling are many judgments that affect the results. The complexity of the modeling creates a 'black box' that makes the embedded judgments and their implications difficult to assess.

In this paper, we provide a simple model that avoids much of the complexity of the full Monte Carlo model while preserving the core of the ELCC calculation. We demonstrate the model by applying it to PJM. Although too simplified to generate precise estimates of ELCC, the model shows that different ELCC methods have important impacts on how much resources are credited for their capacity. The model results also show that the ELCC for variable renewable resources declines quickly as their share of total power production increases in the grid. This implies that increases in variable renewable resources will create a strong need for grid operators to have access to complementary resources such as electricity storage facilities.

Part II describes the ELCC concept and how ELCC is calculated. Part III explains the paper's convulsion model, including the base scenario and the data used. Part IV applies the model to illustrate the impact of adding solar, wind, and storage resources separately to the system. Part V analyzes complementary effects when solar, wind, and storage resources are added together. Part VI illustrates PJM's delta method for calculating ELCC. Part VII compares the loss of load expectation, a measure of reliability, before and after addition of solar, wind, and storage resources.

II. Background

A. The ELCC Concept

The purpose of a capacity market is to enhance the reliability of the electricity grid by compensating resources to be available to provide power when needed and thereby ensuring overall resource adequacy. Similarly, resource adequacy requirements aim to ensure reliability by requiring resources to be available when needed. It is not always clear, however, how to measure the contribution of supply resources to overall system capacity and reliability (Madaeni, Sioshansi, and Denholm 2012, 2). Not all capacity in the system contributes equally to reliability. Overall system capacity and therefore reliability depends not only on the amount of power that a supply resource can contribute to the system when operational but also on other factors such as the likelihood that a resource will be operational at the times when power becomes scarce in the system. An ideal capacity market or resource adequacy requirement would accurately account for these factors in counting a resource's capacity. The issue of how to count capacity has gained in importance as available revenues in capacity markets have grown, variable generation such as wind and solar power has increased, and concerns have arisen about the availability of natural gas plants with potentially insecure fuel sources.

Traditionally, system operators have counted the capacity a resource may offer based on the resource's average availability during certain periods, using factors like a forced outage rate or average historical output (e.g., PJM 2022, 90). These traditional approaches assume that all accredited capacity in the system contributes equally to resource adequacy and that each resource's performance is independent of the performance of other resources (Gillespie and Ewing 2021, 10, 13).

As electricity grids increasingly include a greater variety of resources, these historical assumptions about the relationship between resource performance and system reliability are becoming less tenable. The consequences may be significant. If reliability analyses do not accurately reflect actual reliability conditions, then electricity systems may fail to achieve their reliability targets (Gillespie and Ewing 2021, 12). In addition, capacity market revenues, which run into the billions of dollars annually, may not efficiently compensate resources for their reliability contributions.

More sophisticated methods of evaluating capacity examine the incremental effects that adding a particular resource to the grid has on the overall reliability of the system (Aagaard and Kleit 2022, 147-48). This systemic analysis incorporates two additional factors not fully reflected in a simple capacity factor or forced outage rate. First, some of the same environmental conditions that determine the availability of a variable resource, such as sun and wind, also affect load. Second, a resource's contribution to reliability depends on how the timing of its output coincides with the timing of the output of other resources on the grid. These two factors are especially but not exclusively of concern for variable and storage resources.

ELCC is a method of counting capacity that addresses the limitations of conventional approaches by measuring the incremental demand for power that can be satisfied due to the addition of a resource to the system. This approach, which dates from Garver (1966, 910), incorporates the coincidence of a resource's output with peak load and with output from other existing resources. ELCC analysis reflects the insight that a resource's additional capacity only increases system reliability to the extent it generates electricity during periods in which there is a risk of resource inadequacy.

Many system operators and utilities are using or considering ELCC, primarily to assess variable resources such as wind and solar and energy-limited resources such as storage (Olson, Ming, and Carron 2021, 12). The New York Independent System Operator (NYISO) uses a form of ELCC that it calls Marginal Reliability Improvement to accredit all resources' capacity values based on their marginal contributions to resource adequacy (FERC 2022a, ¶ 21). The PJM Interconnection uses a version of average ELCC to accredit the capacity of variable resources (e.g., wind and solar) and limited duration resources (e.g., storage) (PJM 2022, Schedule 9.1). At this writing ISO New England is in the process of considering whether to adopt an ELCC method for its resources (Chadalavada 2021, 4).

B. ELCC Calculation

Conceptually, calculating ELCC is relatively simple. Holding reliability constant, the analysis determines how much demand an electricity system can support with and without the resource in question. The difference between these two—that is, the incremental additional demand that can be satisfied with the resource (versus without the resource)—determines the ELCC of the resource, often expressed as a percentage of the resource's nameplate capacity (Olson, Ming, and Carron 2021, 21).

Operationally, calculating ELCC is far more complicated. ELCC is a function of the performance of every resource in the system (Olson, Ming, and Carron 2021, 22). Theoretically, the ELCC is a surface in a multidimensional space, with each dimension representing a resource in the system. The number of dimensions therefore equals the total number of individual resources in the system (Olson, Ming, and Carron 2021, 22, 30). Calculating ELCC to reflect this complexity would be overwhelming. In reality, most ELCC analyses simplify the calculations by lumping individual resources into categories by technology—for example, all solar resources.

Because ELCC focuses on the effect of a resource on the overall reliability of the system, it concentrates on periods during which the risk of system failure is highest (Levitt 2021, 5). As a result, ELCC is highly sensitive to resource performance during such periods. Resource performance during hours that do not pose a high risk of shortage, by contrast, are largely irrelevant to ELCC (Levitt 2021, 12).

ELCC measures for both variable resources and energy-limited resources generally decline as a category of resources increases its penetration of the market, due to saturation effects (Olson, Ming, and Carron 2021, 24). ELCC for variable resources falls because, as a technology saturates the market, reliability risks shift to other times when the resource is not as effective, For example, if system has great deal of solar power, reliability risks may move to the early evenings. Increasing solar penetration, at least without synergistic technologies such as storage, cannot buttress reliability in the evenings when solar power wanes. Thus, the ELCC of solar power declines as solar saturates the market and reliability risks shift away from times during which solar is effective. ELCC for energy-limited resources such as storage may decline because the ability of energy-limited resources to deliver power declines as the number of hours that they deliver power increases.

An important and controversial decision when adopting an ELCC for any system is how to count the ELCC of an individual resource or category of resource. Different specific approaches have been proposed, which fall into two general methods: Marginal ELCC and Average ELCC.

1. Marginal Method

The *marginal method* assigns each resource's ELCC value based on the resource's incremental contribution to the reliability of the system, measured relative to the rest of the system's portfolio of resources. In operating its capacity market, NYISO counts the capacity of all resources in the market according to their marginal ELCC (FERC 2022a, ¶ 21). Proponents of the marginal method assert that, by counting capacity's contribution at the margin, the method sends accurate price signals to resource developers about the value of an additional resource to the market (FERC 2022a, ¶ 49).

Critics of the marginal method of counting capacity contend that, because for some categories of resources the marginal ELCC will be lower than the average ELCC, the marginal method does not give a category of resources credit for its full contribution to the reliability of the system (FERC 2021, ¶ 19). This leads the marginal method, its critics assert, to undercount reliability contributions from resources with a declining marginal contribution of capacity to reliability (Ho and Pappas 2022, 3).

2. Average Method

The *average method* calculates the ELCC for a category of resources based on the category's average contribution to reliability. PJM uses the average method in counting capacity for variable and limited-duration resources (FERC 2021, 2). PJM uses a particular method of calculating average ELCC that calculates the ELCC of a category of resources based on the average of the marginal ELCC of the resource if it were the first in the category to be added to the system and the marginal ELCC of the resource if it were the last in the category to be added to the system, with adjustments so that the sum of the average ELCC values across all categories of resources equals the ELCC of the entire portfolio of resources in the system (FERC 2021, ¶ 19). Similar methods are sometimes known as the 'delta method' (Schlag and Ming 2020, 12).

Advocates for the average method argue that it fairly compensates resources for their contributions to reliability by counting the full contribution to reliability, including inframarginal reliability benefits (Ho and Pappas 2022, 6). Critics of the average method contend that it overcounts capacity from resources with declining marginal reliability contributions, leading to investments in a resource type even after the marginal cost of a resource exceeds its contribution to reliability (LeeVanSchaick and Coscia 2021, 26). This creates inefficiencies in the capacity market.

III. The Convulsion Model

We created a relatively simple "convulsion" or "enumeration" ELCC model, using the approach of Malik and Albadi (2020) and data from the PJM system from 2021to calculate ELCCs for solar, wind, and storage power in that RTO. The simplicity of the model limits the accuracy and precision of its outputs, so it is not intended to predict actual ELCC values. It can, however, qualitatively illustrate how ELCC is calculated from the characteristics of an electricity grid system; how ELCC varies depending on the characteristics of the supply resources, including variable and limited-duration resources; and how the interaction of different categories of resources can affect ELCC values.

A. Base Scenario

We assume a simple system composed of five different generators, each with a certain capacity and operating/outage probability.[1] Table 1 presents the five generators, their capacities, and their operating and outage factors.

Table 1: Generator Capacities and Operating Factors

Generator	Capacity	Operating Factor	Outage Factor
A	50	0.94	0.06
B	74	0.95	0.05
C	92	0.96	0.04
D	108	0.97	0.03
E	125	0.98	0.02

Note that in this scenario the smaller generators arbitrarily have slightly lower operating factors than the larger generators.

The number of generator combinations is 2^N, where N is the number of generators in the system. Thus, with 5 generators there are 32 different outcomes, each with its own probability of occurring. We assume that forced outages are uncorrelated for these resources. From the data in

[1] Alternatively, because the model later scales this simple system to the size of PJM, these five generators can be conceptualized as tranches of numerous generators.

Table 1 we create a table of event probabilities (Table 2), in declining order of available capacity:

Table 2: Capacity Supply Probabilities

Scenario	Online Resources	Offline Resources	Event Probability	Available Capacity
1	ABCDE	None	0.81493	449
2	BCDE	A	0.05202	399
3	ACDE	B	0.04289	375
4	ABDE	C	0.03396	357
5	ABCE	D	0.02520	341
6	CDE	AB	0.00274	325
7	ABCD	E	0.01663	324
8	BDE	AC	0.00217	307
9	BCE	AD	0.00161	291
10	ADE	BC	0.00179	283
11	BCD	AE	0.00106	274
12	ACE	BD	0.00133	267
13	ACD	BE	0.00088	250
14	ABE	CD	0.00105	249
15	DE	ABC	1.14072E-04	233
16	ABD	CE	6.92968E-04	232
17	CE	ABD	8.46720E-05	217
18	ABC	DE	5.14368E-04	216
19	CD	ABE	5.58720E-05	200
20	BE	ACD	6.70320E-05	199
21	BD	ABE	4.42320E-05	182
22	AE	BCD	5.52720E-05	175
23	BC	ADE	3.28320E-05	166
24	AD	BCE	3.64720E-05	158
25	AC	BDE	2.70720E-05	142
26	E	ABCD	3.52800E-06	125
27	AB	CDE	2.14320E-05	124
28	D	ABCE	2.32800E-06	108
29	C	ABDE	1.72800E-06	92
30	B	ACDE	1.36800E-06	74
31	A	BCDE	1.12800E-06	50
32	None	ABCDE	7.20000E-08	0

Consider, for example, combination #2. In this combination, generators B,C, D and E operate, but generator A is off-line. The probability that these five events will occur simultaneously is as follows:

Pr(BCDE, not A) = Pr(not A) * Pr(B) * Pr(C) * Pr(D) * Pr(E)

Substituting in the probabilities from Table 1,

Pr(BCDE, not A) = 0.06 * 0.95 * 0.96 * 0.97 * 0.98 = 0.05202.

Thus, the probability of this combination of events is a little more than five percent. Moreover, the operating generators—B, C, D, and E—supply 399 MW of capacity to the system in this scenario.

Using the probabilities from Table 2, we then calculate the probability of a system outage (loss of load) if the demand is between the amount of capacity in the relevant combination and the amount of capacity in the next-highest combination. Table 3 reports the system power output and the resulting probability of a system outage in each scenario (combination of resources).

For example, assume that the system demand is 240 MW. At that level of demand, the system will be able to meet demand if operating in Scenarios 1 through 14, but a system outage will occur in Scenarios 15 through 32. The probability of a system outage—that is, the probability of any of Scenarios 15 through 32 occurring--equals the sum of the probabilities of Scenarios 15 through 32, which is 0.176 percent. Table 3 reports the system outage probabilities for the 32 scenarios.

Table 3: Capacity Outage Probability Table Using Convulsion Algorithm

Scenario	Online Resources	Offline Resources	Threshold	System Outage Probability
1	ABCDE	None	449	1
2	BCDE	A	399	0.18506963
3	ACDE	B	375	0.1330528
4	ABDE	C	357	0.09016173
5	ABCE	D	341	0.0562063
6	CDE	AB	325	0.03100226
7	ABCD	E	324	0.02826454
8	BDE	AC	307	0.0116333
9	BCE	AD	291	0.00946594
10	ADE	BC	283	0.00785717
11	BCD	AE	274	0.00607004
12	ACE	BD	267	0.00500847
13	ACD	BE	250	0.00368194

14	ABE	CD	249	0.00280662
15	DE	ABC	233	0.00175645
16	ABD	CE	232	0.00164238
17	CE	ABD	217	0.00094941
18	ABC	DE	216	0.00086474
19	CD	ABE	200	0.00035037
20	BE	ACD	199	0.0002945
21	BD	ABE	182	0.00022746
22	AE	BCD	175	0.00018323
23	BC	ADE	166	0.00012796
24	AD	BCE	158	9.5128E-05
25	AC	BDE	142	5.8656E-05
26	E	ABCD	125	3.1584E-05
27	AB	CDE	124	2.8056E-05
28	D	ABCE	108	6.624E-06
29	C	ABDE	92	4.296E-06
30	B	ACDE	74	2.568E-06
31	A	BCDE	50	0.0000012
32	None	ABCDE	0	7.2E-08

The failure probability in each scenario is the sum of event probabilities in Table 2 from that scenario to the last scenario (Scenario 32). For example, if the load is more than 182 MW but less than 199 MW—that is, between Scenario 21 and Scenario 20—then the probability of a system outage can be calculated as the sum of the probabilities of Scenario 21 through Scenario 32, which is 0.0227 percent.

B. Data Description

We acquire hourly load data for the PJM system for 2021, a total of 8760 hours (add reference). We refer to this data series as the "gross load." The average gross load is 89,347 MWh and the maximum gross load is 148,770 MWh. The percentage standard deviation of the load data is 18.03 percent, and the skew is 0.793. The positive skew indicates a skew towards higher load amounts.

On the supply side, PJM also reports power contributions to the system per hour by resource type (add reference). Relevant to our model, the data includes the quantity of solar power generated, the quantity of wind power generated, and the quantity of power delivered from storage for each hour of 2021.

For solar power, the mean generation quantity in the 2021 hourly data is 793 MWh and the maximum is 3455 MWh. On average, solar generation is equal to 0.89% of load. The percentage standard deviation of solar generation is 133.55% and its skew is 0.964. The correlation between load and solar generation is -0.0259, which is very close to zero.

For wind power, the mean generation quantity is 3153 MWh and the maximum is 8910 MWh. On average, wind generation is equal to 3.54% of load. The percentage standard deviation of wind is 69.33% and its skew is 0.581. The correlation between load and wind generation is -0.205. The amount of storage and storage power was negligible in PJM 2021, so similar numbers cannot be computed for storage.

Solar and wind generation often occur at different times, as Figure X shows. Solar generation is highest around noon and fades rapidly in the late afternoon. Wind generation can take place at any time but may be slightly higher at night. For the 2021 PJM data, the correlation between solar and wind generation is slightly negative, -0.1274.

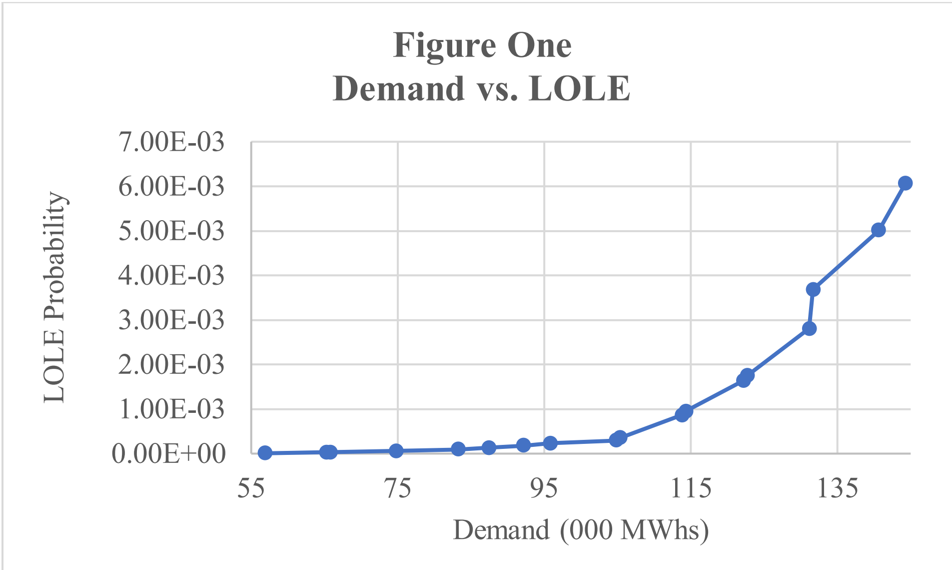
In addition to data regarding system load and power delivered to the system from solar, wind, and storage resources, our model also requires data regarding the quantity of solar, wind, and storage capacity in the PJM system. PJM does not report nameplate capacity for solar and wind but instead reports values for "installed capacity" of solar and wind that are calculated based on recent years' performance during peak summer periods (Levitt and Bell 2020). As proxies for the actual nameplate capacities of PJM's solar and wind resources, we use the maximum hourly quantity of solar generation and maximum hourly quantity of wind generation during 2021, which, as reported above, are 3455 MWh for solar power and 3153 MW of wind power. Because the quantity of solar generation capacity can be greater than, but not below, the maximum hourly generation, this approach may slightly overestimate the ELCCs for wind and solar.

C. Scaling the Load Data to the Model and Calculating Loss of Load Expectation

To apply the Capacity Outage Probability Table (Table 3) to PJM, we need to scale the PJM load data to the size of the model as represented by the capacity values in the Table. The often-used target for Loss of Load Expectation (LOLE) is one day per ten years, or 2.4 hours per year (add reference). The scaling factor can be calculated as the number by which we can divide PJM gross load data to yield hourly load values that, using Table 3, create an annual LOLE of 2.4 hours per year. This scaling factor for our model for PJM in 2021 is 526.694—that is, if we divide the PJM hourly load values in 2021 by 526.694 and insert the resulting load numbers into Table 3, the estimated annual LOLE is 2.4 hours. We use the scaling factor to scale the PJM gross load; solar and wind generation; and solar, wind, and storage capacity.

After scaling the PJM load data to our model, we can calculate the hourly LOLE for the load data in the baseline scenario of the model. The mean value of the hourly LOLE is 0.000274 with a percentage standard deviation of 236.55% and a skew of 5.493. A high skew implies that total outages are driven by relatively few positive outliers. The highest hourly LOLE is 0.00607

(0.6%), which applies for capacities between 144,000 and 149,000 MW. The lowest hourly LOLE is 6.624E-6, which applies to capacities between 57,000 and 65,000 MW, which is three orders of magnitude lower than the highest hourly LOLE. Figure X shows the LOLEs at different levels of capacity.



For levels of load below 105,000 MWh, the LOLE probability remains negligible. At higher levels of load it rises quickly, so that when load reaches 144,000 MWh, the LOLE has increased by a ratio of over 17.

It is commonly reported that as more renewable power is added to the system, the ELCC of that power source declines. Figure 1 can give some intuition why that is the case. For example, the slope of the LOLE line from 75,000 to 95,000 MWhs is only about 20 percent of the slope of the line from 95,000 to 115, 000 MWhs.

Table 4 presents summary statistics for gross load, hourly LOLE, solar generation, and wind generation.

Table 4: Summary Statistics for Model Baseline [scale down gross load]

	Mean	Standard Deviation	% Standard Deviation	Skew
Gross Load	89,347.48	16,111.18	18.03%	0.793
Hourly LOLE	2.740E-04	6.482E-04	236.55%	5.493
Solar generation (MWh)	792.95	1,058.98	133.55%	0.964
Wind Generation (MWh)	3,153.28	2,186.28	69.33%	0.581

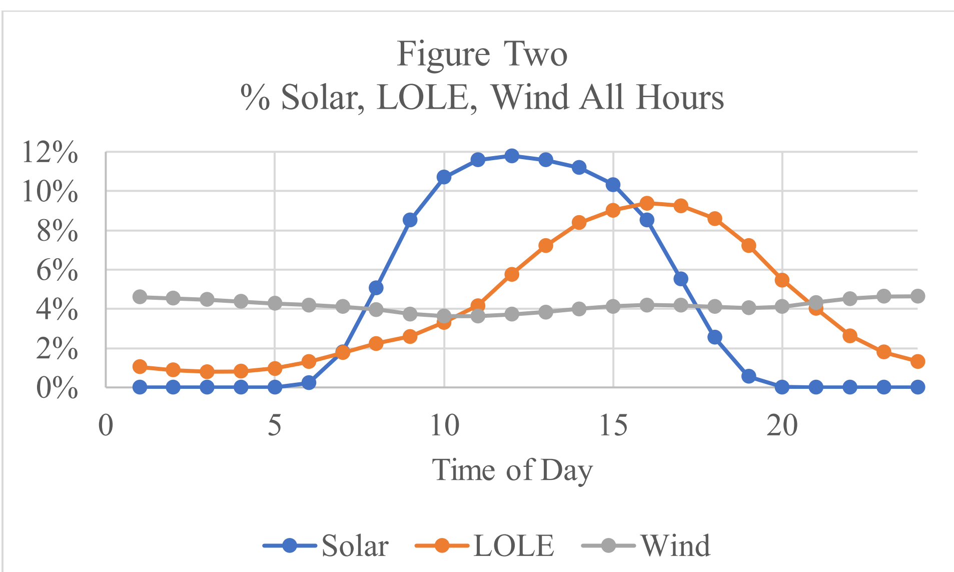
The percentage standard deviations for hourly LOLE and solar generation are above one hundred percent, implying they are quite variable. For solar generation, this is likely due in part because there is no solar generation at night. All four data sets have positive skew. This implies that the majority of the data points in each set are below the mean value, and that points above the mean may be relatively distant from the mean value. For hourly LOLE, with a skew of nearly 5.5, positive skew may imply that the results are driven by a relatively small number of high-valued points.

Table 5 presents the correlations between the data series. Both the gross load and the outage probability are positively correlated with solar generation but negatively correlated with wind generation. By itself, this implies that solar generation will be more valuable to the system than wind generation. Solar and wind generation and negatively correlated, implying that the two types of energy might complement each other.

Table 5: Correlations

Correlation	Outage Probability	Solar Generation	Wind Generation
Gross Load	0.700	0.304	-0.205
Outage Probability (LOLE)		0.264	-0.186
Solar Generation			-0.127

Figure X shows the percentage of LOLE, solar power, and wind power by hour for all hours across 2021. (The numbers are similar when only using summer hours.) The probability of LOLE is very low overnight. It climbs gradually from Hour 5 to Hour 16, and then falls fairly rapidly until Hour 24. Solar power has the expected bell-shaped curve, peaking at Hour 12. LOLE and solar power thus can be seen as four hours "out of phase."



IV. Applying the Convulsion Model

This section calculates the ELCCs for solar, wind, and storage, under the assumption that each of these technologies is the first introduced into the system. Thus, we evaluate the ELCC for solar without additional wind and battery power, the ELCC for wind without additional solar and battery power, and the ELCC for storage without additional solar and wind power.

A. Calculating Solar ELCC

As explained above in Part II, ELCC measures the additional load that a system can serve as more capacity is added to the system. Accordingly, to calculate the ELCC for solar power, we start by estimating the additional load that the system can serve as more solar capacity is added (the "ELCC Addition"). We exclude additional wind generation or storage to isolate the effects of additional solar capacity on the existing PJM system. The model calculates the solar ELCC for ten successive increments of additional solar capacity, with each increment equal to the quantity of solar capacity existing in the PJM system in 2021. Thus, after the final increment, the PJM system in the model would include eleven times the amount of solar capacity in the PJM system actually in place in 2021.

To calculate the ELCC Addition for solar power using the capacity data, we add solar capacity to the system and estimate hourly solar power generation with the additional solar capacity by proportionately increasing solar generation for each hour of 2021. Then, for each hour, we subtract the modeled quantity of solar generation from load, which reduces the LOLE for each hour. We then add load to each hour until the LOLE returns to the target reliability level of 2.4 hours of outage per year.[2] The additional load that can be served by the additional solar capacity is the ELCC Addition for that increment of solar power.

Using the ELCC Addition, we calculate the ELCC using both an average and a marginal approach. The Average ELCC reflects the additional load served as more solar capacity is added to the system. Thus, to calculate the Average ELCC, we divide the ELCC Addition for the increment by the total quantity of solar capacity added:

$$\text{Average ELCC} = \frac{\text{ELCC Addition}}{\text{Total Additional Solar Capacity}} \qquad \textit{Eq. 1}$$

For example, applying Equation 1 to the fourth increment of additional solar capacity in Table 5 yields the following calculation:

$$\text{Average ELCC} = \frac{\text{ELCC Addition}}{\text{Total Additional Solar Capacity}} = \frac{5339\ \text{MWh}}{13{,}820\ \text{MW}} = 36.20 \text{ percent} \qquad Eq. 2$$

The Marginal ELCC reflects the additional load served by each increment of solar capacity. To calculate the Marginal ELCC, we take the increase in ELCC Addition from the previous increment of solar capacity and divide by the incremental increase in solar capacity:

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[2] All additions and subtractions in this and the next section are divided by the scaling factor to fit the convulsion model, and then rescaled back up to present the results at the scale of the PJM system.

$$\text{Marginal ELCC} = \frac{\text{Marginal ELCC Addition}}{\text{Marginal Solar Capacity}} \qquad \textit{Eq. 3}$$

For example, applying Equation 3 to the fourth increment of additional solar capacity in Table 5 yields the following equation:

$$\text{Marginal ELCC} = \frac{\text{Marginal ELCC Addition}}{\text{Marginal Solar Capacity}} = \frac{(5339\text{ MWh} - 4166\text{ MWh})}{3455\text{ MW}} = 32.47\text{ percent} \qquad \textit{Eq. 4}$$

Table 5 reports the results of the Average and Marginal ELCC calculations for solar power.

Table 5: Solar ELCCs

Increment	Capacity Added (MW)	ELCC Addition (MW)	Average ELCC	Marginal ELCC
1	3,455	1,374.67	39.79%	
2	6,910	2,691.41	38.95%	38.11%
3	10,365	3,876.47	37.40%	34.30%
4	13,820	5,003.59	36.20%	32.62%
5	17,276	5,904.24	34.18%	26.07%
6	20,731	6,847.02	33.03%	27.29%
7	24,186	7,768.74	32.12%	26.68%
8	27,641	8,574.58	31.02%	23.32%
9	31,096	9,327.75	30.00%	21.80%
10	34,551	9,980.85	28.89%	18.90%

As Table 5 shows, both the Average Solar ELCC and the Marginal Solar ELCC decline quickly as solar capacity is added to the system. When the solar capacity is added initially in the first increment, the solar ELCC is over 39 percent. But for the final increment, when the solar penetration has increased to slightly below 9 percent of load, the Average ELCC has declined to 29 percent, while the Marginal ELCC has declined all the way from 38 percent to below 19 percent. As compared to the gross load, the net load (the gross load minus the additional contribution of solar power plus the additional demand) standard deviation only declines slightly to 17.91%, but the skew declines from 0.793 to 0.239. The standard deviation of outage probability declines from 266 to 189 percent, while the skew declines from 5.493 to 0.180. These results are consistent with solar output being positively correlated with both gross load and outage probability,

B. Calculating Wind ELCC

For wind power, as we did with solar power, we add an increment of wind capacity to the system and model the impact of this additional capacity on generation by proportionately increasing solar generation for each hour of 2021. We exclude additional solar generation or storage to isolate the effects of additional wind capacity on the existing PJM system. To calculate the ELCC for wind power, we start by estimating the additional load that the system can serve as more wind capacity is added (the "ELCC Addition"). Because there already are significant quantities of wind capacity in the PJM system, we model only five successive increments of additional wind capacity, with each increment equal to the quantity of wind capacity existing in the PJM system in 2021.

We then calculate the ELCC for each of the five successive increments of PJM wind capacity, using the same method as with the solar ELCC. Table 6 reports the results.

Table 6: Wind Generation ELCCs

Increment	Capacity Added (MW)	ELCC Addition	Average ELCC	Marginal ELCC
1	8,911	1,986	22.28%	
2	17,821	3,908	21.93%	21.57%
3	26,732	5,609	20.98%	19.09%
4	35,642	7,110	19.95%	16.85%
5	44,553	8,469	19.01%	15.25%

The first increment, which doubles the amount of wind capacity from the 2021 levels, has an ELCC of 22.28 percent. Overall, the Average ELCC declines slightly over three percent, from 22.28 percent to 19.01 percent, as the remaining four increments are added. Marginal ELCC declines slightly more, about 6.25 percent, from 21.57 percent to 15.25 percent. Adding in wind power increases the percentage standard deviation of net load to 25.89% but decreases the skew to 0.532. Increasing wind power by the amount indicated in the table above increases the percentage standard deviation of outage probabilities to 285 percent but decreases the skew to 0.364.

B. Calculating Storage ELCC

For storage ELCC, we exclude additional solar or wind generation to isolate the effects of additional storage (battery) capacity on the existing PJM system. We then add storage power to the PJM system in increments, with each increment such that the available flow of power from storage in the system equals one percent of the average PJM load. We do this for ten increments, in the end creating total storage with a flow equal to 10 percent of average PJM load.

We assume that the batteries operate with 8 hours of flow capacity. For each hour, we add the incremental power from storage in four separate steps. At each step, our model allocates

1/32 of the battery power flow capacity to each of the eight hours with the highest load in the system. Thus, one-quarter of the available flow capacity is added in four different steps. This allocation attempts to simulate, with some simplification, the optimal use of battery power.

As with the solar ELCC and wind ELCC, calculating the storage ELCC requires taking the amount of load served by power provided from storage and dividing it by the amount of storage capacity in the PJM system, with capacity measured as the maximum output of all storage resources in the system. We then calculate the ELCC for each of the ten successive increments of PJM battery storage capacity by calculating the ELCC Addition, Average ELCC, and Marginal ELCC. Table 7 reports the results.

Table 7: Storage ELCCs

Increment	Flow Capacity (MWh)	ELCC Addition	Average ELCC	Marginal ELCC
1	893	695	77.51%	
2	1,787	1,288	71.79%	66.07%
3	2,680	1,910	70.94%	69.25%
4	3,574	2,434	67.82%	58.45%
5	4,467	2,981	66.45%	60.99%
6	5,361	3,506	65.12%	58.45%
7	6,254	4,041	64.35%	59.72%
8	7,148	4,560	63.53%	57.81%
9	8,041	5,090	63.04%	59.09%
10	8,935	5,637	62.83%	60.99%

Average ELCC starts at over 77 percent but falls to slightly less than 63 percent. The Marginal ELCC falls quickly to around 60 percent and stays near that level. From the gross load, the net load percentage standard deviation declines slightly to 15.9%, while the skew declines slightly to 0.651. Battery usage has a correlation of 0.535 with gross load, 0.262 with solar generation, and -0.016 with wind generation.

Unlike solar and wind, the ELCC for storage does not consistently decline. This is likely because storage can be used strategically to address the highest demand hours, whenever they occur. Solar and wind generation, by contrast, are constrained by the availability of sun or wind. In longer-run terms, it may imply that, even in grids with large amounts of storage, storage at the margin may be able to contribute to grid reliability.

V. Complementary Effects and Other Applications

A. Complementary Effects

The negative correlation between solar and wind power implies that adding solar power and wind power together may result in higher ELCCs than adding them separately. Battery storage also can contribute power to the system at times that solar and wind power are less available. In other words, solar, wind, and battery power may complement each other in ELCC calculations. To model these effects, we analyzed the effect of wind and battery power on solar ELCCs, the effect of solar and battery power on wind ELCCs, and the effect of wind and batter power on solar ELCCs.

To evaluate the effect of wind and battery power on solar ELCCs, we calculated the Average and Marginal ELCCs for solar at the ten increments, each reflecting a different level of solar penetration into the market, in a system that already included all five increments of additional wind power and ten increments of additional storage power. As a measure of complementarity, we also calculated the amount by which the solar ELCC for each solar increment changed from the scenario in Section III.B.2 in which new wind power and battery power were excluded. Table 8 reports the results.[3]

Table 8: Complementary Effect of Wind and Battery Power on Solar ELCCs

		ELCC Effects		Complementary Effects	
Increment	Solar Generation (% of load)	Average ELCC	Marginal ELCC	Average ELCC	Marginal ELCC
1	0.89%	42.38%		2.59%	
2	1.77%	42.38%	42.38%	3.43%	4.27%
3	2.66%	40.19%	35.82%	2.79%	1.52%
4	3.55%	39.06%	35.67%	2.86%	3.05%
5	4.44%	37.74%	32.47%	3.57%	6.40%
6	5.32%	36.94%	32.93%	3.91%	5.64%
7	6.21%	35.58%	27.44%	3.46%	0.76%
8	7.10%	34.64%	28.05%	3.62%	4.73%
9	7.99%	33.42%	23.63%	3.42%	1.83%
10	8.87%	32.53%	24.54%	3.64%	5.64%

[3] When using all three power sources, the percentage standard deviation of net load is 21.77%, with a skew of 0.702. The percentage standard deviation of outage percentage is 212.88 with a skew of 0.254.

The complementary effects are positive, though not terribly large, for each of the Average and Marginal ELCCs. Average complementary effects run from 3.31 to 7.23 percent, as compared with marginal complementary effects from 0.87 to 6.41 percent.

To evaluate the effect of solar and battery power on wind ELCCs, we calculated the Average and Marginal ELCCs for wind at the five increments, each reflecting a different level of wind penetration into the market, in a system that already included all ten increments of additional solar power and ten increments of additional storage power. As a measure of complementarity, we also calculated the amount by which the wind ELCC for each wind increment changed from the scenario in Section III.B.2 in which new solar power and battery power were excluded. Table 9 reports the results.

Table 9: Complementary Effect of Wind and Battery Power on Solar ELCCs

Increment	Wind Generation (% of load)	ELCC Effects		Complementary Effects	
		Average	Marginal	Average	Marginal
1	3.53%	28.37%		6.09%	
2	7.06%	26.45%	24.53%	4.52%	2.96%
3	10.59%	24.79%	21.46%	3.80%	2.36%
4	14.12%	23.22%	18.50%	3.27%	1.66%
5	17.65%	22.18%	18.03%	3.17%	2.78%

Again, all complementary effects are positive but small, similar to the results for solar. The average complementary effect runs from 3.17 to 6.09 percent, while the marginal complementary effect is more narrowly bound, from 1.66 to 2.96 percent.

To evaluate the effect of solar and wind power on storage ELCCs, we calculated the Average and Marginal ELCCs for battery storage at the ten increments, each reflecting a different level of storage penetration into the market, in a system that already included all ten increments of additional solar power and five increments of additional wind power. As a measure of complementarity, we also calculated the amount by which the storage ELCC for each storage increment changed from the scenario in Section III.B.2 in which new solar power and wind power were excluded. Table 10 reports the results.

Table 10: Complementary Effect of Solar and Wind Power on Storage ELCCs

Increment	Storage Capacity/Hour (% of load)	ELCC Effects		Complementary Effects	
		Average	Marginal	Average	Marginal
1	1.00%	71.34%		-6.17%	
2	2.00%	68.61%	65.91%	-3.18%	-0.17%
3	3.00%	69.25%	70.52%	-1.69%	1.27%
4	4.00%	70.04%	72.43%	2.22%	13.98%
5	5.00%	69.00%	64.80%	2.54%	3.81%
6	6.00%	68.61%	66.71%	3.49%	8.26%
7	7.00%	68.34%	66.71%	3.99%	6.99%
8	8.00%	68.38%	68.61%	4.84%	10.80%
9	9.00%	68.33%	67.98%	5.29%	8.89%
10	10.00%	67.34%	58.45%	4.51%	-2.54%

For storage, the complementary effects start out negative, and then become positive. (The marginal complementary effect becomes negative at step 10.) These effects vary over wider ranges than the similar results for solar and wind.

VI. The Delta Method

PJM uses its "Delta Method" to calculate ELCC for wind, solar, storage, solar-storage hybrid, intermittent hydropower, and landfill gas (PJM 2021, 9). The Delta Method attempts to capture the interactive effects of different resource technologies by calculating the difference between the overall ELCC for the portfolio of resources and the sum of the ELCCs of individual categories of resources. The Delta Method adjusts each resource category's "first-in" ELCC—that is, its ELCC as calculated in the absence of other additional resources—upward or downward based the category's ELCC's synergistic or antagonistic interaction with other categories of resources in the system (Levitt 2020, 2).

We applied the Delta Method to our model, with the calculations presented in Table 11 and then explained below. We note that the total ELCC value of the added solar, wind, and storage in Part A above is 25,836 MW.

Table 11: Delta Method Calculations

	Definition	Derivation	Solar	Wind	Storage	Total
A	Capacity added (MW)	Model output	34,551	44,552	8,290	87,393
B	Last-in ELCC (%)	Model output	24.54%	18.03%	58.45%	
C	First-in ELCC (%)	Model output	39.79%	22.28%	77.51%	
D	Delta ELCC (%)	B - C	- 15.25%	-4.25%	- 19.06%	
E	Delta ELCC (MW)	D * A	-5,269	-1,893	-1,580	-8,743
F	% share Delta ELCC (MW) of Total ELCC (MW) Delta	E/Total E	60.27%	21.66%	18.07%	
G	ELCC amount implied by First-in ELCC	A * C	13,748	9,926	6,426	30,100
H	Extra ELCC allocated to source (PDI share) (MW)	F * "extra ELCC	-2,570	-923	-771	-4,264
I	PDI share (%)	H/A	-7.44%	-2.07%	-9.30%	
J	ELCC Rating	C + I	32.35%	20.21%	68.21%	
K	Implied ELCC Addition	A * J = G + H	11,178	9,003	5,655	25,836

Row A reports the total capacity added for each category of resources—solar, wind, and storage, from Tables 5, 6, and 7, are a total of 87,393 MW.

Row B reports the Last-in ELCC percentage from the model for each category of resources as calculated in Section III.C and reported in Tables 8, 9 and 10.

Row C reports the First-in ELCC percentage in the model for each category of resources as calculated in Section III.B and reported in Tables 6, 7 and 8.

Row D is the change in ELCC percentage from First-in ELCC to Last-in ELCC, calculated as Row B minus Row C. Thus, for solar, the Last-in ELCC % is 24.54%, the First-in ELCC is 39.79, and so the value for this row is -15.25%.

Row E is the additional amount of ELCC capacity implied by the change in ELCC percentage from the First-in ELCC to the Last-in ELCC. It is calculated as the total capacity for the resource category times the change from First-in ELCC to Last-in ELCC—that is, Row A times Row D. Thus, for solar, this equals 34,551 MW * (-15.25%) = -5,269MW. Note the sum of this row across the three categories of solar, wind, and storage is -8,743 MW.

Row F is each resource category's share of the additional ELCC capacity from Row E. For example, solar resources contribute 5,260, or 60.27%, of the additional 8,743 MW of capacity.

Row G is the amount of ELCC capacity by resource category implied by the First-in ELCC from Row C. It is calculated as the First-in ELCC from Row C times the amount of additional capacity from Row A. Thus, for solar, this is 39.79% times 34,551 MW = 13,748 MW. The total across the three categories of solar, wind, and storage is 30,100 MW.

At this point, it is necessary to calculate the "extra" ELCC implied by Row G. As discussed in the beginning of the section, the model estimates that adding solar, wind, and storage to the system adds 25,836 MW of total ELCC. As calculated in Row G, however, the sum of the ELCC capacities implied by the First-in ELCCs is 30,100 MW. This implies that 30,100 - 25,836 = 4264 MW of ELCC reductions must be allocated across the three categories.

Row H reports how the overall ELCC adjustment is allocated to the categories, weighted by their share of the additional ELCC capacity from Row F. For example, since Row F reports that solar resources account for 60.27% of the change in ELCC, the ELCC reduction allocated to solar is -4264 * 60.27% = -2570 MW.

Row I is the share of capacity of each resource category represented in Row H. It equals the ELCC MW reduction in Row H divided by the additional capacity in Row A. For solar, that equals -2,570 MW/34,551 MW, or -7.44%.

Row J represents the "delta" ELCC, equal to the First-in ELCC % plus the adjustment calculated in Row I. For solar, this is 39.79 - 7.44 = 32.35%.

Finally, Row K shows the ELCC additions of each source, which can be calculated either as the additional capacity in Row A times the delta ELCC in Row J or as the sum of the ELCC implied by the First-in ELCC and the allocated ELCC adjustment from Row H.

The ELCC ratings calculated in Table 11 correspond, albeit only roughly, to the ratings PJM has calculated (PJM 2021, 9). For 2023, for example, PJM calculated the ELCC rating of onshore wind to be 15% as compared with the model's result of 20%, the ELCC of fixed solar to be 38% and tracking solar to be 54% as compared with the model's result of 32%, and the ELCC of four-hour storage to be 83% as compared with the model's result of 68%.

In contrast, using our model, the delta method results would imply different ELCCs for solar, wind and storage than a marginal approach would, where the margin is all other resources installed before measuring the resource in question. Table 12 compares the two results, using the complementary marginal results from Part A above.

Table 12: Comparison of Marginal and Delta Methods

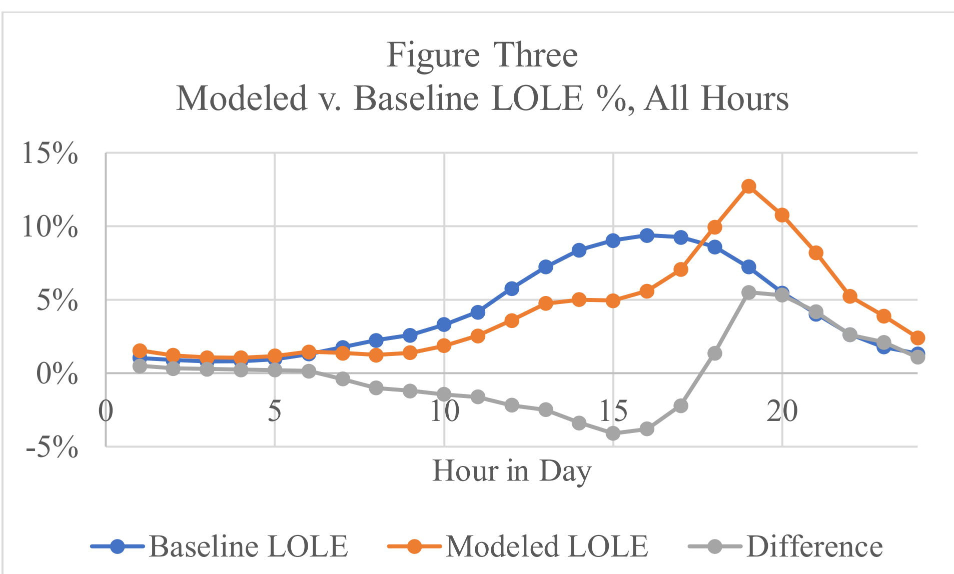
	Solar	Wind	Storage
Installed Capacity (MWs)	34,551	44,552	8,290
Marginal ELCC %	24.54%	18.03%	58.45%
Delta ELCC %	32.35%	20.21%	68.21%
Marginal ELCC addition (MW)	8478.86	8032.73	4845.51
Delta ELCC addition (MW)	11178.25	9002.76	5654.99
Difference	2699.38	970.04	809.49
% Difference	31.84%	12.08%	16.71%

Using the delta method would have increased the ELCC ratings of each source significantly. In particular, it would have increased the ELCC ratings of solar power by over 30 percent.

We also note that using marginal methods reduces the ELCC allocation for these three resources from 25,836 MW to 21,357 MW, or 4479 MW. A potential problem in using marginal ELCCs is that they understate the total addition to reliability from added sources. A method to alleviate this problem would be to reduce the overall demand for capacity by the relevant amount.

VII. Comparing LOLE Probability Before and After Modeling

We also calculate the hourly LOLE resulting after applying the increases in solar and wind power as well as the establishment of battery storage. We refer to this as the "modeled" LOLE. Figure X compares the baseline LOLE to the modeled LOLE by hour and shows the difference between the two series.



The difference between the baseline and modeled LOLE are small for the overnight hours. Essentially, the increase in wind power is counterbalanced by the increase in load over this period. The LOLE begins to fall as solar power increases, with the decline in LOLE reaching its highest level of 4.1% in Hour 15. Past that hour, the decline in solar power (together with the increase in gross load to Hour 16) causes a rapid increase in the hourly LOLE percentage. The modeled LOLE peaks at Hour 18 (12.74%), and at a much higher level than the baseload LOLE peak in Hour 16 (9.39%). Positive changes in the LOLE% occur through the rest of the day. This is caused in large part by solar power being four hours out of phase with gross load.

VI. Conclusion

A full ELCC model is very complex to build and to understand. But a relatively simple model can be built, using the convulsion technique, that is both transparent to understand and shows the same impacts as a more sophisticated model.

Here the simple model yields some important outcomes. First, Average ELCC and Marginal ELCC can differ significantly. Because the ELCC affects the capacity accreditation of a resource, and therefore the revenues it can earn in the capacity market, the consequence of a divergence between Average ELCC and Marginal ELCC is that the choice between the two approaches has significant impacts on revenues to resources.

Second, Marginal ELCC can decline rapidly as renewable generation penetration in the system increases. This seems especially important for solar power, probably because solar resources, without assistance from storage, are inherently limited to certain hours of the day. This prevents them from contributing to reliability at other hours when they are not available. In contrast, storage, which has no such limitation, does not have similar declines in Marginal ELCC.

Third, there are small but potentially important complementary effects caused by adding solar generation and wind generation.

Fourth, adding on these resources changes the shape of the LOLE curve. In particular, the threat of blackout is pushed three hours back, from Hour 16 to Hour 19 in the day. In addition, the new peak LOLE period has a higher probability of a blackout than the peak period before the new resources were added.

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