APPENDIX K – CAPACITY CONTRIBUTION

Introduction

The capacity contribution of a resource is represented as a percentage of that resource's nameplate or maximum capacity and is a measure of the ability of a resource to reliably meet demand. This capacity contribution affects PacifiCorp's resource planning activities, which are intended to ensure there is sufficient capacity on its system to meet its load obligations inclusive of a planning reserve margin. Because of the increasing penetration of variable energy resources (such as wind and solar) and energy-limited resources (such as storage and demand response), planning for coincident peak loads is no longer sufficient to determine the necessary amount and timing of new resources. To ensure resource adequacy is maintained over time, all resource portfolios evaluated in the integrated resource plan (IRP) have sufficient capacity to meet PacifiCorp's load obligations and a planning reserve margin in all hours of each year. Because all resources provide both energy and capacity benefits, identifying the resource that can provide additional capacity at the lowest incremental cost to customers is not straightforward. A resource's energy value is dependent on its generation profile and location, as well as the composition of resources and transmission in the overall portfolio. Similarly, a resource's capacity value (or contribution to ensuring reliable system operation) is also dependent on both its characteristics and the composition of the overall portfolio. To further complicate the analysis, PacifiCorp's portfolio composition changes dramatically over time, as a result of retirements and expiring contracts.

In the 2019 IRP, PacifiCorp developed initial capacity contribution estimates for wind and solar capacity that accounted for expected declining contributions as the level of penetration increased. A key assumption in this analysis was that only a single variable was modified, for example, when evaluating solar penetration level, the capacity from wind and energy storage resources in the portfolio were held constant. As the preparation of the 2019 IRP continued, PacifiCorp identified that these initial estimates did not adequately account for the interactions between solar, wind, and energy storage and thus did not ensure that each portfolio was adequately reliable. Therefore, as part of the 2019 IRP PacifiCorp assessed each portfolio to verify that it would support reliable operation in each hour of the year.

At the conclusion of the 2019 IRP, PacifiCorp recalculated the capacity contribution values for wind and solar resources using the capacity factor approximation method (CF Method) as outlined in a 2012 report produced by the National Renewable Energy Laboratory (NREL Report)[1]. The CF Method calculates a capacity contribution based on a resource's expected availability during periods when the risk of loss of load events is highest, based on the loss of load probability (LOLP) in each hour. This final CF Method analysis was performed using a portfolio that was very similar to the 2019 IRP preferred portfolio. For the reasons discussed above, this final CF Method analysis provides a reasonable estimate of capacity contribution value so long as the changes relative to the preferred portfolio are small, since in effect, the CF Method calculates the marginal capacity contribution of a one megawatt resource addition. Changes to the locations and quantities of wind, solar, and energy storage are key drivers of the marginal capacity contribution results.

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[1] Madaeni, S. H.; Sioshansi, R.; and Denholm, P. "Comparison of Capacity Value Methods for Photovoltaics in the Western United States." NREL/TP-6A20-54704, Denver, CO: National Renewable Energy Laboratory, July 2012 (NREL Report) at: www.nrel.gov/docs/fy12osti/54704.pdf

The capacity contribution analysis for the 2021 IRP is comparable to that in PacifiCorp's 2019 IRP in two key ways. First, rather than assigning a capacity contribution at the start of the analysis, the hourly reliability of portfolios was assessed to identify periods of shortfalls. Second, a final CF Method analysis was performed using a portfolio that is similar to the 2021 IRP preferred portfolio. The final CF Method analysis for the 2021 IRP is presented in this Appendix.

CF Methodology

The NREL Report summarizes several methods for estimating the capacity value of renewable resources that are broadly categorized into two classes: 1) reliability-based methods that are computationally intensive; and 2) approximation methods that use simplified calculations to approximate reliability-based results. The NREL Report references a study from Milligan and Parsons that evaluated capacity factor approximation methods, which use capacity factor data among varying sets of hours, relative to a more computationally intensive reliability-based metric. As discussed in the NREL Report, the CF Method was found to be the most dependable technique in deriving capacity contribution values that approximate those developed using a reliability-based metric.

As described in the NREL Report, the CF Method "considers the capacity factor of a generator over a subset of periods during which the system faces a high risk of an outage event." When using the CF Method, hourly LOLP is calculated and then weighting factors are obtained by dividing each hour's LOLP by the total LOLP over the period. These weighting factors are then applied to the contemporaneous hourly capacity factors to produce a capacity contribution value.

The weighting factors based on LOLP are defined as:

$$w_i = \frac{LOLP_i}{\sum_{j=1}^{T} LOLP_j}$$

where w_i is the weight in hour i, $LOLP_i$ is the LOLP in hour i, and T is the number of hours in the study period, which is 8,760 hours for the current study. These weights are then used to calculate the weighted average capacity factor as an approximation of the capacity contribution as:

$$CV = \sum_{i=1}^{T} w_i C_i,$$

where C_i is the capacity factor of the resource in hour i, and CV is the weighted capacity value of the resource.

For fixed profile resources, including wind, solar, and energy efficiency, the average LOLP values across all iterations are sufficient, as the output of these resources is the same in each iteration. To determine the capacity contribution of fixed profile resources using the CF Method, PacifiCorp implemented the following three steps:

1. A 50-iteration hourly Monte Carlo simulation of PacifiCorp's system was produced using the Plexos Short-Term (ST) model. The key stochastic variables assessed as part of this analysis are loads, thermal outages, and hydro conditions. The LOLP for each hour in the

year is calculated by counting the number of iterations in which system load and/or reserve obligations could not be met with available resources and dividing by the total number of iterations.[2] For example, if in hour 19 on December 22nd there are three iterations with shortfalls out of a total of 50 iterations, then the LOLP for that hour would be 6 percent.[3]

2. Weighting factors were determined based upon the LOLP in each hour divided by the sum of LOLP among all hours within the same summer or winter season. In the example noted above, the sum of LOLP among all winter hours is 58 percent.[4] The weighting factor for hour 19 on December 22nd would be 1.0417 percent.[5] This means that 1.0417 percent of all winter loss of load events occurred in hour 19 on December 22nd and that a resource delivering in only in that single hour would have a winter capacity contribution of 1.0417 percent.

3. The hourly weighting factors are then applied to the capacity factors of fixed profile resources in the corresponding hours to determine the weighted capacity contribution value in those hours. Extending the example noted, if a resource has a capacity factor of 41.0 percent in hour 19 on December 22nd, its weighted winter capacity contribution for that hour would be 0.4271 percent.[6]

For resources which are energy limited, such as energy storage or demand response programs, the LOLP values in each iteration must be examined independently, to ensure that the available storage or control hours are sufficient. Continuing the example of December 22nd described above, consider if hour 18 and hour 19 both have three hours with energy or reserve shortfalls out of 500 iterations. If all six shortfall hours are in different iterations, a 1-hour energy storage resource could cover all six hours. However, if the six shortfall hours are in the same three iterations in hour 18 and hour 19 (i.e. 2-hour duration events), then a 1-hour storage resource could only cover three of the six shortfall hours.

Additional considerations are also necessary for hybrid resources which share an interconnection and cannot generate their maximum potential output simultaneously.

Final CF Method Results

The final CF Method results described below provide a reasonable capacity contribution value so long as the changes relative to the preferred portfolio are small, since in effect, the CF Method calculates the marginal capacity contribution of a one-megawatt resource addition. Please note that marginal capacity contribution values reported herein are applicable to small incremental or

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[2] In the past, PacifiCorp assumed that the first hour of any shortfall would be covered as part of its participation in the Northwest Power Pool (NWPP) reserve sharing agreement, which allows a participant to receive energy from other participants within the first hour of a contingency event. While this reserve sharing remains in effect, shortfalls in the 2021 IRP are much more likely to result from changes in load, renewable resource output, or energy storage limitations, and not in the first hour after a contingency event occurs. In light of this, PacifiCorp's 2021 IRP analysis no longer excludes the first hour of every shortfall event.

[3] 0.6 percent = 3 / 500.

[4] For each hour, the hourly LOLP is calculated as the number of iterations with ENS divided by the total of 500 iterations. There are 288 winter ENS iteration-hours out of total of 5,832 winter hours. As a result, the sum of LOLP for the winter is 288 / 500 = 58 percent. There are 579 summer ENS iteration-hours out of total of 2,928 summer hours. As a result, the sum of LOLP for the summer is 579 / 500 = 116 percent.

[5] 1.0417 percent = 0.6 percent / 58 percent, or simply 1.0417 percent = 3 / 288.

[6] 0.4271 percent = 1.0417 percent x 41.0 percent.

decremental changes relative to the composition of the IRP preferred portfolio in 2030 and do not represent the average capacity contribution for each of the megawatts of a given resource type included in the preferred portfolio. In general, wind, solar, and energy storage have declining marginal capacity contribution values as the quantity of a given resource type increases. This results in average capacity contribution values that exceed the marginal capacity contribution values reported herein.

Table K.1 – Final CF Method Capacity Contribution Values for Wind, Solar, and Storage

	Capacity Factor (%)	**Capacity Contribution (%)**	
Summer/Winter:	**Annual**	**S**	**W**
Solar			
Idaho Falls, ID	28%	14%	7%
Lakeview, OR	29%	13%	18%
Milford, UT	32%	15%	7%
Yakima, WA	25%	9%	4%
Rock Springs, WY	30%	14%	13%
Wind			
Pocatello, ID	37%	33%	39%
Arlington, OR	37%	46%	17%
Monticello, UT	29%	14%	42%
Goldendale, WA	37%	47%	21%
Medicine Bow, WY	44%	30%	32%
Stand-alone Storage			
2-hour duration		49%	75%
4-hour duration		74%	90%
9-hour duration		90%	96%

Table K.2 – Final CF Method Capacity Contribution Values for Solar Combined with Storage

	Capacity Factor (%)	Capacity Contribution (%)	
Summer/Winter:	**Annual**	**S**	**W**
Solar & 100% x 4-hour Storage			
Idaho Falls, ID	28%	81%	92%
Lakeview, OR	29%	82%	93%
Milford, UT	32%	80%	95%
Yakima, WA	25%	79%	91%
Rock Springs, WY	30%	80%	94%

The above CF Method results are from a one-year study period (2030) and shortfall events are identified separately for every hour in that period. The details of the wind and solar resource modeling in the study period are important for interpreting the results. The study includes specific wind and solar volumes by resource for each hour in the period, and includes the effects of calm and cloudy days on resource output. Where data was available, the modeled generation profiles for proxy resources are derived from calendar year 2018 hourly generation profiles of existing resources, adjusted to align with the expected annual output of each proxy resource.

The use of correlated hourly shapes produces variability across each month and a reasonable correlation between resources of the same type that are located in close proximity. It also results in days with higher generation and days with lower generation in each month. As one would expect, days with lower renewable generation are more likely to result in shortfall events. As a result, basing CF Method capacity contribution calculations on an average or 12-month by 24-hour forecast of renewable generation will tend to overstate capacity contribution, particularly if there is a significant quantity of similarly located resources of the same type already in the portfolio, or if an appreciable quantity of resource additions are being contemplated. Even if an hourly renewable generation forecast is used, capacity contributions can be overstated if the weather underlying the forecast is not consistent with that used for similarly located resources used to develop the CF Method results. Because similarly located resources of the same type would experience similar weather in actual operations, a mismatch in the underlying weather conditions used in renewable generation forecasting will create diversity in the generation supply than would not occur in actual operations.

Because they are both influenced by weather, a relationship between renewable output and load is expected. To assess this relationship, PacifiCorp gathered information on daily wind and solar output from 2016-2019, and compared it to the load data from that period, the same load data that was used to determine stochastic parameters.

Each of the days in the historical period was assigned to a tier based on the rank of its daily average load within that month. This was done independently for the east and west sides of the system. The seven tiers were defined as follows:

Tier 1: The peak load day

Tier 2: 2nd – 5th highest load days

Tier 3: Days 6-10

Tier 4: Days 11-15

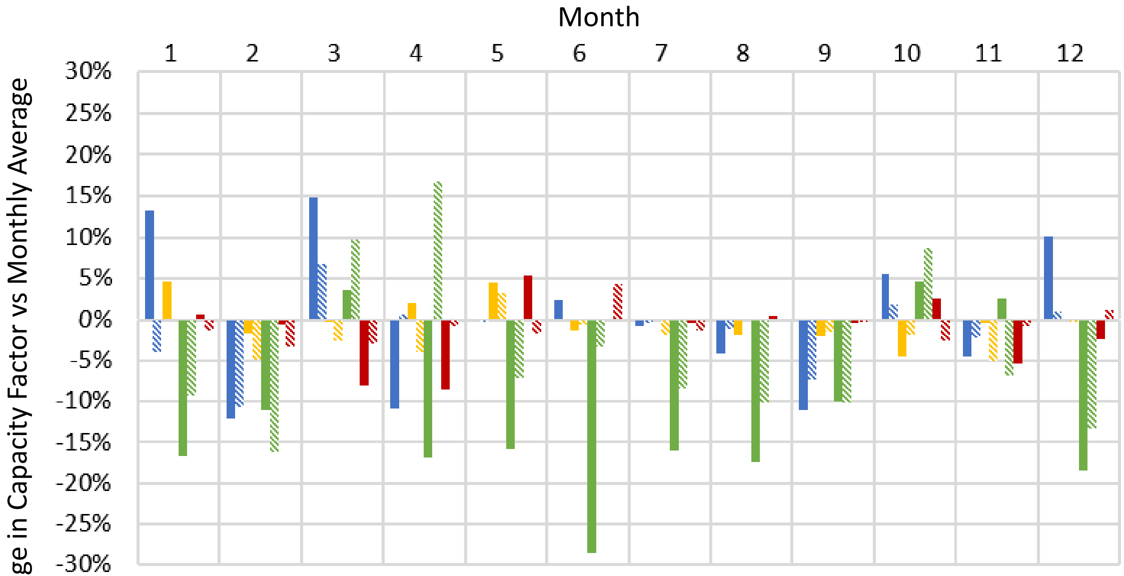
Tier 5: Days 16-20

Tier 6: Days 21-25

Tier 7: Days 26-31

The average wind and solar generation on the days in each tier was then compared to the average wind and solar generation for the entire month. The results indicated that west-side wind is often below average during the highest load days in a month, and above average during the lowest load days in a month. The results for other resource types were less pronounced, but do exhibit some patterns, as shown in Figure K.1 and Figure K.2.

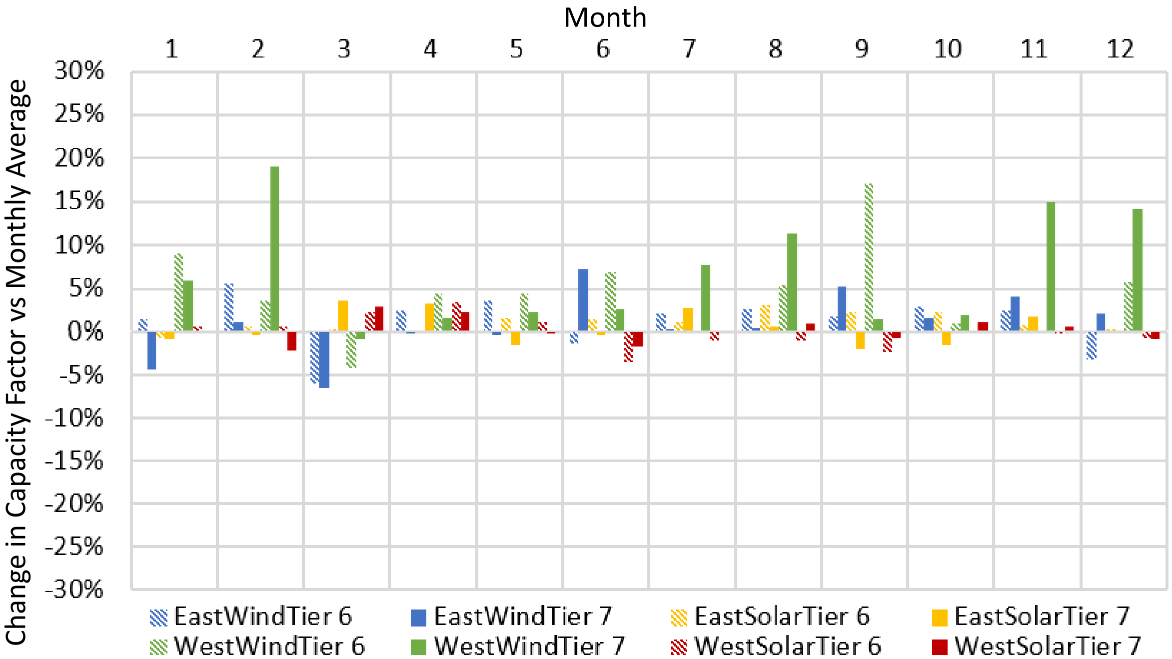
Figure K.1 – Renewable Resources vs. High Load Conditions



Tier 1: Monthly Peak Load Day
Tier 2: Top Days Ranked 2-5

- West wind is generally below average during high load days
- East wind is often above average during high load days in the winter
- Solar output is mostly near average during high load days

Figure K.2 – Renewable Resources vs. Low Load Conditions



Tier 1: Low Days Ranked 21-25
Tier 2: Lowest Days Ranked 26-31

- All renewables tend to be above average during low load days
- The impact is greatest for West wind

Standard stochastic evaluation of prices, loads, etc. is based on standard deviations and mean reversion statistics. The results indicate that wind and solar output does exhibit relationships with load, but they are poorly represented by standard deviations – a different modeling technique is necessary.

Because of the complexity of the data, PacifiCorp did not attempt to develop wind and solar generation that varies by stochastic iteration for the 2021 IRP. Instead, PacifiCorp developed a technique using the existing input framework: a single 8760 profile for each wind and solar resource that repeats every year. Because the load forecast rotates with the calendar, such that the peak load day moves to different calendar days, this creates differences in the alignment of load and renewable output across the IRP study horizon.

The order of the 2018 historical days was rearranged so that the forecasted intra-month variation in renewable output was reasonably aligned with the intra-month variation observed in the historical period for the days in the same load tier. Each day of renewable resource output derived from the 2018 history is mapped to a specific day for modeling purposes – only the order of the days changes. To maintain correlations within wind and solar output, all wind and solar resources across the entire system are mapped using the same days.

While this technique builds on previous modeling and produces a reasonable forecast that captures some of the relationships between wind, solar, and load, additional work is needed in future IRPs to explore the variation and diversity of solar and wind output and further relationships with load.