DEPARTMENT OF PUBLIC SERVICE REGULATION
BEFORE THE PUBLIC SERVICE COMMISSION
OF THE STATE OF MONTANA

IN THE MATTER OF NorthWestern Energy's Application for Approval of Capacity Resource Acquisition	REGULATORY DIVISION Docket No. 2019.12.101

PREFILED DIRECT TESTIMONY
OF MICHAEL MILLIGAN
ON BEHALF OF MONTANA ENVIRONMENTAL INFORMATION CENTER
("MEIC")

Department of Public Service Regulation
Montana Public Service Commission
Docket No. 2019.12.101
MEIC

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I. Expert Witness Information

Q: PLEASE PROVIDE YOUR NAME, TITLE AND EMPLOYER.

A: My name is Michael Milligan. I am the principal consultant at Milligan Grid Solutions, Inc.

Q: PLEASE PROVIDE A DESCRIPTION OF YOUR EXPERIENCE.

A: I have a Ph.D. in Economics from the University of Colorado and a B.A. from Albion College in Mathematics. My experience includes working in the power system industry for about seven years. I was Principal Researcher at the National Renewable Energy Laboratory ("NREL") for twenty-five years, where I authored/co-authored more than 225 technical reports, journal articles, and book chapters. I served on multiple technical committees at the Western Electricity Coordinating Council and the North American Electric Reliability Corporation ("NERC"), which is the official reliability regulator in the U.S., and I was a charter member of the Institute of Electrical and Electronics Engineers ("IEEE") Wind and Solar Coordinating Committee. For many years I served on the International Energy Agency Task 25 – Large-scale Wind Integration – research team where I led multiple international research papers on integrating wind into the power system. At NREL I led research into the potential benefits of the Western Energy Imbalance Market ("EIM") prior to its inception, working closely with the PUC EIM Group. This work was influential in the eventual formation of the EIM. As an independent consultant, I have undertaken a wide range of projects that include (a) advising a wind plant owner/operator on ancillary service tariffs, (b) submitting comments to FERC on reliability and resilience, (c) writing papers for publication, and (d) providing workshops on grid reliability at state commissions, FERC, NERC, RTOs, and other stakeholders. I have provided expert review for technical publications by the International Energy Agency, advised stakeholders in Alaska regarding the impacts of control area consolidation on the Railbelt system, and advised many stakeholder groups on utility economics and reliability as part of ISO/RTO transmission planning processes, especially related to renewable integration on the bulk power system, resource adequacy, and capacity contributions of renewable energy sources. I have submitted expert testimony in state public utility commission proceedings, focusing especially on resource adequacy and renewable integration issues, and also on flexibility and wholesale markets. My clients have included RTOs, trade groups, and educational organizations. I am a member of GridLab's expert team, and also serve as an ad hoc technical advisor to the Western Interstate Energy Board.

A copy of my professional resume, which includes my employment history, education, awards, and professional associations and activities, is attached as Exhibit MM-1 to this testimony.

II. Purpose and Summary of Testimony

Q: WHAT IS THE PURPOSE OF YOUR TESTIMONY?

A: I was asked by the Montana Environmental Information Center ("MEIC") to provide testimony that may assist the Montana Public Service Commission ("PSC" or "Commission") with assessing NorthWestern Energy's consideration of resource adquacy and capacity contributions from renewable energy, and to provide testimony regarding NorthWestern's evaluation of the value of flexibility in connection with its proposed acquisition of a 92.5 MW share of Colstrip Unit 4 ("CU4").

Q: PLEASE DESCRIBE THE MATERIALS YOU REVIEWED IN PREPARATION FOR YOUR TESTIMONY.

A: I have reviewed NorthWestern's Application in this docket, the April 24 Supplement to that Application, the July 2 Corrected Filing from NorthWestern, and the discovery requests and responses in this docket. I also reviewed other material that is cited in my testimony.

Q: PLEASE SUMMARIZE YOUR PRINCIPAL CONCLUSIONS AND FINDINGS REGARDING NORTHWESTERN ENERGY'S APPLICATION FOR APPROVAL OF CAPACITY RESOURCE ACQUISITION IN THIS DOCKET.

A: I conclude that NorthWestern's analyses of two of the primary bases it uses to justify the proposed CU4 acquisition – resource adequacy and flexibility – are fundamentally flawed in at least the following ways:

- NorthWestern has greatly underestimated the capacity contribution of renewables by using a flawed methodology that does not recognize the uncertainty of timing of the annual peak, which can occur in summer or winter. By using an approximation to Effective Load Carrying Capacity ("ELCC") methodology, I estimate that wind and solar resources in NorthWestern's system provide a capacity value of approximately 36% of rated capacity for both wind and solar energy, which is significantly higher than the 0.1% to 6% for existing wind and 5% to 10% for existing solar, and the 5% for potential new wind and 0% for potential new solar, assumed by NorthWestern.

- NorthWestern's assessment of resource adequacy does not conform to basic resource adequacy principles, as it fails to include the contribution of imports in measuring resource adequacy, and is not based on a reliability model that can calculate Loss of Load Probability ("LOLP") and Loss of Load Expectation ("LOLE").

- NorthWestern greatly overstates the flexibility value of the proposed CU4 acquisition by relying on a flawed analysis that combines electricity price data from different time periods. The calculation uses historical price data for sub-hourly periods that will not be accurate representations of future prices especially given expected future downward pressure on prices resulting from a combination of an increase in renewable resources and from the EIM. In addition, even NorthWestern's own analysis shows that the per-MW value of flexibility from CU4 is significantly lower than that of other resources.

- NorthWestern fails to account for the benefits that will accrue to NorthWestern after it joins the EIM in 2021. Those benefits will include a reduction in the need for flexibility and qualitative increase in reliability, and will further increase after the Enhanced Day Ahead Market is implemented.

III. NorthWestern has Significantly Underestimated the Capacity Value of Wind and Solar Resources

Q: WHAT CAPACITY CONTRIBUTION FOR RENEWABLE RESOURCES DID NORTHWESTERN ASSUME IN ITS ANALYSIS OF THE PROPOSED CU4 ACQUISITION?

A: According to the Direct Testimony of NorthWestern witness Bleau LaFave, NorthWestern assumed wind capacity contributions ranging from about 0.1% to about 6% of rated capacity. Solar capacity values ranged from approximately 5%-10% of rated capacity from existing resources.[1] For future wind and solar resources, it appears that NorthWestern used 5% for wind energy and 0% for solar capacity.[2] This corresponds to the findings of Synapse Energy Economics ("Synapse") in its comments on NorthWestern's 2019 Electric Supply Resource Procurement Plan ("2019 Plan"), which concludes that this undervaluation of wind and solar energy increases the cost of any portfolio that includes them by overbuilding other resources.[3]

Q: HOW DOES NORTHWESTERN USE ITS ASSUMED CAPACITY CONTRIBUTIONS FOR RENEWABLE RESOURCES?

A: The assumed capacity contributions from all resources provide the fundamental basis of NorthWestern's development of potential future portfolios. For example,

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[1] Pre-filed Dir. Test. of Bleau J. LaFave ("LaFave Test.") at BJL-23.
[2] Id. at BJL-30.
[3] In the Matter of NorthWestern Energy's 2019 Electric Supply Resource Procurement Plan, Docket No. 2019.08.052, R. Wilson, B. Fagan, S. Kwok, Synapse Energy Economics, Inc., Comments on NorthWestern Energy's Final 2019 Electricity Supply Resource Procurement Plan, at 8 (Feb. 14, 2020) ("Synapse Comments"), attached as Exhibit TJS-5 to Thomas J. Schneider's testimony in this docket.

LaFave describes the No Carbon Additions Portfolio as more expensive than any alternative, and uses this to help justify the CU4 acquisition.[4] For a given capacity deficit, undercounting renewable capacity in any portfolio will require additional, unneeded capacity to be added to ensure resource adequacy. However, if renewable capacity were properly accounted for, some of this additional capacity could be avoided, therefore lowering the level of capacity that NorthWestern must acquire to meet its target. The unreasonably low capacity value that NorthWestern assigns to wind and solar resources means that the Company is systematically discounting the wind and solar capacity in *all* portfolios. This will result in less expansion of renewables, more expansion of other capacity resources, and the appearance of a larger capacity deficit than is the case in reality.

Q: HOW DO NORTHWESTERN'S ASSUMED CAPACITY CONTRIBUTIONS FOR WIND AND SOLAR RESOURCES COMPARE WITH THOSE USED BY SIMILAR UTILITIES?

A: NorthWestern's assumed solar and wind capacity contributions of less than 10% are dramatically lower than those assumed by other western utilities. For example, a recent study by Xcel Energy in Colorado found that solar capacity value, based upon a metric called effective load carrying capability ("ELCC," which I describe in more detail below) ranges from 35% to 50% of solar rated capacity, for non-tracking and tracking systems, respectively.[5] Xcel's recent

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[4] LaFave Test. at BJL-30.
[5] See Xcel Energy Services, Inc. An Effective Load Carrying Capability Study of Existing and Incremental Solar Generation Resources on the Public Service Company of Colorado System (May 27, 2016) available at https://www.xcelenergy.com/staticfiles/xe/PDF/Attachment%20KLS-2.pdf.

work on the ELCC of wind found that it is about 16% of rated capacity.[6] Recent work by E3on behalf of Puget Sound Energy, Avista, NorthWestern Energy, and the Public Generating Pool examined the ELCC of wind and solar in the Northwest.[7] The study finds that new wind in the Montana/Wyoming area has an ELCC of just under 60% of rated capacity, falling to about 40% when there is approximately 30 GW of wind resources in the region.[8] Although the study did not evaluate solar ELCC in the Montana region, it found solar ELCC in the Greater Northwest region to be about 26% of rated capacity, falling to about 15% when solar in the region reaches 15 GW of installed capacity.[9]

In work that I did with some colleagues a few years ago, we calculated the capacity value of wind and solar resources on a regional basis in the Western Interconnection.[10] We compared our calculations with the standard values that were, at the time, used in the planning process by the Western Electricity Coordinating Council ("WECC"), which was 60% of rated capacity for all solar in the West. Our calculations showed a range of solar capacity values that ranged from about 30% to just under 60%, depending on geographic location. Our calculations for wind energy were approximately 30% in the Northwest Power

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[6] Xcel Energy Services, Inc., An Effective Load Carrying Capability Study of Existing and Incremental Wind Generation Resources on the Public Service Company of Colorado System (May 13, 2016) available at https://www.xcelenergy.com/staticfiles/xe-responsive/Company/Rates%20&%20Regulations/CO-Rush-Creek-Attachment-JFH-2.pdf.
[7] Energy+Environmental Economics, Resource Adequacy in the Pacific Northwest (Mar. 2019) available at https://www.ethree.com/wp-content/uploads/2019/03/E3_Resource_Adequacy_in_the_Pacific-Northwest_March_2019.pdf.
[8] Id. at 55.
[9] Id. at 57.
[10] M. Milligan, B. Frew, E. Ibanez, J. Kiviluoma, H. Holttinen, and L. Söder, Capacity Value Assessments for Wind Power: An IEA Task 25 Collaboration, WIREs Energy Environ 2016 (attached as Exhibit MM-2).

Pool region, which is where much of NorthWestern's system is located. In my opinion, NorthWestern's much lower assumed values are unjustified, and NorthWestern has presented no evidence that it has performed a rigorous assessment of resource adequacy and capacity value of renewable resources.

Q: WHAT CAN YOU CONCLUDE ABOUT THE CAPACITY CONTRIBUTION OF WIND AND SOLAR FROM THESE STUDIES?

A: It is clear that all of these studies find significantly higher capacity contributions from wind and solar than the values assumed, but not calculated, by NorthWestern. NorthWestern itself helped sponsor the E3 study, and yet did not use any of the information from that study. I conclude that NorthWestern's assumed values for wind and solar capacity contribution are not valid, and do not correspond with values obtained from other rigorous studies.

Q: WHAT METHOD DID NORTHWESTERN USE TO CALCULATE ITS ASSUMED CAPACITY VALUE OF WIND AND SOLAR RESOURCES?

A: NorthWestern used what is referred to as the "exceedance" method developed by the Southwest Power Pool ("SPP") to calculate its assumed capacity contribution for wind and solar energy. The SPP exceedance method was designed to standardize the demonstration of resource adequacy for load responsible entities participating in the SPP. NorthWestern's Montana utility does not participate in the SPP.

Q: HOW DID NORTHWESTERN USE THE SPP EXCEEDANCE METHOD TO DEVELOP ITS ASSUMED CAPACITY CONTRIBUTIONS FOR WIND AND SOLAR RESOURCES?

A: The SPP method calculates the annual capacity value of a wind or solar resource for the top 22 load hours from each month of the year.[11] The date and time of each of these 22 hours are noted, and then the renewable generation from the same set of hours is identified. SPP allows for calculations on a monthly, seasonal, or annual basis. If monthly, the hourly generation from the top 22 load hours of each month is arranged so that the 60th percentile of renewable generation can be calculated. This number is the annual capacity value of the renewable resource. For seasonal calculations, the capacity contribution is calculated based on the top 22 load hours for each month in the season of interest. And for annual calculations, the capacity contribution is calculated based on the top 22 load hours and corresponding generation for a single peak-load month. The SPP Planning Criteria describe how multiple years' data can be used. To modify the process for multiple years, the top 22 load hours from the peak month or months are aggregated, and the 60th percentile value is based on the aggregated data.[12]

My understanding is that NorthWestern uses the SPP exceedance method to calculate an annual net capacity contribution for each resource type using

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[11] Southwest Power Pool, SPP Planning Criteria, Rev. 2.2 § 7.1 (Mar. 16, 2020) available at https://www.spp.org/Documents/58638/SPP%20Planning%20Criteria_V2.2_0316020.docx.
[12] Id.

production data associated with the top 3% of load hours in a single peak load month for each year over a period of 10 years, or a total of 220 hours of data.

Q: DOES THE SPP STILL USE THIS EXCEEDANCE METHOD?

A: SPP is currently transitioning away from this exceedance approach, as described in the SPP Solar and Wind ELCC Accreditation report.[13] As the title of the report indicates, SPP is moving to a different approach, called effective load carrying capability ("ELCC"). The ELCC approach has been recommended by the professional power engineering society[14] and by NERC,[15] which is the federally-recognized organization that sets grid reliability rules in the U.S. One of the key motivations for the change in method is that SPP prefers a method that can account for the changing penetration of renewable energy on the grid, which can reduce the capacity value at higher penetrations.

Q: WHAT IS THE BASIS OF THE ELCC METHOD?

A: The capacity contribution of any resource, not just renewable resources, is calculated by using a reliability model of the power system. This is usually done as part of a planning process, where one of the key objectives is to produce a portfolio of resources that is sufficient to serve future demand at a given level of

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[13] Southwest Power Pool, Solar and Wind ELCC Accreditation (Aug. 2019) available at https://www.spp.org/documents/61025/elcc%20solar%20and%20wind%20accreditation.pdf.

[14] R. Duignan, C. J. Dent, A. Mills, N. Samaan, M. Milligan, A. Keane, M. O'Malley, Capacity Value of Solar Power, Proceedings of the 2012 IEEE Power and Energy Society General Meeting, July 2012, San Diego, California. Piscataway, NJ (2012) (attached as Exhibit MM-3); A. Milligan, M. D'Annunzio, C. Dent, K. Dragoon, B. Hasche, H. Holttinen, N. Samaan, L. Söder, M. O'Malley, Capacity Value of Wind Power. IEEE Transactions on Power Systems, Vol 26, No. 2 (May 2011) (attached as Exhibit MM-4).

[15] North American Electric Reliability Corporation, Methods to Model and Calculate Capacity Contributions of Variable Generation for Resource Adequacy Planning (Mar. 2011) ("NERC, Capacity Contributions") available at https://www.nerc.com/comm/PC/Integration%20of%20Variable%20Generation%20Task%20Force%20IVGT/Sub%20Teams/Probabilistic%20Techniques/IVGTF1-2.pdf .

reliability. This reliability level is a policy decision and is discussed further below.

Q: CAN YOU PROVIDE A BASIC EXPLANATION OF HOW THE ELCC DETERMINES THE CAPACITY CONTRIBUTION OF A RENEWABLE RESOURCE?

A: The ELCC of a resource is determined with a reliability model that calculates various metrics that quantify the risk of having insufficient installed resources to meet demand. The fundamental reliability metrics include loss of load probability (LOLP) and loss of load expectation (LOLE). The power system is first modeled at a given risk (LOLP or LOLE) level. The renewable resource in question is then added to the resource mix, and the model is re-run to calculate the new LOLP/LOLE. Because there is extra capacity compared to the base case, both LOLP and LOLE will have declined. Then, demand is increased until the LOLP/LOLE match the original value. This increase in demand is the ELCC of the resource.

Q: PLEASE EXPLAIN LOLP AND LOLE.

A: LOLP is a probability, and can be calculated for every hour of the year (or multiple years). LOLE is an expected value (expected in the probabilistic sense), and is often expressed in days per year, or days per 10-year period. Because LOLP is a probability, it must have a value between zero and one, inclusively. As an example, the probability of tossing a coin that results in a "head" is 0.5. Expected value is often expressed as a probability multiplied by the number of trials, such as a coin toss. One would expect, in the probabilistic sense, that tossing a coin 10 times would result in 5 heads (probability of heads multiplied by the number of trials equals 5 heads). LOLE can be thought of in a similar way, although the most common LOLE metric is the number of days per year that an outage would occur, caused by insufficient resources. A common resource adequacy target is an LOLE of 1 day per 10 years. This is often changed to 0.1 days per year because of either insufficient data or policy guidelines. For example, if the resource adequacy target is 0.1 days per year, then the power system achieves adequacy if its LOLE is no greater than 0.1 days per year. If LOLE does exceed 0.1 days per year, then the system is not adequate, and additional resources must be procured if the resource adequacy target is to be achieved.

Q: WHEN ELCC IS CALCULATED, HOW IS A RESOURCE PORTFOLIO EVALUATED IN TERMS OF ITS RESOURCE ADEQUACY?

A: The reliability models for resource adequacy calculations using the ELCC method use detailed information about the power system. These data include hourly demand, hourly wind and solar generation, hourly hydro generation capability including all flow constraints, and thermal resource installed capacity and forced outage rates. The forced outage rate is a rate at which a generation resource is expected to fail or become unexpectedly unavailable. Forced outage data is collected and housed at the NERC in a database called the Generation Availablility Data Set. Any resource, regardless of its vintage, type, or size, can fail as a result of mechanical or electrical malfunction at any time. System planners and operators account for these unexpected failures in the way they plan and operate the power system.

The reliability models that are used for resource adequacy calculate LOLP by using data on forced outage rates. LOLP is the probability that one or more resources can fail, resulting in some combination of curtailed demand or insufficient operating reserves. The reliability model will typically calculate one LOLP value for every hour of the year, based upon hourly demand and renewable data, and a probabilistic convolution of the many probabilities that account for potential resource outages. Each of these calculated probabilities will be between zero and one, inclusively. For most hours of the year, the LOLP is indistinguishable from zero, indicating no risk. The highest risk hours occur primarily during peak load periods, but can also occur during times of high exports or low imports, during scheduled maintanence of resources which reduces overall system capability, or other factors. The probabilistic calculations indicate whether the resource portfolio is adequate.

Q: IS THERE A LEVEL OF LOLE THAT IS REQUIRED BY NERC OR OTHER REGULATORY BODIES?

A: No. NERC does not prescribe a given reliability level with LOLE or any related metric. NERC does, however, recommend the use of LOLP-related models to assess resource adequacy.[16]

The LOLE target is established by policy. Because reliability is expensive, there is a tradeoff between total system cost and the desired reliability level. It would

[16] More information can be found in the NERC publication "Probablistic Adequacy and Measures," Technical Reference Report Final (July 2018) available at https://www.nerc.com/comm/PC/Probabilistic%20Assessment%20Working%20Group%20PAWG%20%20Relat/Probabilistic%20Adequacy%20and%20Measures%20Report.pdf.

normally be more expensive to achieve a LOLE target of 1 day per 20 years, than a target of 1 day per 10 years. This is because additional resources would be required to meet the higher reliability (lower LOLE) target.

Q: HOW DOES ELCC RELATE TO LOLP?

A: The ELCC of a resource represents the resource's contribution to resource adequacy, and is referred to as "capacity value" or "capacity contribution." The ELCC method determines how much additional demand can be served by a new resource, holding reliability (LOLE) constant.[17]

To use the ELCC method, the modeled power system is evaluated and adjusted so that it achieves the LOLE target. The new resource, such as a solar or wind generator, is added to the resource mix and the LOLE is recalculated. The new LOLE will have fallen because of the new resource. Then, demand is incremented until the LOLE increases to its original target. The amount of increased load that can be served while holding reliability constant is the ELCC of the new resource. Figure 1, below, is an adaptation of a graphic from a NERC report that illustrates the concept.[18] At point one, the system target of 0.1 day/year is achieved. A new resource is added, which shifts the reliability curve down and to the right. The new reliability level is depicted by point 2, and it is approximately 0.09 days/year. This is more reliable than the target, and because reliability is expensive, we gradually increase demand until the target reliability

[17] Roy Billinton and Ronald N. Allan, Reliability Evaluation of Power Systems (2d. ed. 1996) (excerpt attached as Exhibit MM-5).
[18] See NERC, Capacity Contributions.

level is reached again, traveling thru point 3 and arriving at point 4. In this example, the horizontal distance between point 1 and point 4 is the ELCC of the new resource.

Q: IS ELCC ONLY CALCULATED FOR WIND AND SOLAR RESOURCES?

A: Because ELCC calculations can be relatively computationally expensive, a simpler method is sometimes used for conventional thermal resources. This method calculates a metric called “unforced capacity” (“UCAP”). UCAP = (1 – EFOR) x (Rated Capacity). EFOR represents the forced outage rate of the resource. The UCAP of a resource is generally “close” to its ELCC, and is much easier to calculate.

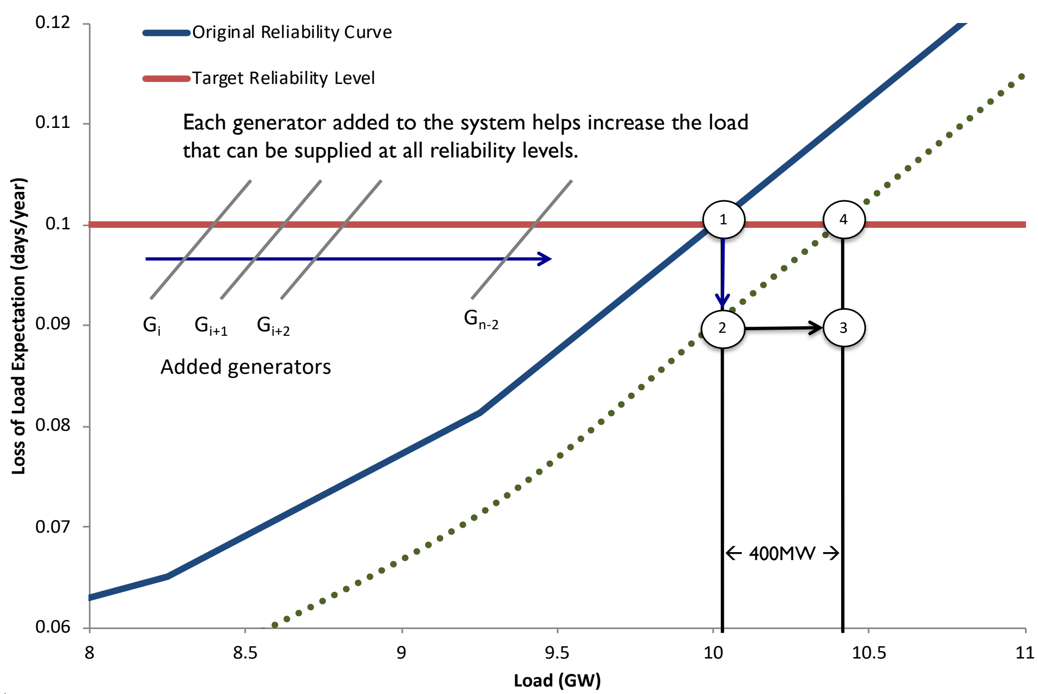

Figure 1. Graphical depiction of ELCC

Q: IS THE ELCC METHOD ALWAYS THE BEST APPROACH TO CALCULATE THE CAPACITY CONTRIBUTION OF RENEWABLE RESOURCES?

A: ELCC is the preferred method because it is a true reliability metric; it captures the probability of loss of load. However, it is a relatively complex calculation, not particularly transparent, and requires significant data and specialized software and computing capability. Because of these factors, there are several methods that simplify or approximate ELCC. Some of these simplified methods have been benchmarked against ELCC so their ability to approximate ELCC is well understood. Without performing this type of benchmarking and subsequent calibration of a simple method to ELCC, it is not possible to predict the performance of a simplified method. Generally, however, simplified approaches tend to work well if they can capture potential times of risk of loss of load. ELCC is recommended for renewable resources by various IEEE task force papers;[19] other methods should be benchmarked against ELCC.

Q: HOW DOES THE NORTHWESTERN ENERGY APPROACH TO RENEWABLE CAPACITY CREDIT UNDER THE SPP EXCEEDANCE METHOD COMPARE TO THE ELCC METHOD?

A: The ELCC method is far superior to NorthWestern's SPP approach because ELCC is grounded in a framework that is used for resource adequacy. The NorthWestern Energy approach has no relationship to a resource adequacy target

[19] See Exhibit MM-2 and Exhibit MM-3.

using LOLP/LOLE methods, which NorthWestern Energy has acknowledged is the approach recommended by NERC and by WECC.[20]

Q: WHY DOESN'T NORTHWESTERN ENERGY'S APPROACH RELATE TO A LOLE RESOURCE ADEQUACY CONSTRUCT?

A: NorthWestern's method ignores reliability because it does not use any information about LOLP or any related metric. Instead, the NorthWestern Energy method focuses on a very limited number of peak hours. Although these hours might be associated with Loss of Load risk, there could be other hours that have similar, or even higher, risk that would not be recognized by NorthWestern's approach. The NorthWestern method does not account for this and therefore does not capture reliability. The implication is that NorthWestern has not really undertaken an appropriate analysis to assess its future reliability risk, and has not properly quantified the contribution that renewable energy sources can make to support the required level of resource adequacy.

Q: ARE ELECTRICIY IMPORTS PART OF THE RESOURCE ADEQUACY CALCULATION UNDER THE ELCC METHOD?

A: Yes. Imports can be a critical component of resource adequacy under an ELCC method. For example, as WECC has explained:

> Each of the subregions have some risk in their areas when they are studied individually. However, as discussed in the Margin section, at WECC, we study risk before and after imports. One of the greatest benefits of the Western Interconnection is its geographic diversity as it relates to demand and resources. When one part of the interconnection is experiencing peak demands, other areas may

[20] LaFave Test. at BJL-6:11-12 and BJL-15:20-23.

> not be. While resources may not be available in one subregion due to weather, fuel, etc., other subregions may have plenty of resource availability. It is important in resource adequacy to consider each subregion's ability to import energy from other subregions to cover the hourly risk in its system.[21]

Q: DID NORTHWESTERN INCLUDE IMPORTS IN ITS RESOURCE ADEQUACY ANALYSIS?

A: No. In his Direct Testimony, NorthWestern witness LaFave provided an analysis that purports to show the number of resource deficits over the past 10 years, and how increased levels of capacity could reduce such deficits.[22] In doing so, however, NorthWestern only considered its own resources and long-term contracts, and failed to include imports in the analysis.[23] As a result, Mr. LaFave's analysis overestimates NorthWestern's claimed resource adequacy deficit.

Q: ARE THERE ANY OTHER WAYS IN WHICH THE NORTHWESTERN ENERGY APPROACH DOES NOT RELATE TO RESOURCE ADEQUACY IN A LOLP FRAMEWORK?

A: Yes. The use of a percentile level of generation—or exceedance method—in the NorthWestern Energy calculation arbitrarily ignores any capacity below the percentile threshold. This is most easily demonstrated by comparing it to a UCAP calculation. Consider an example 100 MW (capacity) resource that has a high forced outage rate of 50%. During the top 22 hours of the year, this resource

[21] Western Electricity Coordinating Council, The Generation Resource Adequacy Forecast Webpage available at https://www.wecc.org/ePubs/GenerationResourceAdequacyForecast/Pages/Introduction.aspx.
[22] LaFave Test. at BJL-16-17, Table 1.
[23] NorthWestern's response to MEIC-048 states that resource adequacy only applies to their portfolio and therefore doesn't include external resources/imports.

generates 100 MW for 11 hours, and generates 0 MW for 11 hours. In this case the 60th percentile for this resource is zero. However, the UCAP for this plant is 50 MW. This value of UCAP is relatively low (50%), but is not zero. The NorthWestern Energy method, however, would give this resource a capacity value of 0.

Q: YOUR EXAMPLE IS BASED ON UCAP. DOES THE EXAMPLE HOLD UP IN THE CASE OF A FULL ELCC CALCULATION?

A: Yes. In a paper published by a colleague and I, we showed that percentile-based methods for calculating capacity value are flawed.[24] We constructed a reliability model of a system that reached a resource adequacy target of 1 day in 10 years. We then replaced a subset of the resource fleet with less reliable resources—resources that have gradually increasing forced outage rates. Each time we increased forced outage rates, reliability was reduced below the target. To compensate, we then added new resources with the incrementally higher forced outage rates. We repeated this process using forced outage rates as high as 95% on this subset of resources.

Q: WHAT DID YOU CONCLUDE FROM THIS STUDY?

A: We found that resource adequacy can be achieved even with resources with extremely high forced outage rates – up to 95%. Generally, a resource with a 95% forced outage rate that could experience an outage at any time would achieve 100 MW during peak periods about 5% of the time. Its 60th percentile generation

[24] M. Milligan and K. Porter, Capacity Value of Wind in the United States: Methods and Implementation. 19 Electricity Journal 91 (Mar. 2006), attached as Exhibit MM-6.

would be zero. This shows that resources that have very low percentile generation can still contribute to resource adequacy, and that applying a percentile in the first place discounts capacity that can help achieve resource adequacy. In terms of the UCAP example described above, a 100 MW resource with a 95% forced outage rate would have a UCAP of 5 MW.

Q: **HOW DOES THIS ANALYSIS RELATE TO THE CURRENT PROCEEDING?**

A: NorthWestern finds extremely low capacity contributions from wind and solar because it uses the old SPP exceedance method for capacity assessment. As a result, wind and solar capacity are nearly non-existent in NorthWestern's determination of resource adequacy and modeling, inducing the capacity expansion model to build or acquire more capacity than is needed. This is also recognized by Synapse in its comments on NorthWestern's 2019 Electricity Supply Resource Procurement Plan, which found that: "The capacity credit the Company gives to potential new solar and wind resources is prohibitively low in the PowerSimm modeling…As a result, NorthWestern's Base portfolio builds only new gas resources and fails to build any solar or wind projects."[25] A similar criticism appears in a court order from the Montana Eighth Judicial District Court, Cascade County, which says "In focusing only on a handful of peak demand hours (220 hours over a ten-year period) that reflect primarily infrequent wintertime spikes, the Commission overlooked evidence that NorthWestern lacks

[25] Synapse Comments at 6-7, attached to Schneider Test. as Ex. TJS-5.

sufficient capacity to meet peak customer demand in both the summer and winter."[26] [27]

The approach used by NorthWestern therefore suffers from two flaws: (1) the overall resource adequacy analysis is not performed in a framework that addresses long-term reliability, and (2) as a result of using a metric for capacity value that is detached from the reliability assessment framework, NorthWestern finds an inflated need for capacity in the future. These two flaws will needlessly increase other capacity acquisitions and costs for Montana consumers.

Q: ARE THERE ANY SIMPLIFIED APPROACHES TO CALCULATING WIND AND SOLAR CAPACITY VALUE THAT YOU COULD RECOMMEND FOR THIS PROCEEDING?

A: A common proxy method for ELCC, similar to what has been used by PJM, can be a reasonable approach.[28] PJM identifies certain hours during which peak demand risk occurs – hours ending 3pm–6 pm, June, July, and August. Wind and solar capacity value is the capacity factor of the resource during this window of time, and uses a rolling average of up to three years of data if available.

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[26] Vote Solar v. Mont. Dept. of Pub. Serv. Regulation, Cause No. BDV-17-0776 (Apr. 2019), Order Vacating and Modifying Montana Public Service Commission Order Nos. 7500c and 7500d at 12.
The Montana Supreme Court affirmed the district court's decision that the Commission improperly calculated the capacity contribution of solar resources, although on different grounds. See Vote Solar v. Mont. Dept. of Pub. Serv. Regulation, 2020 MT 213, ¶ 64.
[28] PJM Manual 21: Rules and Procedures for Determination of Generating Capability. Revision 14 (Aug. 1, 2019), available at https://www.pjm.com/~/media/documents/manuals/m21.ashx, at 34-36. The NYISO is another example and uses a similar approach. See New York ISO, Installed Capacity Manual Attachments (June 5, 2020), https://www.nyiso.com/documents/20142/2923635/app_a_attach_icapmnl.pdf/503354b6-0607-9a12-f2d4-f866c25eac65.

Q: WOULD YOU RECOMMEND THE PJM METHOD FOR NORTHWESTERN?

A: The best approach is to use ELCC. But in the case that ELCC evaluation is not possible, I recommend that the PJM method could be adjusted so that it accounts for appropriate times of peak demand risk as experienced by NorthWestern. During periods of potential risk, the wind and solar capacity factors–calculated on the basis of their generation during these risk periods–could be used as a proxy for ELCC. Although there is no widely recognized term for this type of proxy, I herein refer to them as peak hour capacity factor method.

Q: WHAT TIME PERIODS WOULD YOU RECOMMEND FOR NORTHWESTERN?

A: The appropriate time periods have been addressed in another Montana Public Service Commission Docket: D2019.09.059 in the pre-filed testimony of R. Thomas Beach.[29] These times of risk occur June 15-September 15, from 2:00-6:00 PM, and from December-February from 5:00-8:00 PM. These time periods correspond to periods during which NorthWestern has experienced peak demand in recent years.

Q: HOW WOULD THE APPLICATION OF BEACH'S METHOD CHANGE THE CAPACITY CONTRIBUTION OF WIND AND SOLAR FOR NORTHWESTERN?

A: Using this method results in wind capacity contributions of 33.6% and 35.6% of rated capcity in 2018 and 2019, respectively. For solar, the capacity contributions are 30.5% and 36.1% of rated capacity for 2018 and 2019, respectively.[30]

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[29] In the Matter of NorthWestern Energy's QF-1 Tariff Update Application, Docket No. D2019.09.059, Pre-filed Dir. Test. of R. Thomas Beach on Behalf of Vote Solar and Montana Environmental Information Center (attached as Exhibit MM-7).
[30] Milligan Workpapers, "Summary results" tab, attached as Exhibit MM-8.

Q: WHAT WOULD YOU RECOMMEND FOR CAPACITY CONTRIBUTIONS GOING FORWARD?

A: My recommendation is to use the capacity contribution calculated with Beach's method, as described above. Because there may be some inter-annual variation, I recommend calculating the average of the annual values for each technology. For wind energy the capacity contribution would therefore be 34.6% of rated capacity, and for solar energy the capacity contribution would be 33.3% of rated capacity.

Q: PLEASE SUMMARIZE YOUR TESTIMONY RELATED TO RESOURCE ADEQUACY AND CAPACITY CONTRIBUTION OF WIND AND SOLAR ENERGY.

A: NorthWestern's method for assessing the capacity contribution of wind and solar energy is flawed. The percentile method does not relate in any way to resource adequacy assessment using LOLE modeling and targets, which NorthWestern itself cites as WECC and NERC standards. The flawed method results in undervaluing wind/solar capacity and artificially increasing the need for additional capacity. This systematic underevaluation of capacity contribution of existing renewables also results in undervaluing potential new renewable resource additions as an alternative to non-renewable resources such as the proposed CU4 acquisition. The impacts of undervaluing renewable capacity therefore: (1) increases NorthWestern's apparent need for new capacity, and (2) makes it impossible to fulfill this potential need, whether real or apparent, with renewables.

IV. NorthWestern Has Failed to Establish that the CU4 Acquisition Would Provide Significant Flexibility Value.

Q: PLEASE DESCRIBE THE ROLE THAT FLEXIBILITY PLAYS IN THIS DOCKET.

A: NorthWestern has identified a significant need for both peaking and "flexible" capacity.[31] NorthWestern claims that the proposed CU4 acquisition has both attributes.

Q: HOW DID NORTHWESTERN ASSESS THE VALUE OF FLEXIBILITY?

A: NorthWestern witness LaFave states that to calculate the flexibility credit, or value, of a resource, that resource is dispatched twice; once to an hourly price, and once to a 5-minute price.[32] In response to discovery, NorthWestern clarifies that the "sub-hourly credit is based on historical price data, not on simulations. Therefore, it is calculated separately from the 100 simulations of the system over 20 years."[33]

Q: IS THIS A PLAUSIBLE METHOD TO CALCULATE THE VALUE OF THE FLEXIBILITY THAT CAN BE PROVIDED FROM A GIVEN RESOURCE?

A: No. The sub-hourly historical price will have little, if any, relationship to the hourly prices over a 20-year simulation period.

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[31] LaFave Test. at BJL-8, 14.
[32] Id. at BJL-27-28.
[33] NorthWestern Resp. to MEIC-060.

Q: WHY WOULD HISTORICAL SUB-HOURLY PRICES BE UNREPRESENTATIVE OF FUTURE PRICES?

A: There are two trends that will have an impact on prices generally. The first one is NorthWestern's entry into the Western Energy Imbalance Market ("EIM"). According to the EIM web site, members have saved $919.69 million since the EIM's inception in November 2014,[34] including $50.7 million in benefits in the first quarter of 2020 alone.[35] This saving is accomplished as follows: "The EIM platform balances fluctuations in supply and demand by automatically finding *lower-cost resources* to meet real-time power needs.[36] The EIM manages congestion on transmission lines to maintain grid reliability and supports integrating renewable resources. In addition, the market makes excess renewable energy available to participating utilities at low cost rather than turning the generating units off."[37] The impact of the EIM will therefore put downward pressure on prices.[38]

The second trend is the increase in wind and solar energy. Because wind and solar resources have a marginal cost of zero, they will also exert downward pressure on energy prices. In most cases, the wind/solar energy will reduce the size of the thermal dispatch stack, which means that the most expensive resource (in terms of marginal cost) will be dispatched down or turned off. In a few cases

[34] See https://www.westerneim.com/pages/default.aspx.
[35] California ISO, Western EIM Benefits Report, First Quarter 2020 (Apr. 30, 2020) available at https://www.westerneim.com/Documents/ISO-EIMBenefitsReportQ1-2020.pdf.
[36] Emphasis added
[37] See https://www.westerneim.com/Pages/About/HowItWorks.aspx
[38] Prices and power production costs will decrease with the EIM. See M. Milligan, K. Clark, J. King, B. Kirby, T. Guo, and G. Liu, Examination of Potential Benefits of an Energy Imbalance Market in the Western Interconnection (Mar. 2013) available at https://www.nrel.gov/docs/fy13osti/57115.pdf.

it is possible that wind or solar energy is on the margin, effectively setting the electricity price to zero. This aligns with NorthWestern's 2019 IRP, which cites Ascend Analytics' expectation that increasing renewable resources will "continue to put downward pressure on energy prices (since they have zero variable cost) in the WECC and increase the volatility of energy prices."[39]

Q: WHAT IMPACT, IF ANY, WILL THESE LOWER PRICES HAVE ON NORTHWESTERN'S OPERATIONS?

A: Without performing detailed modeling that compares operations with and without the EIM, I cannot quantify impacts precisely. However, because the EIM will generally put downward pressure on prices, and because of the increasing level of renewable energy, lower prices will make some of NorthWestern's resources—including CU4—less competitive reducing their overall generation with a corresponding decrease in capacity factor. Although lower prices generally benefit the customer, NorthWestern customers will miss out on at least some of that benefit if they are having to pay for an increased share of the more costly CU4 rather than increased amounts of the wind and solar resources that help to drive down costs. MEIC witness Anna Sommers testifies in this docket that the PowerSimm modeling projects a much lower capacity factor for CU4 in later years, quite possibly caused by lower energy prices.

[39] With renewable energy added to the power system, prices decline. Volatility will generally increase because of the variable nature of wind and solar energy. But this increase in price variability is countered by the downward average price. Put another way, the lower levels of prices are more volatile than the high prices without wind/solar energy. A fact sheet at the United States Department of Energy shows this for several organized electricity markets: https://www.energy.gov/eere/analysis/downloads/impacts-high-variable-renewable-energy-futures-wholesale-electricity-prices.

Q: DID NORTHWESTERN ANALYZE THE IMPACT OF THE EIM ON THE CU4 ACQUISITION, OR ANY EIM PRICE ANALYSIS SUCH AS DESCRIBED IN YOUR PREVIOUS ANSWER?

A: According to NorthWestern's reply to MCC-005, NorthWestern assessed its opportunity to participate in the EIM prior to entertaining the CU4 acquisition, and no documents exist that analyze NorthWestern's potential sales of excess energy or capacity into the EIM.

Q: DID NORTHWESTERN CALCULATE THE FLEXIBILITY VALUE OF RESOURCES?

A: Yes. However, the results are compromised because of the incompatibility of the subhourly prices and the hourly prices. Witness LaFave reports a sub-hourly flexibility credit of $270,268 for a 9 MW reciprocating engine, and $210,811 for the 95 MW share of Colstrip Unit 4.[40] This translates to approximately $2,200/MW for CU4, and $30,000/MW for the reciprocating engine, a nearly 14-fold difference in flexibility value. It is important to remember that the sub-hourly prices used to value the flexibility of both CU4 and hypothetical RICE units are likely too high. However, the relative difference between the two resources on a per-MW basis will still be substantial.

Q: WHAT CAN YOU CONCLUDE REGARDING THE FLEXIBILITY OF CU4 COMPARED TO A RECIPROCATING ENGINE USING THIS INFORMATION?

A: Clearly CU4 is not capable of providing significant flexibility. The relatively low flexibility value is driven by its slow ramp rate, which is approximately 1.2

[40] LaFave Test. at BJL-29.

MW/minute. When the unit's minimum generation level of 25 MW is accounted for, the unit range is from 25 MW to 92.5 MW at a ramp rate of 1.2 MW/minute.[41]

There are other types of resources that are flexible, providing relatively fast ramping capability and rapid start times, and NorthWestern has not undertaken a comparison of resources that would include various natural gas combined cycle or single cycle turbines.[42] Aerderivative gas turbines can cycle and ramp quickly.[43] It is also possible for relatively inflexible, older plants to be retrofit so that they can attain some combination of lower turn-down or faster ramping or startup.[44]

V. NorthWestern Fails to Account for the Benefits that the Energy Imbalance Market Will Provide.

Q: HOW DOES NORTHWESTERN ADDRESS IN ITS APPLICATION ITS PLANNED 2021 ENTRY INTO THE EIM?

A: In its Application, NorthWestern is largely silent about its pending entry into the EIM with the exception of a handful of statements from witness LaFave that with its current resources NorthWestern will not be able to "participate in" the EIM.[45]

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[41] All data from this answer from NorthWestern's response to MEIC-093. The unit range refers to NorthWestern Energy's share of CU4.

[42] See S. Simmons and G. Charles, Northwest Power and Conservation Council GRAC, Natural Gas Combined Cycle Combustion Turbines (Oct. 16, 2013) available at https://www.nwcouncil.org/sites/default/files/Final_CCCT-Presentation_101613.pdf.

[43] GE Energy's LMS-100 specifications, available at https://www.ge.com/power/gas/gas-turbines/lms100.

[44] S. Venkaataraman, G. Jordan, M. O'Connor, K. Kumar, S. Lefton, D. Lew, G. Brinkman, D. Palchak, and J. Cochran, National Renewable Energy Laboratory, Cost-Benefit Analysis of Flexibility Retrofits for Coal and Gas-Fueled Power Plants (Dec. 2013) available at https://www.nrel.gov/docs/fy14osti/60862.pdf; See https://www.ge.com/news/press-releases/ge-technology-provide-flexible-power-104-megawatt-combined-cycle-power-plant-italy.

[45] LaFave Test. at BJL-8, BJL-20.

Q: WILL NORTHWESTERN BE UNABLE TO PARTICIPATE IN THE EIM WITHOUT THE CU4 ACQUISITION?

A: No. In response to discovery, NorthWestern clarified that with or without the CU4 acquisition, there may be certain hours in which NorthWestern will not with its own resources be able to satisfy the balancing, capacity, and flexibility tests set forth by the EIM. NorthWestern, however, has not specifically analyzed the ability of its current portfolio with or without the CU4 acquisition to meet each of those three EIM sufficiency tests.[46] NorthWestern's claim about potentially being unable to satisfy the sufficiency tests in certain hours also does not account for market purchases even though, as the company acknowledges, such purchases would be a component in determining whether the sufficiency tests are satisfied in a given hour.[47]

Q: WILL NORTHWESTERN'S ENTRY INTO THE EIM INCREASE THE COMPANY'S BALANCING REQUIREMENTS?

A: No. Absent its membership in the EIM, NorthWestern must fulfill balancing requirements. The EIM may require some additional reporting or verification that the Company has scheduled resources according to EIM requirements. NorthWestern raises concerns that it will be unable to meet the balancing, capacity, and flexibility requirements in the EIM. Although these requirements are required of entities in the EIM, they are not fundamentally different operationally than what NorthWestern must do if it is not an EIM member. To

[46] NorthWestern Resp. to MEIC-098(b).
[47] NorthWestern Resp. to MEIC-098(a).

serve demand, NorthWestern must schedule sufficient resources that can balance its system, and it must ensure that it can reliably operate. Balancing requirements are not only a part of EIM membership, but are also mandated by NERC. NERC Standard BAL-001-2, "Real Power Balancing Control Performance," sets out rules for Balancing Authorities responsibilities to maintain system balance and support interconnection frequency.[48] BAL-001-2 is required whether a utility is in the EIM or not. The EIM does not require the Balancing Authority or utility to own all its resources, but necessary arrangements to serve demand are required. Today, NorthWestern must set up its day ahead schedule and provide its own flexibility, supplemented by purchases. The EIM rules are not necessarily and fundamentally different than what NorthWestern does today, except NorthWestern must certify its position in accordance with the EIM rules.

Q: WILL THE EIM PROVIDE ANY BENEFITS TO NORTHWESTERN OPERATIONALLY?

A: Yes. The EIM will provide flexibility in the real-time 5- and 15-minute market, potentially alleviating constrained resources in the NorthWestern balancing area. The EIM will result in lower costs, and, subject to transmission constraints, will enhance NorthWestern's ability to find economic energy at times, and will enhance NorthWestern's ability to sell excess generation if it experiences time of excess supply. Even though the Company must provide a resource schedule that is largely self-sufficient ahead of real time, during real time cost-effective flexibility will sometimes be available via the EIM. Furthermore, as the

[48] North American Electric Reliability Corporation, Real Power Balancing Control Performance, BAL-001-2 (Apr. 16, 2015) available at https://www.nerc.com/pa/Stand/Reliability%20Standards/BAL-001-2.pdf.

Enhanced Day Ahead Market is added to the current EIM, day-ahead schedules will become more cost-effective.

Q: ARE THERE ANY BENEFITS FROM THE EIM IN TERMS OF REDUCING FLEXIBILITY REQUIREMENTS ON NORTHWESTERN'S SYSTEM?

A: Yes. Membership in the EIM will reduce the need for flexibility because ramps of net load will be reduced. This was extensively analyzed by two NREL studies which quantified ramp reduction under various assumptions regarding renewable development and EIM membership.[49] According to the EIM web site, the EIM produces benefits such as: "Reduced costs for participants by lowering the amount of costly reserves utilities need to carry, and more efficient use of the regional transmission system. Reduced carbon emission and more efficient use and integration of renewable energy. For instance, when one utility area has excess hydroelectric, solar or wind power, the ISO can deliver it to customers in California or to another participant. Likewise, when the ISO has excess solar energy, it can help meet demand outside of California that otherwise would be met by more expensive – and less clean – energy resources.[50]

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[49] J. King, B. Kirby, M. Milligan, S. Beuning, National Renewable Energy Laboratory, Operating Reserve Reductions from a Proposed Energy Imbalance Market with Wind and Solar Generation in the Western Interconnection (May 2012) available at https://www.nrel.gov/docs/fy12osti/54660.pdf; J. King, B. Kirby, M. Milligan, S. Beuning, National Renewable Energy Laboratory, Flexibility Reserve Reductions from an Energy Imbalance Market with High Levels of Wind Energy in the Western Interconnection (Oct. 2011) available at https://www.nrel.gov/docs/fy12osti/52330.pdf.
[50] See https://www.westerneim.com/Pages/About/HowItWorks.aspx

Q: WILL JOINING THE EIM ENHANCE THE RELIABILITY OF NORTHWESTERN'S SYSTEM?

A: Yes. The EIM will enhance reliability by improving visibility across the grid. As explained on EIM's web site, the EIM will provide for "Enhanced reliability by increasing operational visibility across electricity grids, and improving the ability to manage transmission line congestion across the region's high-voltage transmission system."

VI. Summary and Conclusion

Q: PLEASE SUMMARIZE YOUR TESTIMONY.

A: I conclude that NorthWestern undervalues wind and solar generation capacity contribution to resource adequacy. This results in excess capacity acquisitions which will increase consumer costs. I am in agreement with Synapse on these points. I also conclude that NorthWestern has significantly overstated the flexibility value of CU4, while failing to account for the likely higher flexibility value of other resource options. I further conclude that NorthWestern will benefit from the EIM, which will help by reducing the need for flexibility and will provide cost-effective generation on a subhourly basis. However, this benefit may be reduced by the impact that lower prices may have on the capacity factor of CU4, which would be expected to decline when NorthWestern joins the EIM.

Q: DOES THIS CONCLUDE YOUR TESTIMONY AT THIS TIME?

A: Yes.

Exhibits to Direct Testimony of Michael Milligan
on behalf of Montana Environmental Information Center

Exhibit MM-1

Docket No. 2019.12.101

Michael R. Milligan, Ph.D.
Milligan Grid Solutions, Inc.

Michael R. Milligan, Ph.D.

Education and Training

Ph.D., Economics, University of Colorado, Boulder
M.A., Economics, University of Colorado, Denver
B.A., Mathematics, Albion College, Albion, MI

Professional Experience

Dr. Michael Milligan recently retired as Principal Researcher at the National Renewable Energy Laboratory, and he is now an independent power system consultant. He has more than 30 years' experience in analysis and modeling the bulk power system, and more than 25 years focusing on the impacts of wind and solar generation integration into the bulk system. He is the author/coauthor of more than 220 journal articles, conference papers, technical reports, and book chapters on topics that include the physical impacts of variable generation on power system operations, reserves, economics, and resource adequacy. He has also published articles and book chapters on variable generation and energy markets, the impacts of variability pooling and wide-area energy management, conditional firm transmission potential in the West, the application of genetic algorithms and fuzzy logic to wind power plant location optimization, and short-term wind forecasting. He has given papers and presentations in in China, Japan, India, Portugal, Spain, Italy, France, Ireland, England, Scotland, Germany, Netherlands, Malaysia, Canada, Denmark, Sweden, Norway, and Finland, and has developed methods that are used for many aspects of integration analysis.

As a consultant, Michael has undertaken a wide range of projects that include (a) advising a wind plant owner/operator on ancillary services tariffs, (b) submitting comments to FERC on reliability and resilience, (c) writing papers for publications, (d) providing workshops on grid reliability at state commissions, FERC, NERC, RTOs, and other stakeholders. He has provided expert review for technical publications by the International Energy Agency, advised stakeholders in Alaska regarding the impacts of control area consolidation on the Railbelt system, and has advised many stakeholder groups on utility economics and reliability as part of ISO/RTO transmission planning processes, especially related to renewable integration on the bulk power system. He has submitted expert testimony in several state public utility commission proceedings, focusing on resource adequacy and renewable integration issues. His clients include RTOs, trade groups, and educational organizations. He is a member of GridLab's expert team, and also serves as an ad hoc technical advisor to the Western Interstate Energy Board.

Dr. Milligan has provided expert testimony in public utility proceedings and workshops around the United States. For many years when he was at NREL, he collaborated with the Western Interstate Energy Board, was a member of the Western Governors' Association's Clean and Diverse Energy Advisory Committee (CDEAC), and he was the primary author of the wind integration and scenario chapters. He led and contributed to multiple projects analyzing the potential benefits of the then-proposed Energy Imbalance Market in the West, including reserves and ramping analysis and electricity production simulation. This work was influential in the formation of the EIM, which is now operating and expanding in the Western Interconnection—parts of California, Nevada, Arizona, Utah, Wyoming, Idaho, Oregon, and Washington are participating. Since its launch in 2014 the EIM has enhanced grid reliability and reduced costs for the market participants, and it improves the ability of the bulk power system to effectively manage the increasing levels of wind and solar power, now and in the future.

Michael has advised the 21st Century Clean Power Partnership (http://www.21stcenturypower.org/projects.cfm), a multilateral effort of the Clean Energy Ministerial, operated by the Joint Institute for Sustainable Energy Analysis. In this role, he has provided guidance to governments and utilities in China, India, South Africa and others on methods to improve the ability of their power systems to efficiently integrate renewable energy. He recently served as a principal technical advisor to a large-scale renewable energy integration study in India. His work was influential in influencing the Indian Grid Operator (POSOCO) to embark on a Pilot Project on 5-Minute Scheduling in India that is currently underway.

Dr. Milligan is an internationally recognized expert in loss-of-load probability analysis and resource adequacy. He led the North American Electric Reliability Corporation (NERC) Task Force for Capacity Value of Variable Generation and co-led the Institute of Electrical and Electronics Engineers (IEEE) Wind Power Coordinating Committee Capacity Value Task Force. He advises regional transmission organizations and utilities on resource adequacy methods and has advised many power system industry task forces and working groups. He was a charter member of the NERC Integrating Variable Generation Task Force and Essential Reliability Services Task Force (now Working Group) and the Western Electricity Coordinating Council's (WECC's) Variable Generation Subcommittee; and has served on multiple WECC committees and has been a key contributor to multiple NERC and WECC reports.

Michael led the Bulk Electric Power System Task Force for NREL's groundbreaking Renewable Electricity Futures study (http://www.nrel.gov/analysis/re_futures/). On behalf of the U.S. Department of Energy, he led the Power System Integration and Transmission task forces for the Wind Vision (https://energy.gov/eere/wind/wind-vision) and the Hydro Power Vision (https://energy.gov/eere/water/new-vision-united-states-hydropower) studies.

Dr. Milligan has advised many power system industry and utility commissions, including the Mid-Continent Independent System Operator; New York Independent System Operator; Independent System Operator of New England, California Independent System Operator; Xcel Energy (Minnesota and Colorado); Portland General Electric; Arizona Public Service; PacifiCorp; Grant County Public Utility District; Nebraska Public Power District; Western Electricity Coordinating Council; Western Interstate Energy Board; North American Electric Reliability Corporation; British Columbia Hydro; Hydro Quebec; Alberta Electric System Operator; commissions in California, Alaska, Minnesota, and Colorado; and the Public Utility

Commissioners' (PUC) Energy Imbalance Market (EIM) group in the West. He has also provided technical reviews for several National Renewable Energy Laboratory (NREL) studies, including the Western Wind and Solar Integration Study, the Eastern Wind Integration and Transmission Study, and the Nebraska Statewide Wind Integration Study. Many of these studies are available at www.esig.energy.

Dr. Milligan has presented at hundreds of technical conferences, stakeholder meetings, and webinars. Audiences range from experts in the power system industry to groups with little background in power system operations, design, or markets. He has regularly presented at the Utility Variable-Generation Integration Group (UVIG, now ESIG), including as a keynote speaker on variable-generation integration state of the art, and is on the faculty for the UVIG Short Course on Variable Generation Integration, offered bi-annually. His sustained participation on the International Energy Agency Task 25 for large-scale wind integration (https://www.ieawind.org/task_25.html) helped launch a continuing series of international technical papers on integration issues. International collaborations include papers and projects with VTT Finland, Royal Institute of Technology Sweden, DTU Delft Netherlands, University College Dublin, University of Castilla-La Mancha Spain, LNEG Portugal, Energinet.dk Denmark, ECAR Ireland, Sintef Norway, and Kansai University Japan. He was an invited panelist in 2012 to the Royal Irish Academy in Dublin and an invited keynote speaker at the 2011 Power System Computation Conference in Stockholm. He has hosted visiting researchers from Germany, Ireland, Spain, Australia, and France, and has served on Ph.D. dissertation committees and mentored Ph.D. students at MIT, Stanford, University of Colorado, University College Dublin, Northern Arizona University, University of Delaware, and University of California Berkeley.

In response to the Federal Energy Regulatory Commission (FERC) Notice of Inquiry, he provided comments based on research results to FERC. Based in part on this input, FERC eventually issued Order 764, which directs the conditions under which a transmission provider can assess integration charges for variable generation. His work on cost-causation and integration charges has also influenced the development of integration rates and resulted in an international paper with IEA collaborators.

Awards

- *Lifetime Achievement Award for sustained contributions to wind and solar power system integration studies*, awarded by the Energy Systems Integration Group (formerly UVIG): 2018.
- *Technical Achievement Award for sustained advances in renewable energy integration methods*. Utility Variable-Generation Integration Group (UVIG): 2012.
- *H.M. Hubbard Award for two decades of outstanding research contributions and leadership in research and technology*, National Renewable Energy Laboratory: 2010.
- *President's Award* (team, 2010), National Renewable Energy Laboratory,
- *National Wind Technology Center Technical achievement awards* in 2008 and 2009, National Renewable Energy Laboratory (team).

- *Best paper awards*, including papers at the 12th and 13th International Workshops on Large-Scale Integration of Wind Power.

Employment History

2017 – present:	Independent Power System Consultant
2015-2016:	Ph.D. advisor, University of California, Berkeley
2014 – 2020:	Adjunct Professor and Ph.D. Advisor, Northern Arizona University
2013 – 2014	Ph.D. advisor, MIT, Cambridge, MA
2013 – 2015:	Adjunct Professor, University of Denver
2009 – 2013:	Ph.D. advisor (3), University College, Dublin
2008 – 2009:	Ph.D. advisor, University of Maryland
2008 – 2017:	Principal Researcher, Power Systems Engineering Center, NREL
2006 – 2007:	Ph.D. advisor, University of Colorado, Boulder
1992 – 2008	Consultant, Power System Integration, NREL
1982 – 2008:	Professor, Economics (1998–2008); Professor, Computer Science and Mathematics (1995–1998); Professor (1982–1995) and Chair (1990–1992), Computer and Information Science Department, Front Range College
1975 – 1982:	Power system planner, Tri-State G& T. Developed software for load forecasting and resource analysis. Developed long-range planning models and documents for power and energy requirements, resource utilization, and long-term planning

Technical Articles, Reports, Book Chapters, FERC Filings

1. Goggin, M., Milligan, M. (2019), Quantifying the Consumer Benefits of the Market Reforms in the Report: *Customer Focused and Clean.* Available at https://windsolaralliance.org/wp-content/uploads/2019/10/WSA-Consumer-Benefits-Quantification-FINAL-9.27.19.pdf.

2. Milligan, M. (2018). Sources of grid reliability services. The Electricity Journal, 31(9), pp. 1-7.

3. Reply Comments of Michael Milligan, Ph.D.: Grid Resilience in Regional Transmission Organizations and Independent System Operators. Docket AD18-7-000. Available at

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7. Palchek, David; Cochran, Jaquelin; Ehlen, Ali; McBennet, Brandon, Milligan, Michael; Chernyakhovskiy, Ilya; Deshmukh, Ranjit; Abhyankar, Nikit; Soonee, Sushil Kumar; Narasimhan, S.R.; Joshi, Mohit; Sreedharan, Priya. Greening the Grid: Pathways to Integrate 175 Gigawatts of Renewable Energy into India's Electric Grid, Vol 1 – National Study. National Renewable Energy Laboratory, 2017. https://www.nrel.gov/docs/fy17osti/68530.pdf

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11. (Multiple Authors), M. Milligan, Hydropower Vision: A New Chapter for America's 1st Renewable Electricity Source. United States Department of Energy. Available at http://energy.gov/eere/water/articles/hydropower-vision-new-chapter-america-s-1st-renewable-electricity-source.

12. Peña, I.; Milligan, M.; Ela, E.; Bloom, A.; Botterud, A.; Townsend, A.; Levin T. **Market designs for revenue sufficiency and flexibility provision for the integration of renewable energy**.

13. Holttinen, H.; et al (2016). Design and operation of power systems with large amounts of wind power: Final summary report, IEA Wind Task 25, Phase three 2012-2014. http://www.vtt.fi/inf/pdf/technology/2016/T268.pdf

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Exhibits to Direct Testimony of Michael Milligan
on behalf of Montana Environmental Information Center

Exhibit MM-2

Docket No. 2019.12.101

Advanced Review

Capacity value assessments of wind power

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This article describes some of the recent research into the capacity value of wind power. With the worldwide increase in wind power during the past several years, there is increasing interest and significance regarding its capacity value because this has a direct influence on the amount of other (nonwind) capacity that is needed. We build on previous reviews from IEEE and IEA Wind Task 25[a] and examine recent work that evaluates the impact of multiple-year data sets and the impact of interconnected systems on resource adequacy. We also provide examples that explore the use of alternative reliability metrics for wind capacity value calculations. We show how multiple-year data sets significantly increase the robustness of results compared to single-year assessments. Assumptions regarding the transmission interconnections play a significant role. To date, results regarding which reliability metric to use for probabilistic capacity valuation show little sensitivity to the metric.

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INTRODUCTION

During the past several years, there has been a significant increase in the level of installed wind and solar power on electric power systems around the world. As the capacity and energy share of generation from these power sources has become more significant, the question of how to take variable generation into account in resource (power) adequacy assessment has received more attention.[1] How much of the installed capacity of wind and solar should count toward planning reserve margins (firm capacity that can be counted on during peak demand or other high-risk periods) is a critical issue—if these resources can deliver a high fraction of installed capacity during high-risk time periods, then the required level of capacity from other sources would be less than if wind or solar provided little capacity value.

In the literature, there are many ways to estimate capacity value. The preferred method for assessing the capacity value of wind and solar generation is a probabilistic approach grounded in the well-known loss of load probability (LOLP) and related reliability metrics. This recommendation has emerged from the IEEE Wind Power Coordinating Committee Task Force paper for wind power[2] and Duignan et al.[3] for solar power. The North American Electric Reliability Corporation (NERC) approved this method in a task force paper,[4] and it was included in the Recommended Practices for Wind Integration Studies.[5] Other studies have echoed the preference for these probabilistic methods, specifically highlighting the effective load-carrying capability (ELCC) method.[2,6,7] Other standard, but less commonly used, reliability metrics include equivalent conventional power (ECP), equivalent firm power (EFP), and secured capacity.[8,9]

The objective of this article is to summarize recent work on wind capacity valuation methods that has helped to answer some of the questions raised in Ref 2 and NERC.[4a] We find that some of the interesting questions regarding multiple years of

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data, transmission interconnections, and the choice of underlying reliability metric have begun to be addressed. The article closes with a summary of future areas of research.

CAPACITY VALUE OF WIND POWER

Power system planning and investment activities include assessments of whether the installed level of generation is sufficient to meet demand at some future date. Because it is possible that some generation will be unavailable to help serve system peak demand due to forced outages, planners adopt a target level of generation that accounts for this and other uncertainties. The difference between the target level of generation and peak demand is often referred to as planning reserve. Historically, the planning reserve margin was often determined as a percentage by which installed capacity would exceed peak demand. However, with the increasing use of variable renewable generation, such as wind and solar power, there is a significant difference between the installed capacity and the contribution that these variable generation resources could make toward planning reserves. This has rekindled interest in LOLP-based probabilistic methods for assessing resource adequacy that are robust against these large differences between installed capacity and the contribution to planning reserves.[11]

Models for resource (or power) adequacy assessment use probabilistic methods to calculate LOLP, loss of load expectation (LOLE), or a related metric. Resource adequacy of a power system is met when a given portfolio of resources meets the designated reliability target. Often, a LOLE of 1 day/10 years is used in the analyses. It is often of interest to also calculate the contribution that individual resources, or groups of resources, make toward resource adequacy. This is the capacity value of the resource, and it represents its contribution to the planning reserve level that corresponds to the reliability target.

In this section, we review and discuss some selected international results from wind capacity value studies. We then focus on methodological considerations using LOLE-based methods for assessing capacity value.

Results From Selected International Wind Power Capacity Value Studies

An example of results from selected international capacity value studies for wind power is presented in Figure 1. There are two main findings. First, the capacity value is often close to the average power produced by wind power (25–40%) when the share of wind power in the system is small, but adding a larger share of wind power results in a decreasing capacity value. This decrease of capacity value can be seen more dramatically with a smaller system size and more concentrated wind (Norway examples).

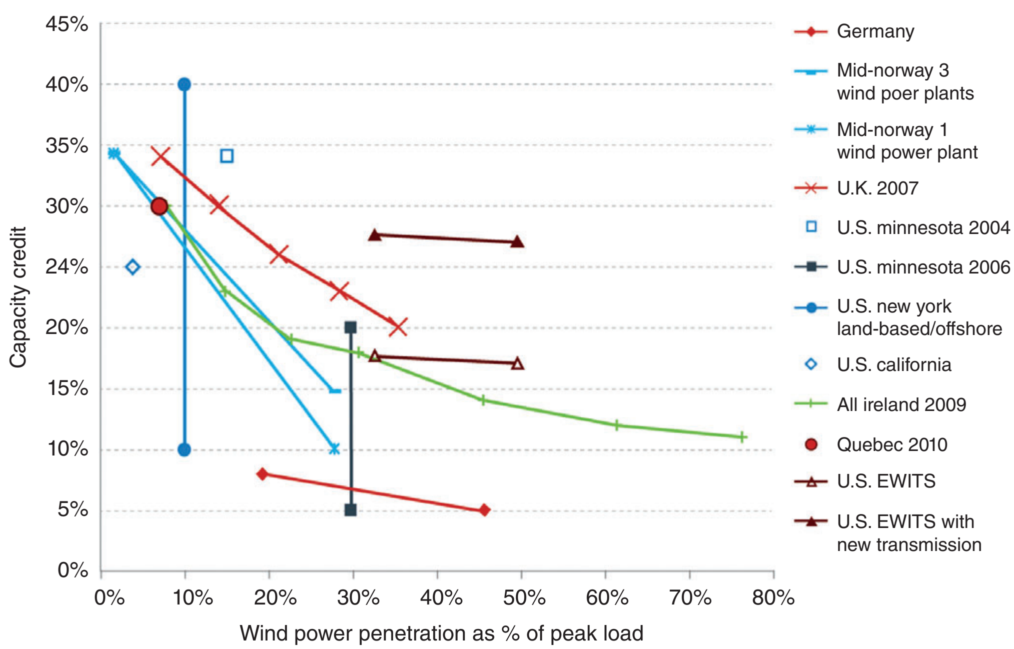

FIGURE 1 | Summary of results for the capacity value of wind power for several regions as a function of the share of wind power installed in the system (image from Ref 5, formatted for consistency).

Second, the results can be very different if there is a systematic correlation of wind with climatic conditions causing peak demand. For example, the New York results show that land-based wind resource is often poor when low temperatures cause the highest loads to occur, and thus, the capacity value is only 10%. However, the wind resource offshore is strong even in low temperatures, so the capacity value for offshore wind is as high as 40%. The Minnesota 2006 study calculated capacity value for 3 years and found a significant difference in the annual capacity value of wind among those years.

The results presented in Figure 1 for capacity value of wind power are from the following studies:

- Germany[12]
- Ireland All Island Grid study[13]
- Norway[14]
- Quebec[15]
- U.K.[16]
- U.S. Minnesota[17,18]
- U.S. New York[19]
- U.S. California[20]
- U.S. Eastern Wind Integration and Transmission (EWITS) study.[21]

Methodological Foundations of Capacity Value Assessments

The calculation of resource adequacy—whether there is sufficient generation capacity to meet demand at a future point in time (usually one or more years)—has traditionally been built on reliability-based techniques. These methods explicitly take into account the uncertainty surrounding the availability of resources, accounting for unplanned outages that cannot be forecasted. The capacity value of a resource reflects its ability to contribute to improving the reliability of the system, and this is both time and location dependent. This section defines and compares various probability-based reliability metrics, discusses special considerations for using these metrics with wind power, and describes the impact of transmission on reliability metrics and capacity value.

LOLP and Related Metrics

LOLP and related methods, first introduced by Calabrese,[22] are well-known and are described by Billinton and Allen.[23] The emerging standard approach to estimating the capacity value of wind energy is based on these and related metrics. In this section, we describe the analysis method in more detail.

LOLP is calculated by a suitable convolution algorithm or Monte Carlo analysis using generator capacity and forced outage data along with demand. A typical application involves calculating LOLP on an hourly or daily basis, although it is possible to use alternative time steps. For example, if we wish to calculate a daily value, LOLP is thus

$$\mathrm{LOLP} = P[C_i < L_i]$$

where P = probability, C_i = capacity available during day i, and L_i = load/demand at day i. If suitable adjustments are made to the demand data, this basic calculation can be performed hourly.

There exists a family of reliability metrics that are related to LOLP. As a probability, LOLP is necessarily 0 < = LOLP < = 1. However, it is sometimes more convenient to represent an expected value, LOLE, in days per year, hours per year, etc. Thus, a daily LOLE can be calculated as

$$\mathrm{LOLE} = \sum_{i=1}^{N} P[C_i < L_i]$$

where P, C_i, and L_i = are defined as before, and N = number of days in the year. An estimate of loss of load hours (LOLH) can be calculated by adapting the equation by applying the summation across all hours of the year.

Modern power systems are generally combinations of networks that are interconnected. This means that if one balancing region experiences shortfalls in generation, this may not result in disconnecting load but could induce an unplanned import from a neighboring system as inertial and governor responses increase output from units responding to frequency drops. In other cases, a given system may be short on capacity but has made plans to import capacity from a neighboring system. A situation such as this would likely be handled by including the import in the LOLP calculation, but the implication of these points is that LOLP may not necessarily refer to disconnecting load but may mean that some combination of the following occur: (1) operating reserve margins are not maintained, (2) neighboring capacity is planned to alleviate shortfalls, or (3) unanticipated imports may occur. For the purposes of this article, we do not distinguish between these potential events so that we can focus on the underlying issue addressed by LOLP, which is the level of resource adequacy. There are, however, some methods developed considering multiarea reliability, which we list in the Role of Transmission Interconnections section.

The capacity value (sometimes called capacity credit) of a resource is the MW level that the resource contributes to the reliability target, and it is illustrated in Figure 2. The original reliability curve shifts to the right as a new resource is added to the mix. This means that a higher level of peak demand can be supplied at the same reliability level as before. Using the target of 1 day/10 years, the diagram shows an increase in the demand that can be served as 400 MW. This is the ELCC of the plant in question.

The concept of ELCC can also be applied to the power system as a whole. Using the example in Figure 2, the generation mix originally has an ELCC of about 10,020 MW. Once the additional resource is added to the system, the overall generation mix ELCC increases to about 10,420 MW. When discussing system ELCC, it is important to distinguish between the ELCC level that results in a given LOLE level and the actual ELCC of the system as given. For example, the actual ELCC of a given power system may be 8000 MW, but the level ELCC needed to achieve 1 day/10 years may be 9000 MW. Thus, actual ELCC is 8000 MW, but desired ELCC is 9000 MW, resulting in an ELCC shortage of 1000 MW.

It is important to note that if a system is extremely reliable, with LOLE ≅ 0, then virtually no generator will have any meaningful capacity value. This is because there is essentially no LOLE, and thus, there is no way that any generator could meaningfully contribute to lowering LOLE. In many systems, LOLH is 0 for most hours of the year, becoming significantly greater than 0 for a relatively small number of days or hours. The specific days/hours of potential reliability shortfall is dependent on the reliability target that is chosen. It is therefore common to adjust demand or other system parameters so that the LOLE represents a desired target level. An example of this type of adjustment can be found in Ref 24. Amelin[25] shows that the capacity value of a resource is dependent on the initial system reliability level. A target LOLE level of 1 day/10 years is often used. This is a common target used in the models to get reasonable results, but other targets can also be adopted.

Several academic and industry task forces have recommended the use of LOLP methods for wind capacity value calculations, including the IEEE Wind Power Coordinating Committee,[2] NERC,[4] and the International Energy Agency (IEA) Wind Task 25.[1,5,26] This literature recommends using time-synchronized wind and load data and cautions against the use of simplified methods unless they have been suitably benchmarked. We discuss both of these issues further in later sections of this article. NERC suggests that alternative metrics such as LOLH and expected unserved energy (EUE) be compared to the traditional daily LOLE value because of the variable nature of wind and solar energy and the possibility that the daily approach may miss reliability events. NERC also recommends transparency in the way interconnected systems are treated in the assessment because of the potentially significant impact this can have on the reliability calculations

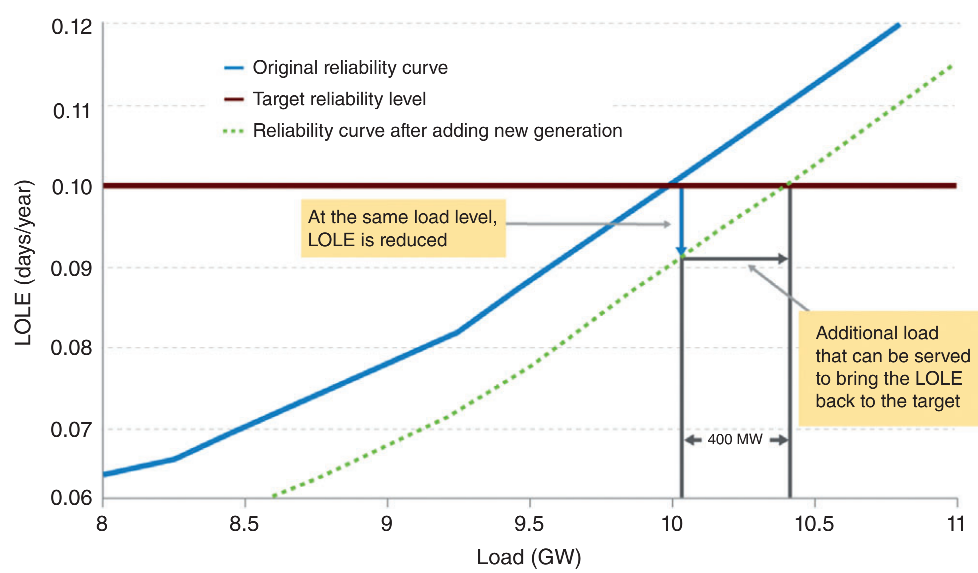

FIGURE 2 | Example of effective load-carrying capability (adapted from Ref 4).

and results. We also address the issues of alternative metrics and transmission impacts below.

Methodological Considerations for Variable Generation—Wind Power

The growing presence of variable generation, such as wind power, in power systems results in additional considerations for these traditional probabilistic methods, both from a planning and operation standpoint. Such considerations include properly accounting for (1) the uncertainty of load and variable generation, (2) the variability of wind and solar, and (3) operational issues. Historically, the variability of wind was deterministically included in LOLP calculations by using the net load (load minus wind plant output) as the system load value. Numerous studies have now incorporated the long-term uncertainty in the evolution of load or wind power.[27,28] This typically involves an exogenous statistical characterization of the uncertainty using, for example, sequential Monte Carlo approaches, time-series models, or Markov models, and then convolving the resulting profiles and probabilities into the capacity outage probability table. Similarly, the variability of wind can be incorporated into the capacity outage probability table through a multipoint convolution method with a chronological sliding window approach.[29] However, fewer studies have investigated the *joint* distributions of load and wind profiles and/or their uncertainty to capture their important correlations.[30,31] Operational issues include the treatment of noncommitted units, transmission congestion, energy-constrained generation, time-coupling constraints of generators (start-up and shut-down times, ramping, etc.) that limit their availability, and flexible load resources such as storage. Studies are beginning to account for these impacts[31,32]; other related methods could also apply to operational decisions, such as the allocation of reserves due to wind forecasting errors (Milligan[33] used an adaptation of Strbac and Kirschen[34]).

Interest in these additional considerations has primarily been contained within the academic world, and the resulting methods have not yet been widely adopted by industry. Many of the proposed stochastic methods are not only related to reliability and wind capacity value analyses, but as discussed in a recent Integration of Variable Generation Task Force (IVGTF) report, there may be many other fruitful applications of these methods for factors with high levels of uncertainty, such as fuel prices, generator retirements, extreme meteorological conditions, policies and regulations, and unforeseen economic stagnation or growth.[10]

Reliability Metric Comparison

One of the recommendations in NERC[4] was to further investigate the impact of using alternative metrics that are based on LOLE analysis but represent different ways of capturing the risk of inadequacy. Examples of such metrics include LOLH and EUE. LOLH improves upon the daily LOLE metric because it evaluates LOLP at every hour of the year, discarding those hours during which there is zero LOLP. Daily LOLE is based on the single peak hour of the day. Although the traditional approach prior to the advent of significant wind and solar energy has been to focus on peak demand, some analysis of wind/solar has focused on the peak net demand (demand less wind and solar generation). An often-used reliability target for daily LOLE is 1 day/10 years, whereas there has been little if any development of similar LOLH targets or characterizations of the relationship between these metrics for systems with significant wind and solar energy.

Ibanez and Milligan[35,36] undertook some analysis to shed light on the use of LOLH and EUE using models of the U.S. Western Interconnection, shown in Figure 3. These analyses were based on either the WWSIS-2 reference case with 8% wind and 3% solar energy penetration[36] or the Western Electricity Coordinating Council's (WECC's) Transmission Expansion Planning Policy Committee (TEPPC) 2024 data set with roughly 9% wind and 5% solar capacity penetration.[35]

Modeling runs were performed to establish the relationship between LOLE and LOLH and also between LOLE and EUE. These modeling runs calculated all reliability metrics so that the relationship between pairs of metrics—for example, EUE and LOLH—could be investigated. For alternative values of LOLE, the reliability model was run, and a trace was developed to show how LOLH or EUE varied as a function of LOLE. This was performed for several balancing authority areas, subregions, and the entire interconnection. In all cases, the relationship between LOLH or EUE and LOLE is log-linear, with parallel curves for all regions.[35] The differences among the regions depends both on the number and size of the generators (smaller areas tend to have larger slopes), as well as the net load shape (profiles that show higher relative peaks tend to have larger slopes).[36]

Related work by Ibanez and Milligan[36] also calculated the ELCC of the system with and without wind and solar to determine the impact of these same reliability metrics on capacity value, using equivalent levels of reliability for each metric. They analyzed alternative wind/solar build-outs in the West that were taken from the Western Wind and Solar

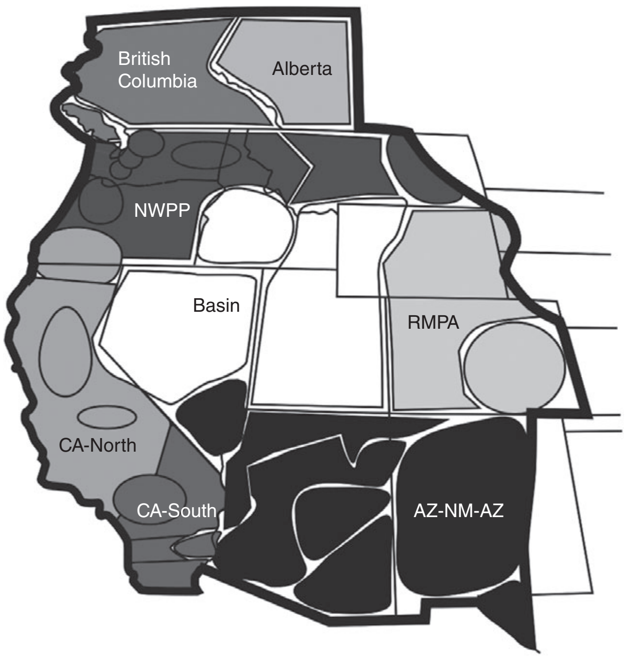

FIGURE 3 | Map of U.S. Western Interconnection. Shaded areas show zones.

Integration Study Phase 2 (WWSIS-2).[37] A reference case had 8% annual energy from wind and 3% from solar (29 GW of installed wind and 14 GW of solar). Alternative cases had 33% of annual demand supplied by wind and solar, split evenly, and high wind/low solar and high solar/low wind combinations. The resulting curves had similar shapes, which further confirmed that the various reliability metrics are capturing the same phenomena. The results for two subregions of the Western Interconnection based on a single-year analysis with an LOLE of 0.1 day/year are shown in Figure 4. In several cases, the lines representing alternative reliability metrics are hard to distinguish; this is because the capacity value from the metrics in these cases are so close that they do not have any meaningful differences. The results of this work indicate that the capacity value of wind and solar is relatively robust against the underlying reliability metric if LOLE, LOLH, or EUE are used. Note that this LOLE of 0.1 days/year is a common use of the 1 day/10 years standard, but these are not necessarily equivalent as an average annual reliability performance does not capture interannual variability among individual years. We discuss more on these multiyear considerations in the Multiple-Year Data Sets section.

Role of Transmission Interconnections

Interconnecting two or more systems together will have an impact on resource adequacy. As pointed out in early LOLE work by Calabrese,[22,38] interconnecting two nonidentical systems will increase reliability (decrease LOLP) in both systems. This is because of the principle of diversity—demand in different areas is only partially correlated. However, the degree of this benefit for a given area depends on its location in the system, the system load level, and the transmission limitations.[39] Numerous studies have demonstrated this interconnection benefit through multiarea generation reliability analyses, which consider tie line and/or transmission line constraints and inter-regional cooperation in addition to the regular reliability considerations. Proposed methods for calculating the multiarea reliability include the 'system failure mode' approach that accounts for each failure mode probability and expected capacity,[40] Monte Carlo simulations to account for uncertainty,[41] modifications to the capacity outage probability table to account for uncertainties and capacity limitations of both the generators and transmission lines,[42] and more advanced algorithms that explicitly consider individual components in the network (e.g., minimal cuts method in Ref 43). This multiarea issue is widely known, and in NERC,[4] one of the key recommendations for adequacy studies is to clarify the assumptions regarding transmission interconnections to the neighboring system.

Ibanez and Milligan[24,44] undertook an analysis in the Western Interconnection in the United States to analyze the upper-bound role that transmission could play in resource adequacy assessments. They used the WWSIS-2 scenarios to compare the ELCC of the full transmission system at three different aggregations that represent alternative levels of interconnectedness: (1) business as usual, in which each balancing authority area operator is constrained by transmission to the neighboring system; (2) regional transmission is a copper sheet, but each region is isolated from the remaining system; and (3) perfect transmission exists throughout the interconnection (full copper sheet). The objective of the study was to determine how much effective installed capacity could be replaced by transmission using LOLE analysis. Key results are presented in Figure 5. The graph shows the reduction in required ELCC made possible by perfect transmission within each subregion and by perfect transmission across the interconnection—with Balkanized system planning, the total required ELCC needed to achieve 1 day/10 years LOLE is 244 GW, whereas with copper-sheet planning, the levels of ELCC needed for 1 day/10 years is 184 GW. Although copper sheet transmission is unlikely to ever be built, the example does show the trade-off between transmission and generation and

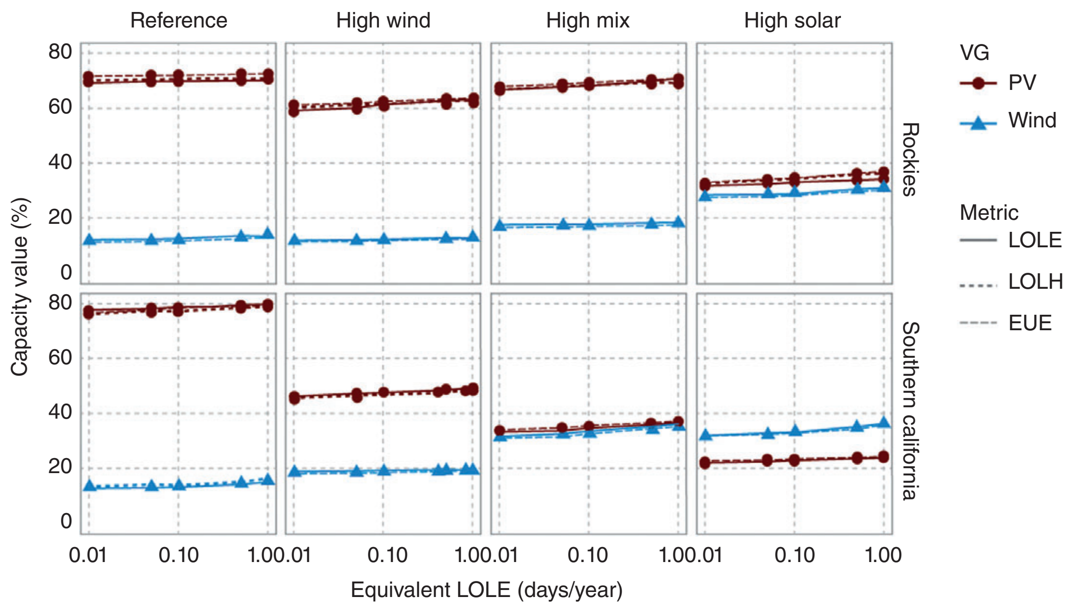

FIGURE 4 | Capacity value calculated on the basis of LOLE, LOLH, and EUE for selected subregions of the U.S. Western Interconnection (image from Ref 36, formatted for consistency).

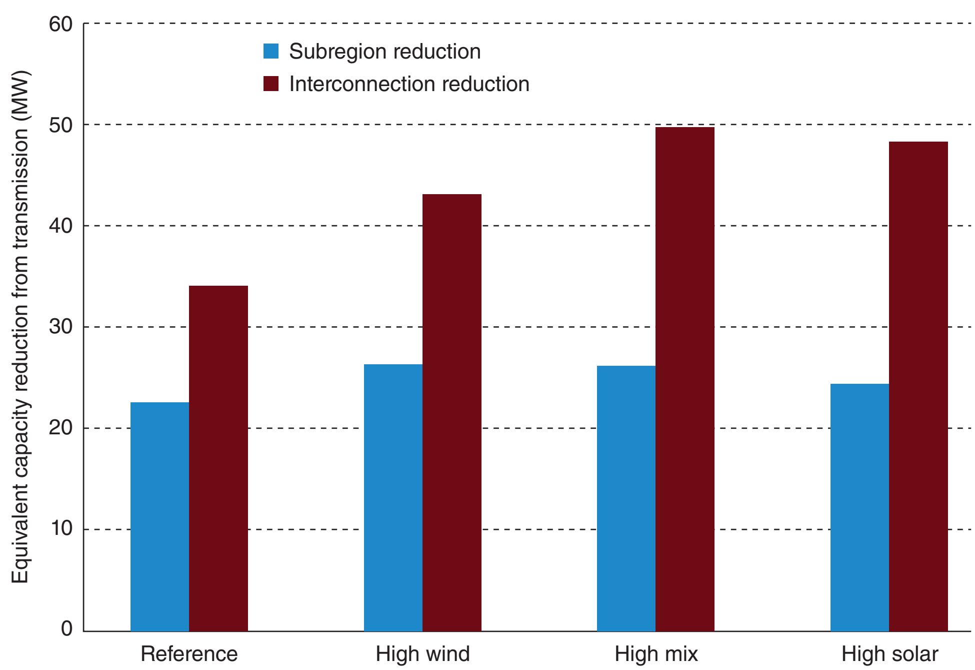

FIGURE 5 | Impact of interconnection on resource adequacy in the U.S. Western Interconnection (wind installed capacity by scenario: reference = 29 GW, high wind = 64 GW, high mix = 43 GW, high solar = 23 GW).

the impact that transmission can potentially have on the need for new resource additions.

Simplified Methods for Calculating Capacity Value of Wind Power

While reliability-based methods are widely accepted and provide accurate measures of wind and solar capacity values, they require detailed system data and can be computationally expensive to evaluate. Many attempts have been made to develop simplified methods that can provide a good estimate of wind/solar capacity value without requiring a reliability model. Many of these simplified methods estimate the ELCC by approximating the relationship between capacity additions and LOLP or LOLE. These include Garver's method,[45] Garver's method extended to multistate generators,[46] and the Z-method.[47]

Other approximation approaches calculate the capacity factor of wind and solar over some subset of hours when the system may have the greatest risk of not meeting the load. One of the first applications of this was in PJM in the United States,[6,48] which uses three years of wind production data, for hours ending 3:00–7:00 pm. The wind power plant capacity factor is calculated for this time period using a standard assumption if there are fewer than three years of operating data. The accuracy of these capacity factor methods, however, is very sensitive to both the number of hours used and the methods used to select those hours.[49] The accuracy is also often system- and technology-specific. For instance, considering too many of the peak-load hours for photovoltaic (PV)[8] or too few of the peak-load hours for wind[49] can underestimate the respective capacity value. Capacity factor approximation methods that use peak-load hours have also been shown to have decreasing accuracy with higher penetrations of PV as the highest LOLP hours shift from afternoon (without PV) peak load to early evening (with PV) peak 'net load' hours.[50,51] Munoz and Mills[51] found that the capacity factor approximations based on peak load hours can provide a relatively accurate estimation of the capacity contribution of PV for penetration levels less than 5%.

In practice, various reliability-based and approximation methods, such as those listed here, as well as ad-hoc rules of thumb are used for calculating wind and solar capacity values.[48] For instance, the Western Electricity Coordinating Council uses several 'standard' values for the capacity credit of wind. Ibanez and Milligan[36] compared the WECC rules of thumb to results from a full reliability model and found significant differences in several subregions of the interconnection. The key results are shown in Figure 6.

As shown in the graph, the rule of thumb sometimes overestimates and sometimes underestimates the wind capacity value that is calculated from a full LOLE model.

The same study found a significant difference in ELCC for solar based on geography. Figure 7 shows the capacity value by zone compared to the WECC simplified rule, which uses 60% capacity value for all solar resources in the interconnection.

From the results, it is clear that the capacity value for solar energy is overestimated by the rule of thumb because the actual ELCC values are less than the assumed 60% of rated capacity.

Data Requirements for Wind Capacity Value Calculations

Because of the variable nature of wind power plants, using a small number of data inputs, such as rated capacity and forced outage rates, will not provide sufficient information regarding the impact that these power plants will have on system LOLE (or related metrics) because specific combinations of wind power and demand will not be apparent. This section describes the issue of data synchronicity, or chronological data pairing, and why a single year of wind power data is not likely sufficient for most studies.

Chronological Data Pairing

The IEEE Wind Capacity Value Task Force paper recommends that hourly demand and wind data should be paired chronologically.[2] This is because the underlying weather drives the behavior of wind (and solar) and, to some extent, demand. Although correlations may be nonlinear and complex, calculating wind capacity value with a hot sunny still day of demand data paired with a cool windy day of wind production data appears to be inconsistent and problematic. For systems with significant hydropower, it is also important to ensure that the underlying weather—and thus its combined influence on demand, wind power, and hydropower—is preserved. This may be especially important if the system is energy restricted more than capacity restricted.

The chronological pairing of data is motivated by the concern that there is an underlying weather driver that influences both demand and wind (and solar) energy. In Sweden, the annual energy consumption does not vary significantly from year to year, but peak demand does. Figure 8 shows the variation in peak demand for a 20-year period.

Limitations of a Single-Year Data Set

Many capacity value studies have used a single year of data; however, in recent years, there has been more interest in long-term contributions to adequacy and multiyear data sets. This is because there is considerable interannual variation in many of the inputs for capacity value evaluation. This section discusses how to deal with variations in forced outage rates, peak load, and energy demand.

When conventional resource data is input into LOLP models, one of the relevant variables is the unit's forced outage rate. These are typically determined by size and type of unit and take into account many years of data. In some cases, forced outage rates are adjusted to take into account particular unit

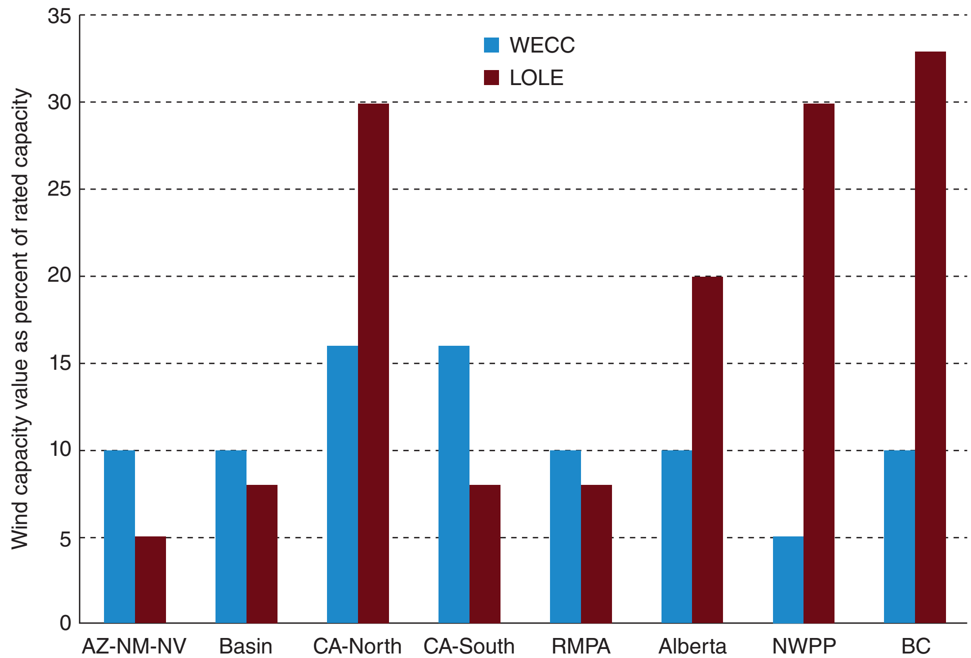

FIGURE 6 | Comparison of WECC simplified rule for wind capacity value with full ELCC/LOLE calculations for a single year by subregion (image from Ref 35, formatted for consistency).

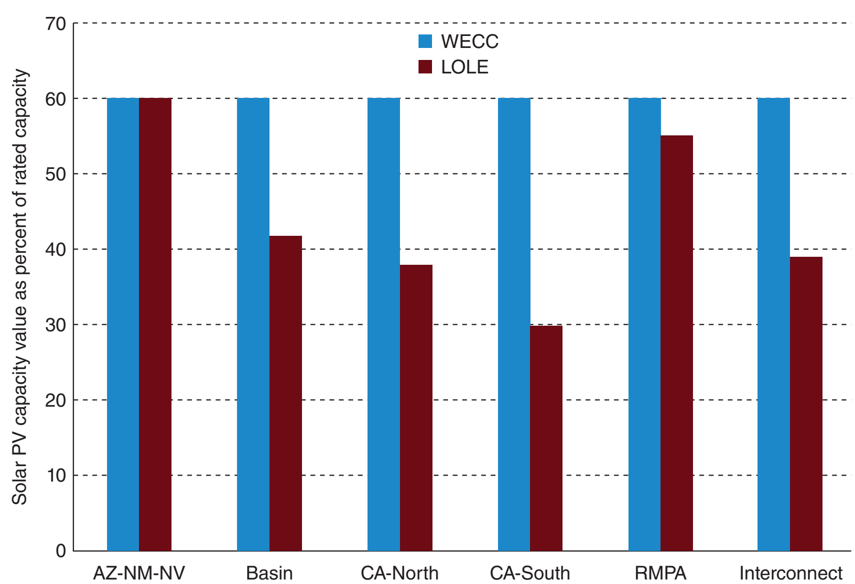

FIGURE 7 | Comparison of WECC simplified rule for solar capacity value with full ELCC/LOLE calculations for a single year by subregion (image from Ref 35, formatted for consistency).

characteristics. The determination of a plant's capacity value is a subset of solving the resource adequacy assessment, which is determining the level of installed generation needed for a time period that may cover many years in the future. Thus, a long-term average is appropriate because the power supply must be robust against a large number of potential forced outages and still deliver power and energy consistent with the resource adequacy target.

This raises the question of how many years of wind production data are necessary to produce a reasonable long-term result that is consistent with what is already performed for conventional generators. Because the primary influence on wind production is

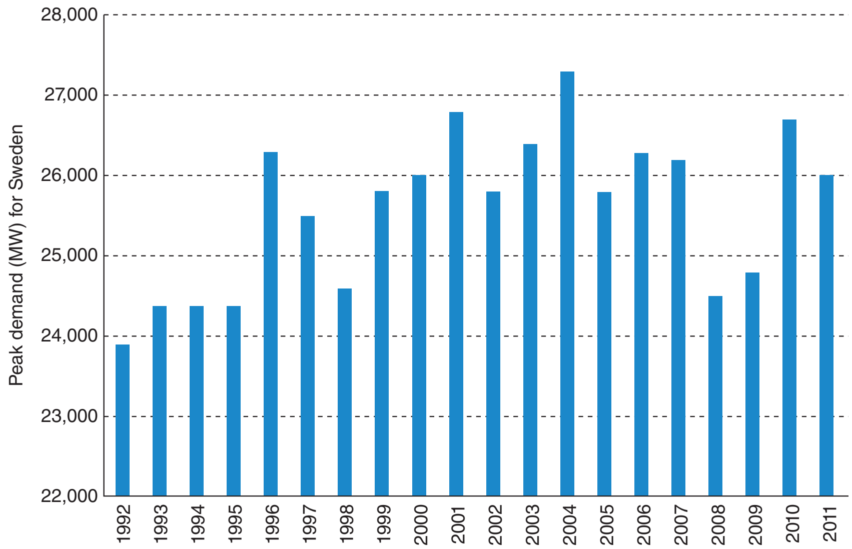

FIGURE 8 | Peak demand (MW) for Sweden, 1991–2011.

wind speed, and because wind turbine forced outage rates are very low (approximately 1–2%) and statistically independent of each other, the question of inter-annual variability requires the use of multiple years of wind data. For example, Zachary et al.[52] claim that the 25 years of data they analyzed for Great Britain is not enough, and they present an analysis of prevalent weather patterns during high demand situations to demonstrate the statistical difficulties. The question of how many years of wind data are necessary for stable capacity value has begun to be explored.

When using multiple years of synchronized time series, it should be taken into account that electricity demand does not stay constant throughout the years. For capacity value evaluation, it is important to capture only the weather-driven changes in electricity demand that are possibly correlated with wind (and solar). Historical time series data for demand contains the impact of economic activity, changes in energy efficiency, and other drivers of demand for electricity—for example, increased use of air source heat pumps for heating instead of direct electric heating. If these changes are not removed, the LOLP is not comparable throughout the years and the capacity value calculation may be mainly based on those years that have had the highest nonweather-induced consumption. To distinguish the economic or technical changes, it is necessary to have a proxy for their impact. This can be some measure of economic activity, like GDP, industrial output for energy-intensive sectors, number of installed new devices, etc. The data can then be used to perform a statistical operation such as regression analysis to estimate how different factors influence consumption, along with unchanging signals such as time of day, day of week, temperature, and possibly wind and solar irradiation.[53,54] The correlation coefficients can then be used to normalize the changes that should not influence the capacity value evaluation. Finally, expected future changes in electricity demand and wind power can be overlaid on the processed historical data when analyzing future years.

Hasche et al.[27] analyzed the question of how many years of data should be used for capacity value in the Irish power system. Using a 10-year data set of demand and wind power production data, they calculated the ELCC for various subsets of the data and then compared them to the 10-year ELCC. The objective was to estimate the number of consecutive years of data needed to approximate the long-term average. Therefore, each single year of data was run separately with 1000 MW of installed wind capacity, and the capacity value (in MW) is calculated and plotted in the first column of Figure 9. Next, all possible consecutive 2-year sequences were used to calculate the 2-year capacity values, which are plotted in the same graph in Column 2. This process was repeated for 3, 4, …, 10 years. The results show that increasing the number of consecutive years of data improves the results, which tend to converge to the long-term value. Using 8 years of data, the range of capacity value is within approximately 2% of the 10-year value, whereas using a single year has a wide spread of results and can under- or overestimate the result by 10–20%.

Kiviluoma and Helistö[54] calculated wind power capacity value for Finland using 9 years of measured

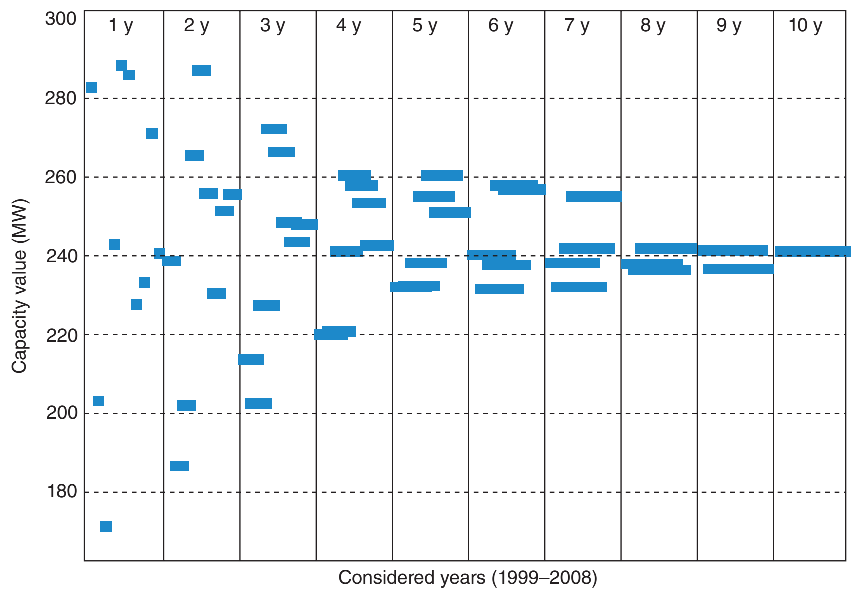

FIGURE 9 | Multiple-year ELCC results for 1000-MW wind power in Ireland (image from Ref 27, formatted for consistency).

wind power production data. The same data set was employed for this article to replicate and extend the work by Hasche et al.[27] Similar to the results shown in Figure 9 by Hasche et al., Figure 10 shows how the capacity value of wind power evolves with an increasing number of years. However, the figure also includes another data set from the same 9-year period based on National Aeronautics and Space Administration MERRA (Modern-Era Retrospective Analysis for Research and Applications) ReAnalysis data, which was also used to train electricity demand and wind power generation time series for 35 years (see Ref 54 for more details). Using ReAnalysis wind data for wind power has significant shortcomings even when the data are scaled to match average historical wind power generation. Consequently, the resulting capacity values are not reliable. However, ReAnalysis data should still give a relevant demonstration for using multiple years in the capacity value calculation. The spread in the ReAnalysis-based capacity value is somewhat higher than it is in the real data, but it shows a similar decrease as more years are added.

Figure 11 shows how the capacity value behaves with 35 years of ReAnalysis data. The capacity value spread for the 1-year cases (leftmost) is not significantly different from the 9-year analysis, although there is an outlier close to 40% (400 MW) capacity value. The last (rightmost) set has only two temporally independent 17-year periods (left blue lines). They are still approximately 1.2% from each other. Therefore, even with 17 years of data, there is still considerable uncertainty surrounding the capacity value of wind power. This gives only a lower bound because using more decades of data could show more variation.

SUMMARY AND FUTURE WORK

This article builds on previous reviews of wind power capacity value calculations and methods that begin to answer some of the questions posed by Keane et al.[2] Areas of analysis and research have continued to show differences in capacity value by location. Some additional research has begun to examine long-term capacity valuations of wind energy, which is part of resource adequacy. This is an important issue because single-year estimates of wind ELCC are not likely to represent the long-term value, and thus, decisions regarding overall resource needs will not be well informed. Two studies have shown that 8–9 years of data are needed to provide a robust estimate of wind capacity value, but more work is needed to verify this conclusion and to determine whether it is robust across different geographic areas.

Additional work has examined the contribution of transmission to resource adequacy and the related impact on wind capacity value. It is clear from this work that assumptions concerning interconnections with neighboring systems will be critical to assessing overall resource adequacy and also the contribution that can be made by wind energy.

Questions regarding the comparison of alternative LOLE-related metrics that were posed by NERC[4] have begun to be addressed. From work so

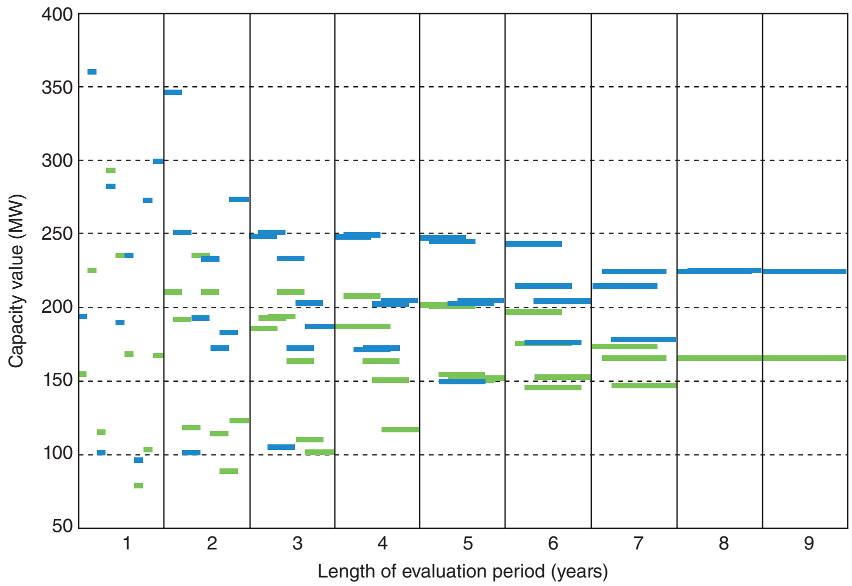

FIGURE 10 | Multiple-year ELCC results from Finland using real data (green) and NASA/MERRA ReAnalysis-based data (blue) from 2005 to 2013 for 1000 MW of installed wind capacity.

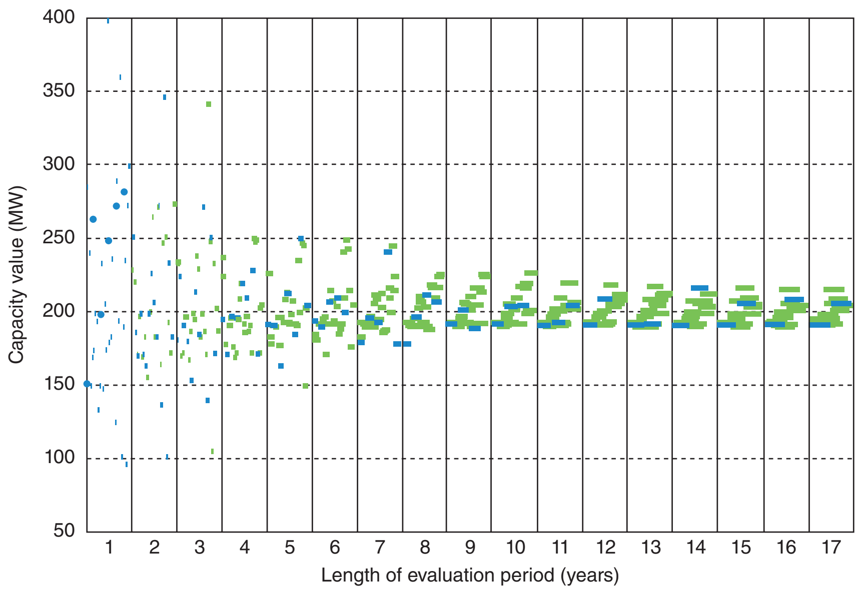

FIGURE 11 | Multiple-year ELCC results from Finland using NASA/MERRA ReAnalysis data from 1979 to 2013. Temporally independent year combinations are shown in blue for 1000 MW of installed wind capacity.

far, it appears to make little difference whether daily LOLE, hourly LOLH, or EUE are used as the basis of wind ELCC calculations. Similar methodologies should be applied to solar, as well as to the combination of the two, for future power systems.

At present, there is ongoing work to develop capacity value methods for larger interconnected systems in Europe by ENTSO-E. Multiarea methods as well as simplified methods are a research topic also at KTH in Sweden. NREL has released an open-source version of the REPRA (Renewable Energy Probabilistic Resource Adequacy) tool, and IEA Wind Task 25 plans to produce international comparisons to this tool in the near future. There is also considerable interest in evaluating new capacity market structures and questions about how this type of market can incorporate the reliability component of capacity value.

There is significant interest today in developing methods to assess flexibility, such as those from Lannoye.[55] This interest is driven primarily by the anticipation of large quantities of wind and solar energy on the future grid, and it points toward the development of flexibility-adequacy metrics and, by implication, metrics that can quantify the contribution of different resources to the flexibility target.

NOTE

[a] IEA Task 25 is a research program as part of the International Energy Agency. Task 25 focuses on Design and Operation of Power Systems with Large Amounts of Wind Power. See http://www.ieawind.org/task_25.html.

[b] A related NERC report examined stochastic methods generally.[10]

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Exhibits to Direct Testimony of Michael Milligan
on behalf of Montana Environmental Information Center

Exhibit MM-3

Docket No. 2019.12.101

Capacity Value of Solar Power

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Abstract — **Evaluating the capacity value of renewable energy sources can pose significant challenges due to their variable and uncertain nature. In this paper the capacity value of solar power is investigated. Solar capacity value metrics and their associated calculation methodologies are reviewed and several solar capacity studies are summarized. The differences between wind and solar power are examined, the economic importance of solar capacity value is discussed and other assessments and recommendations are presented.**

Index Terms — **capacity value, power system operation and planning, solar power.**

I. Introduction

Electricity is a unique commodity in that supply must be balanced with demand instantaneously at all times [1]. The system ultimately delivers energy to consumers, but if at any time insufficient generating capacity is available to meet demand, then that demand must be reduced to ensure system stability. Electric generation facilities thus provide value by supplying energy, but they also deliver value through their capacity contribution. The concept of capacity value (or capacity credit, the terms are used interchangeably) measures the contribution of a facility, or group of facilities, to the reliability of the overall electrical supply system. This is usually assessed with respect to system adequacy (whether there is sufficient capacity available to support demand in steady state at all times), rather than system security (the ability of the system to withstand sudden faults or disturbances.

Renewable energy sources differ from conventional plant in that available capacity of the former depends on the prevailing weather, and hence near zero available capacity across a large power system is possible. Realistic assessment of the capacity value for these resources is thus essential. This paper will review methods which have been used for calculating the capacity value of solar power. In Section II the different solar capacity value metrics being used today are reviewed. A summary of several recent solar capacity value studies, their results and conclusions are also presented. In Section III, the differences between wind and solar power are examined and the economic importance of solar capacity value is discussed. Section IV presents other assessments and recommendations while section V offers conclusions.

II. Solar Capacity Value Metrics

Capacity value metrics are widely used to quantify the contribution of renewable generators within generation adequacy risk calculations. This is often interpreted as an indicative measure of the amount of dispatchable generation it could replace, however it is important to choose carefully the most appropriate metric for any given application. This Section will first discuss general definitions of capacity value metrics, and then review methods which have been used specifically for solar power.

A. Effective Load Carrying Capability (ELCC)

The ELCC of a generator (or ensemble thereof) is the additional demand which the system may support at a given level of reliability on addition of that extra generation. The concept of ELCC was first introduced by Calabrese in 1947 [2], and is the most commonly used capacity value metric. Garver in 1966 [3] proposed a simplified method of calculating ELCC based on an exponential approximation to the distribution of margin of existing supply over demand.

The most commonly used generation adequacy index is loss of load expectation (LOLE), the sum over time periods of loss of load probabilities (LOLP); LOLE is typically computed over a year or more. Therefore the LOLE for a year can be written as [1]:

$$[\text{LOLE}]=\sum_{t=1}^{N} P[X_i < D_i] \qquad (1)$$

where N is the number of hours in the year, C_i represents the available capacity in period t, and D_i is the load. To calculate the additional reliability that results from adding generators,

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we can write LOLE' for the LOLE after intermittent generators are added to the system as:

$$[\text{LOLE}'] = \sum_{t=1}^{N} P\left[X_t + Y_t < D_t\right] \quad (2)$$

where Y_t is the available capacity during period t from the generation of interest. The ELCC of the generator is thus the solution to

$$\sum_{t=1}^{N} P[X_t < D_t] = \sum_{t=1}^{N} P[X_t + Y_t < D_t + [\text{ELCC}]] \quad (3)$$

ELCC may be calculated in a similar manner with respect to alternative adequacy indices such as expected energy unserved. The most common LOLE calculation method is so-called hindcast, in which the empirical historic joint time series for demand and available renewable capacity is used directly in the calculation as the joint distribution of demand and available renewable capacity. The LOLE is then calculated as

$$[\text{LOLE}'] = \sum_{t=1}^{N} P\left[X_t + y_t < d_t\right] \quad (4)$$

Where y_t and d_t are now the historic observations, and the sum is over the historic data (which may come from multiple years).

Traditionally calculations were based on only the peak hour of each day. To help reduce the computational burden, weekends were often excluded (if their lower demands made minimal contribution to adequacy risk), and an LOLE target of 1 day/10 years was typically used. With the advance of computing power, hourly LOLP calculations were made possible, allowing for the calculation of LOLE using hourly data (sometimes called LOLH). Daily LOLE does not account for the variation of adequacy risk throughout days, and hence it is not correct to equate the 1 day/10 years LOLE with 2.4 hours/year.

B. Other Assessments and Recommendations

The North American Electric Reliability Corporation (NERC) released a Task Force report in March that discussed capacity contributions of variable generation [4]. The report recommends a number of areas in which new work should be done. These include

- Comparing various reliability-based metrics, including LOLE days/year, LOLH (loss of load hours).
- Simplified approaches, such as calculating capacity factors over peak periods, should be carefully benchmarked against a full reliability calculation.
- Assumptions regarding interconnection with neighbouring areas should be carefully developed and should be transparent in the analysis
- Multiple years of time-coincident data should be used for variable generation capacity analysis, as is also done for conventional generation

In addition, **Error! Reference source not found.** argues that peak period capacity factor methods should be used for screening, but recommends a full reliability-based approach to assess wind capacity value; thus agreeing with [4].

C. Reaching Consensus in the Definition of PV Capacity Value: the Solar Power 2007 Conference

The rest of this Section reviews methods which have been used to calculate capacity values for solar generation. We present here a survey of previous work, but do not in this section make detailed discussion of preferred methods. This discussion may be found in Section IV (Future Work).

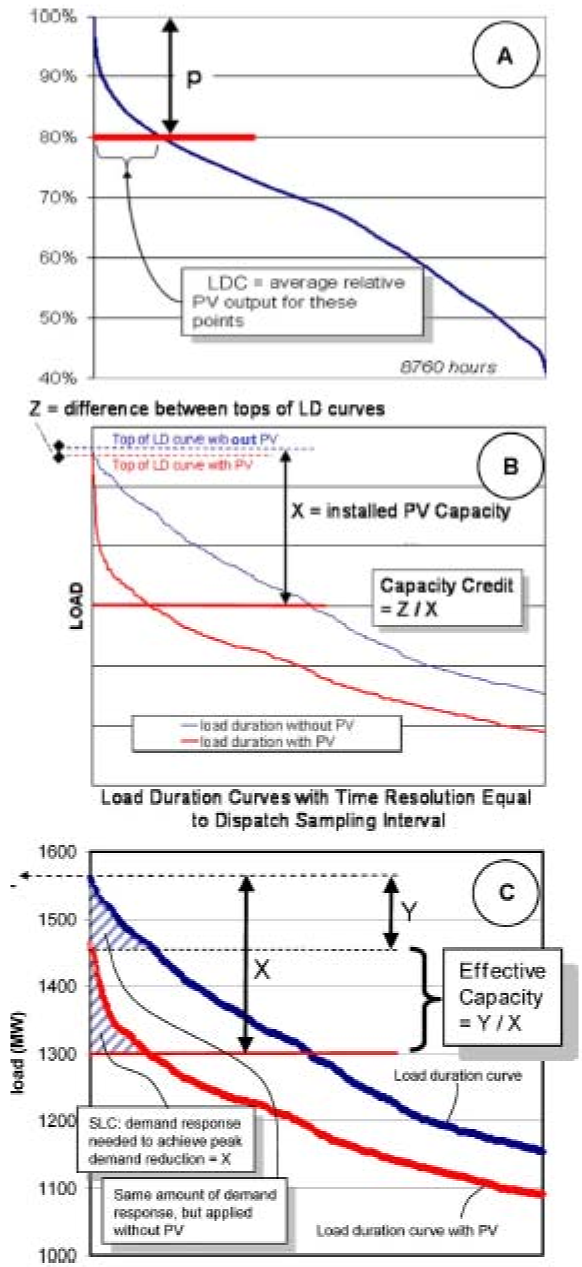

Fig. 1 [6] (A) Illustration of the LDC metric, (B) the DTIM metric, and (C) the SLC metric. Note: In all figures, X represents installed PV capacity while p represents percent penetration of PV relative to peak demand

Because various capacity value metrics have been used to determine the capacity value of solar resources in recent years considerable effort has been made to reach consensus on the most valuable metrics. Following discussions at a PV Capacity workshop held during the Solar Power 2007 conference [6], Perez et al [7] published a paper focusing on categorising methodologies as a first step towards achieving consensus on PV generation capacity value. The methodologies presented in this paper fall into four broad categories:

1) Methodologies that measure capacity based on the concept of loss of load probability: The Effective Load Carrying Capability (ELCC)-as discussed above;
2) Methodologies based on the analysis of load duration curves: Load Duration Capacity (LDC) and Demand Time Matching (DTIM);
3) Methodologies that build on the synergies that exist between short term storage/load control and PV generation: Solar Load Control Capacity (SLC) and Minimum Buffer Energy Storage Capacity (MBESC);
4) Peak-Period Capacity Factor Methodologies.

LDC: LDC is a direct analysis of the load duration curve. The LDC is defined as the mean relative PV output for all loads greater than a threshold defined as the utility's peak load L, minus the installed PV capacity X as illustrated in Fig. 1(A) where p is the PV penetration fraction, defined as p= X/L.

DTIM: DTIM [8] may be explained simply as the reduction in the highest net demand (i.e. demand minus available renewable capacity) when the PV is added, over a given evaluation period (in [8] this is done over 10-s dispatch cycle time intervals). The capacity value is based on the worst-case difference between the load duration curves sampled at the dispatch cycle rate over the selected evaluation period. As illustrated in Fig. 1(B) the capacity value may be expressed as DTIM=Z/X, where Z=(L-L'), with L representing the highest point on the load duration curve for the evaluation period being considered and the selected sampling rate and L' representing the top of the same duration curve minus coincident PV output.

SLC: The SLC metric is illustrated in Fig. 1(C). SLC aims to answer the following question: Given a certain amount of Demand Response (DR) available to a utility, how much more guaranteed load reduction is possible if PV is deployed? Given a penetration p=X/L, the effective capacity is given by: SLC=(X-Y)/X, where Y is the amount of load reduction achieved in the absence of PV, but with the same amount of DR (where DR available is measured in terms of energy, not capacity) load management added a load reduction of X is achieved with PV.

MBESC: The MBESC metric is comparable to the SLC metric, but is determined by the storage needed to guarantee firm peak reduction— the minimum buffer energy storage, MBES, concept [9], [10]—rather than cumulative DR requirements. As in the case of SLC, the metric is an answer to a certain question, in this case: Given a certain amount of dispatchable storage available to a grid or substation operator, If PV is deployed how much more guaranteed load reduction is possible? Given a PV penetration of p=X/L, the method computes the minimum amount of storage necessary to guarantee that PV-plus-storage meets all loads above the threshold defined in the previous sections for the LDC and SLC metrics. The MBESC capacity is obtained from: MBESC= (X-Y')/X, where Y' is the peak load achieved using the same amount of storage but without PV.

Both SLC and MBESC intend to calculate how the capacity value should vary with different penetration levels. Also these methodologies might be regarded as somewhat esoteric quantities which are associated with storage/demand response as well as the solar.

TSW: Several utilities have used mean output over selected peak demand periods to estimate the capacity value of intermittent generators [11]. Time/Season window method calculates capacity value during some fixed peak time window for example, May-October 10AM -6PM. This method is often referred to as the ERCOT method, named after the practice to assign capacity value to wind generators operating in the ERCOT regional reliability council. With this method there is no obvious way of capturing different grid penetration levels and also other loads outside the selected peak time window are disregarded. This method does not classify the different hours over which the capacity factor is calculated as having different risk levels instead it gives the same weight to all hours and an average is used. Furthermore the peak time window could possibly exclude high-risk load hours.

As well as TSW, another peak demand interval method commonly used associates Photovoltaic (PV) capacity value with the mean PV output, (capacity factor), over all hours where the load is within a given percentage deviation of the peak. Similarly, as in the TSW method no differentiation is made between the risk levels of the different hours in the averaging period. Also all hours outside the averaging period are disregarded.

Perez et al [7] also carried out case studies to examine the effectiveness of the above methodologies. Three utilities (Nevada Power (NP), Rochester Gas and Electric (RG&E) and Portland General (PG)) were selected for the case studies and one year of load and PV penetration data were analysed for each. All of the methodologies discussed were applied to the data and the results from each methodology were compared but not contrasted. It was found that for all methodologies that are based on a physical measure of PV penetration (ELCC, LDMC, MBESC, SLC, and DTIM), all measures of capacity value are comparable (when comparing capacity value metrics as a function of PV penetration). However methodologies that are based on defining a peak demand time frame led to different measures of capacity value. Perez et al [7] also presented the results of a straw poll on methodology preference carried out at the PV Capacity workshop [6], which determined ELCC to be the preferred method.

D. Further Solar Capacity Value Studies

A summary of several other solar capacity studies are presented below. The majority of these studies are based on methodologies which have already been described here, including ELCC [9]-[17] and peak-period capacity factor [12]-[13], [18].

Madaeni et al [12] estimate the capacity value (using ELCC and peak-period capacity factor based methods) of concentrating solar power (CSP) plants without thermal energy storage in the southwestern U.S. They calculated capacity values for CSP plants that are between 45% and 95% of nameplate capacity, depending on their location and configuration.

The PV capacity values presented vary from around 2% [18] (using peak-period capacity factor based methods) to 80% (using ELCC metric) in the PG&E Kerman grid support project in California [15]. The breadth of this range is indicative of the fact that calculated capacity values depend on the coincidence of solar output with peak demands, daily load patterns, and other factors in addition to the intrinsic properties of the solar plants themselves. Perez et al [9]-[10] found substantial correlation between PV capacity value results and the ratio between a utility's summer/winter peak loads ratio (SWPR), with higher PV capacity values associated to higher SWPR values.

Several studies observed that PV capacity value is influenced by the PV system orientation [9]-[10], [14]. Two-axis tracking systems generate more power at all times and have the highest capacity value, differing from non-tracking systems in the order of 10–15%.

Pelland et al [13] calculated the PV capacity value (using ELCC and peak-period capacity factor based methods) through a case study for the city of Toronto yielding capacity values of roughly(40±7)% for the city of Toronto at low grid penetration levels (~2%) for all PV array orientations examined.

PV capacity value is also dependent on whether the PV output considered is that of a single PV system or the aggregated output of several PV systems. Investigations in the Netherlands [14] found that PV capacity value increased from between 11–24% to 15–28% when the output of a single PV system was replaced by the aggregated output of five dispersed systems. This result is intriguing, as for wind generation calculated percentage capacity values typically decrease when generating units are aggregated.

Several studies have also found that PV capacity value decreases with increasing amounts of PV on the grid relative to peak load [9]-[10], [14] i.e. a saturation effect is observed.

III. Differences between Solar and Wind Capacity Value

Several issues make capacity value calculations for solar energy differ from wind energy.

1) Solar technology: PV solar has no storage producing energy during day time only. While concentrated solar power (CSP) can have thermal storage and consequently can more closely resemble a dispatchable plant as it can produce energy during day or night time, depending on the size of the solar thermal storage [19]. The use of time series production of PV is similar to wind, but with CSP there are many possible time series to represent the plant output. Since there is uncertainty in the degree of cloudiness or opacity and the timing of system needs, uncertainty should be accounted for in the dispatch of CSP when calculating the capacity value (i.e. you might deplete thermal storage in the early night only to find that it is unexpectedly cloudy the next day when the system is at risk for shortage of generation).

2) Solar is expected to have high penetrations in distribution system, and should be taken into consideration in the analysis method

3) Time frame for energy production: While wind energy can produce energy at any time during the day, and geographic diversity tends to increase the chances that the wind is blowing somewhere over larger regions, solar energy without storage has limited time period of energy production governed by the position of the sun . Consequently, the following question arises for a system with a peak demand after sunset, will solar energy without storage has no capacity value? And even for systems with late summer afternoon peak demands, at what point will the marginal capacity value begin to diminish as the peak net load shifts into the early evening (see Fig. 2 below for illustration: California loads with increasing CSP penetration without thermal storage)?

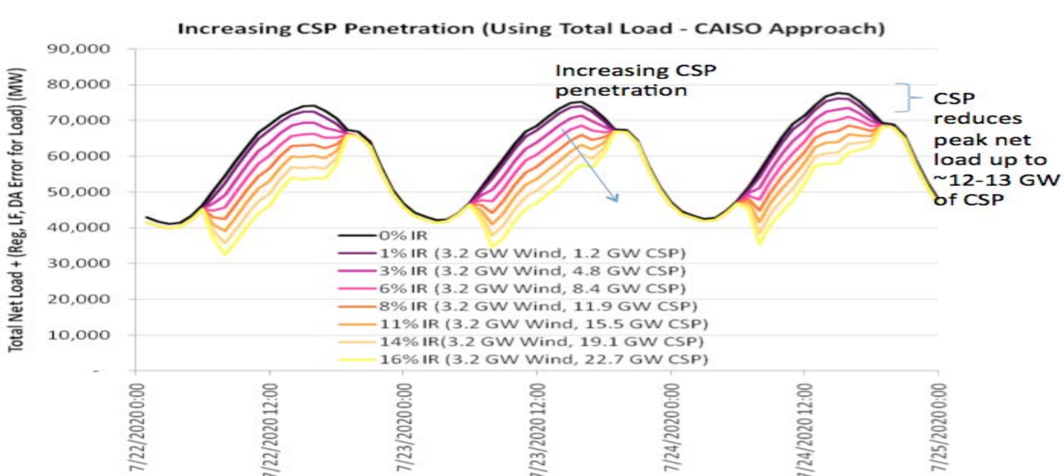

Fig. 2: Source: LBNL analysis of hourly data in PG&E RIM model

4) Also PV output has an ideal production curve, i.e. the plant maximum output is function of the time of the day, in comparison with wind energy where maximum production can occur at any time. It may be more suitable to calculate capacity value for solar energy as function of the time of the day.

Capacity value of solar in some cases can be more economically important for solar than it is for wind. Consider a region where the cost of capacity is based on a relatively inexpensive peaker plant with an annualized cost of \$88/kW-yr (or \$10/MW-h). The economic benefit from wind displacing the need to build peaker plants is typically modest. If wind has a capacity value of 20% (within the typical range reported in [5]) and a capacity factor of 30% then the avoided peaker plant cost per unit of wind energy is about \$6.7/MWh. In some regions, particularly where the peak demand is driven by summer cooling loads, the capacity value of PV has been estimated to be in the range of 30% [20] to 60%-75% (depending on if it is fixed tilt or 1 axis tracking [21]). If the capacity factor of PV in these cases were 25% then the avoided peaker plant cost of PV would range from \$12/MWh to \$30/MWh. Even in Toronto the capacity value was estimated to be around 40% for PV plants with capacity factors lower than 12% [13] which leads to an avoided peaker plant cost of \$33/MWh of PV. In regions where the demand is dominated by winter nighttime heating loads, on the other hand, the capacity value of solar could easily be much closer to zero. It is important to better understand the capacity value of solar due to the potential for such a wide range of economic benefits per unit of solar energy production.

IV. Future Work

As described above, many different approaches to assessment of the capacity value of solar generation have been presented in the literature. The work of the IEEE Task Force in recommending a preferred approach will fall into a number of main strands:

- *Resource assessment*. There is much less knowledge of methods for solar resource assessment in the power systems community, as compared to methods for wind resource assessment.
- *Solar device models.* Differently from wind generation, where concentrated solar power includes intrinsic storage it will be necessary to model this as part of the capacity value assessment.
- *Statistical estimation and uncertainty assessment.* It will be necessary to estimate probability distributions of demand and available solar resource, and also the statistical relationship between these. As there is typically limited historical data from times of extreme demand, if such events dominate the adequacy risk there may be very large sampling uncertainty in capacity value results. Methods for assessing uncertainty thus for a critical part of the capacity value assessment process.

Our main guiding principle is that capacity value assessment should be based on calculation of an appropriate adequacy risk index including the renewable resource, and then calculating a metric (e.g. ELCC or an alternative such as Equivalent Firm Capacity) which quantifies the renewable source's contribution within this risk calculation structure. Assuming that the risk calculation and capacity value metric are indeed specified appropriately, then when combined with assessment of uncertainties, this approach provides a systematic means of assessing capacity values. Capacity factor-based metrics in contrast are often defined in a somewhat arbitrary manner, and in particular miss the key point that renewable resources often have limited capacity value precisely because of high variability about their mean outputs.

V. Conclusions

This paper reviews the current approaches used for evaluating the capacity value of solar power and is a first step in providing clarity on the calculation of solar capacity value. The next step would be to establish a taskforce for solar capacity value that would reach consensus on preferred methodologies for both PV and CSP capacity value calculations similar to the taskforce that was established to describe a preferred method for the calculation of capacity value of wind generation [5].

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Exhibits to Direct Testimony of Michael Milligan
on behalf of Montana Environmental Information Center

Exhibit MM-4

Docket No. 2019.12.101

Capacity Value of Wind Power

Task Force on the Capacity Value of Wind Power, IEEE Power and Energy Society
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***Abstract*—Power systems are planned such that they have adequate generation capacity to meet the load, according to a defined reliability target. The increase in the penetration of wind generation in recent years has led to a number of challenges for the planning and operation of power systems. A key metric for generation system adequacy is the capacity value of generation. The capacity value of a generator is the contribution that a given generator makes to generation system adequacy. The variable and stochastic nature of wind sets it apart from conventional energy sources. As a result, the modeling of wind generation in the same manner as conventional generation for capacity value calculations is inappropriate. In this paper a preferred method for calculation of the capacity value of wind is described and a discussion of the pertinent issues surrounding it is given. Approximate methods for the calculation are also described with their limitations highlighted. The outcome of recent wind capacity value analyses in Europe and North America, along with some new analysis, are highlighted with a discussion of relevant issues also given.**

***Index Terms*—Capacity value, effective load carrying capability, power system operation and planning, wind power.**

I. Introduction

POWER system reliability is divided into two basic aspects, system security and system adequacy. A system is secure if it can withstand a loss (or potentially multiple losses) of key power supply components such as generators or transmission links. Generation system adequacy refers to the issue of whether there is sufficient installed capacity to meet the electric load [1]. This adequacy is achieved with a combination of different generators that may have significantly different characteristics. Capacity value can be defined as the amount of additional load that can be served due to the addition of the generator, while maintaining the existing levels of reliability. It is central to determining a system's generation adequacy. It is used by system engineers to assess the risk of a generation capacity deficit [2].

In recent years it has gained importance, in light of the increased uncertainty arising from wind power availability, which is a function of the local weather conditions.

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The metrics that are used for adequacy evaluation include the loss of load expectation (LOLE) and the loss of load probability (LOLP). LOLP is the probability that the load will exceed the available generation at a given time. This criterion only gives an indication of generation capacity shortfall and lacks information on the importance and duration of the outage. LOLE is the expected number of hours or days, during which the load will not be met over a defined time period. The effective load carrying capability (ELCC) is the metric used in this paper to denote the capacity value [3].

The topic of capacity value of wind power has been attracting attention in recent times with a number of publications dealing with this issue. In [4] methods for capacity value are described, and classified as either chronological or probabilistic. A range of methods for the calculation of capacity value are assessed in [5] and [6]. A generalized version of [3] is presented in [7] with the key innovation being a multi state representation of wind power. A new approximate method for the adequacy assessment called the Z method is given in [8]. The utilization of an autoregressive moving average model of wind power along with sequential Monte Carlo simulation is presented in [9]–[12]. In [13] a well being analysis framework is used to combine deterministic and probabilistic approaches to determining system adequacy. Currently a wide range of approaches have been implemented in academia and industry, each with their own inherent limitations and approximations. This paper is the result of work undertaken by the Taskforce on Capacity Value of Wind, which was proposed by the Wind Power Coordination Committee and Power Systems Analysis, Computing and Economics committee of the IEEE Power and Energy Society (PES). The overall objective of the taskforce has been to provide clarity on the calculation of capacity value of wind. This paper is the outcome of the taskforce meeting and panel session which took place at the IEEE PES General Meeting in Pittsburgh, 2008.

The paper classifies the current approaches used for the assessment of the capacity value of wind power generation. In particular, a preferred method is recommended and described in detail in Section II. Other approximate methods are described in Section III, with the limitations of each highlighted and recommendations made as to their usage. The results of relevant international studies are described in Section IV. A discussion of relevant issues is given in Section V, with conclusions and recommendations given in Section VI.

II. Preferred Methodology

A. Method Description

This method is based directly on the definition of capacity value given above. Conventional thermal generation is still the most common form of generation in power systems. They are modeled by their respective capacities and forced outage rates (FOR). Each generator capacity and FOR is convolved via an iterative method to produce the analytical reliability model [capacity outage probability table (COPT)] of the power system. The COPT is a table of capacity levels and their associated probabilities [1]. The cumulative probabilities give the LOLP for each possible available generation state. Wind power cannot be adequately modeled by its capacity and FOR as wind availability is more a matter of resource availability than mechanical availability. This leads to a different treatment of wind generation in the traditional ELCC calculation method, which is now summarized in the following three steps:

1) The COPT of the power system is used in conjunction with the hourly load time series to compute the hourly LOLPs without the presence of the wind plant. The annual LOLE is then calculated. The LOLE should meet the predetermined reliability target for that period. If it does not match, the loads can be adjusted, if desired, so that the target reliability level is achieved.
2) The time series for the wind plant power output is treated as negative load and is combined with the load time series, resulting in a load time series net of wind power. In the same manner as step 1, the LOLE is calculated. It will now be lower (and therefore better) than the target LOLE in the first step.
3) The load data is then increased by a constant ΔL across all hours using an iterative process, and the LOLE recalculated at each step until the target LOLE is reached. The increase in peak load (sum of ΔLs) that achieves the reliability target is the ELCC or capacity value of the wind plant.

B. Factors Influencing Capacity Value Calculation

For thermal units, the primary characteristics that influence the overall system adequacy are the units' available capacity and FORs. Long-term FORs are typically available by type and size of unit, compiled from a large data set of similar units. Modelling wind power using 2-state distributions in this manner is not recommended as wind is a highly variable resource which cannot be adequately modeled by a two state model.

With respect to wind power, the relationship between the wind and the load is a key factor to be captured by the calculation method. The correlation between wind and load is site dependent. In some areas there is a diurnal and/or seasonal wind pattern. Although the hourly correlation between wind and load can be nearly zero, there may be a considerable correlation among wind and load data when binned according to rank. A physical mechanism for this may be that load extremes are often due to relatively infrequent large-scale high-pressure weather systems that typically bring calm winds. This implies the existence of systematic patterns of wind generation during system peaks and other time periods that cannot be ignored. As an example, data used in the Minnesota 20% Wind Integration Study [14] was used to calculate correlation coefficients by deciles (10 equal divisions) and vigiciles (20 equal divisions). Deciles are data that is sorted into ten equal parts. Vigiciles refer to the same concept where twenty equal parts are employed.

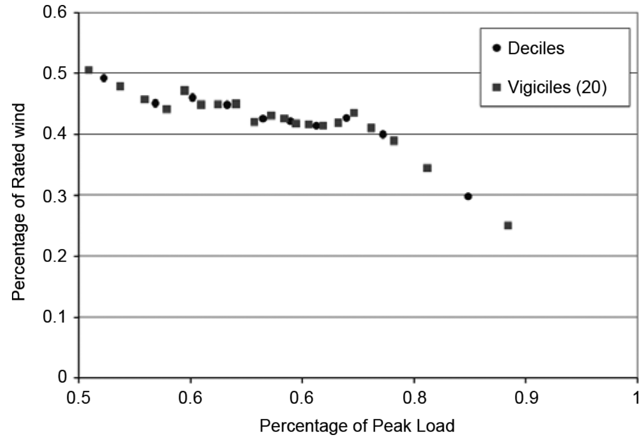

Fig. 1. Correlation between wind and load based on deciles and vigiciles.

The results are shown in Fig. 1. The figure shows the relative ranking of wind and loads by dividing them into deciles and vigiciles and is based on the average wind or load within the grouping. The annual correlation coefficient of the hourly wind and load data is relatively small at -0.158. However, after computing the midpoints of each decile and basing the calculation on those, the correlation coefficient is considerable at -0.908, and the corresponding vigicile correlation coefficient is -0.889. Therefore, it is critical to use hourly wind and load data from the same year so that the underlying relationship between wind and load is implicitly captured in the modeling. The linear correlation coefficients provide limited information about the relationship between two variables, but are used here as part of a simplified illustration.

Although the key driver of wind capacity value comes from the general correlation of wind and load, it is important to remember that ELCC is a function of many different system parameters. Some of these include hydro generation schedules (generally highly correlated with load), import-export schedules (often high imports are correlated with load), and maintenance schedules for conventional units. This latter impact can occur if maintenance outages have a significant impact on LOLP during shoulder seasons, and if there is significant wind generation during those times [15]. The geographic dispersion of both wind and load will also impact ELCC, as will the wind penetration level.

Fig. 2 illustrates the effect of an additional generator on the reliability curve, where it is seen to move to the right. ELCC is the contribution to overall adequacy, represented by the movement of this curve. The case illustrated uses the common LOLE target of 1 day/10 years. This target, although commonly used, can be changed to reflect the acceptable risk level of the region. The selected target reliability level can have a large impact on the capacity value of both conventional power and wind power [5]. When the target reliability level, is lower, and LOLP higher, there is relatively more value in any added capacity than in cases where LOLP is very low [15]. LOLE targets and calculations can be expressed in days per year or hours per year. The relationship between hours per year and days per year is not a factor of 24 and depends on the generating system and load parameters. It is important to note that there is a distinction

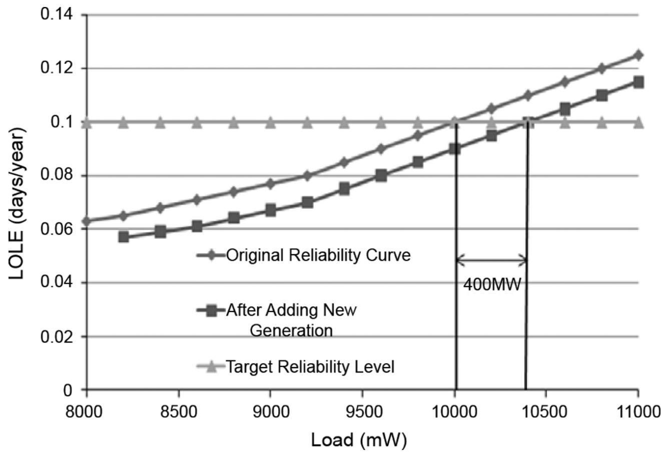

Fig. 2. Effect of generator addition on LOLE.

between these calculation methods that use daily LOLE values and hourly LOLE, respectively. The calculation of a daily LOLE based on peak load values will be more pessimistic and is distinct from an hourly LOLE calculation. Both daily and hourly LOLE are valid metrics, but clarity regarding their application should be ensured.

A common approach is to estimate LOLE and related indices for one balancing area of the whole interconnection, e.g., for a utility, a state or a country. The interpretation of LOLE is then not "loss of load expectation", but instead expectation of requirement to import.

In many systems where the calculations show a given expectation of capacity deficit, the true expectation of capacity deficit is much lower because there is a non-zero probability of available imports which are not otherwise accounted for in the analysis. The impact of imports could be modeled within the preferred method if the data is available for the interconnections into the system. For comparison of capacity values between systems, the system is initially modified to give a standard LOLE value such as 1 day in 10 years; this then allows comparison of the capacity value of wind between systems. This does not give a true measure of the adequacy of the systems where LOLE values are different, but allows for wind's contribution to be assessed and compared against other systems that used this standard value, as well as compared against other energy sources.

The input data employed is a key factor in the calculation of capacity value. It should be noted that regardless of the method employed, if sufficient data of the required quality is not available, the resulting answer cannot be relied upon. The preferred method requires:

1) load time series for the period of investigation (multi-year of at least hourly resolution is preferable);
2) wind power time series for the same period as the loads;
3) a complete inventory of conventional generation units' capacity, forced outage rates and maintenance schedules.

The length of the period of investigation required is an open question with wind power. For wind and other variable generators, it has been common practice to use one or more years of hourly generation data to calculate wind's ELCC. This approach, although a reasonable start, does not adequately represent the long-term performance characteristics of wind power plants in the same way that long-term representations are made for conventional units. Multiple years of time series data are preferred as there can be a significant inter-annual variation of the wind resource [16]. If the wind time series is only for a single year, then the calculated LOLE will be simply a historical assessment rather than a predictive one. The number required to provide a robust answer is dependent on a number of factors including the size of the system, load curve and penetration of wind power on the system. The overall output for each year is important, but the timing of the wind output is also a very important factor to be captured. This reemphasizes the need for time synchronized data with the load.

An important characteristic of wind power is its spatial diversity. With respect to capacity value, weaker geographical relationships are advantageous, as this results in a higher capacity value of the whole wind fleet, due to the smaller probability of very low output across the whole system. This also means that the capacity value increases relatively with larger region sizes. If in contrast the generation profiles are perfectly correlated, the installation of additional capacity does not compensate for the low wind hours; in this case, while additional installed capacity would increase the MW capacity value, the capacity value as a percentage of rated capacity would decrease.

Wind data of the required quality and quantity has been scarce to date due to many wind plants only being recently installed. In addition, this time series data can be commercially sensitive, making it harder to obtain. For other energy resources such as hydro power, this is less of a problem as it is a well established, mature technology with decades of good quality data often being available. As noted above, calculation of the "true" multi-area LOLE and related indices should consider possibilities of import. This means that representative time series for import levels and their respective likelihoods in neighboring systems should be used.

Synthetic time series have been proposed in the literature as a means of reconciling the sometimes limited availability of historical wind time series [9]–[12]. This work has focused on sequential Monte Carlo simulation to provide accurate frequency and duration assessment of wind power. The wind is modeled using an autoregressive moving average model, which captures the correlation between different wind sites. This approach is promising, provided that it can account fully for the relationship between wind availability and load. A key factor is capturing the effect of the underlying weather which drives not only wind output but also the load.

III. Approximate Methodologies

This section outlines some of the approximate methodologies that have been employed for calculation of capacity value. They are included as a means of contrast with the preferred method and also to highlight the approximations and assumptions they make. The preferred method contains approximations also but as it utilizes the datasets which explicitly capture the full relationship between load and wind it does provide the best assessment of wind's capacity value.

It is important to note that with modern computing power the preferred method is not overly time-consuming for moderately sized systems; indeed, a multi-year calculation can be run in a matter of seconds on a desktop PC. Approximation methods must therefore be justified on grounds of ease of coding, lack of data, or on grounds of greater transparency which aids the interpretation of results.

A. Garver Approximation Based Methods

Garver proposed a simplified, approximate graphical approach to calculating the ELCC of an additional generator [3]. This has been an important method in the calculation of capacity values but has been superseded by advances in computing power. Although the paper's focus was on the graphical approach, the same underlying methodology can be used to estimate the ELCC of a wind generator added to a given power system. Garver's approximation and its extension to multi-state units [6] are based on two main assumptions:

- The multi-state unit representation of wind described below is used; the probability distribution for wind availability is the same at all times.
- The LOLE before addition of the wind may be approximated as Be^{md_0}, where d_0 is the peak demand, and m and B are fitting parameters.

The ELCC $(\bar{d})$ of the wind generation is then calculated as

$$\bar{d} = -\frac{1}{m} \ln \left[\sum_i p_i e^{-mw_i} \right] \tag{1}$$

where p_i is the probability that the available wind capacity is w_i.

B. Multi-State Unit Representation

An alternative risk calculation to the preferred method is the multi-state approach, which utilizes a probabilistic representation of the wind plant [7], [17], [18]. Similarly to conventional units with de-rated states, the wind plant is modeled with partial capacity outage states each of which has an associated probability. To evaluate the LOLP at a given time, the wind generation is included in a COPT calculation in the same manner as a multi-state conventional unit. The ELCC calculation then proceeds as described in the preferred method, except using the modified calculation. A multistate approach is adopted in [19] where a Markov model is employed to model wind in discrete states.

The multi-state model for wind power is typically constructed from a histogram of the wind power output for the chosen period. A major concern associated with this approach is the loss of information on wind/load correlation. In most regions there is significant seasonal and diurnal variation in wind energy availability, as well as effects of weather on demand; these cannot be adequately described by a single probability density function for all periods. This concern may be addressed to some extent by using different probability distributions for different categories of hours. The total LOLE would then be evaluated by adding the LOLEs from the various categories of hour. However, such a modification still does not fully account for the correlation between demand and wind availability. Such effects will be captured automatically when the preferred methodology is employed.

C. Annual Peak Calculations

Loss of load probability at time of annual peak demand is used as a proxy for system risk in some regions, for example Great Britain has generally followed this practice [20], [21]. The definition of ELCC for peak calculations remains the same as for year-round risk calculations, except that the risk index used is LOLP at time of annual peak. It follows that probability distributions are required for the demand and available wind capacity at time of annual peak (the distribution for available conventional capacity is derived via a COPT calculation, as in the preferred ELCC calculation method.)

The requirement for a probability distribution for available wind capacity is problematic, because peak demand by definition occurs once a year, and hence by definition the available data is very limited. Two approaches which have been used in investigating the wind resource at annual peak are:

1) Use a histogram of hourly load factors for the entire peaking season. This has the disadvantage that many days are not close to annual peak demand, so their relevance is limited if the wind/demand correlation is substantial.
2) Use a histogram of load factors from hours where demand is within a certain percentage of that year's peak. This ensures greater relevance to peak demand, at the expense of reducing the amount of data used.

The main criticisms of an annual peak calculation are that it does not explicitly consider loss of load at other times of the year, and that it is difficult to obtain appropriate probability distributions for the wind resource at annual peak, and also for the peak load.

D. Peak-Period Capacity Factors

There has been considerable interest in using capacity factors (average output) calculated over suitable peak periods to estimate the capacity value of wind. Some of these approximations are reasonably accurate [5]. In [22] a good approximation was achieved only if hydro and import-export transactions were ignored. As discussed previously, this is no surprise because hydro and transaction schedules are often positively correlated with load. Although capacity factor approximations may be useful as quick screening methods (for instance, a higher capacity factor would usually imply a higher capacity value on the same system), we do not endorse them here as they do not capture the short term or annual variability of wind power, or the correlation of wind availability with demand.

E. Z-Statistic Method

The z-statistic method [8] is based on taking the difference between available resources and load over peak demand hours (surplus availability) as a random variable with an associated probability distribution. The z-statistic for that distribution (mean divided by standard deviation) is taken as the primary system adequacy metric. The incremental load carrying capability for an added power plant is taken to be the load addition that keeps the z-statistic constant. For small changes in the overall system, keeping the z-statistic constant is equivalent to maintaining a constant LOLP. This approach is therefore an approximate method for annual peak ELCC calculation. The following assumptions are involved in its formulation:

- The shape of the probability distribution for the margin of available capacity over demand does not change significantly on adding the wind (though the mean and standard deviation (SD) may change).
- The SD ($\bar{\sigma}$) of the distribution for available wind capacity is small compared to the SD of the distribution for available capacity from the existing generation. As a consequence, the z-method approximation is only valid for low wind penetrations.

These allow a transparent closed-form expression for ELCC to be derived. The method is most conveniently stated by regarding the z-statistic for margin as a proxy for LOLP. The ELCC ($\bar{d}$) is then the load addition that keeps the z-statistic constant:

$$\bar{d} = \bar{\mu} - \frac{z_0 \bar{\sigma}^2}{2\sigma} \tag{2}$$

where $\bar{\mu}$ is the mean wind load factor over peak load hours, and z_0 is the z-statistic representing the LOLP level. Due to it being a perturbation method, and due to the assumption that the shape of the distribution for available margin is unchanged, it is especially accurate for small incremental wind penetrations, and progressively less accurate for evaluating large increments of wind generation on a power system.

This method's principal advantage lies in the transparency of the formula for ELCC; it provides greater insight into what influences the level of ELCC than iterative calculations. The usefulness of the method is in providing a relatively simple rapid method for determining how wind variability and correlations among wind projects affect the load carrying capability.

IV. Case Studies

This section presents summary results from capacity value studies around the world. In each of the studies different methods have been applied which partly explains why there are differing capacity value levels. There are also differences between the results of the studies due to the differing characteristics of the wind and demand profiles in each of the regions under study.

A. Comparison Between Preferred and Approximate Methods

This section details a comparison of capacity value results obtained from studies on the Great Britain and Ireland systems, utilizing wind power and plant portfolio data from each system [23].

This study demonstrates clearly that the benefits of the preferred LOLE-based approach include automatically accounting for the wind-demand relationship and geographical diversity in the resource, and giving a broader picture of risk beyond the time of annual peak. An annual peak LOLP calculation requires a probability distribution to be derived for the available wind capacity at time of annual peak. By definition there are few hours of direct relevance; indeed, as extreme demands tend to be driven in most power systems by extreme weather, it might be expected that the error will be induced if an annual peak distribution is based on either all periods with demand within a certain percentage of peak, or all daily peaks in the peak season.

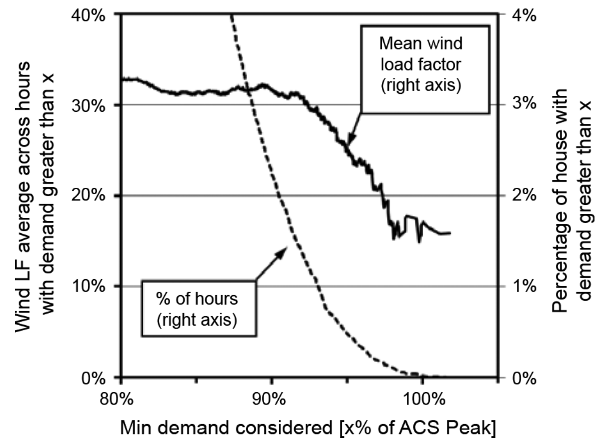

Fig. 3. Relationship between available wind load factor from the transmission-connected wind farms in GB and system-wide demand. Data from the two winters 2007-2008 are plotted. (ACS is average cold spell).

Fig. 3 illustrates the critical importance of accounting correctly for the relationship between wind availability and demand. It shows clearly that over the winters 2007–2008, the mean wind load factor across the hours of very highest demand was considerably lower than the mean load factor across more typical (lower) winter demands. This confirms that any group of hours spread across the whole winter, without consideration of demand level, will not be representative of absolute peak demand; plotting the mean load factor across all hours above a certain demand (as in Fig. 3) combines the degree of aggregation which is needed to reveal any trend, with the necessary focus on the hours of highest demand.

The capacity credit results from the Great Britain and Ireland systems use the preferred LOLE-based approach. The probability distribution for available conventional generating capacity is derived through a capacity outage probability table method as described in Section II. Metered wind and demand data from the years 2007 and 2008 (for which coincident time series were available for both systems) is used. Before adding the wind generation, the GB peak demand and LOLE are 60 GW and 0.061 hour/year; the figures for Ireland are 5.05 GW and 1.87 hour/year. These figures illustrate the relative differences in generation adequacy between a large and small system and should not be taken as definitive figures for the adequacy of these systems.

Capacity credit results are shown in Fig. 4 for the original demands. The Irish wind data gives higher capacity credit results than the GB data, as the Irish wind load factors are on average higher. Also, in common with other studies, the capacity credit as a percentage of installed wind capacity decreases with increasing wind capacity (because at higher wind capacities the possibility of very low output becomes more important on a system scale), and the capacity credit result increases as demand is increased (as any generation is more valuable to the system when risk is higher).

More surprising is the result that the Irish system consistently gives higher capacity credit values that GB for the same wind data. This is explained by the fact that in the smaller Irish system the variations in available conventional capacity are larger relative to installed capacity or peak demand. As a result, when the

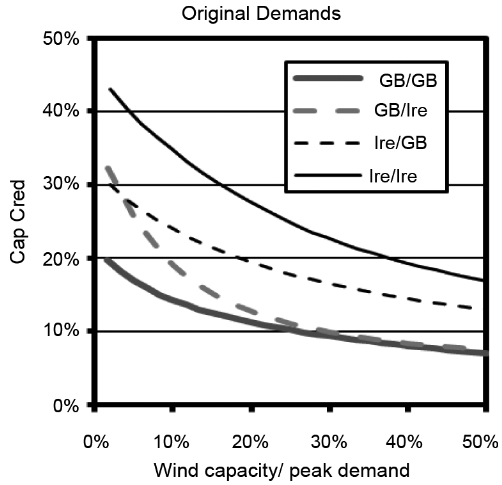

Fig. 4. Capacity credit results from the GB and Irish systems. Sys1/Sys2 denotes demand and conventional generation from Sys1/wind data from Sys2.

same percentage wind penetration is added to the two systems, the distribution for available capacity broadens less in the Irish system than in GB; hence, in this calculation the wind capacity appears 'firmer' in Ireland than in GB, and the calculated capacity credit is then higher.

Fig. 5 shows a comparison between the preferred method and two approximate methods, (Garver and Peak). It can be seen that when load levels below 90% are not considered the ELCC is generally overestimated. When only very high load levels are considered $(> 97\%)$ the ELCC is lowest, corresponding with Fig. 3 which shows that in Great Britain the wind load factor drops off considerably at these demand levels [24].

Fig. 6 shows a comparison between the preferred COPT method, the Z method and the COPT method where a normal distribution is assumed for conventional plant. The Central Limit Theorem implies that the sum of a large number of independent random variables will be approximately Normally distributed, as long as no one variable dominates the sum. If the wind capacity is small enough, these conditions remain satisfied for the available capacity distribution even after the wind is added (a Normal approximation for the wind distribution itself is not required).

Therefore, following the addition of a small wind capacity, the Normal approximation for the total capacity inherent in the Z method remains reasonable. The observations in the previous paragraph suggest that (for this example at least) the assumption that the shape of the available capacity distribution does not change on adding the wind is equivalent to the stronger assumption of a Normal distribution.

Fig. 7 shows the application of the preferred method to the Irish system exposed to different years of wind data. It shows the considerable variation, (up to 35%), that can occur between years depending on the overall wind resource in those years and the timing of the wind output [25].

B. New York State Study

The objective of this study was to assess the effective load carrying capability of future wind resources in the State of New York [26]. The preferred method in Section II was used with the addition of considering the power transfer limits of the tie lines between different control areas. The historical NYISO hourly

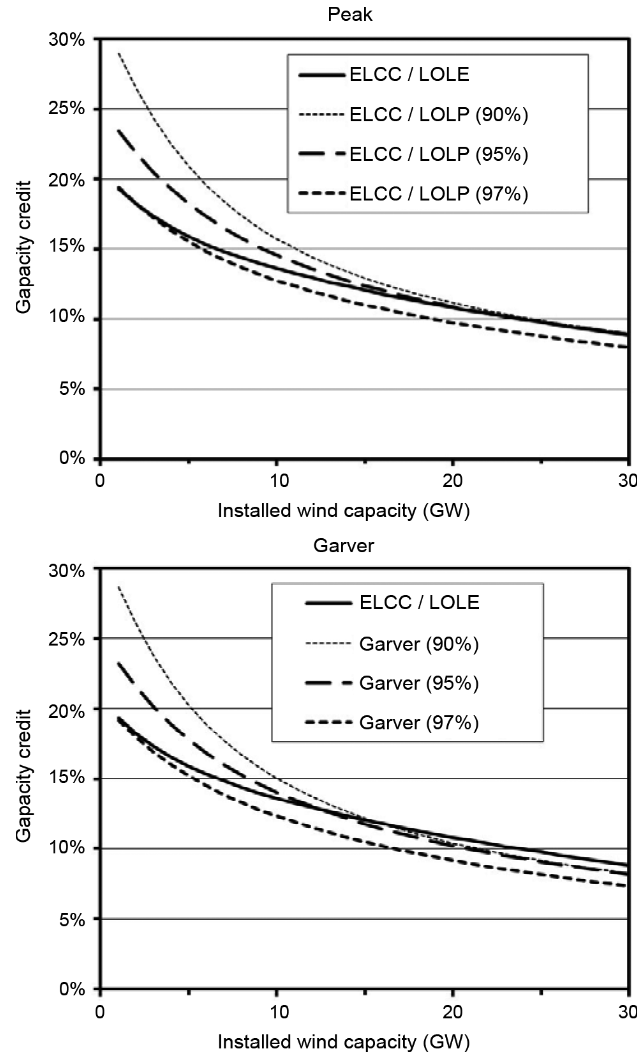

Fig. 5. ELCC as determined using peak and Garver approximations compared to preferred method [24].

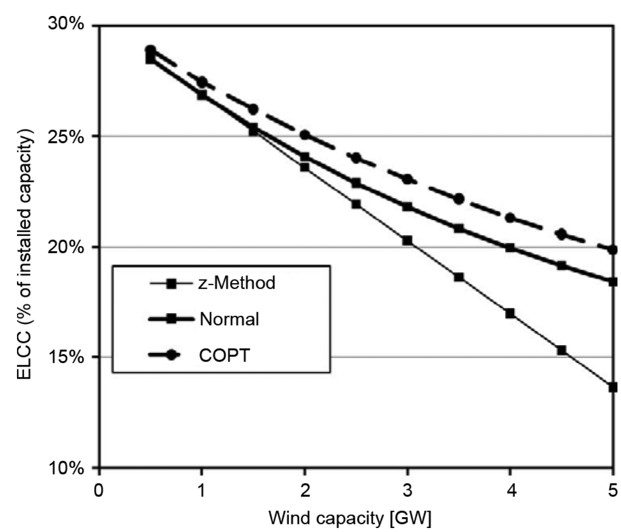

Fig. 6. ELCC as determined by z-method, preferred method and preferred method with normal distribution for conventional plant.

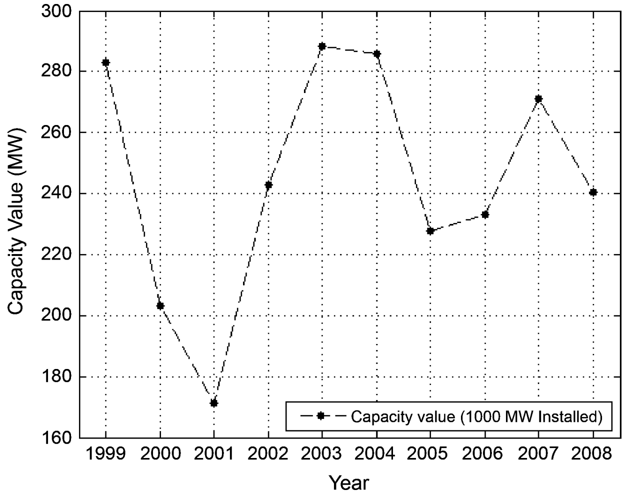

Fig. 7. Variation of Wind ELCC on Irish system over multiple years [25] .

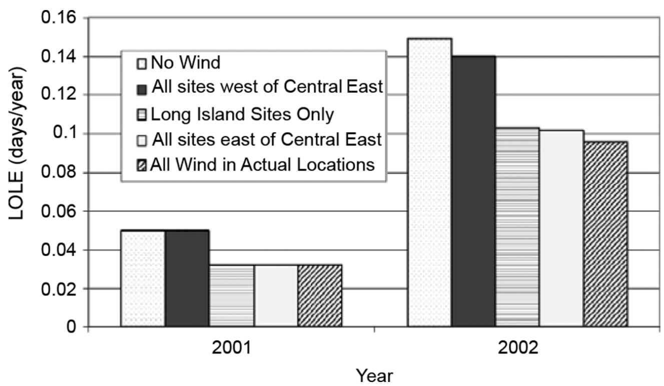

Fig. 8. NY State LOLE analysis results [26].

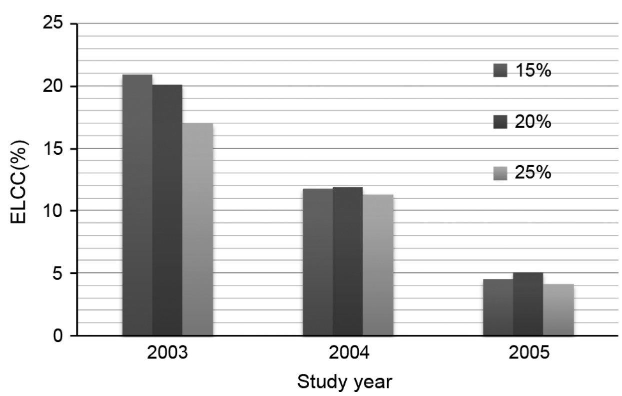

Fig. 9. The ELCC values for three different levels of wind penetration for the Minnesota State study [14].

load data for 2001, 2002 and 2003 at different buses were used. The peak demand for the period of investigation was 30 982 MW.

We have 3300 MW installed capacity, of which 600 MW were assumed to be off-shore. Available historical meteorological data for the same years were used to create time series for hourly wind power generation at different sites. The time synchronized data for loads and output wind power were used in the analysis to maintain their correlation. The LOLE analysis was performed while considering the transfer limits on the tie-lines between the pairs of interconnected areas. The hourly loads for 2001 and 2002 have been modified to be in per unit based on the 2008 peak load.

Results show that most of the reduction in LOLE comes from the 600 MW offshore site. The sites to the west of a major system transmission interface have minimal effect on LOLE due to congestion in the transmission. For 2001, the ELCC for the 3300 MW of wind generation is 270 MW, i.e., 8% of nameplate capacity, if the transmission constraints are removed the ELCC increase to 720 MW (22% of nameplate capacity). Overall, the onshore ELCC is about 10% with the offshore ELCC rising to 40%, as shown later in Fig. 7. Some of the LOLE analysis results are shown in Fig. 5.

C. *Minnesota State Study*

The study was performed in 2006 [14]. Different levels of wind generation 3441 MW, 4582 MW, and 5688 MW which correspond to 15%, 20%, and 25% as a percentage of the forecasted Minnesota retail electric sales in the year of 2020 were assumed. The peak demand in the system was 15 630 MW. Conventional generation was expanded to meet the criteria of LOLE of 1 day/10 years for the year of 2020.

Wind generation was represented as negative load as per the preferred method. The analysis was conducted for three different versions of year 2020, where the hourly wind and load patterns are based on the historical years 2003, 2004, and 2005. The LOLE analysis was performed using a commercial reliability evaluation software package to construct the COPT for the non wind and the three wind penetration scenarios. The preferred method described in Section II was used to evaluate capacity value for each penetration scenario. The study results are summarized in Fig. 6. It can be seen that the effective capacity of wind generation can vary significantly year-to-year. The ELCC of the wind generation corresponding to 15% 20% and 25% wind penetration ranges from approximately 5% to just over 20% of nameplate capacity. Meteorological conditions are the most likely explanation for the trend in the ELCC by year. The highest ELCC values were obtained in 2003 as this year shows the best correlation between wind production during the highest load hours while the lowest ELCC values were obtained in 2005 as this year exhibits the poorest correlation.

D. *Irish Wind Study*

The Irish wind study from 2004 examines the impact of Irish wind power generation on the conventional power plants [27]. The peak load on the system in 2004 was approximately 4500 MW. The calculated capacity value of wind generation is equal to the amount of conventional capacity that can be omitted whilst maintaining the same LOLE. This definition of capacity value is distinct from that recommended here, where capacity value is defined in terms of additional load. The definition in terms of additional conventional capacity requires the definition of a notional typical conventional unit to measure the ELCC against. The hourly wind power generation is modeled as negative demand and added to the hourly load profile capturing corresponding correlation effects. This corresponds to the preferred methodology in Section II. Measurements of 18 onshore wind stations and 1 offshore station for the year of 2001 serve to model the wind power profile. The reference LOLE is 8 h in one year. This is the accepted generation adequacy standard for Ireland. It is the target employed by the TSO for long term generation planning calculations using assumed load growth and planned generator FORs [2]. It is also employed for more short term considerations such as calculating the generation adequacy for the following peak demand season. Given the increasing penetration of wind energy in Ireland, the ELCC of wind is of particular relevance. A capacity market is also operated in Ireland and is based on the calculation of monthly/seasonal ELCC. This calculation is the basis for the allocation of the capacity credit funds to the market participants.

Capacity values of wind generation in a 5 GW peak system and a 6.5 GW peak system consisting of more and more modern conventional power plants are calculated. In the former system the capacity value of 0.5 GW installed wind capacities is 34% of installed capacity. Assuming 1.5 GW it decreases to 23% of installed capacity. The same amount of capacities show a slightly lower capacity value of 22% in the second system dropping to 14% with 3.5 GW of installed wind capacities.

A report on the state of the art of wind integration by the IEA Wind Task 25 compiled the results of these and other wind integration studies into a single document and provides useful comparisons between methods and countries/regions [28]. It is apparent from the results described above that the capacity value is dependent on the method employed but it also depends on the specific characteristics of the region/country. In particular, the characteristics of the wind regime and the characteristics of the demand profile, e.g., whether peak demand occurs in winter or summer [29], [30].

V. Discussion

There remain a number of issues surrounding the calculation of capacity values. These range from the representation of other generation types in the calculation method to the data requirements for calculations.

The use of long-term synchronized load and wind data is encouraged, keeping in mind the difficulty in using old load profile curves to represent the future. However, capacity value calculations are normally based on data sets over limited time periods, but the statistics of the available data sets may not be representative. This becomes more critical if several stochastic variables are present. The relationship patterns between wind and peak load for example vary strongly over different years. It would be valuable to have some estimation of the possible deviations of capacity values that are related to different time periods and hence quantify the impact that limited data sets can have on the calculation results.

Currently, the inclusion of maintenance schedules in the preferred calculation can have an influence on the calculated LOLE. Maintenance schedules in reality may have some flexibility, and if faced with a severe capacity deficit, scheduled maintenance can in some instances be deferred. This may call into question the use of deterministic maintenance schedules in capacity value calculations and would be worth investigating.

The applications of capacity value are in planning. However, the unique characteristics of wind power are giving rise to new interactions between the planning and operations timeframes. Calculations based on a weekly or daily timeframe, with very precise knowledge of system conditions, are necessarily different to those performed under the greater uncertainty of a planning timescale, thus leading to a new concept related but distinct from capacity value. Specific factors that may have influence in this regard are maintenance schedules, unit ramping and certain transmission constraints.

This paper has covered the treatment of wind resources only. As they move towards commercial development, the capacity value of other variable resources such as wave, solar and tidal should also be considered. This will require development of both appropriate system risk assessment techniques, and also the necessary resource models for use as inputs. These calculations will present differing challenges; wave, like wind, is a stochastic resource, whereas tidal is intermittent but predictable [31].

VI. Conclusions and Recommendations

This paper has described a preferred method for calculation of capacity value of wind generation. Key metrics employed in the calculation have been defined. The employment of time synchronized load and wind power output data that captures their correlation is vital. Representation of wind as a two state probability model or assessment of wind's capacity value at peak times is inadequate. Factors such as the correlation between different wind sites and with the load, the geographical area and the target reliability level have been shown to have a considerable impact on the capacity value.

A number of the common approximate methods for capacity value of wind have been described. The accuracy of these methods is varied and while some may be useful given limited data, it is important to be clear about the approximations being made. Several international studies in this area have been undertaken. A summary of the results of these studies has been given, illustrating that diverse methods and wind resources lead to a wide range of values for the capacity value of wind power. Further to this, new analysis showing the comparison of the preferred method to some of the approximate methods has been given.

Acknowledgment

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Exhibits to Direct Testimony of Michael Milligan
on behalf of Montana Environmental Information Center

Exhibit MM-5

Docket No. 2019.12.101

2 Generating capacity—basic probability methods

2.1 Introduction

The determination of the required amount of system generating capacity to ensure an adequate supply is an important aspect of power system planning and operation. The total problem can be divided into two conceptually different areas designated as static and operating capacity requirements. The static capacity area relates to the long-term evaluation of this overall system requirement. The operating capacity area relates to the short-term evaluation of the actual capacity required to meet a given load level. Both these areas must be examined at the planning level in evaluating alternative facilities; however, once the decision has been made, the short-term requirement becomes an operating problem. The assessment of operating capacity reserves is illustrated in Chapter 5.

The static requirement can be considered as the installed capacity that must be planned and constructed in advance of the system requirements. The static reserve must be sufficient to provide for the overhaul of generating equipment, outages that are not planned or scheduled and load growth requirements in excess of the estimates. Apractice that has developed over many years is to measure the adequacy of both the planned and installed capacity in terms of a percentage reserve. An important objection to the use of the percentage reserve requirement criterion is the tendency to compare the relative adequacy of capacity requirements provided for totally different systems on the basis of peak loads experienced over the same time period for each system. Large differences in capacity requirements to provide the same assurance of service continuity may be required in two different systems with peak loads of the same magnitude. This situation arises when the two systems being compared have different load characteristics and different types and sizes of installed or planned generating capacity.

The percentage reserve criterion also attaches no penalty to a unit because of size unless this quantity exceeds the total capacity reserve. The requirement that a reserve should be maintained equivalent to the capacity of the largest unit on the system plus a fixed percentage of the total system capacity is a more valid adequacy criterion and calls for larger reserve requirements with the addition of larger units to the system. This characteristic is usually found when probability techniques are used. The application of probability methods to the static capacity problem provides an analytical basis for capacity planning which can be extended to cover partial or complete integration of systems, capacity of interconnections, effects of unit size and design, effects of maintenance schedules and other system parameters. The economic aspects associated with different standards of reliability can be compared only by using probability techniques. Section 2.2.3 illustrates the inconsistencies which can arise when fixed criteria such as percentage reserves or loss of the largest unit are used in system capacity evaluation.

A large number of papers which apply probability techniques to generating capacity reliability evaluation have been published in the last 40 years. These publications have been documented in three comprehensive bibliographies published in 1966, 1971, and 1978 which include over 160 individual references [1–3]. The historical development of the techniques used at the present time is extremely interesting and although it is rather difficult to determine just when the first published material appeared, it was almost fifty years ago. Interest in the application of probability methods to the evaluation of capacity requirements became evident about 1933. The first large group of papers was published in 1947. These papers by Calabrese [4], Lyman [5], Seelye [6] and Loane and Watchorn [7] proposed the basic concepts upon which some of the methods in use at the present time are based. The 1947 group of papers proposed the methods which with some modifications are now generally known as the 'loss of load method', and the 'frequency and duration approach'.

Several excellent papers appeared each year until in 1958 a second large group of papers was published. This group of papers modified and extended the methods proposed by the 1947 group and also introduced a more sophisticated approach to the problem using 'game theory' or 'simulation' techniques [8–10]. Additional material in this area appeared in 1961 and 1962 but since that time interest in this approach appears to have declined.

A third group of significant papers was published in 1968/69 by Ringlee, Wood *et al.* [11–15]. These publications extended the frequency and duration approach by developing a recursive technique for model building. The basic concepts of frequency and duration evaluation are described in *Engineering Systems*.

It should not be assumed that the three groups of papers noted above are the only significant publications on this subject. This is not the case. They do, however, form the basis or starting point for many of the developments outlined in further work. Many other excellent papers have also been published and are listed in the three bibliographies [1–3] referred to earlier.

The fundamental difference between static and operating capacity evaluation is in the time period considered. There are therefore basic differences in the data used in each area of application. Reference [16] contains some fundamental definitions which are necessary for consistent and comprehensive generating unit reliability, availability, and productivity. At the present time it appears that the loss of load probability or expectation method is the most widely used probabilistic technique for evaluating the adequacy of a given generation configuration. There

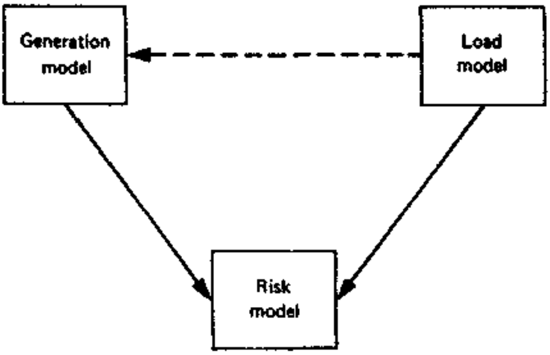

Fig. 2.1 Conceptual tasks in generating capacity reliability evaluation

are, however, many variations in the approach used and in the factors considered. The main elements are considered in this chapter. The loss of energy expectation can also be decided using a similar approach, and it is therefore also included in this chapter. Chapter 3 presents the basic concepts associated with the frequency and duration technique, and both the loss of load and frequency and duration methods are detailed in Chapter 4 which deals with interconnected system reliability evaluation.

The basic approach to evaluating the adequacy of a particular generation configuration is fundamentally the same for any technique. It consists of three parts as shown in Fig. 2.1.

The generation and load models shown in Fig. 2.1 are combined (convolved) to form the appropriate risk model. The calculated indices do not normally include transmission constraints, although it has been shown [39] how these constraints can be included, nor do they include transmission reliabilities; they are therefore overall system adequacy indices. The system representation in a conventional study is shown in Fig. 2.2.

The calculated indices in this case do not reflect generation deficiencies at any particular customer load point but measure the overall adequacy of the generation system. Specific load point evaluation is illustrated later in Chapter 6 under the designation of composite system reliability evaluation.

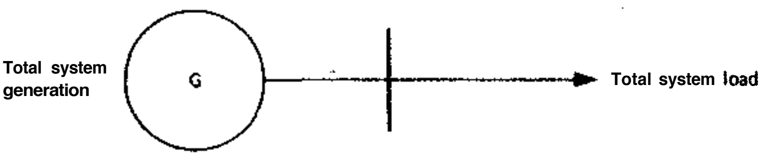

Fig. 2.2 Conventional system model

2.2 The generation system model

2.2.1 Generating unit unavailability

The basic generating unit parameter used in static capacity evaluation is the probability of finding the unit on forced outage at some distant time in the future. This probability was defined in *Engineering Systems* as the unit unavailability, and historically in power system applications it is known as the unit forced outage rate (FOR). It is not a rate in modern reliability terms as it is the ratio of two time values. As shown in Chapter 9 of *Engineering Systems*,

$$\text{Unavailability (FOR)} = U = \frac{\lambda}{\lambda+\mu} = \frac{r}{m+r} = \frac{r}{T} = \frac{f}{\mu}$$

$$= \frac{\Sigma[\text{down time}]}{\Sigma[\text{down time}] + \Sigma[\text{up time}]} \qquad 2.1(a)$$

$$\text{Availability} = A = \frac{\mu}{\lambda+\mu} = \frac{m}{m+r} = \frac{m}{T} = \frac{f}{\lambda}$$

$$= \frac{\Sigma[\text{up time}]}{\Sigma[\text{down time}] + \Sigma[\text{up time}]} \qquad 2.1(b)$$

where λ = expected failure rate
μ = expected repair rate
m = mean time to failure = MTTF = $1/\lambda$
r = mean time to repair = MTTR = $1/\mu$
$m + r$ = mean time between failures = MTBF = $1/f$
f = cycle frequency = $1/T$
T = cycle time = $1/f$.

The concepts of availability and unavailability as illustrated in Equations 2.1(a) and (b) are associated with the simple two-state model shown in Fig. 2.3(a). This model is directly applicable to a base load generating unit which is either operating or forced out of service. Scheduled outages must be considered separately as shown later in this chapter.

In the case of generating equipment with relatively long operating cycles, the unavailability (FOR) is an adequate estimator of the probability that the unit under similar conditions will not be available for service in the future. The formula does not, however, provide an adequate estimate when the demand cycle, as in the case of a peaking or intermittent operating unit, is relatively short. In addition to this, the most critical period in the operation of a unit is the start-up period, and in comparison with a base load unit, a peaking unit will have fewer operating hours and many more start-ups and shut-downs. These aspects must also be included in arriving at an estimate of unit unavailabilities at some time in the future. A working

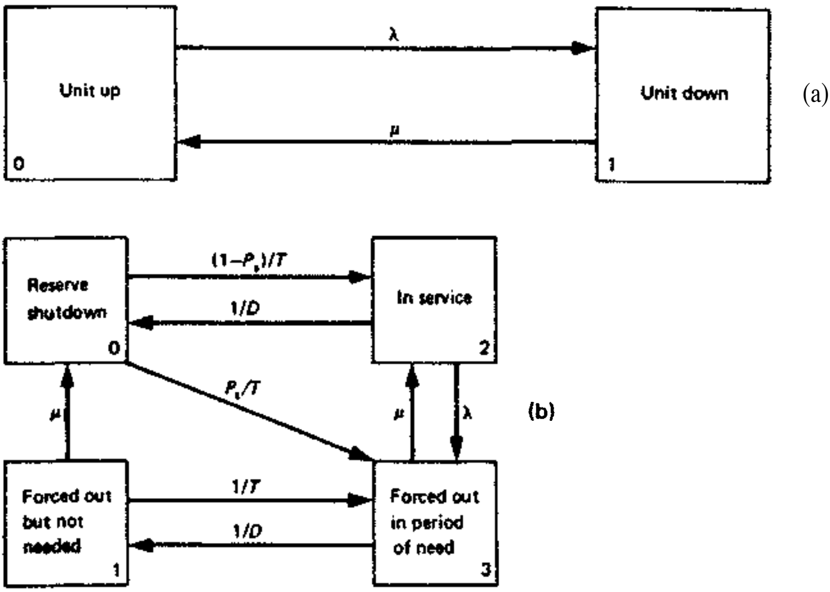

Fig. 2.3 (a) Two-state model for a base load unit
(b) Four-state model for planning studies
T Average reserve shut-down time between periods of need
D Average in-service time per occasion of demand
P_s Probability of starting failure

group of the IEEE Subcommittee on the Application of Probability Methods proposed the four-state model shown in Fig. 2.3(b) and developed an equation which permitted these factors to be considered while utilizing data collected under the conventional definitions [17].

The difference between Figs 2.3(a) and 2.3(b) is in the inclusion of the 'reserve shutdown' and 'forced out but not needed' states in Fig. 2.3(b). In the four-state model, the 'two-state' model is represented by States 2 and 3 and the two additional states are included to model the effect of the relatively short duty cycle. The failure to start condition is represented by the transition rate from State 0 to State 3.

This system can be represented as a Markov process and equations developed for the probabilities of residing in each state in terms of the state transition rates. These equations are as follows:

$$P_0 = \frac{\mu T[D\lambda + 1 + D(\mu + 1/T)]}{A}$$

where

$$A = (D\lambda + P_s)\left[(\mu T + 1) + \left(\mu + \frac{1}{T}\right)D\right] + \left[(1 - P_s) + D\left(\mu + \frac{1}{T}\right)\right](\mu(T + D))$$

$$P_1 = \frac{D\lambda + P_s}{A}$$

$$P_2 = \frac{D\mu(1 - P_s + \mu D + D/T)}{A}$$

$$P_3 = \frac{D(\mu + 1/T)(D\lambda + P_s)}{A}$$

$$\text{The conventional FOR} = \frac{P_1 + P_3}{P_1 + P_2 + P_3}$$

i.e. the 'reserve shutdown' state is eliminated.

In the case of an intermittently operated unit, the conditional probability that the unit will not be available given that a demand occurs is P, where

$$P = \frac{P_3}{P_2 + P_3}$$

$$P = \frac{(\mu + 1/T)(D\lambda + P_s)}{\mu[D(\mu + 1/T) + 1] + D\lambda(\mu + 1/T) + P_s/T}$$

The conditional forced outage rate P can therefore be found from the generic data shown in the model of Fig. 2.3(b). A convenient estimate of P can be made from the basic data for the unit.

Over a relatively long period of time,

$$\hat{P}_2 = \frac{\text{service time}}{\text{available time + forced outage time}} = \frac{\text{ST}}{\text{AT + FOT}}$$

$$(\hat{P}_1 + \hat{P}_3) = \frac{\text{FOT}}{\text{AT + FOT}}$$

Defining

$$f = \frac{P_3}{P_1 + P_3} = \frac{(\mu + 1/T)}{(1/D + \mu + 1/T)} = \frac{(1/r + 1/T)}{(1/D + 1/r + 1/T)}$$

where $r = 1/\mu$.

The conditional forced outage rate P can be expressed as

$$P = \frac{f(P_1 + P_3)}{P_2 + f(P_1 + P_3)} = \frac{f(\text{FOT})}{ST + f(\text{FOT})}$$

The factor f serves to weight the forced outage time FOT to reflect the time the unit was actually on forced outage when in demand by the system. The effect of this modification can be seen in the following example, taken from Reference [17].

Average unit data

$$\begin{aligned}\text{Service time . ST} &= 640.73 \text{ hours}\\ \text{Available time} &= 6403.54 \text{ hours}\\ \text{No. of starts} &= 38.07\\ \text{No. of outages} &= 3.87\\ \text{Forced outage time FOT} &= 205.03 \text{ hours}\end{aligned}$$

Assume that the starting failure probability $P_s = 0$

$$\hat{D} = \frac{640.73}{38.07} = 16.8 \text{ hours}$$

$$\hat{D} + \hat{T} = \frac{6403.54}{38.07} = 168 \text{ hours}$$

$$\hat{r} = \frac{205.03}{3.87} = 53 \text{ hours}$$

$$\hat{m} = \frac{640.73}{3.87} = 166 \text{ hours}$$

Using these values

$$f = \left(\frac{1}{53} + \frac{1}{155.2}\right) \Big/ \left(\frac{1}{16.8} + \frac{1}{53} + \frac{1}{151.2}\right) = 0.3$$

$$\text{The conventional forced outage rate} = \frac{205.03}{640.73 + 205.03} \times 100 = \underline{24.24\%}$$

$$\text{The conditional probability } P = \frac{0.3(205.03)}{640.73 + 0.3(205.03)} \times 100 = \underline{8.76\%}$$

The conditional probability P is clearly dependent on the demand placed upon the unit. The demand placed upon it in the past may not be the same as the demand which may exist in the future, particularly under conditions of generation system inadequacy. It has been suggested [18] that the demand should be determined from the load model as the capacity table is created sequentially, and the conditional probability then determined prior to adding the unit to the capacity model.

2.2.2 Capacity outage probability tables

The generation model required in the loss of load approach is sometimes known as a capacity outage probability table. As the name suggests, it is a simple array of capacity levels and the associated probabilities of existence. If all the units in the system are identical, the capacity outage probability table can be easily obtained using the binomial distribution as described in Sections 3.3.7 and 3.3.8 *of Engineering Systems*. It is extremely unlikely, however, that all the units in a practical

Table 2.1

Capacity out of service	Probability
0 MW	0.9604
3 MW	0.0392
6 MW	0.0004
	1.0000

system will be identical, and therefore the binomial distribution has limited application. The units can be combined using basic probability concepts and this approach can be extended to a simple but powerful recursive technique in which units are added sequentially to produce the final model. These concepts can be illustrated by a simple numerical example.

A system consists of two 3 MW units and one 5 MW unit with forced outage rates of 0.02. The two identical units can be combined to give the capacity outage probability table shown as Table 2.1.

The 5 MW generating unit can be added to this table by considering that it can exist in two states. It can be in service with probability $1-0.02=0.98$ or it can be out of service with probability 0.02. The two resulting tables (Tables 2.2, 2.3) are therefore conditional upon the assumed states of the unit. This approach can be extended to any number of unit states.

The two tables can now be combined and re-ordered (Table 2.4). The probability value in the table is the probability of exactly the indicated amount of capacity being out of service. An additional column can be added which gives the cumulative probability. This is the probability of finding a quantity of capacity on outage equal to or greater than the indicated amount.

The cumulative probability values decrease as the capacity on outage increases: Although this is not completely true for the individual probability table, the same general trend is followed. For instance, in the above table the probability of losing 8 MW is higher than the probability of losing 6 MW. In each case only two units are involved. The difference is due to the fact that in the 8 MW case, the 3 MW loss contribution can occur in two ways. In a practical system the probability of having a large quantity of capacity forced out of service is usually quite small,

Table 2.2 5 MW unit in service

Capacity out	Probability
0 + 0 = 0 MW	(0.9604) (0.98) = 0.941192
3 + 0 = 3 MW	(0.0392) (0.98) = 0.038416
6 + 0 = 6 MW	(0.0004) (0.98) = 0.000392
	0.980000

Table 2.3 5 MW unit out of service

Capacity out	*Probability*
$0 + 5 = 5$ MW	$(0.9604)\ (0.02) = 0.019208$
$3 + 5 = 8$ MW	$(0.0392)\ (0.02) = 0.000784$
$6 + 5 = 11$ MW	$(0.0004)\ (0.02) = 0.000008$
	0.020000

as this condition requires the outage of several units. Theoretically the capacity outage probability table incorporates all the system capacity. The table can be truncated by omitting all capacity outages for which the cumulative probability is less than a specified amount, e.g. 10^{-8}. This also results in a considerable saving in computer time as the table is truncated progressively with each unit addition. The capacity outage probabilities can be summated as units are added, or calculated directly as cumulative values and therefore no error need result from the truncation process. This is illustrated in Section 2.2.4. In a practical system containing a large number of units of different capacities, the table will contain several hundred possible discrete capacity outage levels. This number can be reduced by grouping the units into identical capacity groups prior to combining or by rounding the table to discrete levels after combining. Unit grouping prior to building the table introduces unnecessary approximations which can be avoided by the table rounding approach. The capacity rounding increment used depends upon the accuracy desired. The final rounded table contains capacity outage magnitudes that are multiples of the rounding increment. The number of capacity levels decreases as the rounding increment increases, with a corresponding decrease in accuracy. The procedure for rounding a table is shown in the following example.

Two 3 MW units and one 5 MW unit with forced outage rates of 0.02 were combined to form the generation model shown in Table 2.4. This table, when

Table 2.4 Capacity outage probability table for the three-unit system

Capacity out of service	*Individual probability*	*Cumulative probability*
0	0.941192	1.000000
3	0.038416	0.058808
5	0.019208	0.020392
6	0.000392	0.001184
8	0.000784	0.000792
11	0.000008	0.000008
	1.000000	

Table 2.5

Capacity on outage (MW)	Individual probability	
0	$0.941192 + \frac{2}{5}(0.038416)$	$= 0.9565584$
5	$0.019208 + \frac{3}{5}(0.038416)$	
	$+ \frac{4}{5}(0.000392) + \frac{2}{5}(0.000784)$	$= 0.0428848$
10	$\frac{1}{5}(0.000392) + \frac{3}{5}(0.000784)$	
	$+ \frac{4}{5}(0.000008)$	$= 0.0005552$
15	$\frac{1}{5}(0.000008)$	$= 0.0000016$
		1.0000000

rounded at 5 MW increments, will contain only capacity outage magnitudes of 0, 5, 10 and 15 MW. The rounded table is obtained as shown in Table 2.5.

The general expression for this rounding process is

$$P(C_j) = \frac{C_k - C_i}{C_k - C_j} P(C_i)$$

$$P(C_k) = \frac{C_i - C_j}{C_k - C_j} P(C_i)$$

for all states i falling between the required rounding states j and k.

The use of a rounded table in combination with the load model to calculate the risk level introduces certain inaccuracies. The error depends upon the rounding increment used and on the slope of the load characteristic. The error decreases with increasing slope of the load characteristic and for a given load characteristic the error increases with increased rounding increment. The rounding increment used should be related to the system size and composition. Also the first non-zero capacity-on-outage state should not be less than the capacity of the smallest unit.

The generation system model in the form shown in Table 2.4 can be used to illustrate the basic inadequacies of the conventional deterministic approaches to capacity evaluation.

2.2.3 Comparison of deterministic and probabilistic criteria

It was noted in Section 2.1 that deterministic risk criteria such as 'percentage reserve' and 'loss of largest unit' do not define consistently the ttue risk in the system. In order to illustrate this objectively, consider the following four systems:

—system 1, 24 x 10 MW units each having a FOR of 0.01
—system 2, 12 x 20 MW units each having a FOR of 0.01
—system 3, 12 x 20 MW units each having a FOR of 0.03
—system 4, 22 x 10 MW units each having a FOR of 0.01

All four systems are very similar but not identical. In each system, the units are identical and therefore the capacity outage probability table can be easily constructed using the binomial distribution. These arrays are shown in Table 2.6

Table 2.6 Capacity Outage Probability Tables for systems 1–4

System 1 Capacity (MW)		*Probability*	
Out	*In*	*Individual*	*Cumulative*
0	240	0.785678	1.000000
10	230	0.190467	0.214322
20	220	0.022125	0.023855
30	210	0.001639	0.001730
40	200	0.000087	0,000091
50	190	0.000004	0.000004
System 2 Capacity (MW)		*Probability*	
Out	*In*	*Individual*	*Cumulative*
0	240	0.886384	1.000000
20	220	0.107441	0.113616
40	200	0.005969	0.006175
60	180	0.000201	0.000206
80	160	0.000005	0.000005
System 3 Capacity (MW)		*Probability*	
Out	*In*	*Individual*	*Cumulative*
0	240	0.693841	1.000000
20	220	0.257509	0.306159
40	200	0.043803	0.048650
60	180	0.004516	0.004847
80	160	0.000314	0.000331
100	140	0.000016	0.000017
120	120	0.000001	0.000001
System 4 Capacity (MW)		*Probability*	
Out	*In*	*Individual*	*Cumulative*
0	220	0.801631	1.000000
10	210	0.178140	0.198369
20	200	0.018894	0.020229
30	190	0.001272	0.001335
40	180	0.000061	0.000063
50	170	0.000002	0.000002

and have been truncated to a cumulative probability of 10^{-6}. It can be seen that a considerable number of capacity outage states have oeen deleted using this truncation technique.

The load level or demand on the system is assumed to be constant. If the risk in the system is defined as the probability of not meeting the load, then the true risk in the system is given by the value of cumulative probability corresponding to the outage state one increment below that which satisfies the load on the system. The two deterministic risk criteria can now be compared with this probabilistic risk as in Sections (a) and (b) following.

(a) *Percentage reserve margin*

Assume that the expected toad demands in systems 1, 2, 3 and 4 are 200, 200, 200 and 183 MW respectively. The installed capacity in all four cases is such that there is a *20%* reserve margin, i.e. a constant for all four systems. The probabilistic or true risks in each of the four systems can be found from Table 2.6 and are:

risk in system 1 = 0.000004
risk in system 2 = 0.000206
nsk in system 3 = 0.004847
risk in system 4 = 0.000063

These values of risk show that the true risk in system 3 is 1000 times greater than that in system 1. A detailed analysis of the four systems will show that the variation in true risk depends upon the forced outage rate, number of units and load demand The percentage reserve method cannot account for these factors and therefore, although using a 'constant' risk criterion, does not give a consistent risk assessment of the system.

(b) *Largest unit reserve*

Assume now that the expected load demands in systems 1, 2, 3 and 4 are 230, 220, 220 and 210 MW respectively. The installed capacity in all four cases is such that the reserve is equal to the largest unit which again is a constant for all the systems. In this case the probabilistic risks are:

risk in system 1 = 0.023855
risk in system 2 = 0.006175
risk in system 3 = 0.048650
risk in system 4 = 0.020229

The variation in risk is much smaller in this case, which gives some credence to the criterion. The ratio between the smallest and greatest risk levels is now 8:1 and the risk merit order has changed from system 3–2–4–1 in the case of percentage reserve' to 3–1–4–2 in the case of the 'largest unit' criterion.

It is seen from these comparisons that the use of deterministic or 'rule-of-thumb' criteria can lead to very divergent probabilistic risks even for systems that are very similar. They are therefore inconsistent, unreliable and subjective methods for reserve margin planning.

2.2.4 A recursive algorithm for capacity model building

The capacity model can be created using a simple algorithm which can also be used to remove a unit from the model [19]. This approach can also be used for a multi-state unit, i.e. a unit which can exist in one or more derated or partial output states as well as in the fully up and fully down states. The technique is illustrated for a two-state unit addition followed by the more general case of a multi-state unit.

Case 1 No derated states

The cumulative probability of a particular capacity outage state of X MW after a unit of capacity C MW and forced outage rate U is added is given by

$$P(X) = (1 - U)P'(X) + (U)P'(X - C) \tag{2.2}$$

where $P'(X)$ and $P(X)$ denote the cumulative probabilities of the capacity outage state of X MW before and after the unit is added. The above expression is initialized by setting $P'(X) = 1.0$ for $X \leq 0$ and $P'(X) = 0$ otherwise.

Equation (2.2) is illustrated using the simple system shown in Table 2.7. Each unit in Table 2.7 has an availability and unavailability of 0.98 and 0.02 respectively (Equation 2.1).

The system capacity outage probability is created sequentially as follows:

Step 1 Add the first unit

$$\begin{aligned}
P(0) &= (1-0.02)(1.0) &&+ (0.02)(1.0) &&= 1.0\\
P(25) &= (1-0.02)(0) &&+ (0.02)(1.0) &&= 0.02
\end{aligned}$$

Step 2 Add the second unit

$$\begin{aligned}
P(0) &= (1-0.02)(1.0) &&+ (0.02)(1.0) &&= 1.0\\
P(25) &= (1-0.02)(0.02) &&+ (0.02)(1.0) &&= 0.0396\\
P(50) &= (1-0.02)(0) &&+ (0.02)(0.02) &&= 0.0004
\end{aligned}$$

Step 3 Add the third unit

$$\begin{aligned}
P(0) &= (1-0.02)(1.0) &&+ (0.02)(1.0) &&= 1.0\\
P(25) &= (1-0.02)(0.0396) &&+ (0.02)(1.0) &&= 0.058808\\
P(50) &= (1-0.02)(0.0004) &&+ (0.02)(1.0) &&= 0.020392\\
P(75) &= (1-0.02)(0) &&+ (0.02)(0.0396) &&= 0.000792\\
P(100) &= (1-0.02)(0) &&+ (0.02)(0.0004) &&= 0.000008
\end{aligned}$$

The reader should utilize this approach to obtain Table 2.4.

Table 2.7 System data

Unit no.	*Capacity (MW)*	*Failure rate (f / day)*	*Repair rate (r / day)*
1	25	0.01	0.49
2	25	0.01	0.49
3	50	0.01	0.49

Table 2,8 50 MW unit—three-state representation

State	Capacity out	State probability (p_i)
1	0	0.960
2	20	0.033
3	50	0.007

Case 2 Derated states included

Equation (2,2) can be modified as follows to include multi-state unit representations.

$$P(X) = \sum_{i=1}^{n} p_i P'(X - C_i) \tag{2.3}$$

where n = number of unit states

C_j = capacity outage of state i for the unit being added

p_i = probability of existence of the unit state i.

when n = 2, Equation (2.3) reduces to Equation (2.2).

Equation (2.3) is illustrated using the 50 MW unit representation shown in Table 2.8.

If the two-state 50 MW unit in the previous example is replaced by the three-state unit shown in Table 2.8, Step 3 becomes

$$P(0) = (0.96)(1.0) + (0.033)(1.0) + (0.007)(1.0) = 1.0$$

$$P(20) = (0.96)(0.0396) + (0.033)(1.0) + (0.007)(1.0) = 0.078016$$

$$P(25) = (0.96)(0.0396) + (0.033)(0.0396) + (0.007)(1.0) = 0.0463228$$

$$P(45) = (0.96)(0.0004) + (0.033)(0.0396) + (0.007)(1.0) = 0.0086908$$

$$P(50) = (0.96)(0.0004) + (0.033)(0.0004) + (0.007)(1.0) = 0.0073972$$

$$P(70) = (0.96)(0) + (0.033)(0.0004) + (0.007)(0.0396) = 0.0002904$$

$$P(75) = (0.96)(0) + (0.033)(0) + (0.007)(0.0396) = 0.0002772$$

$$P(100) = (0.96)(0) + (0.033)(0) + (0.007)(0.0004) = 0.0000028$$

2.2.5 Recursive algorithm for unit removal

Generating units are periodically scheduled for unit overhaul and preventive maintenance. During these scheduled outages, the unit is available neither for service nor for failure. This situation requires a Bew capacity model which does not include the unit on scheduled outage. The new model could be created by simply building it from the beginning using Equations (2,2) or (2.3). In the case of a large system this requires considerable computer time if there are a number of discrete periods to consider. Equations (2.2) and (2.3) can be used in reverse, however, to find the capacity model after unit removal.

Consider Equation (2.2):

$$P(X) = (1 - U)P'(X) + (U)P'(X-C) \tag{2.2}$$

$$P'(X) = \frac{P(X) - (U)P'(X-C)}{(1-U)} \tag{2.4}$$

In Equation (2.4) $F(X-C) = 1.0$ for $X < C$ This procedure can be illustrated using the example of case 1 in Section 2.2.4. The 50 MW unit is removed from the capacity outage probability table as follows:

$$P(0) = \frac{(1.0) - (0.02)(1.0)}{0.98} = 1.0$$

$$P(25) = \frac{(0.058808) - (0.02)(1.0)}{0.98} = 0.0396$$

$$P(50) = \frac{(0.020392) - (0.02)(1.0)}{0.98} = 0.0004$$

This is the capacity mode! shown in Step 2. The reader can remove a 25 MW unit to obtain the values in Step 1.

The equation for removal of a multi-state unit is obtained from Equation (2.3):

$$P(X) = \sum_{i=1}^{n} p_i P'(X - C_i) \tag{2.3}$$

$$P'(X) = \frac{P(X) - \sum_{i=2}^{n} p_i P'(X - C_i)}{p_1} \tag{2.5}$$

It is left to the reader to apply Equation (2.5) to the previous case in which the unit shown in Table 2.8 was added to the two 25 MW units. The direct application of Equation (2.5) requires that all the derated states and full outage state of the unit being removed be multiples of the rounding increment used in the capacity outage probability table. In practice, the derated states chosen to model the unit are not the entire set of derated states but a selected representative set of states. It is therefore logical to make the derated states identical to a multiple of the rounding increment. The total capacity of the unit may also not be a multiple of the rounding increment. In this case the removal can be accomplished by removing separately from the existing table two hypothetical units, one having a capacity less than and the other having a capacity greater than the unit to be removed, both being equal to a multiple of the rounding increment. This produces two individual tables which can then be averaged to form the required table.

2.2.6 Alternative model-building techniques

Generating system capacity outages have a discrete distribution and their probabilities are normally evaluated using the well-known recursive technique previously described. It is found that if the system is very large the discrete distribution of system capacity outages can be approximated by a continuous distribution [20]. Such a distribution approaches the normal distribution as the system size increases. If the assumption is made that the distribution of capacity on forced outage is a normal distribution, then the development of the capacity outage probability table is relatively simple. A single entry in the table can be obtained using only the mean and variance of the distribution. The results obtained using this continuous model of system capacity outages are found [37] to be not sufficiently accurate when compared to those obtained using the recursive technique. Schenk and Rau [21] have therefore proposed a Fourier transform method based on the Gram–Charlier expansion of a distribution to improve the accuracy of the continuous model. The complete mathematical description of the proposed method is given in Reference [21]. The step-by-step procedure is summarized as follows.

Let

C_i = capacity of unit i in MW
q_i = forced outage rate of unit i
n = number of generating units

Step 1 Calculate the following quantities for each unit in the system.

$$m_1(i) = C_i q_i$$

$$m_2(i) = C_i^2 q_i$$

$$m_3(i) = C_i^3 q_i$$

$$m_4(i) = C_i^4 q_i$$

$$V_i^2 = m_2(i) - m_1^2(i)$$

$$M_3(i) = m_3(i) - 3m_1(i)m_2(i) + 2m_1^3(i)$$

$$M_4(i) = m_4(i) - 4m_1(i)m_3(i) + 6m_1^2(i)m_2(i) - 2m_1^4(i)$$

Step 2 From the results of Step 1, calculate the following parameters.

$$M = \sum_{i=1}^{n} m_1(i)$$

$$V^2 = \sum_{i=1}^{n} V_i^2$$

$$M_3 = \sum_{i=1}^{n} M_3(i)$$

$$M_4 = \sum_{i=1}^{n} (M_4(i) - 3V_i^4) + 3V^4$$

$$G_1 = M_3/V^3$$

$$G_2 = (M_4/V^4) - 3$$

Step 3 From the results of Step 2 and for any desired capacity outage of x MW, calculate

$$Z_1 = \frac{x - M}{V}$$

$$Z_2 = \frac{x + M}{V}$$

According to the numerical value of Z_2, three cases are considered.

Case 1 If $Z_2 \leq 2.0$

Calculate two areas, Area 1 and Area 2, under the standard normal density function either from tables for the standard Gaussian distribution $N(Z)$ or from the equations given in Section 6.7.3 of *Engineering Systems*. The normal density function can be expressed as

$$N(Z) = \frac{1}{\sqrt{(2\pi)}} e^{-\frac{1}{2}Z^2}, \quad -\infty < Z < \infty$$

and the two areas are defined as

$$\text{Area } 1 = \int_{Z_1} N(Z)\,dZ$$

$$\text{Area } 2 = \int_{-\infty}^{-Z_2} N(Z)\,dZ = \int_{Z_2}^{\infty} N(Z)\,dZ$$

The probability of a capacity outage of x MW or more is given by

Prob[capacity outage $> x$ MW] = Area 1 + Area 2

Case 2 *If* $2 < Z_2 \leq 5.0$

Calculate Area 1 and Area 2 as in Case 1. In addition, calculate the following expressions

$$N^{(2)}(Z_i) = (Z_i^2 - 1)N(Z_i)$$

$$N^{(3)}(Z_i) = (-Z_i^3 + 3Z_i)N(Z_i)$$

$$N^{(5)}(Z_i) = -Z_i^5 + 10Z_i^3 - 15Z_i)N(Z_i)$$

$$K_i = G_1 - \frac{1}{6}N^{(2)}(Z_i) - \frac{G_2}{24}N^{(3)}(Z_i) - \frac{G_1^2}{72}N^{(5)}(Z_i)$$

where i takes on values of 1 and 2.

The probability of a capacity outage of x MW or more is given by

Prob[capacity outage $> x$ MW] = Area 1 + Area 2 + $K_1 + K_2$

Case 3 ***If*** $Z_2 > 5.0$

For this case only Area 1 of Case 1 is used as well as K_1 of Case 2. Area 2 and K_2 can be neglected since their numerical values are very small in this range. The required probability for a given x MW is given by

Prob[capacity outage $> x$ MW] = Area 1 + K_1

The technique described above for developing a capacity outage probability table of a given system has utilized the two-state representation of a generating unit. In situations in which a system has some derated units, the step-by-step procedure is still applicable with the first four expressions in Step 1 taking the form

$$m_1(i) = c_i q_i + \sum_{k=1}^{r} c_{ik} q_{ik}$$

$$m_2(i) = c_i^2 q_i + \sum_{k=1}^{r} c_{ik}^2 q_{ik}$$

$$m_3(i) = c_i^3 q_i + \sum_{k=1}^{r} c_{ik}^3 q_{ik}$$

$$m_4(i) = c_i^4 q_i + \sum_{k=1}^{r} c_{ik}^4 q_{ik}$$

where

q_i - FOR for a full capacity **outage**
q_{ik} = FORs for partial capacity states
c_{ik} = capacities of partial capacity states
r = number of derated states.

When a unit is added or removed from a capacity outage probability table, the new table can be developed using the same procedure after the new parameters M, V, G_1 and G_2 are obtained.

The Fourier transform method for developing the capacity outage probability table is illustrated using the five generator system given in Table 2.11. The numerical results are as follows.

Step 1 The quantities associated with this step are evaluated once, since the units are identical and the values are given below

m_1	m_2	m_3	m_4	V^2	M_3	M_4
0.40	16.0	640.0	25600.0	15.84	620.928	24591.3088

Step 2 The values of the different parameters associated with this step are shown below

M	V^2	M_3	M_4	G_1	G_2
2.0	79.2	3104.64	138010.88	4.4047724	19.0020406

Step 3 For a capacity outage of 40 MW, the values of Z_1 and Z_2 become 4.269932 and 4.719399 respectively. Since $2 < Z_2 < 5.0$, Case 2 applies. The values associated with the different expressions in this step are given below.

Area 1	$N(Z_1)$	$N^{(2)}(Z_1)$
0.9774×10^{-5}	0.43834×10^{-4}	0.7553615×10^{-3}
$N^{(3)}(Z_1)$	$N^{(5)}(Z_1)$	K_1
$-0.2851005 \times 10^{-2}$	-0.0309004	0.0111385
Area 2	$N(Z_2)$	$N^{(2)}(Z_2)$
0.1179×10^{-5}	0.58136×10^{-5}	0.123671×10^{-3}
$N^{(3)}(Z_2)$	$N^{(5)}(Z_2)$	K_2
-0.52878×10^{-3}	-0.791129×10^{-2}	0.0026413

Hence, the probability of a capacity outage of 40 MW or more is given by

$$\text{Prob[capacity outage} > 40\text{ MW]} = \text{Area 1} + \text{Area 2} + K_1 + K_2$$

$$= 0.0137908$$

Note that if the normal distribution [20] is used to approximate the discrete distribution of system capacity outages, the values are much lower than those obtained by the Fourier transform method. The value, for example, of the probability of a capacity outage of 40 MW or more was found to be 09774 x 10^{-5} (Area 1). The cumulative probabilities associated with the rest of the capacity outage states can be similarly obtained using the step-by-step procedure. The results obtained by the recursive and Fourier transform methods are shown in Table 2.9.

It can be seen from Table 2.9 that the values obtained using the Fourier transform method are quite different from those obtained using the recursive technique. This is due to the fact that the system under study has a very small number

Table 2.9

	Cumulative probability	
Capacity on outage (MW)	*Recursive method*	*Fourier transform method*
0.0	1.0	1.0
40.0	0.049009	0.0137883
80.0	0.9800×10^{-3}	0.105844×10^{-12}
120.0	0.900×10^{-5}	$0.2821629 \times 10^{-33}$

of generators. The main intention here is to illustrate the method. The accuracy of the Fourier transform method is to be compared with the recursive technique only when the system is sufficiently large. A comparison has been made for the IEEE–RTS and the results are shown in Appendix 2.

The Fourier transform method is efficient and easy to apply. It provides accurate results when compared with the basic recursive approach in systems with a large number of generating units and particularly when these units have relatively large forced outage rates [22]. It is therefore suited to systems containing a large number of fossil fired units. It can be quite inaccurate at certain outage levels in systems containing hydro units which have relatively low forced outage rates [23].

An alternative approach [24] is to transform the unit capacity tables into the frequency domain using fast Fourier transforms (FFT) and to convolve using a point by point multiplication. An inverse FFT algorithm can then be used to produce the final capacity outage probability table. This method, although not as fast as the previously described Fourier transform method, can be considerably faster than the direct recursive method. On the other hand, because it models the true discrete nature of the generating units, it does not suffer the significant disadvantages of the Fourier transform method and can be applied to both large and small systems alike with no loss of accuracy.

2.3 Loss of load indices

2.3.1 Concepts and evaluation techniques

The generation system model illustrated in the previous section can be convolved with an appropriate load model to produce a system risk index. There are a number of possible load models which can be used and therefore there are a number of risk indices which can be produced. The simplest load model and one that is used quite extensively is one in which each day is represented by its daily peak load. The individual daily peak loads can be arranged in descending order to form a cumulative load model which is known as the daily peak load variation curve. The resultant model is known as the load duration curve when the individual hourly load values arc used, and in this case the area under the curve represents the energy required in the given period. This is not the case with the daily peak load variation curve.

In this approach, the applicable system capacity outage probability table is combined with the system load characteristic to give an expected risk of loss of load. The units are in days if the daily peak load variation curve is used and in hours if the load duration curve is used. Prior to combining the outage probability table it should be realized that there is a difference between the terms 'capacity outage' and 'loss of load'. The term 'capacity outage' indicates a loss of generation which may or may not result in a loss of load. This condition depends upon the generating capacity reserve margin and the system load level. A 'loss of load' will occur only when the capability of the generating capacity remaining in service is exceeded by the system load level.

The individual daily peak loads can be used in conjunction with the capacity outage probability table to obtain the expected number of days in the specified period in which the daily peak load will exceed the available capacity. The index in this case is designated as the loss of load expectation (LOLE).

$$\text{LOLE} = \sum_{i=1}^{n} P_i(C_i - L_i) \quad \text{days/period} \tag{2.6}$$

where C_i = available capacity on day i.

L_i = forecast peak load on day i.

$P_i(C_i - L_i)$ = probability of loss of load on day i. This value is obtained directly from the capacity outage cumulative probability table.

This procedure is illustrated using the 100 MW system shown in Table 2.7. The load data for a period of 365 days is shown in Table 2.10.

Using Equation (2.6).

$$\begin{aligned}\text{LOLE} &= 12P(100-57) + 83P(100-52) + 107P(100-46) \\ &\quad + 116P(100-41) + 47P(100-34) \\ &= 12(0.020392) + 83(0.020392) + 107(0.000792) \\ &\quad + 116(0.000792) + 47(0.000792) \\ &= \underline{2.15108 \text{ days/year.}}\end{aligned}$$

Table 2.10 Load data used to evaluate LOLE

Daily peak load (MW)	57	52	46	41	34
No. of occurrences	12	83	107	116	47

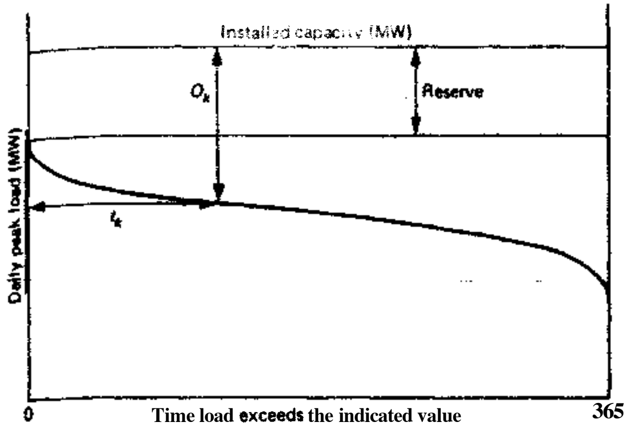

Fig. 2.4 Relationship between load, capacity and reserve
O_k Magnitude of the 4th outage in the system capacity outage probability table
t_k Number of time units in the study interval that an outage magnitude of O_k would result in a loss of load

The same LOLE index can also be obtained using the daily peak load variation curve. Figure 2.4 shows a typical system load–capacity relationship where the load model is shown as a continuous curve for a period of 365 days. A particular capacity outage will contribute to the system LOLE by an amount equal to the product of the probability of existence of the particular outage and the number of time units in the study interval that loss of load would occur if such a capacity outage were to exist. It can be seen from Fig. 2.4 that any capacity outage less than the reserve will not contribute to the system LOLE. Outages of capacity in excess of the reserve will result in varying numbers of time units during which loss of load could occur. Expressed mathematically, the contribution to the system LOLE made by capacity outage O_k is $p_k t_k$ time units where p_k is the individual probability of the capacity outage O_k. The total LOLE for the study interval is

$$\text{LOLE} = \sum_{k=1}^{n} p_k t_k \quad \text{time units} \tag{2.7}$$

The p_k values in Equation (2.7) are the individual probabilities associated with the capacity outage states. The equation can be modified to use the cumulative state probabilities. In this case

$$\text{LOLE} = \sum_{k=1}^{n} (t_k - t_{k-1}) P_k \tag{2.8}$$

Note P_k = cumulative outage probability for capacity state O_k.

If the load characteristic in Fig. 2.4 is the load duration curve, the value of LOLE is in hours. If a daily peak load variation curve is used, the LOLE is in days for the period of study.

The period of study could be a week, a month or a year. The simplest application is the use of the curve on a yearly basis. If no generating unit maintenance were performed, the capacity outage probability table would be valid for the entire period.

The effect of unit maintenance is discussed in Section 2.6. When using a daily peak load variation curve on an annual basis, the LOLE is in days per year. The reciprocal of this value in years per day is often quoted as a reliability index. The use of this reciprocal value has led to considerable confusion, particularly among people who are not aware of the true meaning. The days/year result is simply a mathematical expectation of load loss in time units for the period under study which indicates the average number of days during which a loss of load will be encountered. It must be stressed that it has neither a frequency nor duration connotation.

2.3.2 **Numerical examples**

(a) *Basic study*

The application of Equations *(1.1)* and (2.8) can be illustrated by a simple numerical example.

Consider a system containing five 40 MW units each with a forced outage rate of 0.01. The capacity outage probability table for this system is shown in Table 2.11.

Probability values less than 10^{-6} have been neglected. The system load model is represented by the daily peak load variation curve shown in Fig. 2.5. This is assumed to be linear in order to simplify hand calculations, although such a linear representation is not likely to occur in practice.

The study period in this case is assumed to be a year and therefore 100% on the abscissa corresponds to 365 days. In many studies, weekends and holidays are neglected as their contribution to the LOLE is negligible. The time span is then

Table 2.11 Generation model for the five-unit system.
System installed capacity = 200 MW

Capacity out of service	*Individual probability*	*Cumulative probability*
0	0.950991	1.000000
40	0.048029	0.049009
80	0.000971	0.000980
120	0.000009	0.000009
	1.000000	

Table 2.12 LOLE using individual probabilities

Capacity out of service (MW)	Capacity in service (MW)	Individual probability	Total time t_k (%)	LOLE
0	200	0.950991	0	—
40	160	0.048029	0	—
80	120	0.000971	41.7	0.0404907
120	80	0.000009	83.4	0.0007506
		1.000000		0.0412413

approximately 260 days. The forecast peak load for this system is 160 MW, which corresponds to the 100% condition on the ordinate. The LOLE can be found using either the individual capacity outage probabilities or using the cumulative values. Both methods are illustrated in this example. Table 2.12 shows the calculation using Equation (2.7). The time periods t_k are shown in Fig. 2.6.

The LOLE is 0.0412413% of the time base units. Assuming a 365 day year, this LOLE becomes 0.150410 days or 6.65 years per day. The abscissa and hence the total time t_k could have been in days rather than in percent and identical results obtained.

If the cumulative probability values are used, the time quantities used are the interval or increases in curtailed time represented by T_k in Fig. 2.6. The procedure is shown in Table 2.13.

The LOLE of 0.0412413% is identical to the value obtained previously. Both techniques are shown simply to illustrate that either approach will provide the same result.

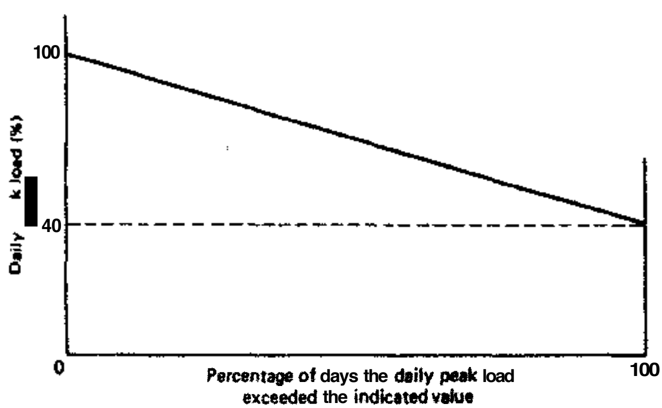

Fig. 2.5 Daily peak load variation curve

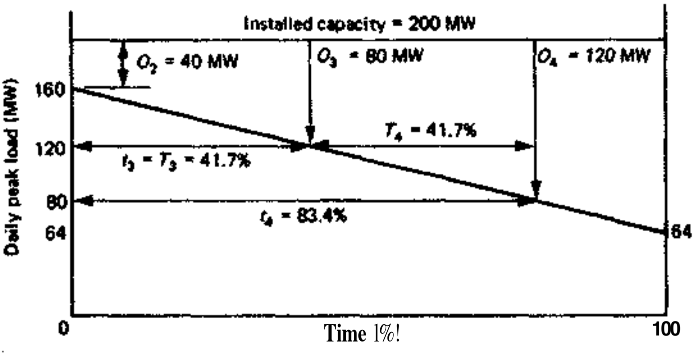

Fig. 2.6 Time periods during which loss of load occurs

(b) *Sensitivity studies*

The system peak load in the above example is 160 MW. Table 2.14 shows the variation in risk as a function of the peak load. The load characteristic for each forecast peak load is that shown in Fig. 2.5. The LOLE is calculated on an annual basis assuming 365 days in the year.

These results can best be displayed in the form of a graph using semi-logarithmic paper as shown in Fig. 2.7.

The system risk for a given capacity composition and forecast peak load is dependent upon the unavailability values for the individual units. This effect is illustrated in Table 2.15. The LOLE values for a range of peak load levels are shown as a function of the unit forced outage rates using the system of Table 2.11.

The system used in this example is very small and therefore the effect of generating unit unreliability is quite pronounced. This effect can also be quite considerable in a big system if the large units have high forced outage rates. This is shown in Fig. 2.8. The system in this case has a total installed capacity of 10100 MW. The largest units have 300 MW and 500 MW capacities and their forced outage rates have been varied as shown. The risk profile as a function of peak load

Table 2.13 LOLE using cumulative probabilities

Capacity out of service (MW)	*Capacity in service (MW)*	*Cumulative probability*	*Time interval T_k (%)*	*LOLE*
0	200	1.000000	0	—
40	160	0.049009	0	—
80	120	0.000980	41.7	0.0408660
120	80	0.000009	41.7	0.0003753
				0.0412413%

Table 2.14 Sensitivity study results

System peak had (MW)	LOLE (days/year!)	LOLE (yean/day)
200.0	6.083	0.16
190.0	4.837	0.21
180.0	3.447	0.29
170.0	1.895	0.53
160.0	0.1506	6.64
150.0	0.1208	8.28
140.0	0.08687	11.51
130.0	0.04772	20.96
120.0	0.002005	498
110,0	0.001644	608
100.0	0.001210	826

is almost a straight line in Fig. 2.8 as compared to the characteristic shown in Fig. 2.7. A large system with a wide range of unit sizes has a more continuous capacity outage probability table resulting in a smoother risk profile. It can however be perturbed by the addition of a relatively large unit. This point is discussed in Section 2.5.

The system peak load carrying capability (PLCC) can be determined as a function of the risk level. In the system shown in Fig. 2.8 the PLCC at a risk level of 0.1 days/year is 9006 MW for forced outage rates of 0.04. Table 2.16 shows the change in PLCC for FOR values from 0.04 to 0.13. The decrease in PLCC is 815 MW. If the forecast peak load is 9000 MW and the forced outage rates of the large

Table 2.15 Effect of FOR and system peak load

System peak load (MW)	System risk level, Unit FOR 0.01	ft 02	0.03	0.04	0.05
200.0	6.083	12.165	18.247	24.330	30.411
190.0	4.834	9.727	14.683	19.696	24.764
180.0	3.446	7.024	10.729	14.556	18.502
170.0	1.895	3.998	6.304	8.804	11.494
160.0	0.150	0.596	1.328	2.337	3.614
150.0	0.121	0,480	1.073	1.894	2.939
140.0	0.087	0.347	0.781	1.388	2.167
130.0	0.048	0.194	0.445	0.805	1.278
120.0	0.002	0.016	0.053	0.124	0.240

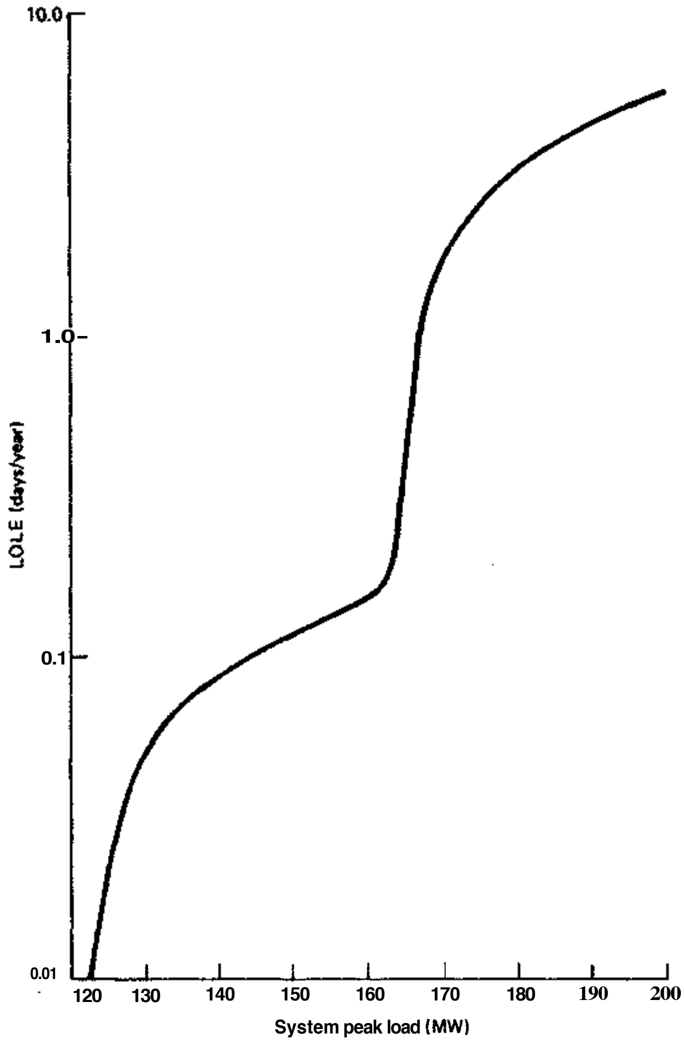

Fig. 2.7 Variation in risk with system peak load

units are 0.13, then this system would have to install approximately 1000 MW additional capacity to satisfy a risk level of 0.1 days/year. At a nominal \$1000/kW installed this would cost approximately 10^9 dollars. The consequences of unit unavailability in terms of additional capacity can be seen quite clearly in this example [25]. Additional penalties in the form of expected energy replacement costs are illustrated in Reference [26].

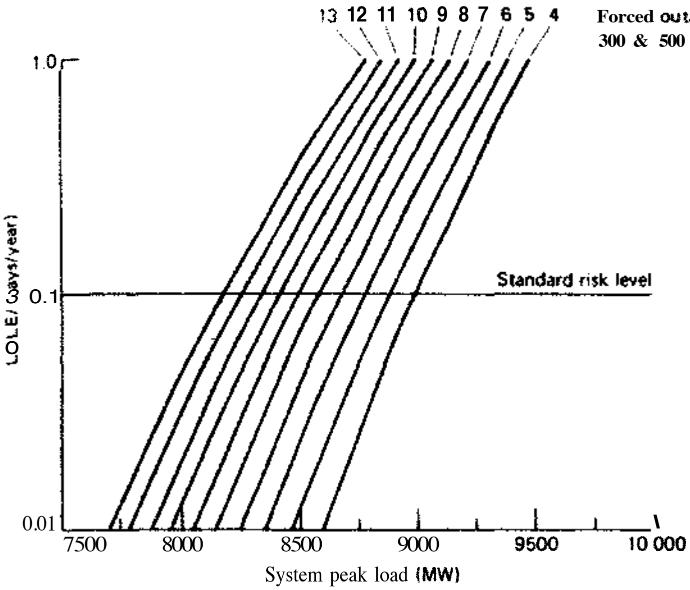

Fig. 2.8 LOLE as a function of unit FOR

Additional investment in terms of design, construction, reliability, maintainability and spare parts provisioning can result in improved generating unit unavailability levels. The worth of the improvement must be appraised on a total system basis and compared with the cost of attaining it.

Table 2.16 **Changes in PLCC**

Forced outage rate (%)	*Peak load carrying capability (MW)*	*Difference (MW)*	*Cumulative difference (MW)*
4	9006	—	—
5	8895	111	111
6	8793	102	213
1	8693	100	313
8	8602	91	404
9	8513	89	493
10	8427	86	579
11	8345	82	661
12	8267	78	739
13	8191	76	815

2.4 Equivalent forced outage rate (EFOR)

Data collection is an essential constituent of reliability evaluation, and utilities throughout the world have recorded the operational history of their units for many years. These data are then either stored in-house by the utility or processed by a central organization such as the Edison Electric Institute (EEI) who regularly publish data on generating unit reliability. Data in North America are now collected and disseminated by the CEA and NERC. The data collected for generating units usually involves the monitoring of residence times for each of the recorded output levels of the unit. This process may therefore recognize many derated states. It is not necessary or even feasible to accommodate a large number of such states and in practice these can be reduced to a very limited number using a weighted-averaging method using the same concept as rounding, which was discussed in Section 2.2.2. In the limit the number of states can be reduced to two; the up state and the down state and all others are weighted into these two states. This leads to the concept known as 'equivalent forced outage rate' or EFOR, which is sometimes defined as the equivalent probability of finding a unit on forced outage at some distant time

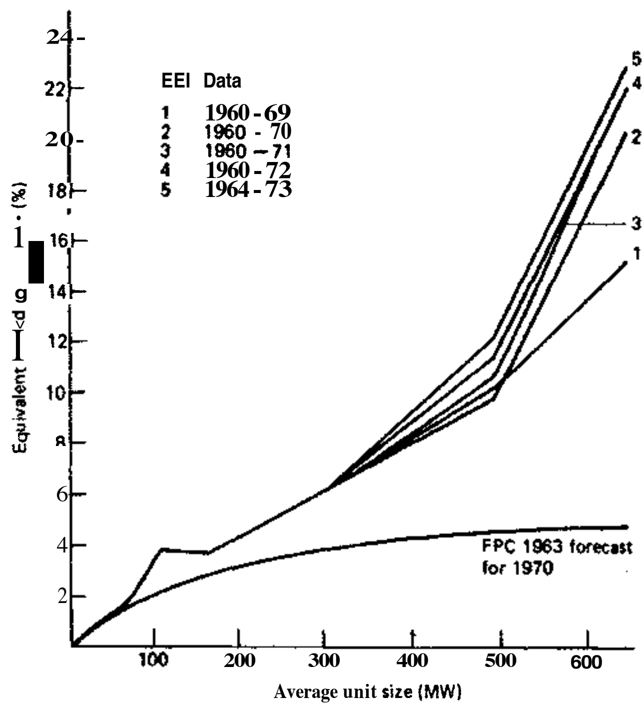

Fig. 2.9 EFOR as a fcnction of unit size

in the future. The evaluation method of EFOR is given in References [16] and [27].

Generating unit unavailability levels have historically increased as unit sizes increase. Figure 2.9 shows the variation in equivalent forced outage rate (EFOR) as a function of fossil fired unit sizes using a series of Edison Electric Institute data. [t can be seen that the EFOR increases dramatically with unit size.

The use of the word equivalent tends to imply that the two-state representation has the same impact as the multi-state representation when utilized in capacity evaluation studies. This is not the case, as the EFOR representation gives a pessimistic appraisal of system reliability by grouping weighted derated state residence times into the full forced outage state. The Canadian Electrical Association has chosen to call this statistic the derated adjusted forced outage rate (DAFOR) to avoid the connotation of equivalence. The effect of using a multi-state representation and an EFOR representation in a practical system study is shown in Fig. 2.10.

Figure 2.10 illustrates that the use of a two-state representation for units which do have significant derated states can result in considerable inaccuracy. These units should be modelled with at least three states.

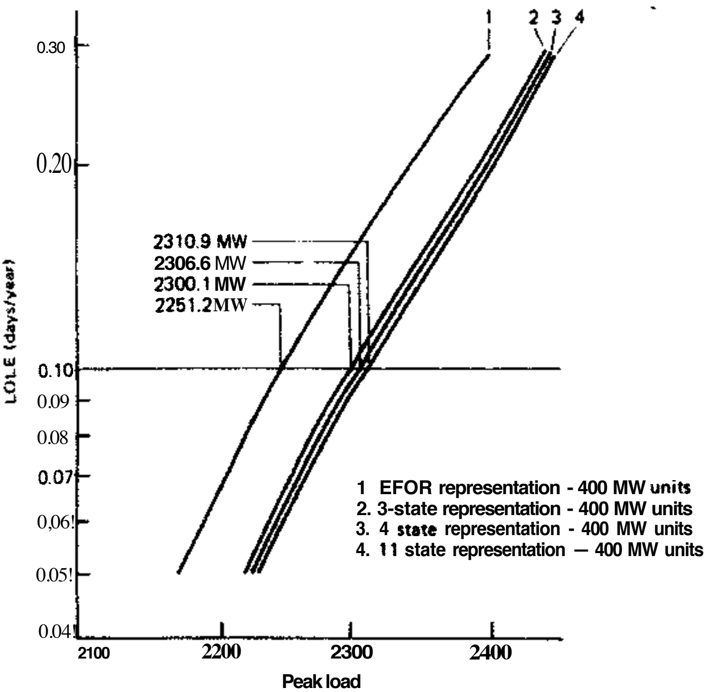

Fig. 2.10 Effect of 2, 3, 4 and 11 state models on load-carrying capability [28]

2.5 Capacity expansion analysis

2.5.1 Evaluation techniques

The time period required to design, construct and commission a large generating station can be quite extensive (5 to 10 years) depending on the environmental and regulatory requirements. It therefore becomes necessary to determine the system requirements considerably in advance of the actual unit in-service date. The actual load at an extended time in the future is also uncertain and should be considered as a random variable. This aspect is discussed in Section 2.8.

The concept of capacity expansion analysis can be illustrated using the system with five 40 MW units, described in Table 2.11. Assume that it has been decided to add additional 50 MW units with forced outage rates of 0.01 to meet a projected future load growth of 10% per year. The question is—in what years must the units be committed in order to meet the accepted system risk level? The change in risk level with the sequential addition of 50 MW units is shown in Table 2.17 for a range of system peak loads. The LOLE is in days for a 365-day year. The load characteristic is the daily peak load variation curve using a straight line from the 100% to 40% points.

The results in Table 2.17 can again be displayed in the form of a graph as shown in Fig. 2.11.

The annual peak load for each of the next eight years is shown in Table 2.18.

Table 2.17 LOLE in generation expansion

System peak load (MW)	LOLE (days/year)			
	200 MW capacity	*250 MW capacity*	*300 MW capacity*	*350 MW capacity*
100.0	0.001210	—	—	—
120.0	0.002005	—	—	—
140.0	0.08686	0.001301	—	—
160.0	0.1506	0.002625	—	—
180.0	3.447	0.06858	—	—
200.0	6.083	0.1505	0.002996	—
220.0	—	2,058	0.03615	—
240.0	—	4.853	0.1361	0.002980
250.0	—	6.083	0.1800	0.004034
260.0	—	—	0.6610	0.01175
280.0	—	—	3.566	0.1075
300.0	—	—	6.082	0.2904
320.0	—	—	—	2.248
340.0	—	—	—	4.880
350.0	—	—	—	6.083

Sfthe assumption that an installed capacity of 200 MW is adequate for a system peak load of 160 MW, then the risk criterion is 0.15 days/year. This risk level can be used to measure the adequacy of the system capacity in the successive years. It must be realized that any risk level could have been selected. The actual choice is a management decision. Using the criterion of 0.15 days/year, the timing of unit additions can be obtained using Fig. 2.11. This expansion is shown in Table 2.19.

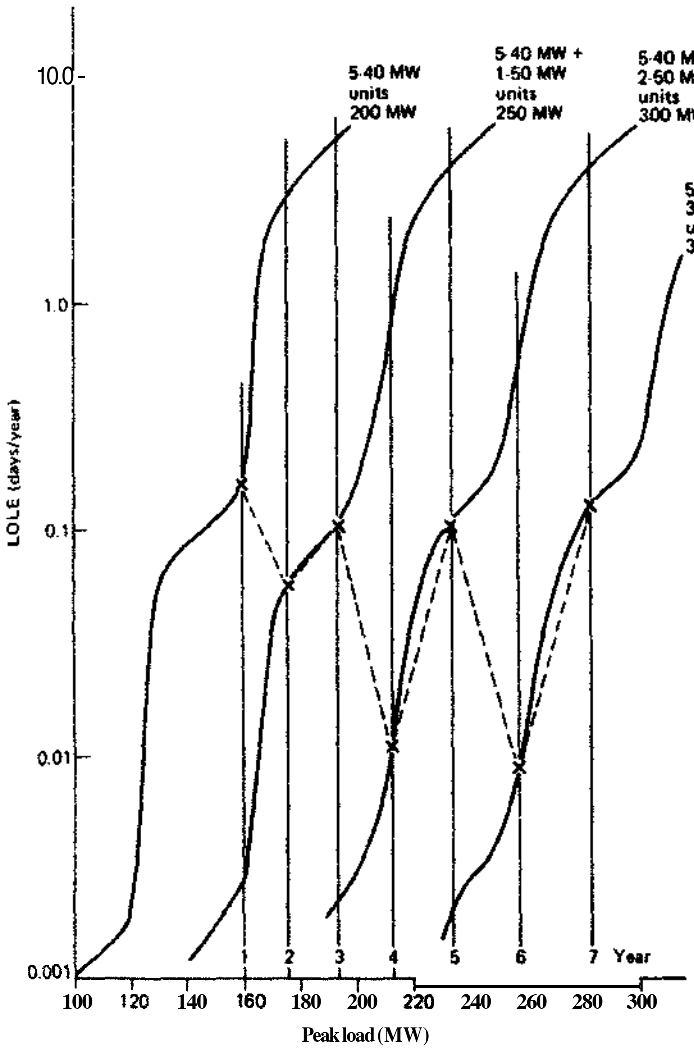

Fig. 2.11 Variation in risk with unit additions

Table 2.18 Load growth at 10% p.a.

Year number	*Forecast peak load (MW)*
1	160
2	176
3	193.6
4	213.0
5	234.3
6	257.5
7	283.1
8	311.4

The 50 MW unit additions would have to be made in years 2, 4 and 6. The variation in annual risk level is shown by the dotted line in Fig. 2.11. This particular expansion study represents a somewhat idealized case. The present worth of this particular scheme would have to be compared with others to determine the optimum expansion pattern for the system. The expansion study should cover a sufficiently long period into the future in order to establish a realistic present worth evaluation and to minimize perturbation effects (see Section 2.5.2). Theoretically this should extend to infinity; however, in practice a period of twenty to thiny years is usually adequate. The generation expansion plan can, and probably will, be varied as real time is advanced.

2.5.2 Perturbation effects

Large capacity unit additions often appear to be economically advantageous due to the so-called 'economy of scale'. Large units generally have relatively low cost per

Table 2.19 Generation expansion results

Year	*Unit added (MW)*	*System capacity (MW)*	*Peak load (MW)*	*LOLE (days/year)*
1	—	200	160.0	0.15
2	—	200	176.0	2.9
	50	250	176.0	0.058
3	—	250	193.6	0.11
4	—	250	213.0	0.73
	50	300	213.0	0.011
5	—	300	234.3	0.11
6	—	300	257.4	0.55
	50	350	257.4	0.009
7	—	350	283.1	0.125
8	—	350	311.4	0.96

Table 2.20 IPLCC for five-unit system

System capacity (MW)	Allowable peak load (MW)	Increase in peak load carrying capability (MW)	
		Individual	Cumulative
(5 × 40) = 200	144	0	0
(5 × 40) + (1 x 50) = 250	186	42	42
(5 x 40) + (2 x 50) = 300	232	46	88
(3 x 40) + (3 × 50) = 350	279	47	135

kW installed and better heat rates than smaller capacity units. Economic evaluation of alternative sizes should, however, include the impact on the system reliability of adding a relatively large unit to the overall system. This effect can be seen in terms of the increased system peak load-carrying capability (IPLCC) due to unit additions. Using Fig. 2.11, the IPLCC can be determined for each 50 MW unit addition at a specified risk level. Table 2.20 shows the individual unit and cumulative IPLCC values for each 50 MW unit at a system risk level of 0.1 days/year.

The 50 MW units added to the system in this case are not much larger than the 40 MW units already in the system and therefore they do not create a large perturbation. The effect of adding relatively large units to a system can be seen by adding the 50 MW units to a system with the same initial 200 MW of capacity but with a different unit composition.

Consider a system composed of 10–20 MW units each with a forced outage rate of 0.01. The total installed capacity in this case is 200 MW and would require the same reserve capacity as the 5 x 40 MW unit system using the percentage reserve criterion. The loss of the largest unit criterion would dictate that the 5 x 40 MW unit system could carry a peak load of 160 MW while the 20 x 10 MW unit system could carry a 190 MW peak load. Note that neither criterion includes any consideration of the actual load shape. Table 2.21 shows the individual unit and cumulative IPLCC values for each 50 MW unit addition to the 20 x 10 MW unit system at a system risk level of 0.1 days/year.

Table 2.21 IPLCC for 20-unit system

System capacity (MW)	Allowable peak load (MW)	Increase in peak load carrying capability (MW)	
		Individual	Cumulative
(20x40) =200	184	0	0
(20 x 10) + (1 x 50) = 250	202	18	18
(20 x 10) + (2 x 50) = 300	250	48	66
(20 x 10) + (3 x 50) = 350	298	48	114

The initial load-carrying capability of the two systems are considerably different as the system with the smaller units can carry a much higher peak load. The first 50 MW unit addition creates a considerable perturbation in this system and results in an IPLCC of only 18 MW. The second unit appears to create an IPLCC of 48 MW. It may be better, however, to think in terms of the cumulative value of 66 MW created due to the addition of the two 50 MW units. Relatively large units cannot be easily added to small systems or to systems composed of relatively small units without a significant initial PLCC penalty. This penalty will diminish as additional units are added and the basic system composition changes. This is one reason why unit additions must be examined in terms of an expansion plan and considered over a reasonable time period rather than on a single year or single unit addition basis.

This effect is further accentuated if the unit forced outage rate is increased in the first few years to accommodate a break-in or infant mortality period. A common utility practice is to double the unit forced outage rate for the first two years, particularly if the unit size or type is significantly different from others in the system and little experience is available. The utilization of probability techniques even in the relatively simple form of LOLE evaluation permits the factors that do influence the system reliability to be included in the analysis and gives proper weight to unit sizes and outage rates and to the system load characteristic.

2.6 Scheduled outages

The system capacity evaluation examples previously considered assumed that the load model applied to the entire period and that the system capacity model was also applicable for the entire period. This will not be the case if units are removed from service for periodic inspection and maintenance in accordance with a planned program. During this period, the capacity available for service is not constant and

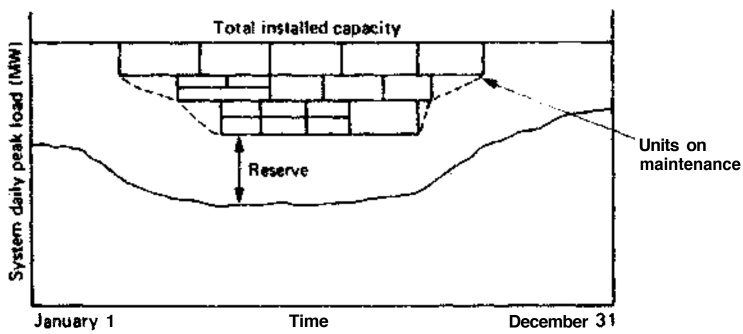

Fig. 2.12 Annual load and capacity model

therefore a single capacity outage probability table is not applicable. Figure 2.12 shows a hypothetical example of a maintenance schedule for a winter peaking system.

The annual $LOLE_a$ can be obtained by dividing the year Into periods and calculating the period $LOLE_p$ values using the modified capacity model and the appropriate period load model. The annual risk index is then given by

$$LOLE_a = \sum_{p=1}^{n} LOLE_p \tag{2.9}$$

The modified capacity model can be obtained by creating a new capacity outage probability table for each capacity condition. The unit removal algorithm illustrated by Equations (2.3) and (2.4) can be used in this case. The total installed capacity may also increase during the year due to the commissioning of a new unit. This can also be added to the capacity model in the appropriate periods. If the actual in-service date of the new unit is uncertain, it can be represented by a probability distribution and incorporated on a period basis using the following equation.

$$LOLE_p = (LOLE_{pa})a + (LOLE_{pu})u \tag{2.10}$$

where $LOLE_p$ = period LOLE value
$LOLE_{pa}$ = period LOLE value including the unit
$LOLE_{pu}$ = period LOLE value without the unit
a = probability of the unit coming into service
u = probability of the unit not coming into service.

The unit still has the opportunity to fail given that it comes into service. This is included in the $LOLE_{pa}$ value. The annual risk index is then obtained using Equation (2.9).

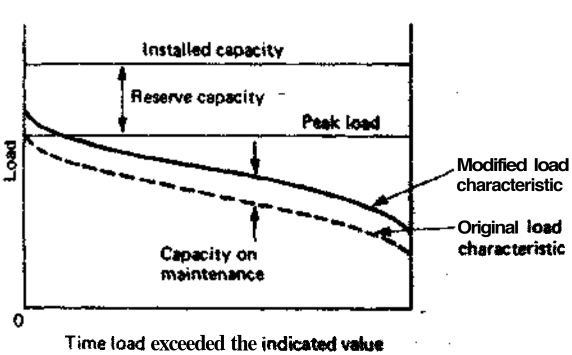

Fig. 2.13 **Approximate method of including maintenance**

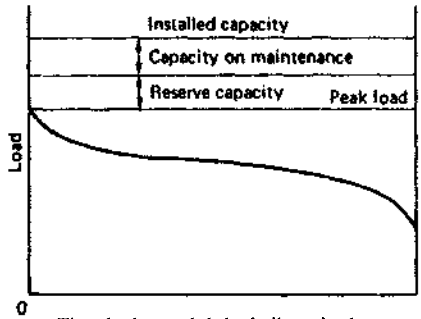

Fig. 2.14 Capacity reduction due to maintenance

Maintenance has been considered by some authors as indicated in Fig. 2.13 by adding the capacity on maintenance to the load and using a single capacity outage probability table.

The approach shown in Fig. 2.13 gives the same results as that of Fig. 2.14, in which the original capacity outage probability table is used, but the total available capacity is reduced by the quantity on outage.

Both of these methods are approximations because the state probabilities in the generation model are unaltered and therefore do not really relate to the system during maintenance.

The most realistic approach is to combine the units actually available to the system into a capacity outage probability table applicable for the period considered as described above. Practical system studies using the approximate methods and the realistic method indicate that adding the capacity on maintenance to the load or subtracting it from the installed capacity without altering the outage probabilities results in higher calculated risk levels and that the error increases with increased maintenance capacity. This error may be negligible in a large system in which the capacity on maintenance is an extremely small percentage of the total installed capacity. Removing units on maintenance from the capacity outage probability table results in negligible error for normal magnitudes of capacity on maintenance for those cases when the units removed are not exact multiples of the rounding increment used in the table.

If the maintenance is scheduled either to minimize [38] risk or in accordance with a constant risk criterion then the reserve shown in Fig. 2.12 may be quite variable. It is important to realize that constant reserve is not the same as constant risk. The system is clearly not as reliable if a unit with a low forced outage rate is removed from service when compared with the situation in which a similar capacity unit with a high forced outage unit is removed from service.

There are a number of approximate techniques for scheduling maintenance. One approach is to reduce the total installed capacity by the expected capacity loss (i.e. the product of the unit capacity and its availability) rather than by the actual unit capacity and then schedule maintenance on a constant reserve basis. A better approach, and one that is often quite accurate if only a few units are on maintenance at any given time, is to determine the decrease in PLCC at the appropriate risk level for each individual unit on maintenance and then use these values in scheduling maintenance on a constant reserve basis. The applicable approach will depend on the capacity composition, the required maintenance level and the system load profile.

2.7 Evaluation methods on period bases

The basic LOLE approach is extremely flexible in regard to the extent to which load models and maintenance considerations can be incorporated. This flexibility also dictates the necessity to thoroughly understand the modelling assumptions used prior to quoting and comparing risk indices for different systems. This important point can be appreciated by considering the following three ways in which the LOLE method can be used to determine an annual risk index:

(a) monthly (or period) basis considering maintenance;
(b) annual basis neglecting maintenance;
(c) worst period basis.

In the monthly approach and assuming constant capacity for the period, the appropriate capacity outage probability table is combined with the corresponding load characteristic. If the capacity on maintenance is not constant during the month, the month can be divided into several intervals during which the capacity is constant. The capacity outage probability table, modified by removing the units on maintenance for each separate interval, can be combined with the monthly peak and a load characteristic using the interval as its time base. This method assumes that the normalized monthly load characteristic holds for any portion of a month and that the monthly peak can occur on any day during the period. The total risk for the month is obtained by summing the interval values. The annual risk is the sum of the twelve monthly risks.

In the annual approach neglecting maintenance, the annual forecast peak and system load characteristic are combined with the system capacity outage probability table to give an annual risk level. The basic assumption in this approach is that a constant capacity level exists for the entire period. The justification for this assumption is dependent upon the time of generating unit additions, the planned maintenance and the monthly load levels relative to the annual peak. If the year can be divided into a peak load season and a light load season, the planned maintenance may be scheduled entirely in this latter period. The contribution of the light load season to the annual risk may be quite low and therefore the assumption of a constant capacity level is justified. The relative period risk contributions for any particular system should be examined before adopting this approach.

In some cases, the load level in a particular season or even month may be so high that this value dominates the annual figure. A reliability criterion for such a system can be obtained using only this 'worst period' value. A study of the Saskatchewan and Manitoba Systems indicated that the month of December generally constitutes the highest monthly risk period. An annual risk figure can be obtained by multiplying the December value by twelve. This approach assumes twelve possible Decembers in a year and is designated the '12 December basis'.

Computing risk levels on a monthly basis considering maintenance can be quite laborious, especially when the maintenance capacity is not constant during a month. This approach can be used to determine if the risk levels for specific maintenance periods exceed a specified amount. This condition can be studied by comparing the risk levels for each of the maintenance intervals converted to a common time base (for example 365 days). If the expectation for a period of ten days is 0.001 hours, then 0.001 x 36.5 = 0.0365 hours is the expectation on an annual basis. This technique is necessary to avoid the tendency to assume that for a particular interval, a low expected value indicates little risk. The low value may be due to the interval itself being very small and not due to having a high reserve capacity margin.

In planning unit additions where risk levels for different years are to be compared, the 'annual basis neglecting maintenance' or the '12 worst months basis' are the simplest methods and generally provide satisfactory results. The '12 worst months basis' cannot be used to compare the risk levels in two different systems with different annual load characteristics. This approach is only consistent when applied continually to the same system.

The above approaches are not exhaustive and various alternatives are possible. It should be stressed, however, that the risk index evaluated depends on the approach used and therefore risk indices of different utilities are not necessarily comparable [29]. This is not a point of concern provided the approach used by a given utility is consistent.

2.8 Load forecast uncertainty

(a) *Method 1*

In the previous sections of this chapter it has been assumed that the actual peak load will differ from the forecast value with zero probability. This is extremely unlikely in actual practice as the forecast is normally predicted on past experience. If it is realized that some uncertainty can exist, it can be described by a probability distribution whose parameters can be determined from past experience, future load modelling and possible subjective evaluation.

The uncertainty in load forecasting can be included in the risk computations by dividing the load forecast probability distribution into class intervals, the number of which depends upon the accuracy desired. The area of each class interval represents me probability the load is the class interval mid-value. The LOLE is computed for each load represented by the class interval and multiplied by the probability that that load exists. The sum of these products represents the LOLE for the forecast load. The calculated risk level increases as the forecast load uncertainty increases.

It is extremely difficult to obtain sufficient historical data to determine the distribution describing the load forecast uncertainty. Published data, however, has suggested that the uncertainty can be reasonably described by a normal distribution. The distribution mean is the forecast peak load. The distribution can be divided into a discrete number of class intervals. The load representing the class interval mid-point is assigned the designated probability for that class interval. This is shown in Fig. 2.15, where the distribution is divided into seven steps. A similar approach can be used to represent an unsymmetrical distribution if required. It has been found that there is little difference in the end result between representing the distribution of load forecast uncertainty by seven steps or forty-nine steps. The error is, however, dependent upon the capacity levels for the system.

The computation of the LOLE considering load forecast uncertainty is shown for a small hypothetical system in the following example.

The system consists of twelve 5 MW units, each with a forced outage rate of 0.01. The capacity model is shown in Table 2.22. The forecast peak load is 50 MW, with uncertainty assumed to be normally distributed using a seven-step approximation (Fig. 2.15). The standard deviation is 2% of the forecast peak load. The monthly load–duration curve is represented by a straight line at a load factor of 70%. The LOLE calculation is shown in Table 2.23.

The LOLE increased from 0.025240 with no load forecast uncertainty to 0.07839425 with 2% uncertainty. The index in this case is in hours/month. Load forecast uncertainty is an extremely important parameter and in the light of the financial, societal and environmental uncertainties which electric power utilities

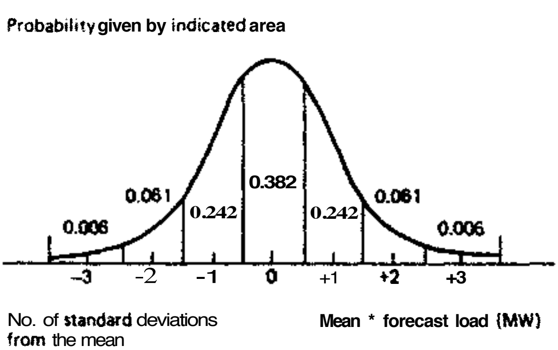

Fig. 2.15 Seven-step approximation of the normal distribution

Table 2.22 Generation model

Capacity on outage (MW)	*Cumulative probability*
0	1.00000000
5	0.11361513
10	0.00617454
15	0.00020562
20	0.00000464
25	0.00000007

(Probability values less than 10^{-8} are neglected.)
Period = 1 month = 30 days = 720 hours
Forecast load = mean = 50 MW
Standard deviation (2%) = 50 x 2/100 = 1 MW

face may be the single most important parameter in operating capacity reliability evaluation. In the example shown in Table 2.23, the risk was evaluated for each peak load level. The seven individual values were then weighted by the probability of existence of that peak load level. The final LOLE is actually the expected value of a group of loss of load expectations.

(b) *Method 2*

The LOLE value including uncertainty can be found using a somewhat different approach. The load characteristic can be modified to produce a load profile which includes uncertainty. This single load characteristic can then be combined with the capacity outage probability table to compute the LOLE index. If the uncertainty is fixed at some specified value and the load shape remains unchanged, then the modified load curve can be used for a range of studies with a considerable saving

Table 2.23 LOLE results

(1) Number of standard deviations from the mean	*(2) Load (MW)*	*(3) Probability of the load in Col. (2)*	*(4) LOLE (hours/month) for the load in Col. (2)*	*(3) x (4)*
-3	47	0.006	0.01110144	0.00006661
-2	48	0.061	0.01601054	0.00097664
-1	49	0.242	0.02071927	0.00501406
0	50	0.382	0.02523965	0.00966679
+1	51	0.242	0.17002797	0.04114677
+2	52	0.061	0.30924753	0.01886410
+3	53	0.006	0.44321350	0.00265928
			Total	0.07839425

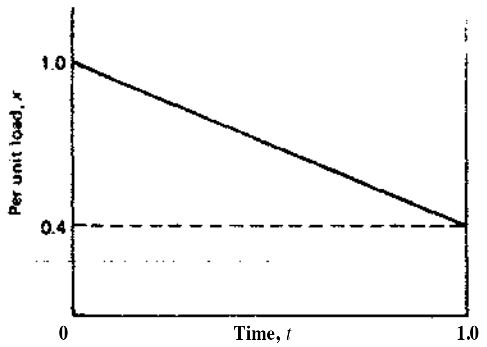

Fig. 2.16 Monthly load-duration curve in per unit

in computer time. This procedure is illustrated using the previous example. The load model used in the example is a monthly load–duration curve represented by a straight line at a load factor of 70% as shown in Fig. 2.16. This is a simplification of a real load–duration curve and in practice the following analysis needs modifying so that either the non-linear equation of the load curve is convolved or the load curve is segmented into a series of straight lines.

The equation for this line is

$$t = \frac{10}{6}(1 - x)$$

if

X = load in MW
L = forecast peak load
$x = X/L$.

The load forecast uncertainty is represented by a seven-step approximation to the normal distribution as shown in Fig. 2.15. The standard deviation of this distribution is equal to 2% of the forecast peak load. In the case of a 50 MW peak this corresponds to 1 MW. There are therefore seven conditional load shapes as shown in Fig. 2.17, each with a probability of existence. Consider two examples of the seven conditional load shapes:

At a peak level of 47 MW,

$$t_1 = \frac{10}{6}\left(1 - \frac{X}{47}\right) \quad \text{for } 0 \le X \le 47$$

which exists with a probability of 0.006.

At a peak load level of 50 MW,

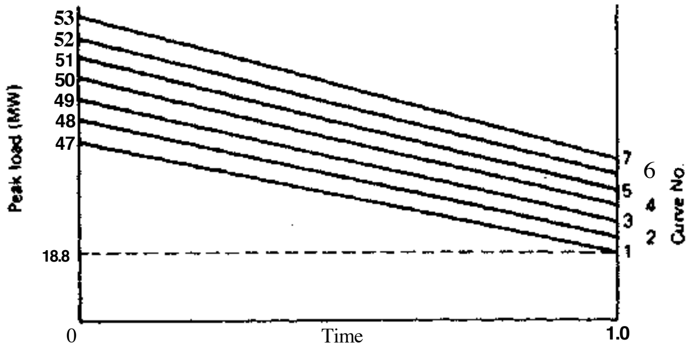

Fig. 2.17 Conditional load–duration curves

$$t_4 = \frac{10}{6}\left(1 - \frac{X}{50}\right) \quad \text{for } 0 \le X \le 50$$

which exists with a probability of 0.382.

The modified load–duration curve is now composed of a group of conditional segments as shown in Fig. 2.18. The evaluation of four of these segments is shown below; the remaining segments can be evaluated similarly.

For Segment 1 $t = 1.0$ for $0 < X < 18.8$

For Segment 2 $t = 0.006t_1 + 0.061t_2 + 0.242t_3$

$0.382t_4 + 0.242t_5 + 0.061t_6$

$0.006t_7$ for $18.8 \le X \le 47$

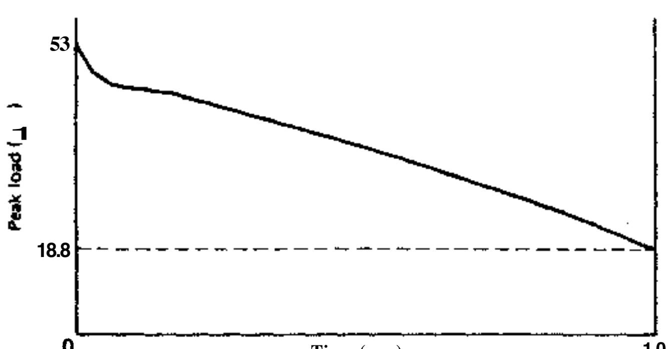

Fig. 2.18 Modified load–duration curve

Table 2.24 *LOLE* results

Capacity Out	*(MW) In*	*Individual probability*	*Time (pu)*	*Expectation*
0	60	0.8863848717	—	—
5	55	0.1074405905	—	—
10	50	0.0059689217	0.0123847909	0.0000739239
15	45	0.0002009738	0.1661845138	0,0000333987
20	40	0.0000045676	0.3330899382	0.0000015214
25	35	0.0000000738	0.4999453626	0.0000000369
				0.0001088809

For Segment 7 $t = 0.061t_6 + 0.006t_7$ for $51 \leq X \leq 52$

For Segment 8 $t = 0.006t_7$ for $52 \leq X \leq 53$

The modified load–duration curve of Fig. 2.18 is shown in terms of MW of peak load. It can also be expressed in percentage or per unit of the forecast peak load and used with any forecast peak assuming the basic characteristic and uncertainty remains constant. The LOLE calculation is shown in Table 2.24.

The LOLE in hours/month = 0.0001088809 x 30 x 24 = 0.07839425. This value is that shown in Table 2.23. In order to illustrate the evaluation of the time values shown in Table 2.24, consider as an example the value at the 50 MW capacity level which corresponds to Segment 6:

$$t = 0.242t_5 + 0.061t_6 + 0.006t_7$$

$$= (0.242\text{X}0.0326797) + (0.061)(0.0641026) + (0.006)(0.0943396)$$

$$= \underline{0.0123847909}$$

where, for example,

$$t_5 = \tfrac{10}{6}\left(1 - \frac{X}{51}\right) [=0.0326797386$$

The concept of conditional load curves leading to a modified curve is a useful technique which can be used in certain cases to save computation time in repetitive studies. If applicable, the modified curve can be used as input data in further studies. This idea is used in Section 2.10 as a load modification technique in loss of energy studies and production cost calculations.

2.9 Forced outage rate uncertainty

The loss of load expectation as computed using the techniques illustrated earlier in this chapter assumes that the generating unit unavailability parameters are single point values. In actual fact these parameters are usually single point best estimates based upon the available data and future forecasts. There is therefore considerable uncertainty in these parameters which creates uncertainty in the calculated LOLE parameter. The actual distribution associated with the calculated LOLE can be obtained by Monte Carlo simulation. If the uncertainty associated with the unit unavailabilities is considered to be normally distributed, then the resultant LOLE uncertainty can be considered to be normally distributed. In all other cases, an exact solution is analytically intractable and simulation must be used. The uncertainty associated with unit unavailability was first considered in Reference [30]. The effect of uncertainty in unit unavailability on LOLE and uncertainty in the unit failure rate on spinning reserve requirements were first considered in Reference [31] using an upper bound confidence limit approach. The combination of the actual unit uncertainties was first considered in Reference [32] and the technique was extended in subsequent publications [33, 34]. The basic approach is to calculate the conventional capacity outage probability table using the conventional recursive equations and also compute the variance associated with the cumulative probability at each capacity level. This involves the successive determination of the covariance matrix associated with each unit capacity addition. The final capacity outage probability table and its covariance matrix can be combined with the load model to obtain the expected value for the calculated LOLE and its variance. The calculation and storage of the covariance matrix can become cumbersome in a large system arid an approximate technique has been developed [34]. Both the exact and approximate approaches are presented, followed by a numerical example using the simple three-unit system given in Table 2.7.

2.9.1 Exact method [32]

The capacity outage probability table together with its covariance matrix are constructed by adding generating units one at a time to an existing table using the following expressions:

$$P(X) = (1 - r)P'(X) + rP'(X - C)$$

$$\begin{aligned}
\mathrm{Cov}[P(X), P(Y)] = {} & [(1 - r)^2 + v]\mathrm{Cov}[P'(X), P'(Y)] \\
& + [r(1 - r) - v]\{\mathrm{Cov}[P'(X), P'(Y - C)] \\
& + \mathrm{Cov}[P'(X - C), P'(Y)]\} \\
& + [r^2 + v]\mathrm{Cov}[P'(X - C), P'(Y - C)] \\
& + v[P'(X)P'(Y) - P'(X)P'(Y - C) \\
& - P'(X - C)P'(Y) + P'(X - C)P'(Y - C)
\end{aligned}$$

where:

X and Y = capacity on outage levels

$P(X)$ - probability of capacity outage of X MW or more after the unit addition

$P'(X)$ = probability of capacity outage of X MW or more before the unit addition

$Cov[P(X),P(Y)]$ = covariance of $P(X)$ and $P(Y)$ after the unit addition

$Cov[P'(X),P'(Y)]$ = covariance of $P'(X)$ and $P'(Y)$ before the unit addition

r = expected value of FOR for the unit being added

C = capacity of unit being added

v = variance of FOR for the unit being added

The initial conditions before the addition of any unit are $P(X \le 0) = 1.0$, $P(X > 0) = 0$ and $Cov[P(X),P(Y)] = 0$ for all X and Y.

2.9.2 Approximate method [34]

A method based on the Taylor-series expansion of a function of several variables can be used to compute the elements of the covariance matrix associated with the capacity outage probability table. The required formula is given by

$$Cov[P(X),P(Y)] \approx \sum_{i=1}^{m} \left(\frac{\partial P(X)}{\partial r_i}\right)\left(\frac{\partial P(Y)}{\partial r_i}\right) Var[r_i]$$

$$+ \sum_{i=1}^{m} \sum_{j=i+1}^{m} \left(\frac{\partial^2 P(X)}{\partial r_i \partial r_j}\right)\left(\frac{\partial^2 P(Y)}{\partial r_i \partial r_j}\right) Var[r_i]Var[r_j]$$

where m denotes the number of generating units. The partial derivations used in the above formula are computed using the following equations:

$$\frac{\partial P(X)}{\partial r_i} = P'(X - C_i) - P'(X)$$

$$\frac{\partial^2 P(X)}{\partial r_i \partial r_j} = P''(X - C_i - C_j) + P''(X) - P''(X - C_i) - P''(X - C_j)$$

where:

$P'(X)$ = the element in the capacity outage probability table after unit of C_i MW and FOR r_i is removed from the original table.

$P''(X)$ - the element in the capacity outage probability table after two units of capacities C_i and C_j are removed from the original table.

2.9.3 Application

The application of these recursive expressions is illustrated using the simple system shown in Table 2.7, with the variance associated with the unit FOR assumed to be 9×10^{-6} (Table 2.25)

Table 2.25

Unit No.	Unit capacity C (MW)	Unit FOR r	Var[FOR] v
1	25	0.02	9×10^{-6}
2	25	0.02	9×10^{-6}
3	50	0.02	9×10^{-6}

The capacity outage probability table and its covariance matrix are developed as follows.

Step 1 Add the first 25 MW unit. The table becomes Table 2.26, and its covariance matrix is given by

$$\mathrm{Cov}[P(X), P(Y)] = \begin{bmatrix} 0.0 & 0.0 \\ 0.0 & 9 \times 10^{-6} \end{bmatrix}$$

Step 2 Add the second 25 MW unit. The new table is Table 2.27 and its covariance matrix is given by

$$\mathrm{Cov}[P(X), P(Y)] = \begin{bmatrix} 0.0 & 0.0 & 0.0 \\ & 1.7287281 & 0.0352719 \\ \text{Symmetric matrix} & & 0.0007281 \end{bmatrix} \times 10^{-5}$$

Step 3 Add the last unit (50 MW) to the table. The complete table is Table 2.28 and its covariance matrix is given by

$$\mathrm{Cov}[P(X), P(Y)] =$$

$$\begin{bmatrix} 0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ & 2.4904173 & 0.8979052 & 0.0680962 & 0.0010367 \\ & & 0.8999794 & 0.0363167 & 0.0003742 \\ & & & 0.0021183 & 0.0000287 \\ \text{Symmetric matrix} & & & & 0.0000004 \end{bmatrix} \times 10^{-5}$$

2.9.4 LOLE computation

The mean and variance of the LOLE are given by

Table 2.26

State No.	Capacity out	Cumulative probability
1	0	1.0
2	25	0.02

Table 2.27

State No.	Capacity out	Cumulative probability
i	0.0	1.0
2	25.0	0,0396
3	50.0	0.0004

$$E[\mathrm{LOLE}] = \sum_{i=1}^{n} E[P_i(C_i - X_i)]$$

$$\mathrm{Var}[\mathrm{LOLE}] = \sum_{i=1}^{n} \sum_{j=1}^{n} \mathrm{Cov}[P_i(C_i - X_i), P_j(C_j - X_j)]$$

where:

n = number of days in the study period
C_i = available capacity on day i
X_i = forecast peak load on day i
$E[P_i]$ = expected value of the loss of load probability on day i
$\mathrm{Cov}[P_i, P_j]$ = covariance of the ioss of load probabilities on day i and day j.

Example

N - 2 days, Forecast peak loads = 65, 45 MW.

$$E[\mathrm{LOLE}] = \sum_{i=1}^{2} P_i(C_i - X_i) = P_1(100-65) + P_2(100-45)$$

$$= P_1(35) + P_2(55)$$

$$= 0.020392 + 0.000792 = 0.021184$$

Table 2.28

State No.	Capacity out	Cumulative probability
1	0.0	1.0
2	25.0	0.058808
3	50.0	0.020392
4	75.0	0.000792
5	100.0	0.000008

$$\mathrm{Var}[\mathrm{LOLE}] = \sum_{i=1}^{2}\sum_{j=1}^{2} \mathrm{Cov}[P_i(100-X_i), P_j(100-X_j)]$$

$$= \mathrm{Var}[P_1(35)] + \mathrm{Var}[P_2(55)] + 2\,\mathrm{Cov}[P_1(35), P_2(55)]$$

If the exact method is used, the variance of LOLE is given by

$$\mathrm{Var}[\mathrm{LOLE}] = 0.8999794 \times 10^{-5} + 0.0021183 \times 10^{-5} + 2 \times 0.0363167 \times 10^{-5}$$

$$= 0.9747311 \times 10^{-5}$$

If the approximate method is used, the different terms in the variance equation of LOLE are given by

$$\mathrm{Var}[P_1(35)] \approx \left(\frac{dP_1}{\partial r_1}\right)^2 v_1 + \left(\frac{\partial P_1}{\partial r_2}\right)^2 v_2 + \left(\frac{\partial P_1}{\partial r_3}\right)^2 v_3 + \left(\frac{\partial^2 P_1}{\partial r_1 \partial r_2}\right)^2 v_1 v_2$$

$$+ \left(\frac{\partial^2 P_1}{\partial r_1 \partial r_3}\right)^2 v_1 v_3 + \left(\frac{\partial^2 P_1}{\partial r_2 \partial r_3}\right)^2 v_2 v_3$$

$$= 2[0.0396 - 0.02]^2 \times 9 \times 10^{-6} + [1 - 0.0004]^2 \times 9 \times 10^{-6}$$

$$+ [1 + 0.02 - 0.02 - 0.02]^2 \times (9 \times 10^{-6})$$

$$+ 2[1 + 0 - 0.02 - 1]^2 (9 \times 10^{-6})^2$$

$$= 0.0006915 \times 10^{-5} + 0.8992801 \times 10^{-5}$$

$$+ 0.778572 \times 10^{-10}$$

$$= 0.8999793 \times 10^{-5}$$

$$\mathrm{Var}[P_2(55)] \approx \sum_{i=1}^{3} \left(\frac{\partial P_2}{\partial r_i}\right)^2 v_i + \sum_{i=1}^{3}\sum_{j=i+1}^{3} \left(\frac{\partial^2 P_2}{\partial r_i \partial r_j}\right)^2 v_i v_j$$

$$= 2[0.02 - 0.0004]^2 \times 9 \times 10^{-6} + [0.0396 - O]^2 \times 9 \times 10^{-5}$$

$$+ [0.02 + 0 - 0.02 - 0.02]^2 (9 \times 10^{-6})^2$$

$$+ 2[1 - 0 - 0 - 0.02]^2 (9 \times 10^{-6})^2$$

$$= 0.0006915 \times 10^{-5} + 0.0014113 \times 10^{-5}$$

$$+ 0.324 \times 10^{-13} + 1.555848 \times 10^{-10}$$

$$= 0.0021183 \times 10^{-5}$$

$$\mathrm{Cov}[P_1(35),P_2(55)] = \sum_{i=1}^{3}\left(\frac{\partial P_1}{\partial r_i}\right)\left(\frac{\partial P_2}{\partial r_i}\right)v_i$$

$$+ \sum_{i=1}^{3}\sum_{j=i+1}^{3}\left(\frac{\partial^2 P_1}{\partial r_i \partial r_j}\right)\left(\frac{\partial^2 P_2}{\partial r_i \partial r_j}\right)v_i v_j$$

$$= 2[0.0396 - 0.02]\,[0.02 - 0.0004] \times 9 \times 10^{-6}$$

$$+ [1 - 0.0004]\,[0.0396 - 0] \times 9 \times 10^{-6}$$

$$+ [1 + 0.02 - 0.02 - 0.02]\,[0.02 + 0 - 0.02 - 0.02]$$

$$\times (9 \times 10^{-6})^2$$

$$+ 2[1 + 0 - 0.02 - 1]\,[1 + 0 - 0 - 0.02](9 \times 10^{-6})^2$$

$$= 0.0006915 \times 10^{-5} + 0.0356257 \times 10^{-5}$$

$$- 0.047628 \times 10^{-10}$$

$$= 0.0363168 \times 10^{-5}$$

$$\mathrm{Var[LOLE]} = \mathrm{Var}[P_1(35)] + \mathrm{Var}[P_2(55)] + 2\,\mathrm{Cov}[P_1(35),P_2(55)]$$

$$= 0.8999793 \times 10^{-5} + 0.021183 \times 10^{-5} + 2 \times 0.0363168 \times 10^{-5}$$

$$= 0.9747313 \times 10^{-5}$$

2.9.5 Additional considerations

The expected value associated with the calculated LOLE parameter can be obtained without recognition of the uncertainty associated with the generating unit unavailability. This parameter is affected by load forecast uncertainty. Uncertainties in forced outage rates and load forecasts can be incorporated in the same calculation [33]. The actual distribution associated with the calculated LOLE can only be obtained by Monte Carlo simulation. It has been suggested, however, that in many practical cases the distribution can be approximated by a gamma distribution which can then be used to place approximate confidence bounds on the LOLE for any particular situation.

The 'exact' technique illustrated in Section 2.9.1 becomes difficult to formulate if derated units are added to the capacity model. The 'approximate' method shown in Section 2.9.2 is, however, directly applicable and is not limited in regard to the number of derated states used. This situation is illustrated in Reference [34].

In conclusion, it is important to realize that there is a possible distribution associated with the calculated LOLE parameter. This distribution depends upon the inherent variability in the two basic parameters of load forecast uncertainty and the individual generating unit forced outage rates. The expected value of the LOLE parameter is not influenced by the uncertainty in the unit unavailabilities although the distribution of the LOLE parameter is affected by both uncertainty considerations. The distribution of the LOLE is useful in terms of determining approximate confidence bounds on the LOLE in any given situation. It is unlikely, however, that further use can be made of it at this time in practical system studies. The expected value of the calculated LOLE parameter is used as a conventional criterion for capacity evaluation. The uncertainty associated with the future load to be served by a proposed future capacity configuration is a significant factor which should be considered in long-term system evaluation.

2.10 Loss of energy indices

2.10.1 Evaluation of energy indices

The standard LOLE approach utilizes the daily peak load variation curve or the individual daily peak loads to calculate the expected number of days in the period that the daily peak load exceeds the available installed capacity. A LOLE index can also be calculated using the load duration curve or the individual hourly values. The area under the load duration curve represents the energy utilized during the specified period and can be used to calculate an expected energy not supplied due to insufficient installed capacity. The results of this approach can also be expressed in terms of the probable ratio between the load energy curtailed due to deficiencies in the generating capacity available and the total load energy required to serve the requirements of the system. For a given load duration curve this ratio is independent of the time period considered, which is usually a month or a year. The ratio is generally an extremely small figure less than one and can be defined as the 'energy index of unreliability'. It is more usual, however, to subtract this quantity from unity and thus obtain the probable ratio between the load energy that will be supplied and the total load energy required by the system. This is known as the 'energy index of reliability.'

The probabilities of having varying amounts of capacity unavailable are combined with the system load as shown in Fig. 2.19. Any outage of generating capacity exceeding the reserve will result in a curtailment of system load energy. Let:

$O_k =$ magnitude of the capacity outage
$P_k =$ probability of a capacity outage equal to O_k
$E_k =$ energy curtailed by a capacity outage equal to O_k

This energy curtailment is given by the shaded area in Fig. 2.19.

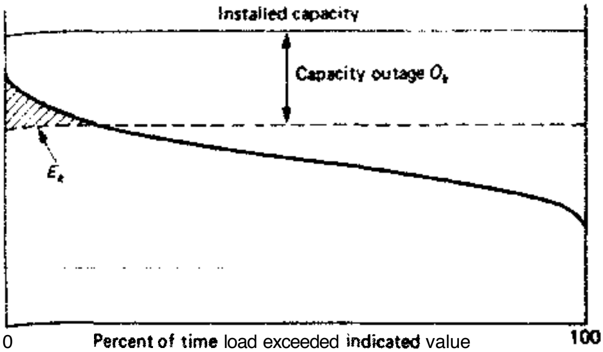

Fig. 2.19 Energy curtailment due to a given capacity outage condition

The probable energy curtailed is E_kP_k. The sum of these products is the total expected energy curtailment or loss of energy expectation LOEE where:

$$\text{LOEE} = \sum_{k=1}^{n} E_k P_k \tag{2.1!}$$

This can then be normalized by utilizing the total energy under the load duration curve designated as E.

$$\text{LOEE}_{\text{p.u.}} = \sum_{k=1}^{n} \frac{E_k P_k}{E} \tag{2.12}$$

The per unit LOEE value represents the ratio between the probable load energy curtailed due to deficiencies in available generating capacity and the total load energy required to serve the system demand. The energy index of reliability, EIR, is then

$$\text{EIR} = 1 - \text{LOEE}_{\text{p.u.}} \tag{2.13}$$

This approach has been applied to the 5 x 40 MW unit system previously studied using the LOLE approach (Section 2.3.2). The system load–duration curve was assumed to be represented by a straight line from the 100% to the 40% load level. The risk as a function of the system peak load is given in Table 2.29. These results can be plotted in a similar form to Fig. 2.7. Although the 'loss of energy' approach has perhaps more physical significance than the 'loss of load' approach, it is not as flexible in overall application and has not been used as extensively.

It is important to appreciate, however, that future electric power systems may be energy limited rather than power or capacity limited and therefore future indices may be energy based rather than focused on power or capacity.

Table 2.29 Variation of EIR

System peak load (MW)	Energy index of reliability
200	0.997524
190	0.998414
180	0.999162
170	0.999699
160	0.999925
150	0.999951
140	0.999974
130	0.999991
120	0.999998
110	0.999999
100	0.999999

2.10.2 Expected energy not supplied

The basic expected energy curtailed concept can also be used to determine the expected energy produced by each unit in the system and therefore provides a relatively simple approach to production cost modelling. This approach, which is described in detail in Reference [35], is illustrated by the following example. Consider the load duration curve (LDC) shown in Fig. 2.20 for a period of 100 hours and the generating unit capacity data given in Table 2.30.

Assume that the economic loading order is Units 1, 2 and 3. The total required energy in this period is 4575.0 MWh, i.e. the area under the LDC in Fig. 2.20. If there were no units in the system, the expected energy not supplied, EENS, would be 4575.0 MW (=$EENS_0$). If the system contained only Unit 1, the EENS can be calculated as shown in Table 2.31.

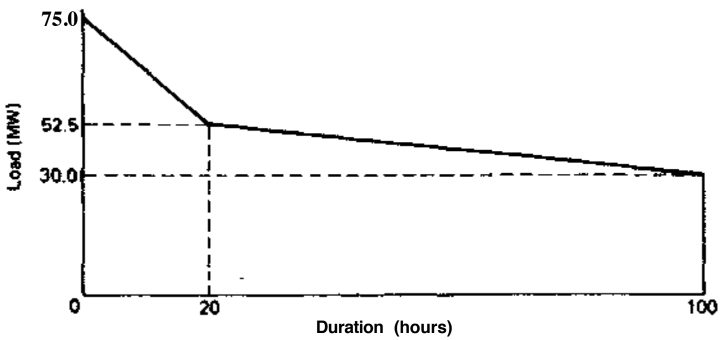

Fig. 2.20 Load model

Table 2.30 Generation data

Unit No.	Capacity (MW)	Probability
1	0	0.05
	15	0.30
	25	0.65
2	0	0.03
	30	0.97
3	0	0.04
	20	0.96

The contribution from Unit 2 can now be obtained by adding Unit 2 to the capacity model of Table 2.31 and calculating the EENS for Units 1 and 2 combined. This is shown in Table 2.32.

The final capacity outage probability table for all three units is shown in Table 2.33 and the $EENS_3$ = 64.08 MWh. The expected contribution from Unit 3 is 401.7 - 64.08 = 337.6 MWh. The individual unit expected energy outputs are summarized in Table 2.34.

The expected energy not supplied in the above system is 64.08 MWh. This can be expressed in terms of the energy index of reliability, EIR, using Equations (2.12) and (2.13):

$$\text{EIR} = 1 - \frac{64.08}{4575.0} = \underline{0.985993}$$

The situation in which Unit 1 is loaded to an intermediate level in the priority order before loading to full output at a higher priority level is illustrated in Reference [35]. Determination of expected unit energy outputs is a relatively simple matter in a system without energy limitations other than those associated with generating capacity outages. The approach illustrated can consider any number of units, derated capacity levels, load forecast uncertainty, station models and radial transmission limitations. The basic requirement is the ability to develop a sequential capacity outage probability table for the system generating capacity.

Table 2.31 EENS with Unit 1

Capacity out of service (MW)	Capacity in service (MW)	Probability	Energy curtailed (MWh)	Expectation (MWh)
0	25	0.65	2075.0	1348.75
10	15	0.30	3075.0	922.50
25	0	0.05	4575.0	228.75
				$EENS_1$ = 2500.0 MWh

The expected energy produced by Unit 1
$= EENS_0 - EENS_1$
= 4575.0 - 2500.0 = 2075.0 MWh.

Table 2.32 EENS with Units 1 and 2

Capacity out of service (MW)	*Capacity in service (MW)*	*Probability*	*Energy curtailed (MWh)*	*Expectation (MWh)*
0	55	0.6305	177.8	112.10
10	45	0.2910	475.0	138.23
25	30	0.0485	1575.0	76.39
30	25	0.0195	2075.0	40.46
40	15	0.0090	3075.0	27.68
55	0	0.0015	4575.0	6.86
				$EENS_2 = 401.7$ MWh

The expected energy produced by Unit 2

$= EENS_1 - EENS_2$

$= 2500.0 - 401.7 =$ 2098.3 MWh.

Table 2.33 EENS with Units 1, 2 and 3

Capacity out of service (MW)	*Capacity in service (MW)*	*Probability*	*Energy curtailed (MWh)*	*Expectation (MWh)*
0	15	0.60528	0	
10	65	0.27936	44.4	12.40
20	55	0.02522	177.8	4.49
25	50	0.04656	286.0	13.32
30	45	0.03036	475.0	14.42
40	35	0.00864	1119.4	9.67
45	30	0.00194	1575.0	3.06
50	25	0.00078	2075.0	1.62
55	20	0.00144	2575.0	3.71
60	15	0.00036	3075.0	1.11
75	0	0.00006	4575.0	0.28
				64.08

Table 2.34 Summary of EENS

Priority level	*Unit capacity (MW)*	*EENS (MWh)*	*Expected energy output (MWh)*
1	25	2500.0	2075.0
2	30	401.7	2098.3
3	20	64.1	337.6

2.10.3 Energy-limited systems

The Simplest energy-limited situation to incorporate into the analysts is the condition in which the output capacity of a unit is dictated by the energy available. An example of this energy limitation is a run-of-the-river hydro installation with little or no storage. The flow rate determines the unit output capacity. The unit is then represented as a multi-state unit in which the capacity states correspond to the water flow rates. This representation might also apply to variable flow availabilities of natural gas. The analysis in this case is identical to that used in Section 2.10.2 for a non-energy-limited unit. This is illustrated by adding a 10 MW generating unit with a capacity distribution due to a flow-rate distribution as described in Table 2.35 to the system analyzed in Section 2.10.2.

The unit can be placed in an appropriate place in the priority loading order and the expected energy outputs calculated using the previous techniques. The expected energy not supplied in this case is 35.5 MWh and the EIR = 0,992236.

Generating units which have short-term storage associated with their prime mover can be used to peak shave the load and therefore reduce the requirement from more expensive units. The approach in this case is to modify the load model using the capacity and energy distributions of the limited energy storage unit and then apply the technique described earlier for the non-energy-limited units. If this load modification technique is used in connection with a non-energy-limited unit system analysis, the results are identical to those obtained by the basic method.

The first step is to capacity-modify the load–duration curve using a conditional probability approach. The modified curve is the equivalent load curve for the rest of the units in the system if the unit used to modify it was first in the priority list. The capacity-modified curve is then energy-modified using the energy probability distribution of the unit under consideration. The final modified curve is then used in the normal manner with the rest of the units in the system to determine their expected energy outputs and the resulting expected energy not supplied.

The approach can be illustrated by adding the unit shown in Table 2.36 to the original three-unit system in Table 2.30.

The capacity-modified curve is shown in Fig. 2.21. The curve is obtained by the conditional probability approach used earlier for load forecast uncertainty analysis. The energy-modified load–duration curve is shown in Fig. 2,22.

Table 2.35 Data for 10 MW unit

Capacity (MW)	*Probability*
0	0.040
2.5	0.192
5.0	0.480
10.0	0.288
	1.000

Table 2.36 Energy-limited unit

Capacity model		*Energy model*	
Capacity (MW)	*Probability*	*Energy (MWh)*	*Cumulative probability*
0	0.03	200	1.00
10	0.25	350	0.70
15	0.72	500	0.20

The resulting load–duration curve in Fig. 2.22 becomes the starting curve for subsequent unit analysis. In the example used, an additional unit of 10 MW with a forced outage rate of 0.04 was added to the previous system. A two-state energy distribution was assumed with 70.0 and 150.0 MWh having cumulative probabilities of 1.0 and 0.6 respectively. Under these conditions, the expected energy not supplied is 15.7 MWh and the EIR of the system for the 100 hour period is 0.996562. Reference [35] illustrates the extension of this technique to the situation in which an energy-limited unit is partly base loaded and partly used for peak shaving.

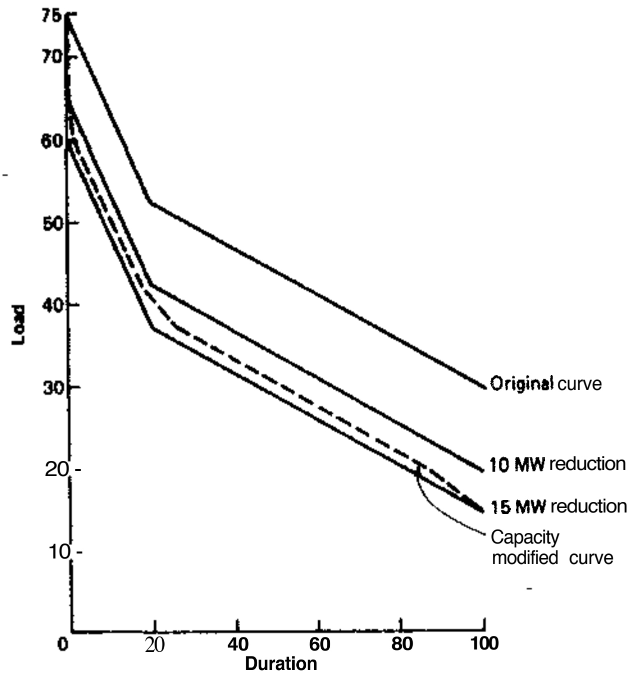

Fig. 2-21 Capacity-modified load-duration curve

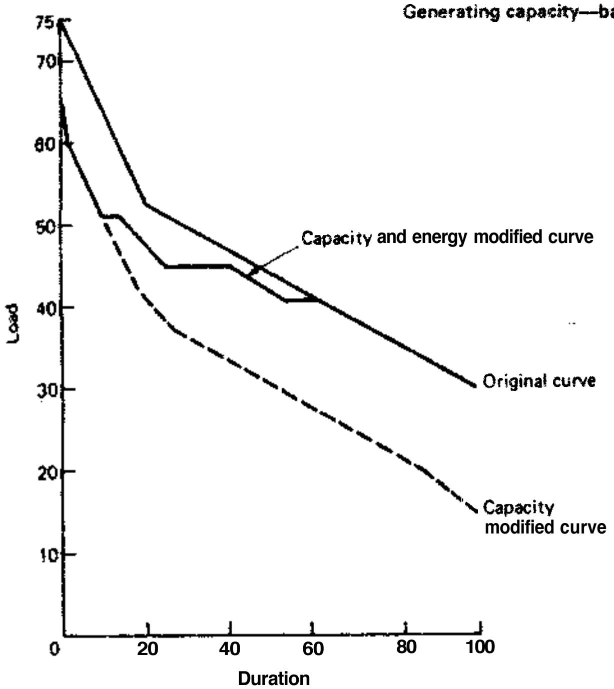

Fig. 2.22 Energy-modified load–duration curve

A farther type of storage facility, which is commonly encountered, is one in which the stored energy can be held for some time and used in both a peak shaving and base load manner. In the case of a hydro facility with a large reservoir, the operation would be guided by a rule curve which dictates how much energy should be used during the specified period. The available energy during each period can vary due to in-flow variations and operating policies. The approach in this case is to capacity-modify the load–duration curve using the non-energy-limited units. This leaves an equivalent load curve for the rest of the units. The units with energy limitations can then be used to peak shave the equivalent load–duration curve. The area under the load–duration curve after these units have been dispatched is the expected load energy not supplied. A numerical example for this type of system is shown in Reference [35].

2.11 Practical system studies

The techniques and algorithms presented in this chapter are suitable for the analysis of both small and large systems. Typical practical systems contain a large number of generating units and cannot normally be analyzed by hand calculations. The algorithms presented can be used to create efficient computer programs for the analysis of practical system configurations. The IEEE Subcommittee on the Application of Probability Methods recently published a Reliability Test System containing a generation configuration and an appropriate bulk transmission network [36]. It is expected that this system will become a reference for research in new techniques and in comparing the results obtained using different computer programs. Appendix 2 contains the basic generation model from the IEEE Reliability Test System (IEEE–RTS) and also a range of results from different reliability studies. These results cannot be obtained by hand analysis. The reader is encouraged to develop his digital computer program using the techniques contained in this book and to compare them with those presented in Appendix 2.

2.12 Conclusions

This chapter has illustrated the application of basic probability concepts to generating capacity reliability evaluation. The LOLE technique is the most widely used probabilistic approach at the present time. There are, however, many differences in the resulting indices produced. These differences depend mainly on the factors used in the calculation procedure, i.e. derated representation or EFOR values, uncertainty considerations, maintenance effects, etc. Different indices are created by using different load models. It is not valid to obtain an LOLE index in hours by dividing the days/year value obtained using a daily peak load variation curve, DPLVC, by 24, as the DPLVC has a different shape from the load–duration curve, LDC. If an LOLE in hours/year is required, then the LDC should be used. The LDC is a better representation than the DPLVC as it uses more actual system data. The energy not supplied is an intuitively appealing index as it tends to include some measure of basic inadequacy rather than just the number of days or hours that all the load was not satisfied.

The basic LOLE index has received some criticism in the past on the grounds that it does not recognize the difference between a small capacity shortage and a large one, i.e. it is simply concerned with 'loss of load'. All shortages are therefore treated equally in the basic technique. It is possible, however, to produce many additional indices such as the expected capacity shortage if a shortage occurs, the expected number of days that specified shortages occur, etc. It is mainly a question of deciding what expectation indices are required and then proceeding to calculate them. The derived indices are expected values (i.e. long run average) and should not be expected to occur each year. The indices should also not be considered as absolute measures of capacity adequacy and they do not describe the frequency and duration of inadequacies. They do not include operating considerations such as spinning reserve requirements, dynamic and transient system disturbances, etc. Indices such as LOLE and LOEE are simply indications of static capacity adequacy which respond to the basic elements which influence the adequacy of a given configuration, i.e. unit size and availability, load shape and uncertainty. Inclusion of additional parameters does not change this fundamental concept. Inclusion of elements such as maintenance, etc., make the derived index sensitive to these elements and therefore a more overall index, but still does not make the index an absolute measure of generation system reliability.

2.13 Problems

1 A power system contains the following generating capacity.

3 x 40 MW hydro units FOR = 0,005
1 x 50 MW thermal unit FOR = 0.02
1 x 60 MW thermal unit FOR = 0.02

The annual daily peak load variation curve is given by a straight line from the 100% to the 40% points.

(a) Calculate the loss of load expectation for the following peak toad values.
(i) 150 MW (ii) 160 MW (iii) 170 MW
(iv) 180 MW (v) 190 MW (vi) 200 MW

(b) Calculate the loss of load expectation for the following peak load values, given that another 60 MW thermal unit with a FOR of 0.02 is added to the system.
(i) 200 MW (ii) 210 MW (iii) 220 MW (iv) 230 MW
(v) 240 MW (vi) 250 MW (vii) 260 MW

(c) Determine the increase in load carrying capability at the 0.1 day/year risk level due to the addition of the 60 MW thermal unit.

(d) Calculate the loss of load expectation for the load levels in (a) and (b) using the load forecast uncertainty distribution shown in Fig. 2.23.

(e) Determine the increase in load carrying capability at the 0.1 day/year risk level for the conditions in part (d).

2 A generating system contains three 25 MW generating units each with a 4% FOR and one 30 MW unit with a 5% FOR. If the peak load for a 100 day period is 75 MW, what

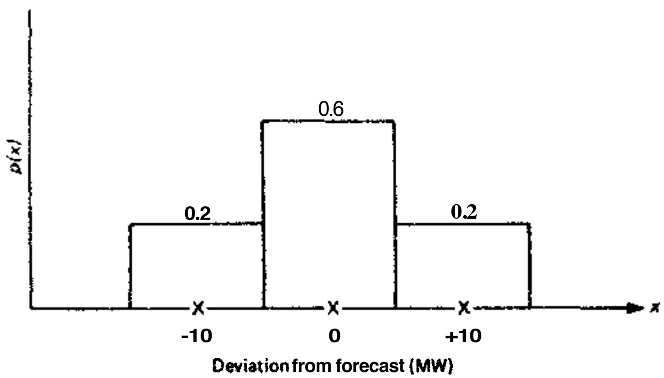

Fig. 2.23

is the LOLE and EIR for this period? Assume that the appropriate load characteristic is a straight line from the 100% to the 60% points.

3 A system contains three non-identical 30 MW generating units each with a 5% FOR and one 50 MW unit with a 6% FOR. The system peak load for a specified 100 day period is 120 MW. The load–duration curve for this period is a straight line from the 100% to the 80% load points.

Calculate the energy index of reliability for this system. The economic loading order for this system is the 50 MW unit first, followed by the 30 MW units A, B and C, in that order. Calculate the expected energy provided to the system by the 50 MW unit and by the 30 MW unit C.

4 A system contains 120 MW of generating capacity in 6 x 20 MW units. These units are connected through step-up station transformers to a high-voltage bus. The station is then connected to a bulk system load point by two identical transmission lines. This configuration is shown in Fig. 2.24.

System data

Generating units	*Transformers*	*Transmission lines*
$\lambda = 3$ f/year	$\lambda = 0.1$ f/year	$\lambda = 3$ f/year/100 m
$\mu = 97$ r/year	$\mu = 19.9$ r/year	$\mu = 365$ r/year

Assume that the load-carrying capabilities of lines 1 and 2 are 70 MW each. The annual daily peak load variation curve is a straight line from the 100% to the 70% points. The annual load–duration curve is a straight line from the 100% to the 50% point.

(a) Conduct a LOLE study at the generating bus and at the load bus for an annual forecast peak load of 95 MW.

(b) Repeat Question (a) given that each pair of generating units is connected to the high voltage bus by a single transformer.

(c) Calculate the expected energy not supplied and the energy index of reliability at the load bus for a forecast annual peak load of 95 MW.

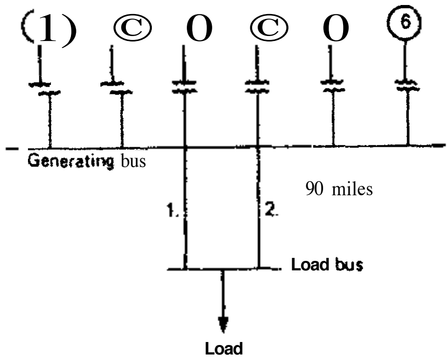

Fig. 2.24

5 A generating system consists of the following units:
(A) 1 x 10 MW unit
(B) 1 x 20 MW unit
(C) 1 x 30 MW unit
(D) 1 x 40 MW unit
The 10, 20 and 30 MW units have forced outage rates of 0.08. The 40 MW unit has a full forced outage rate of 0.08 and a 50% derated state which has a probability of 0.06. (a) Calculate the LOLE for this system for a single daily peak load of 60 MW. (b) What is the LOLE for the same condition if the 40 MW unit is represented as a two-state model using an Equivalent Forced Outage Rate?

6 The generating system given in Question 5 supplies power to an industrial load. The peak load for a specified 100-day period is 70 MW. The load–duration curve for this period is a straight line from the 100% to the 60% load point.
(a) Calculate the energy index of reliability for this system.
(b) Given that the economic loading order for the generating units is (D), (C), (B), (A), calculate the expected energy provided to the system by each unit.

7 A four-unit hydro plant serves a remote load through two transmission lines. The four hydro units are connected to a single step-up transformer which is then connected to the two lines. The remote load has a daily peak load variation curve which is a straight line from the 100% to the 60% point. Calculate the annual loss of load expectation for a forecast peak of 70 MW using the following data.

Hydro units
25 MW. Forced outage rate = 2%.
Transformer
110 MVA. Forced outage rate = 0.2%
Transmission lines
Carrying capability 50 MW each line
Failure rate = 2 f/year
Average repair time = 24 hours

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Exhibits to Direct Testimony of Michael Milligan
on behalf of Montana Environmental Information Center

Exhibit MM-6

Docket No. 2019.12.101

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The Capacity Value of Wind in the United States: Methods and Implementation

As more wind energy capacity is added in the nation, the question of wind's capacity value is raised. This article shows how the capacity value of wind is determined, both in theory and in practice.

Michael Milligan and Kevin Porter

I. Introduction

A fundamental element of the electric industry is not only to ensure generating capacity to meet customer demand but also to have generating capacity in reserve in case customer demand is higher than expected or a generator or transmission line goes out of service. Although a basic concept, the methods used for evaluating capacity adequacy are strikingly different from region to region.

With nearly 7 GW of installed wind capacity in the United States at the end of 2004 and another 2.5 GW expected to have come on-line in 2005, the question of whether wind energy is a capacity resource is gaining more attention. Wind's variability makes this a matter of great debate in some regions. However, many regions accept that wind energy has some capacity value, albeit at a lower value than other energy technologies. Recently, studies have been published in California, Minnesota, and New York that document that wind energy has some capacity value. These studies join other initiatives in the Pennsylvania–Jersey–Maryland (PJM) RTO, Colorado, and in other states and regions.

Wind generators occupy a unique place in the determination of capacity value. Wind generators have typically very high mechanical availability, exceeding 95 percent in many instances (i.e., the forced outage rate is often below 5 percent). However, because wind generators only generate electricity when the wind blows, a wind generator arguably has a forced outage when the wind does not blow. Therefore, the effective forced outage rate for wind generators may be much higher, from 50 percent to 80 percent, when recognizing the intermittent availability of wind. In addition, wind's value to the electric system may also vary. The output from some wind generators may have a high correlation with load and thereby can be seen as supplying capacity when it is most needed. In this situation, a wind generating plant should have a relatively high capacity credit.[1]

This article focuses on different methodologies for determining the capacity value of wind energy. It summarizes several important state and regional studies that examine the capacity value of wind energy, how different regions define and implement capacity reserve requirements across the country, and how wind energy is defined as a capacity resource in those regions.[2] We will start with a discussion of effective load carrying capability (ELCC), consider how capacity credit is derived in practice, and explore the fallacy of applying a random statistical probability to the capacity value. We close with a summary.

II. Effective Load Carrying Capability

ELCC is based on well-established reliability theory and practice and can be applied to all generators. ELCC is based on one of several reliability metrics, such as loss of load probability (LOLP), loss of load expectation (LOLE), or expected unserved energy (EUE). ELCC can be calculated with a power system reliability model, with appropriate tweaking to properly account for the stochastic and variable nature of wind generation. ELCC can discriminate among generators with differing levels of reliability, size, and on-peak versus off-peak delivery. It effectively rewards plants that are consistently able to deliver during periods of high demand and ranks less reliable plants by calculating a lower capacity credit. For intermittent generators such as wind, the method can discriminate between wind regimes that consistently deliver during high-risk periods, sometimes deliver during high-risk periods, or never deliver during high-risk periods.

ELCC is based on well-established reliability theory and practice and can be applied to all generators.

To calculate ELCC, a database is required that contains hourly load requirements and generator characteristics. For conventional generators, rated capacity, forced outage rates, and maintenance schedules are the primary requirements. For an intermittent resource such as wind, at least one year of hourly power output is required, but more data is always better. Over the decades that ELCC has been applied, it has been used with a number of different reference units. Some early work measured the capacity value of a generator against a perfectly reliable unit.[3] Because such a unit does not exist, we prefer the alternative of measuring capacity value relative to a benchmark unit. In any event, it is important that the benchmark unit is clearly identified, and *all* units in a given region should be measured against the same benchmark. **Figure 1** illustrates the ELCC of a hypothetical generic plant, relative to a benchmark gas unit. Because the benchmark unit has a combined outage rate of 10 percent (maintenance and forced), the generic unit can achieve an ELCC value of 100 percent of the benchmark if the generic unit has a 10 percent forced outage rate. But 100 percent of the benchmark is approximately 90 percent of the plant rated capacity.

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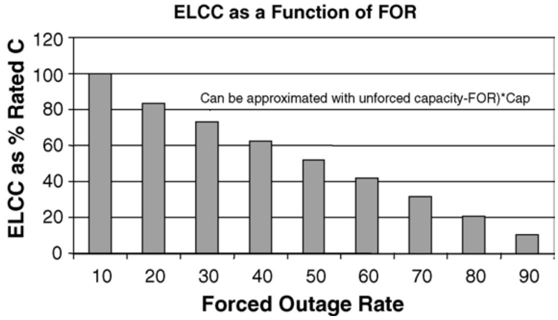

Figure 1: The ELCC of Generic Conventional Generator with Alternative Forced Outage Rates

Although there are some variations, ELCC is calculated in several steps. Most commonly, the system is modeled without the generator of interest. For this discussion, we assume that the generator of interest is a renewable generator, but this does not need to be the case. The loads are adjusted to achieve a given level of reliability, such as a loss of load expectation of 1 day per 10 years. This LOLE can be calculated by taking the LOLP (a probability is between zero and 1 and cannot by definition exceed 1) multiplied by the number of days in a year. Thus LOLE indicates an expected value and can be expressed in hours/year, days/year, or some other unit of time.

Once the desired LOLE target is achieved, the renewable generator is added to the system and the model is re-run. The new, lower LOLE (higher reliability) is noted, and the renewable generator is removed from the system. Then the benchmark unit is added to the system in small incremental capacities until the LOLE with the benchmark unit matches the LOLE that was achieved with the renewable generator. The capacity of the benchmark unit is then noted, and that becomes the ELCC of the renewable generator. It is important to note that the ELCC documents the capacity that achieves the same risk level as would be achieved without the renewable generator.

To derive the ELCC of wind, one ideally would have access to several years of wind generation data, load data, and other generation data. But because a long wind generation record often does not exist, it is reasonable to expect that wind's capacity value could vary from year to year. One way to help solve the problem of the year-to-year variability of the capacity value for wind is to create wind generation scenarios using meso-scale meteorological models. For the Minnesota Department of Commerce (MN/DOC) wind integration study, Enernex and WindLogics developed a three-year wind data record by re-creating the actual weather and normalizing to the long-term trend.[4] A variation of this approach may involve the re-creation of several additional years of weather data, then running the reliability model for each of these several years to capture a longer time period.

A. Factors that influence the ELCC of wind

Regardless of the method used to calculate wind ELCC, a number of factors can influence the results. The key influence is the timing of the wind delivery relative to times of significant LOLP (when the 1-day-per-10 years LOLE is used, significant LOLP is generally a non-zero LOLP for the hour in question). Wind that delivers significant capacity during the times of system risk achieves a high capacity value. Conversely, wind that generates little or no output during these high-risk periods will have a low or zero capacity value. In addition, hourly LOLP is subject to several influences, such as the mix of other generation units and the generation units' and forced outage rates. The way that these parameters interact with the load has an important influence on LOLP.

In a system with significant hydro generation, there can be two additional influences on LOLP. The first is from the non-controllable hydro (run of river) that has arbitrary influences on LOLP. This influence will vary from year to year as a function of the hydro flow and changing load shape. Controllable hydro is generally operated so that it benefits the system in some optimal way. Generally, controllable hydro is used to mitigate high risk

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and therefore will reduce LOLP during peak periods. This has the effect of altering the shape of the LOLP curve and can perhaps shift the highest risk hours to near-peak hours from peak hours.

Off-system purchases can also influence the risk profile. Because system operators want to ensure sufficient resources during peak periods, it is not uncommon to schedule purchases during peak periods. Of course, that will influence the risk profile and the ELCC of wind.

Maintenance on generators is normally deferred to off-peak months in the spring or fall. This is done for obvious reasons: the system operator wants to ensure that all generation is available during the peak periods when the system is most constrained and at highest risk. Because of generators being off-line for scheduled maintenance, it is not uncommon for the spring or fall maintenance periods to drive up the system risk to levels at or near those found during peak periods. This significantly alters the risk profile, and therefore it can play a large role in determining the ELCC of a wind plant.

B. Approximation methods for ELCC

Because of the potential difficulty of assembling the appropriate database to use for the ELCC calculation, interest in simpler methods has emerged over the past several years. Although several methods can be used to approximate ELCC, an unfortunate aspect of all of these methods is that they are indeed approximations.

Broadly speaking, the approximation techniques fall into two categories: risk-based or time-period-based. Risk-based categories develop an approximation to the utility's LOLP curve throughout the year. Time-period-based methods attempt to capture risk indirectly, by assuming a high correlation between hourly demand and LOLP. Although this relationship generally holds, it can be compromised by scheduled maintenance of other units and hydro conditions. A further limitation of time-period-based methods is that all hours considered by the method are generally weighted evenly, whereas ELCC and other risk-based methods place higher weight on high-risk hours and less weight on low-risk hours. However, time-period-based methods are much simpler and are easy to explain in regulatory and other public proceedings.

A more common approach is to use time-period methods that allow the avoidance of reliability model.

Risk-based methods utilize hourly LOLP information either from a reliability model run or as an approximation. One widely known method, described by Garver (1966), can be applied to wind.[5] The Garver technique was developed to estimate ELCC of conventional generators and to overcome the limited computational capabilities that were available at the time. The technique is based on the development of a risk-approximation function.

The approach approximates the declining exponential risk function (LOLP in each hour, LOLE over a high-risk period). It requires a single reliability model run to collect data to estimate Garver's constant, known as m. Once this is done, the relative risk for an hour is calculated by Garver's approximating equation.[6] To use this approach for wind generators simply involves the application of the Garver equation to the net load after subtracting the wind generation. The output of a benchmark unit can be similarly applied to the approximating equation so that the wind ELCC can be approximated relative to the benchmark unit.

A more common approach is to use time-period methods that allow the avoidance of a reliability model. To do so, hourly load and wind data should be collected for at least one year. The data can be used to calculate an approximation to ELCC. This approach is appealing in its simplicity, but it does not capture the potential system risks that are

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part of the other methods discussed above.

One of the most straightforward approaches is to calculate the wind capacity factor (ratio of the mean to the maximum) over several times of high system demand. An early study using this method calculated capacity factors for wind for the top 1 percent to 30 percent of loads, using an increment of 1 percent. The results show that at approximately 10 percent or more of the top load hours, the capacity factor is within a few percentage points of the ELCC.[7]

Several of the approaches below use time-period methods to calculate wind capacity value, and the remainder of this article will be devoted to various forms of time-period methods.

III. Capacity Credit in Practice

In this section we survey some of the approaches to evaluating the capacity credit of wind. These methods come from a variety of entities, including regional transmission organizations, public utility commissions, utilities, and studies carried out on behalf of these organizations.

PJM: The capacity credit for wind in PJM is based on the wind generator's capacity factor during the hours from 3 p.m. to 7 p.m., from June 1 through Aug. 31. The capacity credit is a rolling three-year average, with the most recent year's data replacing the oldest year's data. Because of insufficient wind generation data, PJM has applied a capacity credit of 20 percent for new wind projects, to be replaced by the wind generator's capacity credit once the wind project is in operation for at least one year. As an example, a new wind generator will receive a capacity credit of 20 percent the first year; the average of 20 percent and the wind generator's capacity factor during the hours from 3 p.m. to 7 p.m. from June 1 through Aug. 31 in the second year; and the average of 20 percent and the wind generator's capacity factor during the hours from 3 p.m. to 7 p.m. for June 1 through Aug. 31 for years two and three, and so on.[8]

One of the most straightforward approaches is to calculate the wind capacity factor over several times of high capacity demand.

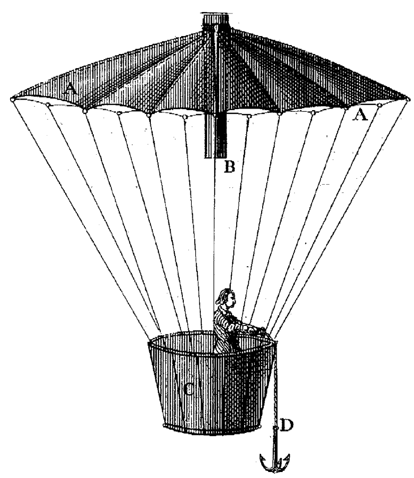
New York Independent System Operator (NYISO): The NYISO allows wind projects larger than 1 MW capacity to qualify for capacity credit. Wind generators can submit the results of a four-hour sustained maximum output test, for summer (June 1 through Sept. 15) and winter (Nov. 1 through April 15). The results of the tests are the wind generator's initial capacity credit in the NYISO. The NYISO adjusts the capacity credit monthly based on data submitted by the generator on actual generation and maintenance hours the previous month.[9] A 2005 study by General Electric (GE) for the New York State Energy Research Development Authority (NYSERDA) found that onshore wind projects had a lower capacity value (9 percent) than is currently provided to wind by the NYISO.[10] The NYISO will likely investigate changing the methodology for determining the capacity credit of wind.

ISO New England: Three wind generators are registered with ISO New England, at a total capacity of about 1.5 MW, so ISO New England has not closely examined the capacity value issue of wind. Currently, wind generators receive a capacity credit equal to the unit's capacity, multiplied by 1 minus its forced outage rate.[11] ISO New England may re-examine this method if the 420 MW Cape Wind offshore wind project off the coast of Massachusetts becomes operational.

Southwest Power Pool (SPP): SPP adopted a method to calculate the capacity contribution of wind. The SPP method is a monthly method, and therefore it results in 12 capacity measures for the wind plant. The process first examines the highest 10 percent of load hours in the month. Wind generation from those hours is then ranked from high to low. The wind capacity value is selected from this ranking, and it is the value that is exceeded 85 percent of the time (the 85th percentile). Up to 10 years of data are used if available. For the wind plants studied in the SPP region, the capacity values ranged from 3 percent to 8 percent of rated capacity. According to a 2004 presentation from the SPP's Generation Working Group (GWG), this method is used for long-term planning.[12] Although it appears counterintuitive to us, the SPP's GWG believes that ELCC/LOLP methods are better used to determine the level of desired spinning or operating reserves and not to determine the reliability impacts of wind.

GE/NYSERDA: The aforementioned GE study for NYSERDA examined the impact of 3,300 MW of wind on the New York bulk power system. Although the study focused on reliability impacts and operational issues, the team assessed the capacity contribution of wind using ELCC. The study used simulated wind data from more than 100 sites throughout the state, matched to the year of load data. This important step accounts for any underlying systematic correlation that may exist between wind and load. (This correlation would be expected to vary by region, and it would likely be nonlinear with a potentially complex lag structure.) The study found that on-shore wind plants would be expected to have approximately 9 percent capacity value relative to rated capacity, and off-shore wind would be approximately 40 percent. For the on-shore wind scenarios, the modelers found that a time-period based approach was effective at approximating the capacity value. For the summer season, the wind capacity factor was measured during the hours from 1 p.m. to 4 p.m.[13]

Minnesota Department of Commerce/Xcel (MN/DOC): The MN/DOC study examined the impact of 1,500 MW of wind capacity distributed at various locations in



southwest Minnesota. This represented approximately a 15 percent wind penetration on Xcel Energy's system, based on the ratio of rated wind capacity to peak load. One of the study tasks was to calculate the capacity contribution of wind. The study used a sequential Monte Carlo (SMC) method, which performed repeated sampling of an annual state transition matrix that was calculated based on the wind data used in the study. The intent of this approach is to capture some of the impact of the interannual variation of wind so that estimates of ELCC may be more robust. The SMC cases found a 26.7 percent capacity contribution for the prospective wind plants. For comparison, the study also used a simple "load-modifier" method that calculates reliability based on a simple netting of the wind generation against hourly load. When this approach was used, the prospective wind capacity value was 32.9 percent of rated capacity.[14]

Pacificorp: In its 2005 integrated resource plan (Pacificorp 2005), Pacificorp modeled wind generation using the same sequential Monte Carlo approach used by Enernex in the MN/DOC study. For the several prospective wind locations analyzed by PacifiCorp, the capacity contribution of wind averaged approximately 20 percent of rated capacity.[15]

Electric Reliability Council of Texas (ERCOT): ERCOT evaluated the operating wind plants to determine the capacity contribution of wind. The analysis was based on wind generation from 4 p.m. to 6 p.m. during July and August, the peak period for ERCOT. During this time period, the average output of the wind was 16.8 percent of rated capacity. Because of the variability of wind generation, the ERCOT Generation Adequacy Task Group is developing a confidence factor. Although the method of evaluation of this confidence factor is unclear, the recommendation under consideration is to use 2 percent of rated wind capacity as the capacity value.[16]

Mid-Continent Area Power Pool (MAPP): The MAPP approach is a monthly method that calculates wind capacity value based on the timing of its delivery relative

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to peak. Up to 10 years of data (wind and load) can be used if available. For each month, a four-hour time window surrounding the monthly peak is selected. Any contiguous four-hour period can be selected, as long as the peak hour falls within the window. The wind generation from that four-hour period in all days of the month is then sorted, and the median value is calculated. The median value is the capacity value of wind for the month. If multiple years of data are available, the process is carried out on the multi-year data set. The results of these calculations are used in operational planning in the power pool.

Portland General Electric (PGE): PGE assumed a 33 percent capacity factor in its 2002 IRP as a placeholder and plans to review additional studies and data as they become available.[17] PGE's IRP calls for 195 MW of wind.[18]

Idaho Power: Idaho Power gives wind a 5 percent capacity credit, based on a 100 MW wind plant's projected output that would occur 70 percent or more of the time between 4 p.m. and 8 p.m. during July, Idaho Power's peak month.[19] Therefore, Idaho Power's method is similar to SPP's by multiplying a subjective statistical number by actual capacity factor values.

Puget Sound Energy (PSE): PSE just released its 2005 IRP that includes a wind integration study as an appendix. Although not specified in the plan, a personal communication with a PSE representative determined that PSE's determination of a capacity credit for wind is the lesser of 20 percent of nameplate capacity, or 2/3 of the capacity factor of a wind project in January, which is PSE's peak month.[20]

Table 1: Wind Capacity Value in the United States

Region/Utility	*Method*	*Note*
CA/CEC	ELCC	Rank bid evaluations for RPS (low 20s)
PJM	Peak period	Jun-Aug HE 3 p.m.–7 p.m., capacity factor using 3-year rolling average (20%, fold in actual data when available)
ERCOT	10%	May change to capacity factor, 4 p.m.–6 p.m., Jul (2.8%)
MN/DOC/Xcel	ELCC	Sequential Monte Carlo (26–34%)
GE/NYSERDA	ELCC	Offshore/onshore (40%/10%)
CO PUC/Xcel	ELCC	PUC decision (30%) and Current Enernex study possible follow-on; Xcel using MAPP approach (10%) in internal work
RMATS	Rule of thumb	20% all sites in RMATS
PacifiCorp	ELCC	Sequential Monte Carlo (20%)
MAPP	Peak period	Monthly 4-hour window, median
PGE		33% (method not stated)
Idaho Power	Peak period	4 p.m.–8 p.m. capacity factor during July (5%)
PSE and Avista	Peak period	PSE will revisit the issue (lesser of 20% or 2/3 Jan C.F.)
SPP	Peak period	Top 10% loads/month; 85th percentile

Table 1 provides results from recent studies, RTO policies, and state regulatory actions to illustrate the range of capacity values found to apply to wind. Most approaches use either ELCC or a time-period basis to calculate wind capacity factor.

IV. The 95 Percent Fallacy: Using *X* Percentile to Calculate Capacity Credit

New gas plants are capable of achieving low forced outage rates—high levels of reliability. Because gas plants have often been the generator technology of choice in recent years, it can be tempting to use this gas plant characteristic in an attempt to estimate the capacity value of an intermittent generator such as wind. To carry out this approach, one collects wind generation over the relevant high-load period (for example, the top 10 percent of load hours). The next step is to calculate the 95th percentile of wind generation—the level of wind generation that is achieved 95 percent of the time during these load hours. A variation of this approach that we have encountered is to then feed this 95th percentile generation into a reliability model to calculate the ELCC of the wind plant. In both of these variations, the method *only* values capacity levels that are exceeded 95 percent of the time. All other capacity levels are assigned a value of zero. Although using different percentage levels, this is equivalent to what SPP and Idaho Power did in estimating the capacity value of wind.

The use of a percentile arbitrarily discounts reliability contributions that are achieved at levels below the percentile value. These approaches are based on the fallacious use of probability theory, and they ignore the statistical independence of outages and the fact that system reliability can be achieved at a very high level (such as 1-day-in-10-years LOLE) even though every unit in the system is somewhat unreliable. Furthermore, when applied to wind, this can result in the acquisition of more reserve capacity than is needed, raising costs unnecessarily.

To illustrate, we set up a series of reliability cases using hourly load data from the California ISO. Instead of using the existing generator fleet, a hypothetical generator mix was developed that consists of 95 500 MW units, each with a forced outage rate of 9 percent. The base case also included 54 100 MW units, each with a forced outage rate of 10 percent. This mix of generation achieved a 1-day-in-10-year reliability level. To illustrate the impact of less-reliable plants, the forced outage rates on the 100 MW units was increased in steps of 10 percent up to 90 percent. And just for fun, we also included a case with all the 100 MW units and a 95 percent forced outage rate. Figure 2 shows that the 1-day-in-10-year reliability target can be achieved even with generators with the 95 percent forced outage rate. The point of this exercise is not to argue for unreliable generators. The point is to show that even unreliable units can contribute to a reliable system, although it would take many of these generators to do so.

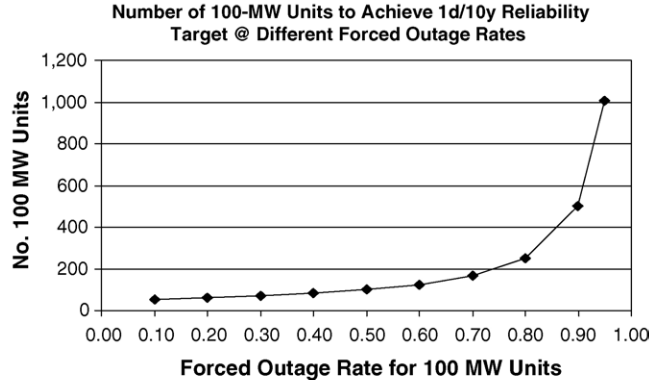

Figure 2: One-Day-in-10-Years can be Achieved with Unreliable Generators

V. Summary

A capacity-based metric is useful in several alternative contexts, from determining resource adequacy to financial markets for capacity. Capacity from a generator at some time in the future is not guaranteed. Because all generators are subject to outages, even during critical times, a probabilistic approach to calculating capacity value is appropriate. This is especially true for intermittent resources such as wind power plants. Because of the stochastic nature of the wind, and therefore wind energy, a method that can explicitly quantify the risks associated with this resource is critical. Standard power system reliability theory exists that can be used for this purpose.

When a reliability-based approach is used to calculate the capacity credit of wind power plants, risk is explicitly embodied in the calculation. The ELCC method is rigorous, data-driven, and can finely distinguish among generators that have different impacts on system reliability. However, the method requires datasets that are not always available and is influenced by many system characteristics. For these reasons and others, simplified methods have been developed. These methods are sometimes based on wind generation during a time period that corresponds to high system risk hours. In other cases, methods can approximate the system LOLP curve so that high-risk hours receive more weight than other hours. We favor experimentation with such methods but suggest

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that it would be helpful to benchmark simple methods against ELCC. This will help eliminate the sometimes-arbitrary assumptions that can be introduced by some simple calculations we have encountered.

Interannual variability of wind generation is an important issue, and it can have an effect on any capacity metric. We recommend that multiple years of data be used in capacity value calculations. If that is not possible, we think that some approaches covered in this article can be useful.

Going forward, we expect that the capacity value of wind generating plants will continue to be a topic that receives significant attention. As more experience with the capacity value of wind energy is gained, we encourage open analysis and reporting of the findings.■

Endnotes:

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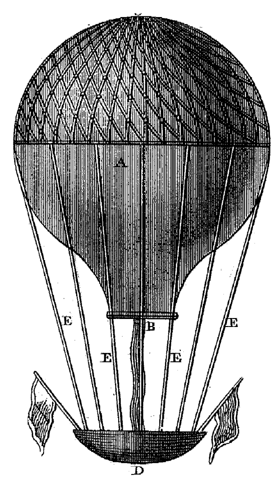
4. Enernex Corp., Wind Logics Inc., Wind Integration Study, Xcel Energy and Minnesota Dept. of Commerce, 2004, available at http://www.state.mn.us/mn/externalDocs/Commerce/Wind_Integration_Study_092804022437_WindIntegrationStudyFinal.pdf.

5. *Id.* One alternative method suggested in the California RPS Integration cost analysis. However, it is important to note that this method was only effective when the hydro system dispatch was ignored. See California Wind Energy Collaborative, *California Renewables Portfolio Standard Renewable Generation



Integration Cost Analysis, Phase III: Recommendations for Implementation*, California Energy Commission, Sacramento, 2004, available at http://www.energy.ca.gov/reports/500-04-054.PDF.

6. The equation used by the Garver approach is $R' = \exp\{-[(P - L)/m]\}$, where P = annual peak load, L = load for the hour in question, R' is the risk approximation (LOLP), measured in relative terms (peak hour risk = 1).

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8. PJM System Planning Department, *Manual 21: Rules and Procedures for Determination of Generating Capability*, Revision 3, Apr. 30, 2004. See, in particular, Appendix B-1. Available at http://www.pjm.com/contributions/pjm-manuals/pdf/m21v04.pdf.

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18. Portland General Electric, *Final Action Plan: 2002 Integrated Resource Plan*, Mar. 2004, available at http://www.portlandgeneral.com/about_pge/regulatory_affairs/pdfs/2002_irp/actionPlan_final.pdf.

19. Bollinger and Wiser, *supra* note 17.

20. Personal Communication, Tom Maclean, PSE Energy, May 24, 2005.

Exhibits to Direct Testimony of Michael Milligan
on behalf of Montana Environmental Information Center

Exhibit MM-7

Docket No. 2019.12.101

Department of Public Service Regulation
Montana Public Service Commission
Docket No. D2019.09.059
Avoided Cost Rate Filing – Schedule QF-1
NorthWestern Energy

PRE-FILED DIRECT TESTIMONY OF

R. THOMAS BEACH

ON BEHALF OF VOTE SOLAR AND MONTANA ENVIRONMENTAL INFORMATION CENTER

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RTB-5	Synapse, Comments on NorthWestern Energy's Final 2019 Electricity Supply Resource Procurement Plan (Feb. 14, 2020)

Executive Summary

This testimony presents the position of Vote Solar and Montana Environmental Information Center (collectively, "Vote Solar") on the proposal of NorthWestern Energy (NWE) to revise its Schedule QF-1 avoided cost rate applicable to small qualifying facilities (QFs) who seek to provide new renewable generation to NWE. These small QFs principally use solar, wind, and hydro resources.

Since NWE's QF-1 rates were last revised, the utility industry has seen the emergence of new types of "hybrid" QF projects that pair solar or wind generation with utility-scale battery storage. The storage allows a significant portion of the wind or solar generation to be stored until exactly when it is most needed by the utility, when the battery can be discharged at a steady rate over the peak load hours. The use of storage substantially increases the capacity value of a hybrid unit, compared to a wind or solar unit of similar size without storage. Further, the variability or intermittency of the output from solar resource is significantly reduced because the stored energy can be dispatched in a controlled manner through the battery. Given this important technological advance, it no longer makes sense to set avoided cost rates for stand-alone solar, wind, and hydro facilities. Instead, NWE's QF-1 rates should be re-formulated into a single set of time-varying avoided cost rates for energy and capacity that correspond to the utility's time-dependent avoided costs for energy and capacity. These new QF-1 rates will apply to all types of small QFs, will correctly value their capacity and energy depending on when the electricity is delivered to the grid, and will align the price incentive for QF design and operation to their value to ratepayers.

Vote Solar has carefully evaluated NWE's current long-term avoided costs. To calculate avoided energy costs, we have used the "proxy" method, as adopted by the Commission in Orders No. 7199e, 7108e, and 7500c/7500d. This is the method that the Commission used to set NWE's present QF-1 rates in Orders 7500c/7500d, in part, because of the transparency of that method compared to the opaque ProSimm modeling methods. That transparency benefit has not changed. However, the proxy unit has. Vote Solar calculated NWE's current avoided energy costs using, as the proxy, the reciprocating internal combustion engine (RICE) units that NWE plans to install beginning in 2022. These ICE units comprise the primary new resources planned in NWE's *2019 Energy Supply Resource Plan* (*2019 ESRP*) scenarios. We do not propose any other changes in how the proxy method calculates avoided energy costs. **Table ES-1** below shows our proposed avoided energy costs (for a 15-year contract), and compares them to the 15-year avoided energy costs for solar QFs in current QF-1(a) rates and in the revised rates that NWE has proposed. Also note that Vote Solar proposes to move to energy pricing based on the standard definitions of high load hours (HLH) and low load hours (LLH), in order to provide greater pricing granularity in non-peak months.

Table ES-1: *Comparison of Avoided Energy Costs*

Energy Prices 15-year levelized	Current QF-1 Tariff (Solar)	NWE Proposed (Solar)*	Vote Solar Updated QF-1 Tariff	
Carbon included?	No	No	No	Yes
Varies by technology?	Yes	Yes	No	No
On-peak price ($/kWh)	0.03434	0.01683		
Off-peak price ($/kWh)	0.03434	0.01683		
HLH price ($/kWh)			0.04086	0.04566
LLH price ($/kWh)			0.03014	0.03014
Baseload ATC ($/kWh)	0.03434	0.01683	0.03626	0.03901

* Does not include proposed deduction for integration costs.

The Commission should reject NWE's proposal to use the peaker method – rather than the proxy method—to calculate avoided costs. The peaker method assumes that the utility system is in equilibrium with a least-cost peaker as the only capacity need, which is inconsistent with NWE's actual needs and current resource plan.

The Commission should further reject NWE's proposal to use production cost modeling that incorrectly assumes avoided energy costs are zero in a substantial portion of hours. In reality, the utility's avoided costs in these hours are the market prices because the utility has access to a wholesale market for power sales. The "cost" to the utility and ratepayers for energy in those hours is the market price, not the artificial price point of generation at the level of native load. That is especially true because NWE will be joining the western Energy Imbalance Market (EIM), an auction-based market that establishes locational marginal prices every five minutes. Additionally, NWE's forecast of Pacific Northwest (PNW) market prices assumes a declining heat rate based on an assumed build-out of new resources that is inconsistent with NWE's own plan to build gas-fired generation. In other recent cases the Commission has repeatedly rejected this declining heat rate forecast.

The technological change represented by hybrid solar and wind units dictates that the method used for avoided capacity costs in the QF-1 rate needs to change. Vote Solar recommends that the avoided capacity costs proposed by NWE, based on simple-cycle combustion turbine costs, should be allocated over a focused set of peak hours in both summer and winter peak months. Doing so compensates QFs only to the extent that they produce during those hours. The summer peak hours should be from 2 p.m. to 6 p.m. from June 15 to September 15; the winter peak hours would be from 5 p.m. to 8 p.m. in December, January, and February. Over the five years 2014 to 2018, these hours have included all of NWE's annual peak load hours, and 74% of the hours with loads within 5% of NWE's annual hourly peak load. The final column of **Table ES-2** summarizes Vote Solar's proposed capacity price applicable to this focused set of peak hours.

Table ES-2: *Capacity Prices*

Capacity Prices For contracts of all lengths	**Current QF-1 Tariff**	**NWE Proposed QF-1**	**Vote Solar Proposed QF-1**
Avoided capacity ($/kW-year)	116.26	176.44	176.44
Varies by technology?	Yes	Yes	No
On-peak price ($/kWh) HLH in five peak months 2,080 total hours	Solar - 0.0091 Wind – 0.0077 Hydro – 0.0568	Solar - 0.0000 Wind – 0.00787 Hydro – 0.03769	
Capacity price ($/kWh) June 15 – September 15: 2p – 6p December – February: 5p – 8p 638 total hours			0.2766

NWE continues to understate significantly the capacity value of utility-scale solar and wind facilities in Montana, to misapply the Southwest Power Pool (SPP) method for assessing solar and wind capacity values, and to refuse to recognize that its system can peak in either the summer or winter months. NWE's 0% capacity value for solar is inconsistent with the results of NWE's own effective load-carrying capacity (ELCC) analysis that appears to conclude that solar's capacity contribution over the next 20 years is 27% and with solar capacity contributions calculated by other utilities in the Pacific Northwest, none of whom uses the SPP method.

NWE's proposal also ignores the fact that small QFs, up to 3 MW in size interconnected to the distribution system, will avoid transmission capacity costs in addition to energy and generation capacity costs. The power produced by such QFs will generally serve loads on the distribution system. As a result, small, widely distributed solar projects will reduce peak loads at the transmission substations to which they interconnect. This reduces loads on the transmission system, making additional transmission capacity available for load growth, for other transmission customers, or for greater access to regional markets. The testimony calculates these avoided transmission capacity costs to be $0.0909 per kWh during a focused set of peak hours, and proposes to add them to those hours in the time-differentiated avoided capacity costs summarized in Table ES-2.

NWE's testimony substantially exaggerates the costs to integrate solar resources into its system. The utility's approach fails to consider the reduction in these costs as a result of the resources that are avoided, or the savings in balancing costs that NWE will realize when it joins the EIM and builds additional flexible gas generation, as it is planning to do. Vote Solar reviews the trends in studies of integration costs by other utilities and control area operators with far higher penetrations of solar resources than Montana. Other utilities are experiencing far lower solar integration costs than expected a few years ago, due to experience in managing these resources, new market innovations such as the western EIM, and the availability of additional flexible gas generation that can provide ancillary services.

This testimony also discusses several other benefits and costs of utility-scale solar QF generation for ratepayers that can be quantified but that have not been included traditionally in the Schedule QF-1 rates. These benefits include the following:

- Hedging against volatility in fossil fuel prices
- Reductions in prices in the wholesale markets in the West
- Local economic benefits from developing Montana's solar resources

These benefits significantly exceed the modest costs that NWE may incur to integrate these new solar resources into its system. Vote Solar is not recommending that these additional net benefits should be included in the Schedule QF-1(a) rate at this time. However, the Commission should consider these added net benefits in its deliberations, and should find that they result in ratepayers receiving a good deal if NWE contracts for new solar generation at the updated QF-1 rates that Vote Solar has presented in this testimony.

Finally, Vote Solar observes that, as has been the case for several years, NWE needs the capacity that these QF contracts can provide, given its significant capacity deficit. NWE has stated that its capacity needs are exacerbated by the tightening of the regional supply/demand balance as the result of significant actual and near-future closures of coal-fired capacity. New QF capacity, especially from solar paired with storage, will add diversity to NWE's existing renewable resources, complementing its wind and hydro assets. These projects also will provide other quantifiable net benefits to NWE ratepayers that are not included in the QF-1(a) rates. Finally, any risk of overcapacity from QF-1(a) projects is limited by the maximum 3 MW size of these projects and by the inherent difficulties in siting and developing successful QF projects.

I. INTRODUCTION

Q: Please state your name, address, and business affiliation.

A: My name is R. Thomas Beach. I am principal consultant of the consulting firm Crossborder Energy. My business address is 2560 Ninth Street, Suite 213A, Berkeley, California 94710.

Q: Please describe your experience and qualifications.

A: I have 35 years of experience in utility analysis, resource planning, and rate design. I began my career at the California Public Utilities Commission (CPUC), working from 1981-1984 on the initial implementation in California of the Public Utilities Regulatory Policies Act (PURPA) of 1978. I also served for five years as a policy advisor to three CPUC commissioners. Since entering private practice as a consultant in 1989, I have served as an expert witness in a wide range of utility proceedings before many state utility commissions. This includes sponsoring testimony on PURPA-related issues, including the calculation of avoided cost prices, in state regulatory proceedings in California, Idaho, Oregon, Nevada, North Carolina, Utah, and Vermont. I also have extensive experience on public policy issues related to the development and deployment of solar generation, both photovoltaic (PV) and solar thermal. This includes assessing the costs and benefits of both small, distributed solar and large, utility-scale systems. Prior to this professional experience, I earned degrees in English and Physics from Dartmouth College and a Masters in Mechanical Engineering from the University of California at Berkeley. My CV is included as Exhibit RTB-1.

Q: On whose behalf are you testifying in this proceeding?

A: I am appearing on behalf of Vote Solar and the Montana Environmental Information Center (collectively, "Vote Solar"). Vote Solar is an independent 501(c)(3) non-profit working through effective policy advocacy to repower the U.S. with clean energy by making solar power more accessible and affordable. Vote Solar seeks to promote the development of solar at every scale, from distributed rooftop solar to large utility-scale plants. Vote Solar has over 80,000 members nationally, including members in NorthWestern's service territory. Vote Solar is not a trade group and does not have corporate members.

Montana Environmental Information Center (MEIC) is a non-profit environmental advocate founded in 1973 by Montanans concerned with protecting and restoring Montana's natural environment. MEIC plays an active role in promoting Montana clean energy projects and policies, including advocating for the expansion of responsible, renewable energy and energy efficiency; and supporting policies that insulate energy consumers from fuel price risk. At the state level, MEIC leads the effort to pass policies that help expand clean, affordable, reliable and efficient energy solutions for Montana. MEIC represents approximately 5,000 members, including roughly 3,500 members in Montana.

Q: Have you previously testified or appeared as a witness before the Montana Public Service Commission?

A: Yes, I have. I testified for Vote Solar and MEIC on avoided cost issues concerning NWE's QF-1 tariff in Docket 2016.05.039.

Q: Do you have any exhibits?

A: Yes. Exhibit RTB-1 is my CV. Exhibit RTB-2 is my calculation of NWE's avoided costs using the proxy method. Exhibit RTB-3 includes certain discovery responses from NWE.

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II. NWE'S PROPOSAL TO REVISE QF-1 RATES

Q: Please describe NWE's proposal in this case.

A: NWE proposes to revise its QF-1 avoided cost rate applicable to small qualifying facilities (QFs) who seek to provide new renewable generation to NWE. The utility proposes revised QF-1 rates with four components: (1) avoided costs of energy, (2) avoided costs of capacity, (3) the costs of integrating the generation resource, and (4) the costs of interconnecting the resource to the system and delivering its generation to load.[1]

Q: What significant revisions does the utility propose for its QF-1 rates?

A: NWE asks the Commission to revise its QF-1(a) rate based on new ways of calculating its long-term avoided energy and capacity costs. Under NWE's proposal, avoided energy costs would be calculated with a production cost model, with certain post-model adjustments. NWE also proposes to include a small amount of avoided capacity costs in the QF-1(a) rate, based on NWE's interpretation of a Southwest Power Pool (SPP) methodology for determining the capacity value of wind and solar resources.[2] The utility also proposes to deduct the costs of purported ancillary services that it contends are required to integrate this QF generation.[3] **Table 1** below shows NWE's current and proposed QF-1(a) rates for solar QFs, including the net effect of the proposed deduction of integration costs.[4] The utility's current QF-1(a) rates, set in the last QF-1 docket, are very low and have not produced any QF development. NWE's proposed QF-1(a) rates are even lower. In fact, NWE proposes a negative price for wind, meaning that a QF would have to pay NWE to accept its power!

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[1] NWE Testimony (Fitch-Fleischmann), at p. BFF-3.

[2] NWE Testimony (Fitch-Fleischmann and Mauch) for avoided energy costs, and NWE Testimony (Babineaux) for avoided capacity costs.

[3] NWE Testimony (Stimatz).

[4] See "20-02-04 CD IN MAIL Compliance filing Workpapers.xlsx" for the most recent avoided cost update filing in February 2020, and "Exhibit_ (BFF-2) AC Rate Summary.xlsx" for the utility's proposed QF-1 rates.

Table 1: *Current and Proposed QF-1(a) Tariff Rates – 15-year Contract ($/kWh)*

Rate	Current QF-1(a) Tariff	NWE Proposed QF-1(a) Tariff	Percent Change
(1) Off Peak Energy Rate			
• Solar	0.03434	0.01683	(51%)
• Wind	0.03261	0.00923	(72%)
• Hydro/Other	0.03250	0.01586	(51%)
(2) Avoided Capacity Rate			
• Solar	0.00912	0.00000	(100%)
• Wind	0.00771	0.00787	2%
• Hydro/Other	0.05705	0.03769	(34%)
(3) = (1) + (2) On-Peak Energy and Capacity Rate			
• Solar	0.04346	0.01683	(61%)
• Wind	0.04032	0.01710	(58%)
• Hydro/Other	0.08955	0.05355	(40%)
(4) Ancillary Service Charge			
• Solar	-	0.01540	
• Wind	-	0.02277	
• Hydro/Other	-	0.00172	
(5) = (1) - (4) Net Off-Peak Energy			
• Solar	**0.03434**	**0.00143**	(96%)
• Wind	**0.03261**	**(0.01354)**	(142%)
• Hydro/Other	**0.03250**	**0.01413**	(57%)
(6) = (2) - (4) NET On-Peak Energy and Capacity			
• Solar	**0.04346**	**0.00143**	(97%)
• Wind	**0.04032**	**(0.00567)**	(114%)
• Hydro/Other	**0.08955**	**0.05183**	(42%)

Q: If NWE's proposed low or negative 15-year QF-1 avoided cost rates are approved by the Commission, would any QFs be developed under this tariff?

A: No, I would not expect any QF development. According to the Company's response to VS-005, no QFs were developed under the rates and contract term provided in Orders 7500c and 7500d. Since the rates NWE now proposes are even lower, and in some cases negative, it is virtually certain that no QFs will be developed under the proposed rates.

III. POLICY AND MARKET BACKGROUND

A. Applicable PURPA Policies

Q: Mr. Beach, as an expert with 35 years of experience in PURPA-related issues, please provide your perspective on the economic intent and regulatory innovations of PURPA that inform your testimony.

A: Congress enacted PURPA to encourage independent development of generation from new, free market, resources that reduce our nation's dependence on fossil fuels, with the goal of increasing the energy security and independence of the United States. PURPA required public utilities, who enjoyed (and in many places, still enjoy) a state-sponsored monopoly in providing electricity to consumers, to purchase power from cogeneration and small renewable power producers, collectively called "qualifying facilities" or "QFs," at prices that do not exceed the utilities' "avoided cost." In the words of the statute, avoided costs are "the cost to the electric utility of the electric energy which, but for the purchase from such cogenerator or small power producer, such utility would generate or purchase from another source."[5]

Congress intended PURPA's must-take requirement at an avoided cost price as the means to offset the monopsony power[6] of the utility as the sole buyer of generation in its service territory. Congress limited the purchase price to the utility's avoided cost to balance between the interests of ratepayers and PURPA generators and to ensure the price met the statutory requirements of "just and reasonable to the electric consumers of the electric utility and in the public interest" and "not discriminate against qualifying cogenerators or qualifying small

[5] Section 210(d) of PURPA (92 Stat. 3117, 16 U.S.C. § 2601).

[6] A monopsony market is similar to a monopoly except that a large buyer, not a large seller, controls a large proportion of the market and drives the prices down. A monopsony is sometimes also referred to as a buyer's monopoly.

power producers" in comparison to the utility's other supply options.[7] The FERC and the courts have found that a price set at 100% of the utility's avoided cost satisfies this dual standard and the intent of PURPA to encourage QF development.[8]

In essence, the economic design of PURPA is to simulate a free and open market to encourage QF development where QFs can offer generation at a competitive cost equal to or less than the incremental cost to the utility of building its own generation or of buying or selling power in the wholesale market. PURPA generation at the avoided cost price is also price neutral for the consumer because it is no more expensive than if the monopoly utility had generated the power itself, or purchased it from another market source. In other words, full avoided cost pricing ensures that the price is not too high, but also that it is just and reasonable and non-discriminatory compared to what the utility pays for non-QF electricity.

Q: Who establishes the avoided cost prices paid to QFs?

A: State regulatory authorities, such as this Commission, adopt avoided cost prices for the regulated utilities under their jurisdiction, following the guidelines set forth in the FERC's rules implementing PURPA.[9]

Q: PURPA was enacted almost four decades ago. Have Congress and the FERC enacted significant changes to PURPA since then?

A: Yes. PURPA was the key first step in developing independent power generation in the U.S. The success of this new industry in many states under the PURPA framework enabled the creation, in the 1990s and early 2000s, of viable and less-regulated markets for electric generation in many regions of the U.S. Over time,

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[7] Section 210(b) of PURPA, 16 U.S.C. § 824a-3(b).

[8] 18 C.F.R. § 292.304(b)(2); *American Paper Inst., Inc. v. American Elec. Power Serv. Corp.*, 103 S. Ct. 1921 (1983).

[9] 18 C.F.R. § 292.304.

these markets expanded to include, in some states, competition in generation at both retail and wholesale levels, as well as non-discriminatory access to electric transmission through regional transmission organizations ("RTOs") with independent system operators ("ISOs") of the transmission grid. In the short-run, this competition occurs through organized, auction-based day-ahead and real-time markets run by the ISO that determine hourly or sub-hourly market-clearing locational marginal prices ("LMPs") across the footprint over which the market is run. In addition, many states enacted renewable portfolio standard ("RPS") programs, based on the states' traditional authority over utility procurement, designed to provide long-term markets for the new renewable generation that had previously been developed principally through PURPA. Responding to these developments, Congress enacted the Energy Policy Act of 2005 ("EPAct"), which implemented a new Section 210(m) of PURPA. This section allows a utility to petition the FERC for relief from the "must purchase" requirement of PURPA if FERC finds that QFs in that utility's territory have access to sufficiently competitive wholesale markets for long-term sales of capacity and electric energy.

Q: Have utilities in other states and regions successfully petitioned the FERC under Section 210(m) to end the PURPA must-purchase obligation?

A: Yes. However, this has occurred in states that have opened their generation market to sufficient competition at the wholesale level. For example, when the major California investor-owned utilities ("IOUs") successfully petitioned the FERC in 2011 to waive the PURPA must-purchase obligation for QFs larger than 20 MW, they were able to show the FERC that California had taken the following steps to provide viable long-term wholesale markets for QF generation:

- A CPUC-approved program for competitive solicitations for long-term contracts with existing or new cogeneration QFs;

- A state-enacted RPS requiring generation from RPS-eligible renewable generators by a date certain, implemented through regular competitive solicitations to procure RPS generation under long-term contracts of up to 25 years;

- A resource adequacy program requiring the IOUs to purchase capacity from QFs and merchant generators to meet near-term resource adequacy requirements; and

- Non-discriminatory access to the transmission system and to an auction-based, day-ahead wholesale energy market operated by a FERC-regulated RTO, the California Independent System Operator ("CAISO").[10]

It is important to note that the PURPA must-purchase obligation remains in place in California (and in most other RTOs/ISOs) for QFs up to 20 MW in size, and that the must-purchase obligation can be re-instated if the FERC finds that long-term wholesale markets are no longer available to QFs. The fact that the U.S. Congress and the FERC have found that a state must create long-term wholesale markets for energy and capacity from QFs before it can end PURPA's must-purchase obligation for larger generators indicates clearly that the PURPA program remains necessary to provide such a long-term market for QF generation outside of those markets and for smaller generators (such as those who take service under the QF-1(a) tariff).

B. QF Development in NWE's Montana Service Territory

Q: What types of renewable QF generation have been developed historically in NWE's service territory?

A: Renewable QF development in NWE's service territory to date has been principally wind and small hydro QFs, with a small number of solar projects. NWE has a number of large wind projects under long-term QF contracts, and about 50 MW of QF wind projects developed under older vintages of Schedule QF-1 rates still hold long-term contracts with NWE.[11] NWE presently purchases power from six small solar QFs on its system with 25-year QF-1 contracts, for a

[10] See *Order Granting Application to Terminate Purchase Obligation* (issued June 16, 2011) in FERC Docket No. QM11-2-000, 135 FERC ¶ 61,234.

[11] *2019 ESRP*, at Table 4-1. Also see NWE's *2015 Integrated Resource Plan (2015 IRP)*, at Volume 1, Table 8-6 for QF wind resources under Schedule QF-1.

total of 17 MW.[12] None of those small QFs were developed under the most recent QF-1 rates established by the Commission in Orders 7500c and 7500d.

Q: Do you agree that the 15-year contracts available to QFs in Montana provide a long-term market for QF generation in the state?

A: In my judgement, and based on the evidence available, 15 years does not appear to be an adequate term to encourage QF generation. The Eighth Judicial District Court overturned the provision of the Commission's Order 7500c which reduced the QF-1 contract term from 25 to 15 years;[13] that order has been stayed and is still pending before the Montana Supreme Court. The Company's response to VS-005 confirms that no QF generation was developed based on the rates and 15-year contract term ordered in the last QF-1 docket. That result is consistent with my experience that, given the significant capital investment required to develop new QF projects, developers need contracts of at least 15 years, and preferably longer, to develop QF projects successfully.

Montana state law expresses a preference for long-term QF contracts, as noted by one of NWE's witnesses.[14] The ability of a project to obtain financing depends on both the price and the term. The revenue over the term of the contract must meet the investor's threshold for returns. A lower rate necessitates a longer term to meet the same return on investment hurdle to attract investors. Given the low avoided cost rates in Montana, a term longer than 15 years appears necessary.

The history of QF development in Montana and other states further confirms this

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[12] *Ibid*., Table 4-1. Also NWE Testimony (Babineaux), Exh. MSB-2.

[13] Montana Eighth Judicial District Court, *Order Vacating and Modifying Montana Public Service Commission Order Nos. 7500(c) and 7500(d)*, issued April 2, 2019 (hereafter, Court Order), at pp. 5-9.

[14] NWE Testimony (Fitch-Fleischmann), at p. BFF-8. See Mont. Code Ann. § 69-3-604(2), which states, "[l]ong-term contracts for the purchase of electricity by the utility from a qualifying small power production facility must be encouraged in order to enhance the economic feasibility of qualifying small power production facilities."

reality. There has been some development of small solar QFs in states such as North Carolina under 15-year standard contracts, but most successful QF development has required 20- or 25-year contract terms. 15 years is significantly shorter than the economic life of QF facilities, and, with longer PPA terms, these projects would be able to use lower-cost, longer-term financing. As a result, contract terms of 20 or 25 years are preferable, and allow for lower-cost projects that can benefit ratepayers.

C. New QF Technologies

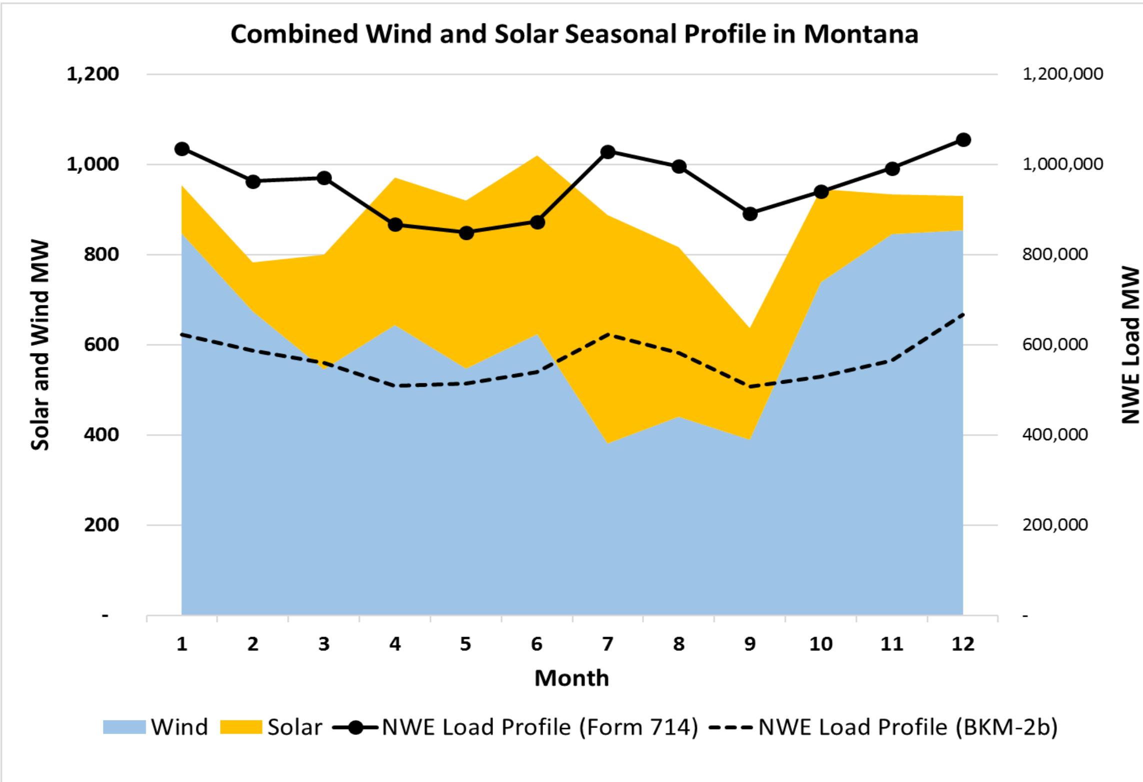
Q: Have there been significant recent developments in the QF technologies that can be deployed in Montana?

A; Yes. Since NWE's QF-1 rates were last revised, the utility industry has seen the emergence of new types of "hybrid" QF projects that pair solar or wind generation with utility-scale battery storage. The storage allows a significant portion of the wind or solar generation to be stored until the time when it is most valuable to the utility, when the battery can be discharged at a steady rate over the peak hours. Using storage changes significantly the production profile of wind and solar generation and, therefore, the avoided cost calculations for the resource. The use of storage substantially increases the capacity value of a hybrid unit, reduces the variability or intermittency of the output from the renewable resource, and changes the hours in which energy is delivered. Each of those changes results in different avoided cost calculations than for a solar or wind resource alone. Such hybrid units have the potential to be dispatched directly by the utility or by the unit's operator in response to price signals from a PPA with the utility, and have the potential to supply the utility with ancillary services.

Further, utility-scale projects have been proposed that include solar, wind, and batteries in one location, to further exploit the seasonal and temporal diversity of wind and solar resources. This could be a fruitful strategy in Montana, where wind resources peak in the winter and solar resources in the summer (see **Figure**

1 below[15]), with the storage available to ensure that the hybrid project provides firm capacity during peak hours.

Figure 1



Q: Does the availability of these hybrid technologies have implications for the basic structure of NWE's QF-1 rates?

A: Yes. To date, the utility has calculated its QF-1 avoided cost rates based on the typical output of solar-only or wind-only QFs in Montana, using hourly output profiles of each of these variable resources under typical meteorological conditions. When combined with a battery, however, the production from the combined generator can be shifted in time and dispatched to the grid in set amounts when most needed. Developers can scale and size the battery to provide

[15] The Figure 1 wind and solar profiles assume about 1,100 MW of solar nameplate capacity and 2,200 MW of the win nameplate capacity, with monthly shapes based on NWE's Musselshell 2 and Black Eagle Solar monthly generation profiles, from "Exhibit_(MSB-2) Capacity Contributions and % On Peak Gen.xlsx."

a wide variety of output profiles to best respond to the utility's needs. There is no single "typical" output profile for a hybrid QF resource. Given this important technological advance, it no longer makes sense to set avoided cost rates for stand-alone solar and wind facilities, or to set the price to a projected production profile. Instead, NWE's QF-1 rates should be re-formulated into a single set of time-varying avoided cost rates for energy and capacity that reasonably reflect the utility's time-dependent avoided costs for energy and capacity. These QF-1 rates would be applicable to all QFs regardless of the mix of technologies that a QF employs. A QF developer can then determine the mix of technologies, including the type of generation and amount of storage, in response to those price signals.

Q: Should the availability of these new hybrid QF technologies impact the term of the QF-1 contract that NWE offers?

A: Yes. As the Commission recently found, longer contracts "enhance[] the economic feasibility of this [hybrid QF] project and provide[] QF developers a sufficiently long period to evaluate the investment opportunity presented to them by individual projects."[16] I agree that the availability of longer contracts will encourage the development of these innovative and beneficial QF projects in Montana.

D. New Markets

Q: Are there recent market developments concerning NWE that are relevant to the calculation of its future avoided costs?

A: Yes. NWE has announced that it plans to join the western Energy Imbalance Market (EIM) in the spring of 2021. The western EIM is an organized, sub-hourly market that seeks out beneficial trades of resources within the hour to reduce balancing and load following costs for participants and to decrease renewable curtailments. The EIM began with an agreement in 2014 between just

[16] See Order No. 7680b in Docket No. 2019.06.034, at p. 48.

the CAISO and PacifiCorp, but since then has spread across almost the entire Western Interconnection.[17] Since its inception, the EIM has saved money for every participating utility; these benefits are tracked and documented by the EIM participants in quarterly reports. The cumulative benefits to EIM participants have reached $800 million as of the end of October 2019.[18] As discussed below, NWE's participation in the EIM should resolve the persistent issue in Montana concerning how to set avoided costs under certain market conditions. I also agree with NWE's assessment in its *2019 Electricity Supply Resource Procurement Plan (2019 ESRP)* that the EIM is likely to lead to a day-ahead market with locational marginal prices (LMPs) and, ultimately, to a regional transmission operator / independent system operator across the entire WECC footprint.[19]

IV. ANALYSIS OF NWE'S CURRENT AVOIDED COSTS

A. NWE's Current Need for Generation Resources

Q: What is NWE's current need for generation resources?

A: Based on NWE's *2019 ESRP*, NWE today has a substantial deficit in committed capacity; its present reserve margin (excluding market purchases) is -46%.[20] By

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[17] See https://www.westerneim.com/Pages/About/default.aspx for the current list of EIM participants. In December 2019, a number of Colorado utilities, including Xcel Energy, Black Hills Colorado Electric, Colorado Springs Utilities and Platte River Power Authority, announced that they will join CAISO's EIM as soon as 2021. See https://rtoinsider.com/eim-lands-xcel-other-colo-utilities-150754/.

[18] See https://www.westerneim.com/Pages/About/QuarterlyBenefits.aspx; see also E3, "NorthWestern Energy, Energy Imbalance Market Analysis" (Feb. 2017), *attached* as Exhibit RTB-4.

[19] See *2019 ESRP*, at pp. 5-9 to 5-10.

[20] *Ibid*., at p. 2-13 and Figure 2-1. NWE's reserve margin Figure 2-1 shows that 46% of its peak load plus the 16% planning reserve margin must be met with market purchases. NWE's system resources can supply peak capacity of 755 MW, compared to its 1,210 MW peak demand. If one adds a 16% reserve margin, this also yields a 46% capacity deficiency. *See* 2019 ESRP, at page 1-3.

any standard measure of resource adequacy in the utility industry, this is a substantial deficit. NWE acknowledges that it needs to add generation capacity as soon as possible in order to provide adequate resources to meet its customers' long-term needs. This deficit is longstanding, and was acknowledged in the utility's *2015 Integrated Resource Plan (2015 IRP)*.[21] In the past, NWE relied on surpluses in the regional market to serve its capacity needs, but NWE stated in both the *2015 IRP* and *2019 ESRP* that these surpluses are ending due to the closure of aging coal-fired plants, with the Pacific Northwest (PNW) expected to exceed its target 5% loss-of-load probability in 2021.[22] NWE's reliance on on-peak market purchases far exceeds other PNW utilities.[23]

Q: Can QFs provide a significant source of capacity to the NWE system?

A: Yes, and this is particularly true for hybrid QFs. Further, as I will discuss in more detail in Section IV.D below, NWE's flawed use of an SPP methodology continues to underestimate substantially the capacity contribution that new QF solar generation could make to NWE's system.

B. Proxy Method

Q: Please describe the methodology the Commission has used to calculate NWE's avoided costs.

A: The Commission has used what is often referred to as the "proxy method" to set NWE's present QF-1 rates.[24] This approach assumes that the QF allows the utility to delay its next planned generating unit, usually the next generating unit identified in the utility's current IRP. The proxy method estimates avoided costs based on the projected capacity and energy costs of that next planned unit. In some states, including Montana, the costs of short-term market purchases (or

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[21] *2015 IRP*, at Figures 1-3 and 7-3.

[22] *2019 ESRP*, at pp. 2-9 to 2-16. *2015 IRP*, at pp.1-10 to 1-11, 7-3 to 7-5.

[23] *2019 ESRP*, at Figure 2-1.

[24] See, generally, Orders No. 7199e, 7108e, and 7500(c) / 7500(d).

system-wide marginal energy costs plus short-term capacity purchases) are used in the years before the year in which the proxy unit is expected to enter service.[25] The proxy method is generally regarded as the simplest and most transparent of the avoided cost methods because it relies on utility and plant-specific data for the proxy resource and avoids the need for long-term modeling of system-wide marginal energy costs through opaque, complex, and proprietary computer models.[26]

Additionally, regular updates are possible and transparent under the proxy method. The key natural gas and power price assumptions used in the method can be updated on a regular basis between avoided cost proceedings, keeping the prices up to date.[27] In Order 7500c, the Commission found the proxy method to be appropriate for setting QF-1 rates:

> 25. The Commission finds that the proxy method is reasonable and appropriate for estimating avoided costs because a primary objective in this case is to set standard tariff rates for relatively small QFs, rather than project-specific rates for large QFs. The proxy method is transparent, easy to replicate, and does not require the use of NorthWestern's proprietary computer model, PowerSimm. Accordingly, the proxy method provides a practical tool for estimating avoided costs for purposes of setting standard QF tariff rates on a periodic basis between QF-1 proceedings.[28]

Q: Have you undertaken an independent analysis of NWE's current long-term avoided costs, using the proxy methodology that the Commission adopted in Orders No. 7199e, 7108e, and 7500c / 7500d?

A: Yes, I have. This methodology is based principally on the long-run, all-in costs of the utility's next resource addition, with market prices used in the years prior to

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[25] Because that next generating unit often has been a gas-fired combined-cycle, this approach also has been called the "blended market + combined cycle" method.

[26] Other states in the Pacific Northwest (Oregon, Idaho, and Utah) also have used the proxy method, and it has been used in California to establish the rates for purchases of energy and capacity from high-efficiency combined heat and power ("CHP") units.

[27] Order 7500c, at p. 8 provided for the updating of QF-1 rates every six months, for prospective contracts only.

[28] Order 7500c, at p. 8.

the year in which that resource is added. NWE's *2019 IRP* shows clearly that the utility plans and intends to add significant new capacity – on the order of 780 MW (195 MW per year) over the 2022 to 2025 period[29] – to meet its critical capacity deficit. The resource additions in all of the scenarios are mostly gas-fired resources, principally reciprocating internal combustion engine ("RICE") units.[30] In fact, RICE units comprise 81% of the additions across all of NWE's scenarios that add gas-fired units.[31] NWE's RICE units have the following key cost and operating parameters, with the costs in 2018 dollars.[32]

Table 2: *Key RICE Parameters (2018 $)*

Parameter	Value
Heat Rate	8,323 Btu/kWh
Variable O&M	$4.66 per MWh
Capital cost	$1,833 per kW
Fixed O&M	$23.15 per kW-year

I have calculated the levelized avoided cost price for the QF-1 tariff, in low-load (LLH) and high-load (HLH) hours under the Commission's currently-adopted proxy method.[33] This analysis uses the operating parameters for the RICE units selected in the *2019 IRP* scenarios, with an on-line date of 2022, when NWE plans to begin major capacity additions. I used the fuel and power forecasts from the most recently updated, February 2020 QF-1 filing, including the recently-released escalation rates in the Energy Information Administration's (EIA) Henry Hub gas forecast for the *2020 Annual Energy Outlook*. These calculations are

[29] *Ibid.*, at p. 10-16.

[30] See *2019 ESRP*, at Tables 10-2 and 10-3.

[31] One of the 2019 ESRP scenarios adds only carbon-free resources.

[32] See *2019 ESRP*, at Tables 7-6 and 7-7, averaging the values for western and eastern Montana.

[33] I calculate a 25-year levelized avoided cost price because that is the maximum QF contract term. A 25-year levelization period is appropriate for 25-year QF contracts. Order No. 7199d, at p. 14, calculated a 24-year levelized price, without explanation. In contrast, Order No. 7108e, at pp. 23-24, calculated a 25-year levelized price for 2011-2035, with the Commission finding that the 25-year calculation is appropriate in order "to capture the full 25-year contract period available under Option 1." For a 25-year contract term, a 25-year levelized price is appropriate in order to reflect full avoided cost.

presented in **Exhibit RTB-2**. The results for 15-year contracts are similar to current QF-1 tariff prices. **Table 3** below shows Vote Solar's proposed Schedule QF-1 avoided cost energy prices for 15-year contracts. The updated calculations and schedule of our Schedule QF-1 avoided cost energy prices start in 2021, as that is likely to be the earliest start year for the QFs impacted by the proposed change in avoided cost prices.

In addition, Vote Solar proposes to have separate heavy load hour (HLH) and light load hour (LLH) prices in all months. The QF-1 schedule currently has different on- and off-peak prices only in the five peak months (July and August in the summer, December through February in the winter); in other months, the off-peak rate applies in all hours. Having separate HLH and LLH prices in all months provides more price granularity than the current structure for QF-1 avoided energy costs and provides a more effective and efficient price signal to QF developers when designing their generation.

Table 3: *Comparison of Avoided Energy Costs*

Energy Prices 15-year levelized	Current QF-1 Tariff (Solar)	NWE Proposed (Solar)*	Vote Solar Updated QF-1 Tariff	
Carbon included?	No	No	No	Yes
Varies by technology?	Yes	Yes	No	No
On-peak price ($/kWh)	0.03434	0.01683		
Off-peak price ($/kWh)	0.03434	0.01683		
HLH price ($/kWh)			0.04086	0.04566
LLH price ($/kWh)			0.03014	0.03014
Baseload ATC ($/kWh)	0.03434	0.01683	0.03626	0.03901

* Does not include proposed deduction for integration costs.

Q: In the last QF-1 proceeding, Vote Solar also proposed to use the proxy method based on the costs of RICE units. The Commission rejected that proposal in Order 7500c. Does your proposal here remedy the problems that the Commission cited with your proposal in Docket 2016.5.39?

A: Yes. At the time of the last QF-1 case, NWE was planning to build only a small number of RICE units in 2019, to provide enhanced load following capability. At that time, the RICE units were not expected to operate often to serve energy needs. The circumstances are dramatically different today. In the current resource plan, not only are more RICE units added, but they are projected to provide significant energy.

All of the scenarios in the *2019 ESRP* add almost 800 MW of new capacity from 2022-2025, and almost all of the added capacity is RICE units. Thus, unlike the prior IRP, the *2019 ESRP* clearly identifies RICE units as the avoidable resource for NWE.

In addition, in Order 7500c the Commission found that the baseload 90% capacity factor that Vote Solar used in its analysis did not reflect the much lower capacity factor at which the utility planned to operate the RICE units for load following.[34] In this case, I have assumed that the RICE units run during high-load hours, at a 57% capacity factor. This is consistent with the expected capacity factor for these units in their initial years (about 50% to 55%), as modeled by NWE for the *2019 ESRP*.[35] Further, as shown in Exhibit RTB-2, the current gas and power forecasts used for QF-1 pricing show that the RICE units are economic in high load hours, but not in light load hours.

Q: Your schedule of Schedule QF-1 avoided cost prices in Exhibit RTB-2 includes contract terms of up to 25 years. Please explain why you have included terms longer than 15 years.

A: As noted above, the reduction of the QF-1 contract term from 25 to 15 years was overturned by the Eighth Judicial District Court, produced no QF-1 development

[34] See Order No. 7500(c), at p. 9.

[35] NWE models declining capacity factors for the RICE units over time, but this appears to be due to the utility's use of a market price forecast with declining heat rates over time, which the Commission rejected in Order No. 7680b.

since Order 7500c, is inconsistent with the terms necessary to develop new QF generation, and is inconsistent with many other states' QF terms. The 25-year contract term is important for QFs to obtain financing, and should be maintained, for the reasons that Vote Solar presented on the record in Docket 2016.05.039 and that I summarize above. A longer contract term is also consistent with the Commission's recent approval of a 20-year contract term for an innovative hybrid wind QF.[36] A summary of 20-year and 25-year contract prices under our proposal is provided below in **Table 4**.

Table 4: *Proxy Method with RICE Units (20- and 25-year contracts)*

Energy prices	**Vote Solar Updated QF-1 Tariff**			
	20-year levelized		***25-year levelized***	
Carbon included?	No	Yes	No	Yes
Varies by technology?	No	No	No	No
HLH price ($/kWh)	0.04268	0.04871	0.04421	0.05131
LLH price ($/kWh)	0.03206	0.03206	0.03369	0.03369
Baseload ATC ($/kWh)	0.03813	0.04157	0.03970	0.04376

Q: Tables 3 and 4 show your proposed QF-1 rates both with and without carbon. Please explain.

A: The issue of whether QF-1 rates should include assumptions for future carbon emission costs for fossil resources is also on appeal before the Montana Supreme Court. The Eighth Judicial District Court found that the Commission's Order 7500c failed to justify the removal of carbon costs from QF-1 rates, given that other QF orders had included such costs in avoided cost prices. The Court noted that "although there is uncertainty regarding the measure of these costs, they are not zero," citing a similar statement in NWE's own *2015 IRP*.[37] I have included carbon costs in Vote Solar's proposed QF-1 rates based on NWE's carbon cost forecast in its *2019 ESRP*.

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[36] See Order No. 7680b in Docket No. 2019.06.034, at p. 48.

[37] See Court Order, at pp. 9-10.

The Commission has previously observed that carbon costs are an inherent component of energy costs.[38] While the Commission has expressed concern about the uncertainty of future carbon regulation, that uncertainty is already captured by the range of industry predictions, which vary by both onset date and level of costs. But it is almost universally accepted in the industry that the future costs of operating fossil-fuel generators will include regulatory costs on carbon emissions, very likely within the 15- to 25-year term of QF-1 contracts.

Further, it would not be sufficient to address this issue by stating that QFs could simply accept a shorter contract now, and renew at a later time when carbon prices are known. QFs are entitled to long-term, fixed-priced contracts. It is therefore essential to use the best available information to project such costs now. Therefore, I have included carbon costs in Vote Solar's proposed QF-1 rates based on the average of NWE's carbon cost forecasts in its *2019 ESRP*.

Q: Do the Public Utilities Regulatory Policies Act of 1978 ("PURPA") or the Federal Energy Regulatory Commission's ("FERC") rules implementing PURPA explicitly require state regulators to set a certain term for QF contracts?

A: No, they do not. However, PURPA and the FERC rules do require the states to encourage the development of QFs, including the development of renewable QFs using hydro, solar, biomass, geothermal and wind resources. These renewable resources typically have low or zero fuel costs, but significant capital costs that must be financed over their expected useful life in order to be economic. In my experience, financing entities are not willing to lend money to renewable QF projects without a long-term contract at fixed prices that provides certainty that the renewable QF will be able to meet its debt repayment obligations if it operates as anticipated.

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[38] Order 7505b ¶ 58, Docket No. 2016.7.56; Order 7500d ¶ 37, Docket No. 2016.5.39.

Q: How do long-term QF contracts benefit ratepayers?

A: Ratepayers benefit most from a low, stable price. This is not always a price that simply equals the market price. Ratepayers can be substantially harmed if their costs for energy at times are very high due to volatility in energy market prices. As a result, consumers generally are willing to pay a premium to expected market prices in order to eliminate the future volatility in those prices. In essence, this premium represents insurance that consumers are willing to buy against the high costs of periodic spikes in market prices.

Q: Utilities sometimes argue that long-term QF contracts are too risky for ratepayers. Is it too risky for consumers to commit to long-term fixed-price contracts?

A: No. With any fixed-price power purchase contract – and with any significant capital investment by the utility in generation or transmission – there is always a risk that the alternatives will prove to be less expensive over the long-term. This is a risk that consumers bear with PURPA contracts, with other purchases in wholesale markets, and with the alternative of utility-owned fossil-fuel plants whose capital costs are largely fixed once they are approved for cost recovery through rate base and whose fuel costs are subject to significant market risk. NWE has complained that the prices or terms of QF contracts are "irrevocable" and cannot be modified once they are signed, yet it is also difficult to modify the costs for utility-owned generation included in the rate base once they have been authorized. And ratepayers become exposed to the market risk associated with the fuel costs for the utility-owned units. This can result in exposure to very high prices during times of scarcity or to stranded assets if plants become uneconomic in the market, as has happened recently with many coal units in the U.S. Utility-owned fossil generation, and in particular coal units, also face the risk that long-term capital or operating costs for rate-based units could increase over time because additional capital additions or operating expenses necessary to continue to operate the utility-owned units adds to the ratepayer cost of those units over time. Such long-term increase in the effective price to customers from pancaked expenditures in the rate base does not happen under fixed-price QF contracts.

Put another way, if it is too uncertain and too risky to forecast avoided cost prices for 25 years, then by the same argument it would also be too risky to evaluate the merits of the alternatives to QF power (such as a new utility-owned resource or retrofitting an existing fossil fuel plant with expensive pollution controls), or even to make decisions based on the long-term projections in an IRP. The North Carolina commission recognized this fact in a 2014 decision that reviewed avoided cost policies in that state, concluding that the uncertainties in future energy markets will impact ratepayers regardless of whether the utility contracts with QFs at long-term avoided costs or builds its own resources which are the basis for those avoided costs:

> Failure to calculate accurately a utility's avoided cost means ratepayers will pay for the additional energy and capacity whether the utility builds the plant and places it in rate base or the utility pays QFs avoided cost rates. The Commission concludes that establishing avoided cost rates based upon the best information available at the time and making such rates available in long-term fixed contracts, as required by Section 201 of PURPA should leave the utilities' ratepayers financially indifferent between purchases of QF power versus the construction and rate basing of utility-built resources.[39]

Q: Does the economic literature commonly ascribe a risk reduction benefit to long-term fixed price contracts?

A: Yes. There are numerous examples and studies that demonstrate that consumers are willing to pay a premium to fix the price of a commodity, including energy commodities.

- Perhaps the most familiar is the fixed-rate home mortgage, which typically carries a higher interest rate than an adjustable rate mortgage as the premium required to eliminate the risk of future interest rate fluctuations.
- The natural gas forward market provides consumers with a means to buy future supplies of natural gas at a price known today. Comparisons between

[39] North Carolina Utilities Commission, *Order Setting Avoided Cost Input Parameters* (Docket No. E-100 Sub-140, issued December 31, 2014), at p. 21.

forward gas market prices and contemporaneous fundamentals-based forecasts of gas prices reveal a consistent premium in the forward prices, perhaps associated with the "risk premium" that sellers in the forward markets require, and that buyers are willing to pay, in order to fix future prices.

- Long-term contracts for natural gas, at publicly-known prices, are not common today. However, such contracts typically show a premium to current price forecasts. For example, in 2011 Public Service of Colorado (PSCo) signed a ten-year gas supply contract with Anadarko Petroleum to support the replacement of a portion of PSCo's coal-fired generation with gas generation, at a fixed price that was $1.38 per MMBtu higher than the Energy Information Administration's contemporaneous forecast of prices in PSCo's market.[40]

C. Issues with NWE's Proposed Avoided Costs Using the "Peaker Method"

1. Methodology

Q: Does NWE's application propose a different method of calculating avoided costs?

A: Yes. NWE's application abandons the "proxy" methodology previously used by the Commission and proposes a calculation of avoided costs using what is known as the "peaker method." The peaker method assumes that a QF allows the utility to reduce the marginal generation on its system and to avoid building a peaking unit, rather than displacing or delaying the need for a particular new generating unit. According to the theory underlying the peaker method, if the utility's generating system is operating in equilibrium, at the optimal point, the cost of a peaker (often a simple-cycle combustion turbine [SCCT]) will be the least-cost source of new capacity, and new generation will have to be less expensive than a peaker plus the system marginal cost. Thus, the peaker method involves a dual calculation: the avoided energy costs are determined by the projected, system-wide marginal cost of energy (often calculated through production cost

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[40] Lisa Huber, *Utility-scale Wind and Natural Gas Volatility: Unlocking the Hedge Value of Wind for Utilities and Their Customers* (Rocky Mountain Institute, July 2012), at p. 13, available at http://www.rmi.org/Knowledge-Center/Library/2012-07_WindNaturalGasVolatility.

modeling), and the avoided capacity costs are established by determining the capacity-related costs of an inexpensive source of capacity, such as a SCCT. In this case, NWE is proposing to use a calculation of its system marginal energy costs from production cost modeling, plus the capacity-related costs of a combustion turbine unit as the avoided cost of capacity.[41]

Q: What are the drawbacks of the peaker method?

A: The peaker method depends on the assumption that the utility's system is operating at an optimal point, such that there is no resource other than a low-cost peaker that would reduce overall system costs. For example, the method assumes that the utility has no need for energy as well as capacity, such that it might be worthwhile to build a resource such as a RICE or combined cycle that provides both capacity and lower-cost energy. However, as indicated in their IRPs, utilities often plan to add resources other than SCCTs, indicating that the utility's system may not always be operating at the "optimal" point of equilibrium, or that the utility must respond to other constraints such as air emission restrictions, RPS requirements, or a need for flexible load-following capacity. Therefore, if a utility is planning to add a resource other than a SCCT, the proxy method is the more appropriate method to establish the utility's full avoided cost. With respect to NWE, the utility is not operating at an optimal point given its major deficiency in both capacity and energy, and the utility's IRP scenarios add a large number of RICE units to move toward resource adequacy. This argues for retaining the current proxy method instead of adopting NWE's proposed peaker approach.

In addition, the peaker method requires modeling of the utility's system-wide marginal costs in each hour, which then are used to produce avoided energy prices. Such modeling is complex, uses many assumptions (some of which may be confidential and whose impact on the results may not be transparent), and requires resources and capabilities which may not be available to any party except the utility.

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[41] NWE Testimony (Fitch-Fleischmann), at pp. BFF-14 to BFF-15 and BFF-25 to BFF-29.

2. Avoided Energy Costs

Q: Do you have concerns with NWE's modeling of its system marginal costs?

A: Yes, I have several concerns:

- Zero avoided costs in certain hours,
- Market price forecast with declining heat rates after 2025, and
- Load and wind resource assumptions used in PowerSimm.

Q: What concerns do you have with NWE's assignment of zero or internal production cost values to hours when the utility is "long"?

A: NWE's modeling of its avoided energy costs makes the erroneous assumption that its avoided costs are zero in hours in which the utility is long on resources and a zero-variable-cost or must-take resource is the last resource dispatched to serve load.[42] The utility argues that the Federal Energy Regulatory Commission ("FERC") rules implementing PURPA provide that "the purchase rate should only include payment for energy or capacity which the utility can use to meet its total system load" and that the FERC "rules impose no requirement on the purchasing utility to deliver unusable energy or capacity to another utility for subsequent sale."[43] Based on this reading of the FERC rules, NWE's PowerSimm modeling sets the avoided cost to zero in a significant percentage of "Condition 3" hours (39% in 2021).[44]

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[42] NWE Testimony (Fitch-Fleischmann), at p. BFF-15: "When NorthWestern's generation from resources with variable costs of $0 (such as other QFs or hydro) plus must-take or must-run resources (such as other QFs or thermal resources with minimum-run requirements) is greater than NorthWestern's loads, additional generation from a new QF cannot be used to serve NorthWestern's load and is therefore valued at zero."

[43] *Small Power Production and Cogeneration Facilities; Regulations Implementing Section 210 of the Public Utility Regulation Policies Act of 1978*, 45 Fed. Reg. 12,214, 12,216 (February 25, 1980), cited in NWE Testimony (Fitch-Fleischmann), at p. BFF-9 to BFF-10.

[44] See workpapers for NWE testimony (Mauch), at "Exhibit_BKM-2b_HourlySupplyStack_AvoidedCost_QF1_Solar.xlsx." Column AQ of the "Full Dataset" tab shows the marginal cost to serve load in each hour. There are 3,449 hours in 2021 (i.e. 39% of 8,760 hours) that are Condition 3 hours with avoided costs set equal to zero. The "Notes" tab for these workpapers define Condition 3 as "Long Power from Must Run Generation (forced sale): Base load generation exceeds load requirements - forced sale to MIDC. Avoided Cost is 0."

The utility's "cost to serve load" legal theory is premised on statements that the FERC made forty years ago, in 1980, in a world of vertically integrated utilities that were economically dispatched to meet their native load.[45] At that time the bilateral wholesale markets were not visible, and there were no large, centrally-organized, independently-run markets with ISOs that dispatched resources on a regional basis. In today's utility industry, however, economic dispatch incorporates market prices, either from the bilateral market or an ISO-run market. Pretending that the company's generation and load operate separate from the market, rather than as part of the regional market, ignores the economic reality that the marginal cost to serve native load is the market price. Put another way, because NWE dispatches (or should dispatch) its generation based on the market price, and returns market sale revenue to ratepayers, a unit of energy used to serve native load has the same "cost" to ratepayers as the market price that could have been realized if that unit of energy was sold instead.

That is true with the current Mid-C trading hub, but will be especially true once NWE joins the EIM in the spring of 2021. At that point, NWE's resources will be dispatched within the hour to EIM market-clearing prices, and not dispatched to serve the utility's native load.

Q: Please explain why, as a matter of economics, the market price reflects the avoided cost of energy even in hours when the total amount of zero-cost generation available to NWE exceeds NWE's native load.

A: NWE's proposal to apply a $0/MWh value to hours when it has zero-cost generation that exceeds native load (and a cost of production value when it is long and that cost of production is less than the market price) is based on the false

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[45] Notably, even in 1980 the FERC stated that its "rules impose no requirement on the purchasing utility to deliver unusable energy or capacity to another utility for subsequent sale." (emphasis added). In this case, the QF generation is not "unusable" because it can be profitably sold into the market, producing "usable" revenues for the utility that will benefit ratepayers.

premise that market transactions occur only after, and separate from, dispatch decisions to meet native load.

Market prices define the effective price of energy used to serve native load. NWE dispatches its generation to maximize profitable sales to the market whenever possible.[46] In fact, it would be imprudent not to. The revenue from those sales are returned to customers as credits under the Power Costs and Credits Adjustment Mechanism (PCCAM).[47] Thus, having additional generation available for sale produces more revenue, which increases the credits to customers, and reduces the net costs to customers. Conversely, having less generation available for sale produces less revenue, which decreases credits, and increases net costs to customers. Thus, every MWh used to serve native load instead of being sold to the market has a net cost to the customer of the market price.[48] In short, because the market price is recovered and returned through the PCCAM, the marginal "cost" to serve native load is the market price, not zero, in the hours NWE is a net seller to the market.

Q: What concerns do you have with NWE's market forecast that assumes declining heat rates after 2025?

A: NWE's modeling uses a forecast for Mid-Columbia market prices that features declining market heat rates over time, especially after 2025. This forecast is a key driver of the very low avoided costs that the utility recommends, as shown by Mr. Babineaux's much higher avoided costs that do not use this market price forecast.[49] The declining market heat rate forecast is premised on an assumption

[46] NWE Response to DR VS-014(c); VS-015(b).

[47] NWE Response to DR VS-015(b).

[48] In other words, because there is a market available for selling and buying energy, NWE's decision to characterize its portion of generation as serving its native load and the remaining portion as producing the energy sold to the market does not change the fact that the net marginal "cost" to the native customers of their energy is the same as it would be if all generation was sold to the market and all load was served by simultaneous market purchases.

[49] NWE Testimony (Babineaux), at p. MSB-13.

that a significant amount of new, zero-variable-cost renewable resources in Montana and the PNW will be added, in amounts that are far in excess of current RPS requirements or resource plans. In Montana, for example, this forecast assumes the addition of 760 MW of solar and 1,400 MW of wind in Montana from 2018 to 2030. That amount of additional renewable generation is not in NWE's current resource plan. Nor would *any* additional generation be developed – much less over 2 GW – if NWE's 15-year avoided costs are really $1.43 per MWh for solar and -$1.35 per MWh for wind, as NWE proposes.[50] In effect, NWE projects an unprecedented amount of new renewable generation development to derive declining Mid-C price projections that, if correct, would result in no additional renewable generation development. NWE's projected widespread renewable development for purposes of its market price projections in this QF-1 docket is also inconsistent with the Company's *2019 ESRP*, which includes almost entirely gas-fired additions.

Finally, the Commission recently reviewed NWE's declining market heat rate forecast in Docket No. 2019.06.034 and two other recent cases, and declined to adopt it in all three proceedings.[51] In Order No. 7680b, the Commission found:

> While the Commission recognizes that increasing renewable penetration will lead to declining heat rates in future years, it is not convinced that electricity market prices will decline as a result. NorthWestern has not satisfactorily demonstrated that declining market prices are consistent with increasing demand for electricity and the significant retirement or replacement of ageing coal and natural gas fueled resources with new natural gas fueled baseload and flexible capacity resources.[52]

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[50] The scenario in the *2019 ESRP* with the most renewables adds only 105 MW of wind and 210 MW of solar (the Solar scenario). The Ascend Analytic assumptions for renewable development that are included in its Mid-C forecast were provided in NWE response to Vote Solar Data Request (DR) 1-020, 3-045, and 3-046.

[51] See Order No. 7680b, at pp. 13-14.

[52] *Ibid*.

Q: What are your concerns regarding NWE's assumptions used in its PowerSimm modeling?

A: NWE's testimony in this case does not discuss the load and resource assumptions used in its PowerSimm modeling. My review of the resources assumed in the utility's modeling raises several concerns with the load and resource assumptions used in the modeling:

- Figure 3-1 in the *2019 ESRP* shows that NWE's retail loads will increase to over 8,000 GWh per year by 2033. However, the PowerSimm runs performed by Mr. Mauch for NWE assume retail loads in 2033 that are just 6,988 GWh in 2033 (13% lower).
- NWE assumes over 2,700 GWh of wind generation in 2021, or over 900 MW assuming a 35% capacity factor. This is significantly more wind generation than included in the *2019 ESRP*.[53]

D. Avoided Capacity Costs

Q: NWE proposes an avoided capacity cost of $176.44 per kW-year, based on the costs of a new simple-cycle combustion turbine installed on its system. Do you support this value?

A: Yes, I do. My concerns about NWE's capacity value relate to the capacity contribution credit, not the per-kW value of capacity.

1. Vote Solar's Proposed Capacity Prices

Q: How should the Commission design rates to compensate QFs for the avoided capacity value that they provide to NWE?

A: I recommend that the Commission establish a more focused, and more important for reliability, set of on-peak hours for the QF-1 tariff, over which NWE's avoided capacity costs would be paid. Today, avoided capacity costs are spread

[53] The *2019 ESRP*, at Table 4-1, shows about 470 MW of owned or contracted wind generation in 2021.

over more than 2,000 6x16 high load hours in the five peak months (July and August in the summer, December through February in the winter). A more focused set of on-peak hours would ensure that small QFs provide capacity to the utility when it is most needed and most valuable for reliability. It would also ensure that QFs are compensated for capacity only to the extent they produce during the peak hours and are not rewarded with payments for capacity if they do not deliver during peak hours. A small QF's output over these focused peak periods will provide an accurate measure of the amount of capacity that they supply. The more focused set of on-peak hours that I propose are as shown in **Table 5**. There would be 638 hours in these summer and winter peak capacity periods, with three summer peak months (June 15 to September 15) and three winter peak months (December to February).

Table 5: *Proposed New On-peak Hours*

Season	On-peak Hours
Summer	2 p.m. to 6 p.m., on all days, from June 15 to September 15
Winter	5 p.m. to 8 p.m., on all days, in December, January, and February

Over the five years 2014 to 2018, these hours have included all of NWE's annual peak load hours and the large majority of NWE's loads that have been within 5% of NWE's annual hourly peak.[54] The summer peak capacity period is expanded to three months, from June 15 to September 15, because NWE's summer peak hour has occurred outside of the current peak months of July and August (on June 29, 2015). Given the likelihood of warmer summers in the future, it makes sense to extend to three months the summer on-peak hours for capacity rates.[55] Similarly,

[54] These hours have included a weighted average of 74% of the utility's loads within 5% of its peak hour load, with the hours with loads closest to the peak hour load weighted more heavily. The weightings use the peak capacity allocation factors discussed in Section E below.

[55] In 1980 in Billings, there were, on average, 29 summer days with temperatures above 90 F. Today there are an average of 32 such days, and by 2060 it is anticipated that there will be 52, with a possible range of 40 to 61. See https://www.nytimes.com/interactive/2018/08/30/climate/how-much-hotter-is-your-hometown.html.

due to the fact that a small number of hours with loads within 5% of the annual peak occur on Sundays or holidays, it would make sense to include all days of the week in the new on-peak period.

Thus, the capacity rate for the QF-1 tariff would be $176.44 per kW-year divided by 638 hours, or $0.2766 per kWh, as shown in **Table 6**.

Table 6: *Capacity Prices*

Capacity Prices **For contracts of all lengths**	**Current** **QF-1 Tariff**	**NWE** **Proposed QF-1**	**Vote Solar** **Proposed QF-1**
Avoided capacity ($/kW-year)	116.26	176.44	176.44
Varies by technology?	Yes	Yes	No
On-peak price ($/kWh) HLH in five peak months 2,080 total hours	Solar - 0.0091 Wind – 0.0077 Hydro – 0.0568	Solar - 0.0000 Wind – 0.00787 Hydro – 0.03769	
Capacity price ($/kWh) June 15 – September 15: 2p – 6p December – February: 5p – 8p 638 total hours			0.2766

2. Critique of NWE's Wind and Solar Capacity Contributions

Q: How does NWE establish the capacity contributions of wind and solar QFs?

A: The utility continues to use its interpretation of a method that the Southwest Power Pool (SPP) has used to establish the capacity contributions of wind and solar resources, an approach which the Commission approved in Order 7500c. In overturning Order 7500c on this point, the Eighth Judicial District Court found that, in applying the SPP method, the Commission improperly overlooked both that (1) NWE is a dual-peaking utility, with significant summer peaks and (2) the PNW market, on which NWE depends for market purchases in peak periods, also is summer-peaking. As a result, it was incorrect to establish the capacity value of solar based solely on the fact that solar generation will be low or zero during winter peaks.[56]

Q: Please explain in more detail why NWE's application of the SPP method is inappropriate for establishing the solar QF capacity contribution on the NWE system.

A: NWE applied the SPP method to evaluate the production of solar QFs in only 220 hours over a 10-year period. These hours reflect primarily infrequent spikes in demand during the coldest winter hours, and exclude the much more frequent high-demand hours in the summer months. NWE has stated that it lacks capacity currently to meet high customer demand in both summer and winter, so focusing exclusively on winter hours ignores the full nature of NWE's capacity needs.

Q: Could the SPP Method be applied in a manner that more accurately reflects the capacity contribution of solar QFs?

A: Yes. The SPP Planning Criteria explain that solar and wind capacity contributions are calculated "on a monthly basis" by identifying the facility's output in the top 3% of load hours in each month that is exceeded in 60% of the hours. Once the monthly contribution is determined, the output may be customized: "[a] seasonal or annual net capability may be determined by selecting the appropriate monthly MW values corresponding to the Load Serving Entity's peak load month of the season of interest[.]"[57] Indeed, NorthWestern used the SPP method to calculate "seasonal net renewable capability" for five 3 MW solar QFs, and identified a summer season capability of 1.6 to 1.7 MW, or 53.3 to 56.7% of nameplate capacity.[58]

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[56] *See* Court Order, at p. 12.

[57] Exhibit MSB-1 contains an excerpt of the SPP Planning Criteria, revision 1.9. The full version of the SPP Planning Criteria, revision 2.1, may be found at the link: https://www.spp.org/documents/58638/spp%20effective%20planning%20criteria%20v2.1%2002182020.pdf. See section 7.1.6.1 for net generation capacity adjustments, including the use of 60% exceedance applied to net power output during the top 3% of load hours.

[58] NWE Response to DR VS-001, "solar" subfolder in "Babineaux" folder. NWE also calculated a "seasonal net renewable capability for a single 2 MW solar QF of 1.1 MW in the summer, or 55% of nameplate.

Thus, NWE should have applied the SPP method to identify the capacity contribution for each of the five months in NWE's on-peak period to accurately reflect the value of solar resources to NWE's system. Order 7500c incorrectly assigned to solar QFs a capacity contribution of zero for four of the five months, then calculated solar's capacity value of 6.1% based on its output in a single, winter peak load month. NWE's testimony in this case continues this misapplication of the SPP method.[59]

Q: Does the use of a single peak load month adequately and accurately characterize NWE's periods of high demand?

A: No, it does not, as shown by the fact that NWE's on-peak time-of-use period spans five months – two summer (July and August) as well as three winter (December to February). NWE is dual-peaking; the utility's winter and summer peak-hour demands are similar. NWE set the all-time record peak demand for its service territory in August 2018, then broke that record in February 2019.[60] Over the last ten years (2009-2018), one-half (50%) of the utility's annual peak-hour loads have occurred in the summer months, considering both NWE's retail customer demand and the higher transmission system demand in the NWE balancing area. Over the last five years (2014-2018), 70% of the annual peaks have occurred in the summer.[61]

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[59] At page MSB-8, line 2, Mr. Babineaux says the methodology uses the "annual peak load month of each year" within the period of study. However, paragraph 7 of Section 7.1.6.1 of the SPP planning criteria says that the "recommended methodology to evaluate the net planning capability established for wind or solar facilities shall be determined on a monthly basis." Section 8(a) describes how hourly net power output values are selected "during the top 3% of load hours for the SPP load Serving Entity for each month of each year for the evaluation period." (emphasis added).

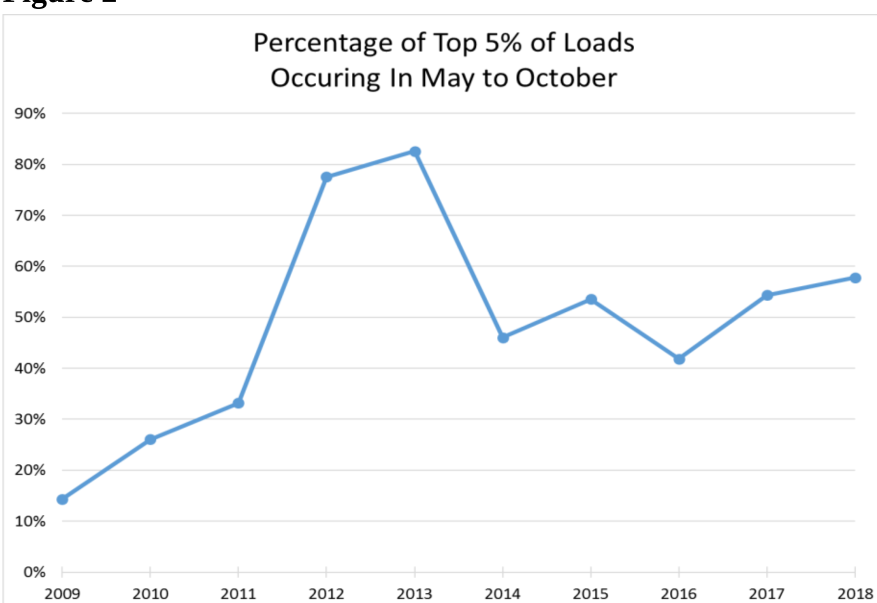
[60] See page 6-16 of the *2019 ESRP*, Volume 1, which notes that "A new summer peak load record for NorthWestern's BA was set on August 10, 2018 (this peak was ultimately eclipsed in February 2019)." The August 10 Hour 17 peak was 1,843 MW. The all-time record peak load was on February 5, 2019 (see page 6-9).

[61] Based on FERC Form 714 data for balancing area peaks and NWE response to VS-050 for retail load data.

Moreover, it is important to look not just at a resource's performance in the top load hours for the peak month of the year, but also at performance in a broader set of high-demand hours throughout the year that are close to the MW level of the annual maximum hourly load. For NWE, these include both summer and winter on-peak hours. Looking at loads that are within 5% of the annual peak hour load, about 55% of these hours have occurred in July and August, using data for the years 2009-2018. As a result, the capacity value of solar must be calculated considering the resource's capacity value over the top load hours in both the summer and winter on-peak hours.

NWE's resource plan characterizes its peak hours as the top 5% of load hours[62], not limited to a single month as the SPP method is. Again, based on the top 5% of load hours definition of "peak hours," about half of the utility's peak hours occur in the summer, as shown in **Figure 2**. This fraction has been increasing over the last decade, as shown in the figure.

Figure 2



[62] See *2019 ESRP*, at Figure 2-3, defining NWE peak loads as the highest 5% of all hours (i.e. 438 hours per year).

Q: Did the structure of the QF-1(a) rate before Order 7500c recognize that solar could make a capacity contribution in the summer on-peak period?

A: Yes. The QF-1 rate structure prior to Order 7500c set the difference between the on- and off-peak rates using the full fixed costs of a SCCT. Thus, a QF resource that operated at its full nameplate capacity in all on-peak hours would earn 100% of the capacity value of a SCCT. As a result, a solar QF under this rate would earn capacity value based on its capacity factor during the 2,038 hours of the on-peak period.[63] Based on modeled data on solar projects in Montana, the average capacity factor for a solar QF over the utility's on-peak hours is approximately 31%.[64] Thus, this past QF-1(a) rate structure assumed that a solar QF has a capacity value equal to 31% of its nameplate capacity.

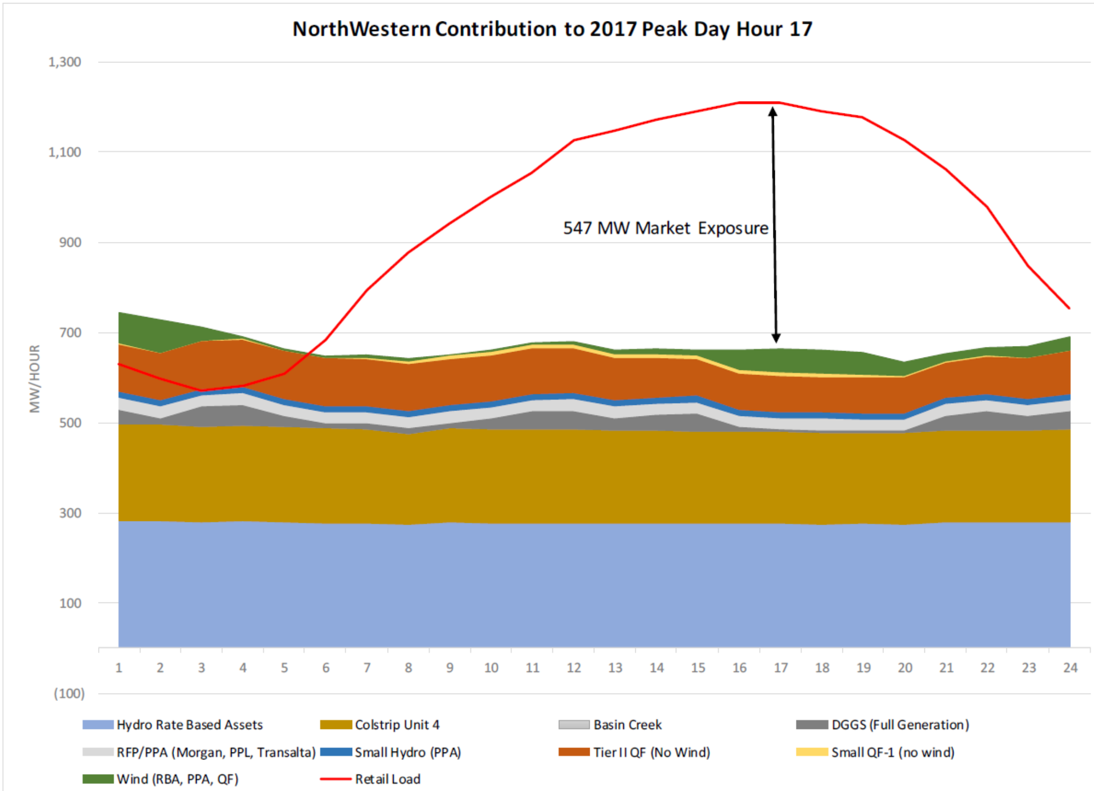
Q: Please provide a simple example of how solar QFs can provide significant capacity contribution.

A: In illustrating its current capacity deficiency, NWE's *2019 ESRP* includes the following Figure 4-7 with its loads and current resources at 5 p.m. on a July peak day, showing a capacity deficiency of 547 MW that must be met with market purchases. In the hour ending 5 p.m. on a July day, a solar unit in NWE's service territory will be operating at an average of 69% of its nameplate capacity, showing that solar can provide significant capacity on such a peak day.

[63] NWE's on-peak period is a 6x16 block of hours over three winter months (December – February) and two summer months (July – August), about 2,038 hours per year. See current Schedule No. QF-1 (defining "Heavy Load Hours" and "On-Peak Hours").

[64] This 31% capacity factor is based on average PVWatts single axis tracker output during the NWE peak period, for three Montana locations, including Billings, Butte, and Great Falls.

Figure 4-7. Capacity Contribution on Peak Load Day



Q: Has NWE's approach to calculating the capacity contribution of solar resources been criticized recently by other experts?

A: Yes. Synapse Energy Economics (Synapse) has prepared a report for the Commission, released on February 14, 2020, that critiques the solar and wind capacity contributions assumed in NWE's final *2019 ESRP*.[65] In particular, the Synapse report, at pages 8-9, criticizes NWE for failing to recognize the capacity contribution of solar to the utility's significant summer peaks:

> The capacity credits given to wind and solar in this resource plan do not align with the historical contributions of these resources in the NorthWestern service territory, nor do they align with industry standard assumptions around capacity crediting. Treatment of ELCC for renewable resources must account for different values based on a summer peak need and a winter peak need, both of which occur on NWE's system. Solar PV generally does not contribute to winter peak needs, but it does contribute to summer peak needs. In contrast, wind

[65] Synapse, *Comments on NorthWestern Energy's Final 2019 Electricity Supply Resource Procurement Plan* (Feb. 14, 2020), *attached* as Exhibit RTB-5.

has a much higher contribution for winter peak needs than for summer peak needs. While a zero-capacity credit for solar in winter months may be reasonable, NorthWestern should allow intermittent resources to provide different capacity requirements on a monthly basis, so that their benefit in summer peak months is recognized.

Q: Do the other utilities in the Pacific Northwest continue to value the capacity contribution of solar resources at far higher levels than NWE?

A: Yes. Recent integrated resource plans from other utilities in the West, including the utilities that neighbor NWE, value solar PV capacity at 20% to 60% of its nameplate capacity, far above the 6.1% capacity credit adopted in Order 7500(c) or the 0% that NWE now recommends. The solar capacity values used by these other Pacific Northwest utilities are summarized in **Table 7**.

Table 7: *Solar PV Capacity Values for Other Western Utilities*

Utility	Solar Capacity Value (% of nameplate)	*Source*
Idaho Power	47% to 62%	*2019 Idaho Power IRP*, at Table 4.1, pp. 37-39. Uses an NREL method based on net load duration curve (NLDC). The capacity contribution is the top 100 hours of the delta between the LDC and NLDC, divided by PV capacity.
PacifiCorp	20% to 60%	*2019 PacifiCorp IRP*, Vol. 1, at Figures 5.3 & 5.4. Uses an effective capacity factor method based on solar penetration.
Avista	52% with 5 MW solar, 22% with 300 MW	Summer only. *2019 Electric IRP*, at Table 9.3.

Q: How do other control area operators assess the capacity value of solar resources?

A: As the North American Electric Reliability Council (NERC) has noted in a special report on this topic,[66] many control area operators assess the capacity contribution of solar resources based on their average capacity factor over a designated set of on-peak hours. As discussed above, this was the approach used in Montana before Order 7500c.

Q: Has NWE been able to cite any other utility that uses such a restrictive approach to determining solar capacity value?

A: No, it has not.[67]

Q: Are you aware of any other utility or control area operator in the U.S. that has calculated solar capacity value by applying an exceedance factor to solar output over a set of peak hours?

A: Yes, but the exceedance percentage is calculated over a far broader set of hours than the 22 hours per year, in a single month, that NWE uses. For example, for many years, including during years of rapid growth in solar resources, California's resource adequacy program calculated monthly capacity values of wind and solar using a 70% exceedance over 1,825 peak hours per year.[68] Using this approach, solar capacity values in California in the peak months typically exceeded 50%. Even using SPP's 60% exceedance over NWE's top 3% of on-peak hours in all five peak months (with ten years of data) results in a solar capacity value of 36%.

Q: Have some studies of the capacity value of solar shown that its capacity value decreases as more solar is added?

A: Yes, but such studies show that this effect does not become significant until

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[66] *See* the report of NERC's Integration of Variable Generation Task Force, *Accommodating High Levels of Variable Generation* (April 2009), available at http://www.nerc.com/files/IVGTF_Report_041609.pdf. See esp. Figure 3.3 on page 40.

[67] Docket No. 16.05.039, NWE response to Vote Solar Data Request VS-005, included in Exhibit RTB-3 of Vote Solar's testimony in that docket.

[68] See CPUC, *Qualifying Capacity Methodology Manual*, at pp. 11-16. Available at http://www.cpuc.ca.gov/General.aspx?id=6311.

substantial amounts of solar capacity have been added, on the order of a 10% penetration of solar in terms of energy (kWh) generated.[69] The small amount (17 MW) of solar capacity on NWE's system today serves about 1% of NWE's peak demand, and an even lower percentage (about 0.5%) of the utility's energy requirements.[70]

Q: As a capacity resource, does solar provide other benefits to utilities?

A: Yes. Solar projects are completely scalable in size, and the lead time to develop solar projects on the scale of 3 MW is short, in comparison to other types of generation. Solar QFs can be constructed on a wide variety of sites in open space or in the built environment. They have no air emissions, no noise impacts, no avian or aircraft impacts, and minimal water use for panel cleaning. The construction time for a 3 MW solar facility can be as short as 2 to 3 months. Solar provides a significant summer peaking resource, with an output profile that complements local wind resources, as shown in **Figure 1** above.

Q: Should the Commission consider using an effective load-carrying capacity (ELCC) analysis to establish the capacity value of wind and solar resources?

A: It is my understanding that parties to past avoided cost dockets in Montana have suggested using an ELCC analysis to establish the capacity value of wind resources.[71] The SPP now appears to be abandoning its exceedance method to

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[69] Over the last 15 years, California has added 20 GW of solar generation to the CAISO system, whose peak demand is about 50 GW. This includes about 12 GW of wholesale, in-front-of-the-meter solar and 8 GW of behind-the-meter rooftop solar. Today, solar penetration on the CAISO grid in California is approaching 20% of the GWh generated. Over most of that period, the capacity value of solar established in the CPUC / CAISO Resource Adequacy program was typically in the range from 40% to 60% of the solar nameplate; in the last two years, with solar penetration exceeding 15%, new ELCC studies in California have reduced solar's capacity value to 15% of nameplate today. See, for example, CPUC Decisions Nos. 17-06-027 (at pp. 19-21 and Appendix A) and D. 19-06-026 (at pp. 46-49 and Appendix A.)

[70] Table 4-3 of the *2019 ESRP*, Volume 1, shows 0.7% MW contribution to the peak 2017 load for small QF-1 solar projects. For their energy contribution, the *2019 ESRP*, at page 7-8, cites a 24% solar capacity factor in Montana. So 17 MW x .24 x 8760 =~ 36,000 MWh/year, which is 0.5% of the 2020 Default supply in the *2019 ESRP*'s Table 3-1.

[71] See Order 7199d, at pp. 15-17.

move to the use of ELCCs.[72] Although some consider ELCC analyses to be the most rigorous method for establishing the capacity value of intermittent renewables, there are a number of practical problems with using an ELCC approach in Montana at this time.

First, the process of performing an ELCC study is generally as follows: an ELCC analysis uses a reliability model of the utility system that includes the candidate resource (e.g. 50 MW of solar plants) and that achieves the utility's reliability standard (e.g. 1 day of outages in 10 years). Then the candidate solar plants are removed, and capacity from a standard resource (e.g. a SCCT) is added until the reliability standard is again achieved. If 20 MW of SCCT capacity must be added to restore the original reliability level, then the ELCC of the 50 MW of solar resources is 40% (20 MW / 50 MW).

However, that analysis presumes the utility is meeting standard reliability criteria as a starting point with the candidate generation source as the main variable being tested. The NWE system is so far from meeting standard reliability criteria that the analysis would need to assume a large number of additional resources beyond the candidate generation source being tested, at which time the system being measured by the ELCC analysis would be artificial rather than the actual NWE system. Second, the literature on using the ELCC method emphasizes the importance of using actual, correlated data for both (1) loads and (2) wind or solar output.[73] Using actual load and solar output data from the same time period is particularly important for solar ELCC studies, due to the fact, noted above, that it

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[72] See SPP, *RSC Wind and Solar ELCC White Paper*, available at https://spp.org/documents/61371/rsc%20additional%20material%2020200127.pdf.

[73] See the NERC report *Accommodating High Levels of Variable Generation* referenced in Footnote 39. The report includes a section on Resource Adequacy Planning, which addresses the methods that utilities and control area operators should use to assess the capacity value of intermittent wind and solar resources. In discussing the data to be used in ELCC analyses, the NERC special report notes that "[c]are should be taken to account for the correlation between hourly variable generation and the hourly demand series. To perform this analysis, a significant amount of time-synchronized 8,760 hourly wind generation and demand data is required and this data is needed for variable generation plants in the specific geographic regions being studied."

is often sunny on hot summer days when electric loads are high. Third, ELCC analyses use reliability models that are complex and costly to run. The ability to run these analyses is not available to most stakeholders. It is difficult to audit the results or to understand how the results are affected by different assumptions such as maintenance schedules, the profile of intermittent resources, or resource availability. These are important reasons why many utilities and control area operators have opted for simpler, more transparent capacity factor approaches. Finally, the addition of hybrid wind and solar resources introduces further challenges to performing an ELCC study, given that the storage can be dispatched to provide a wide range of output profiles.

In discovery, NWE provided the results from an ELCC study for its system.[74] That response confirms my point, above, that the ELCC process is inaccessible to stakeholders and probably to the Commission. All that the utility provided was a single spreadsheet with the results, with no description of when or how the analysis was performed, or the assumptions used. The capacity contribution of solar in this analysis increased from 15% in 2021 to 46% in 2040, and averaged 27% over this 20-year period.

Q: Do you think that the use of a capacity factor methodology can be as accurate as an ELCC methodology?

A: Yes. A 2012 study from NREL found that such methods can accurately approximate the results of more complex, but also more opaque and difficult-to-replicate, methods such as ELCC models.[75]

Q: What would be the capacity contribution of solar-only and wind-only projects over the hours in Table 5?

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[74] See NWE response to Vote Solar DR VS-001, Q37.

[75] *See* Seyed Hossein Madaeni, Ramteen Sioshansi, and Paul Denholm, *Comparison of Capacity Value Methods for Photovoltaics in the Western United States* (NREL, July 2012), available at http://www.nrel.gov/docs/fy12osti/54704.pdf.

A: The solar capacity contribution would be 38%. The wind contribution would be 27%.[76]

Q: Should the design of rates under the QF-1 tariff assume that QFs can provide capacity immediately?

A: Yes. Although NWE may not be adding its own new capacity until 2022, the utility clearly would benefit from QF capacity immediately, and the FERC regulations explicitly state that avoided cost rates for purchases from QFs must take into account "the smaller capacity increments and the shorter lead times available with additions of capacity from qualifying facilities."[77] QF capacity obviously is available in smaller increments, given that long-term contracts under the QF-1 tariff are limited to projects no larger than 3 MW. Capacity from solar QFs can be installed with shorter lead times and much more quickly than traditional utility capacity, with construction requiring as little as two months once permitting is complete. Thus, it is possible that capacity from new small QFs could be on-line in 2021.

E. Avoided Transmission Costs

Q: Are there potential transmission benefits from relatively small, 3 MW solar or wind QFs located on the NWE system?

A: Yes. Solar QF developers bear the costs to interconnect their projects to the NWE system. Solar projects with a maximum size of 3 MW typically will interconnect to the distribution system at primary distribution voltages, and the power produced generally will serve loads on the distribution system. That load is then effectively removed from the transmission system. As a result, small, widely distributed solar projects internal to the NWE system and interconnected to the

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[76] These amounts are based on capacity factors in the proposed peak hours for our Billing, Butte, Great Falls PVWATTS profiles. For the wind calculation, we used the wind profile provided by NWE for Musselshell 2 from Exhibit MSB-2.

[77] *See* 18 C.F.R. § 292.304(e)(2)(vii).

distribution system will reduce peak loads at the transmission substations to which they interconnect. This makes transmission capacity available for load growth, for other transmission customers, or for greater access to regional markets.

Despite these fairly obvious transmission benefits, assigning the benefit to a specific small QF can be a challenge. Transmission substations and lines show greater variations in when they peak than does the system as a whole. To address this issue, we followed an approach developed by Energy and Environmental Economics (E3) to calculate avoided sub-transmission and distribution capacity costs in its cost-benefit studies of distributed solar generation and net energy metering in California. We obtained the available hourly load data for 2015 for 100 of NWE's transmission substations. For each substation we developed an hourly allocation that measures, in each hour, how close that substation is to its annual peak. The allocation calculates a "peak capacity allocation factor" (PCAF) for each hour in which the substation load is within 10% of the annual peak. Thus, all hours where the substation load is below 90% of the annual peak receive a PCAF of zero. The formula for the PCAF allocation factor is as follows:

$$PCAF_s(h) = \frac{(Load_s(h) - Threshold_s)}{\sum_{k=1}^{8760} Max[0, (Load_s(k) - Threshold_s)]}$$

Where:

$PCAF_s(h)$ = peak capacity allocation factor for substation s in hour h
$Load_s(h)$ = the load for substation s in hour h
$Threshold_s$ = 90% of the substation s annual peak load
The summation in the denominator includes all hourly load increments above the threshold.

Figures 3 and 4 show the resulting average PCAF allocation for each hour of the day across all of the transmission substations, weighted by the annual peak demand at each substation. We also show PCAF allocation for NWE's transmission system loads in 2015 and 2018. Figure 3 is the summer PCAF allocations; Figure 4 is for the winter months. The figures show that the PCAF allocations peak during our proposed on-peak periods. This provides a further illustration that our proposed focused set of on-peak hours captures most of the hours when loads are high on the NWE transmission system.

Figure 3

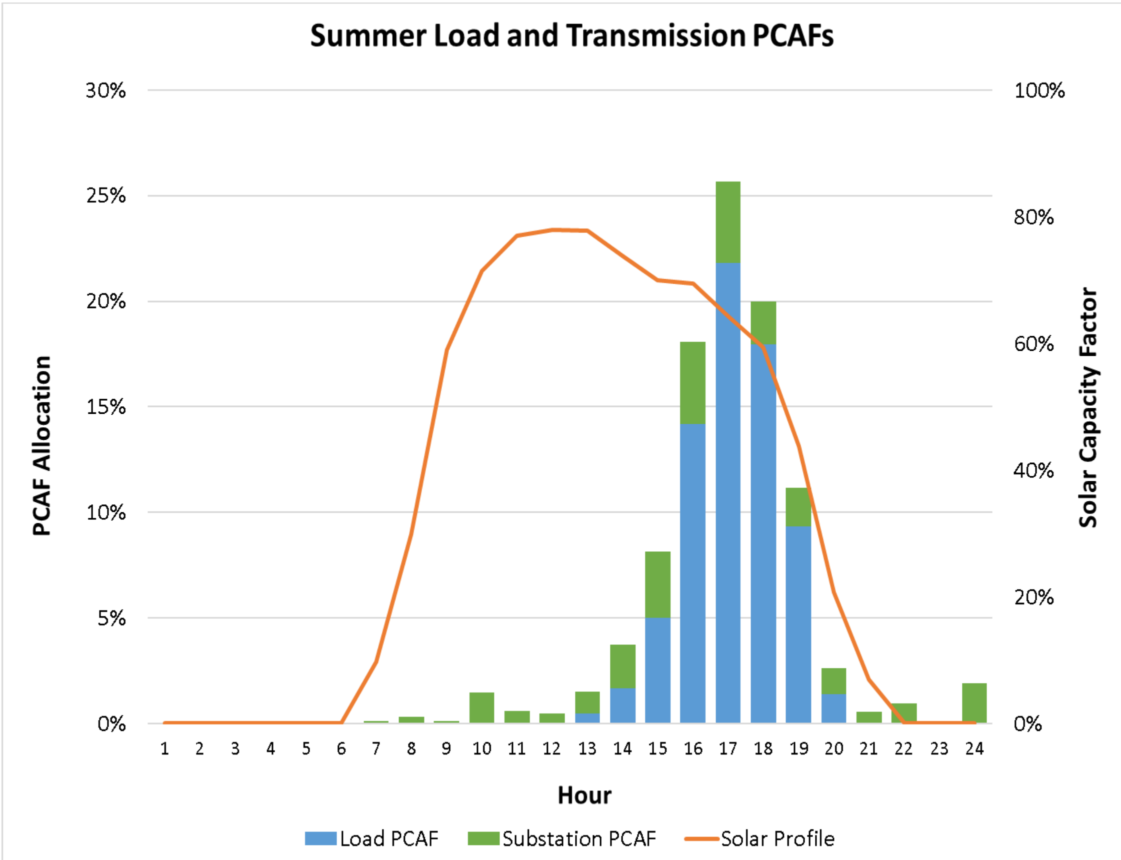
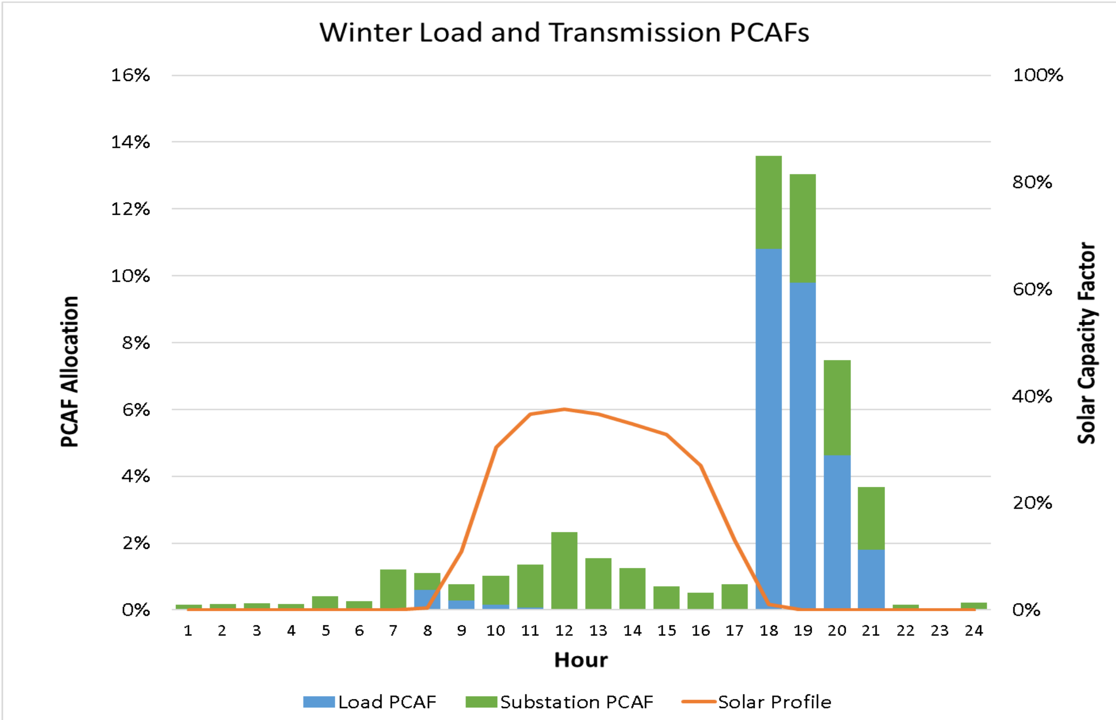


Figure 4



QFs can avoid transmission capacity costs to the extent that they provide on-peak capacity. For avoided transmission capacity costs, we use NWE's 2019 FERC-filed network transmission rate of $4.83 per kW-month, or $57.97 per kW-year.[78] Vote Solar proposes to add these avoided costs to the peak capacity rate developed above, as an avoided transmission adder, as shown in **Table 8**.

Table 8: *Avoided Transmission Adder*

Transmission Adder For contracts of all lengths	Vote Solar Proposed QF-1
Capacity price ($/kWh) June 15 – September 15: 2p – 6p December – February: 5p – 8p	0.0909

[78] Although this FERC rate is an embedded, not a marginal, cost number, it does represent NWE's opportunity cost to use or to sell firm transmission capacity which is made available by reduced transmission system loads resulting from small, distributed solar resources. See NWE's OATT tariff at http://www.oatioasis.com/NWMT/index.html.

E. Integration Costs

Q: Are you concerned that NWE would have difficulty, or incur significant costs, to integrate additional solar generation into its system?

A: No. The integration of higher levels of wind and solar resources has presented a challenge to utilities and grid operators across the U.S., but this issue has been intensively studied since the late 2000s, much experience has been gained as the penetration of these resources has increased, and solutions have emerged. For example, a decade ago the National Renewable Energy Laboratory (NREL) and GE Consulting undertook the Western Wind and Solar Integration Study (WWSIS), a major, multi-phase modeling effort to analyze much higher penetrations of wind and solar resources in the western U.S. The WWSIS showed the ability to integrate levels of wind and solar penetration in excess of today's levels, provided these variable resources could be balanced on a sub-hourly basis over a large geographic footprint, with more accurate forecasts of variable resource output.[79] Notably, the western EIM is implementing the key recommendation of the WWSIS – balancing wind and solar resources more efficiently on a sub-hourly basis over a larger footprint.

Q: Please discuss the experience of other WECC utility systems that have had to integrate high levels of wind and solar generation.

A: I will start with California. Today, California has 20,000 MW of installed solar on the grid of the California Independent System Operator (CAISO) plus 6,700 MW of wind. Of the 20,000 MW of solar on the CAISO system, 12,000 MW are wholesale, utility-scale projects and 8,000 MW are behind-the-meter solar installed by over one million utility customers.[80] The recent annual peak demands

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[79] The high penetration solar results from the WWSIS are reported in *Impact of High Solar Penetration in the Western Interconnection* (NREL and GE Consulting, December 2010), at p. 8 and Figure 19. This report, as well as all reports from the WWSIS, are available on the NREL website at http://www.nrel.gov/electricity/transmission/western_wind.html.

[80] See http://www.caiso.com/informed/Pages/CleanGrid/default.aspx. The data on behind-the-meter solar is from https://www.californiadgstats.ca.gov/.

on the CAISO grid have been in the range of 46,000 to 50,000 MW.[81] Wind and solar now supply about one-quarter (25%) of the electricity on the CAISO system.[82] This is a higher penetration than for NWE, whose generation in 2018 was 15% wind and less than 1% solar.[83] The CAISO has integrated California's high penetration of wind and solar resources without a discernible increase in costs for ancillary services, which it obtains from a market for those services. **Figure 5** below shows the history of ancillary service costs on the CAISO system from 2006-2018 (red dashed line), expressed as a percentage of the CAISO energy market costs in each year. The figure also shows the growth of wholesale wind and solar generation in California (green bars); these resources have increased nine-fold (from about 5,000 GWh/year in 2006 to 45,000 GWh per year in 2018).[84] Ancillary service costs for the CAISO have fluctuated between 0.5% to 2.0% of CAISO energy market costs over this period.[85] The primary cause for these fluctuations has been the availability of large hydro resources (blue bars). Ancillary service costs increase in wet years when hydro generation is abundant (such as 2011 and 2017), because hydro resources are operated to produce energy rather than to supply ancillary services. In dry years, when hydro production is low, the hydro operators participate more actively in the ancillary services market because that is the best way to maximize the revenue from the limited water stored behind the dams. As a result, in those years ancillary service costs fall, as shown by the low ancillary service costs during the recent drought years of 2014-

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81 See http://www.caiso.com/Documents/CaliforniaISOPeakLoadHistory.pdf.

82 This includes about 19% of the wholesale generation and 6% of loads served by on-site solar.

83 See *2019 ESRP*, at Figure 1-3.

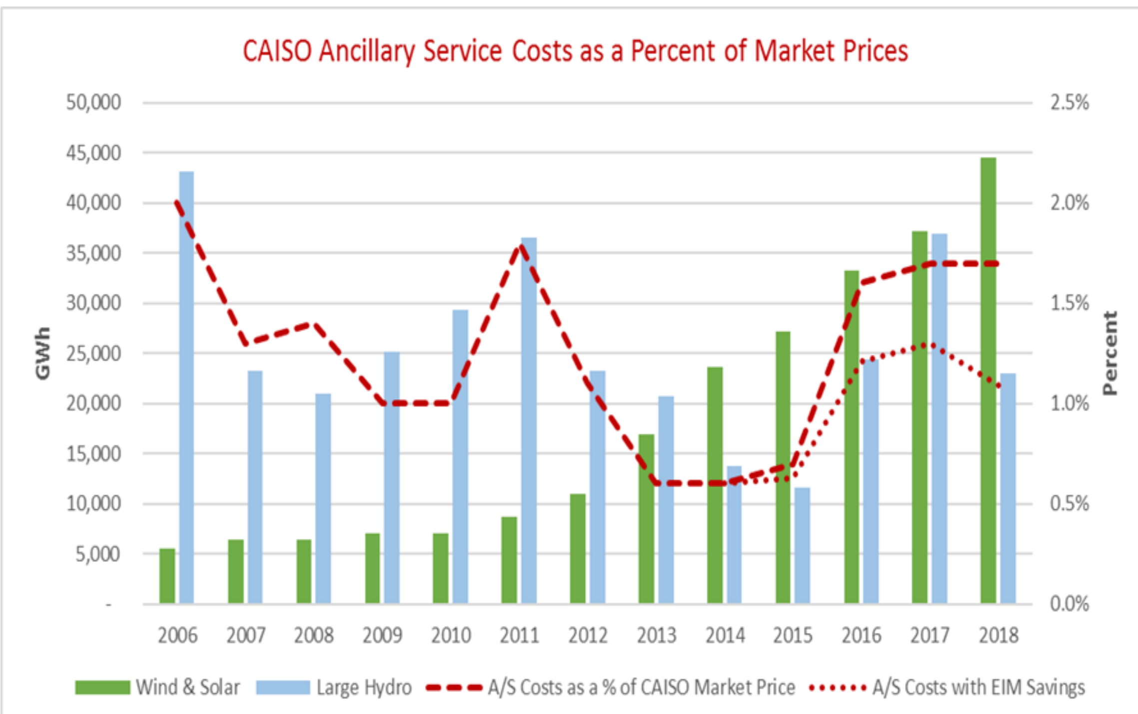
84 From the California Energy Commission's website with power source data for California: https://www.energy.ca.gov/almanac/electricity_data/total_system_power.html. Note that this is wholesale generation, and does not include the generation from on-site, behind-the-meter solar, which supplied approximately 15,000 GWh per year of load in 2018.

85 Data on ancillary service costs as a percentage of CAISO energy market costs is from the CAISO's *Annual Report on Market Issues and Performance* over this period. These reports can be accessed on the CAISO website at http://www.caiso.com/market/Pages/MarketMonitoring/AnnualQuarterlyReports/Default.aspx.

2015. Thus, as Figure 5 shows, ancillary service costs are strongly correlated with hydro conditions.

However, there has not been a discernable trend toward higher ancillary service costs despite the glaring fact that wind and solar generation *has grown by a factor of nine*. The dotted red line in Figure 5 for 2014-2018 shows the CAISO's ancillary service costs in these years including the CAISO's share of the intra-hour savings in balancing costs from the EIM. The EIM savings have reduced significantly the CAISO's costs to operate the California grid, even as the penetration of wind and solar has reached new highs and continues to grow.

Figure 5



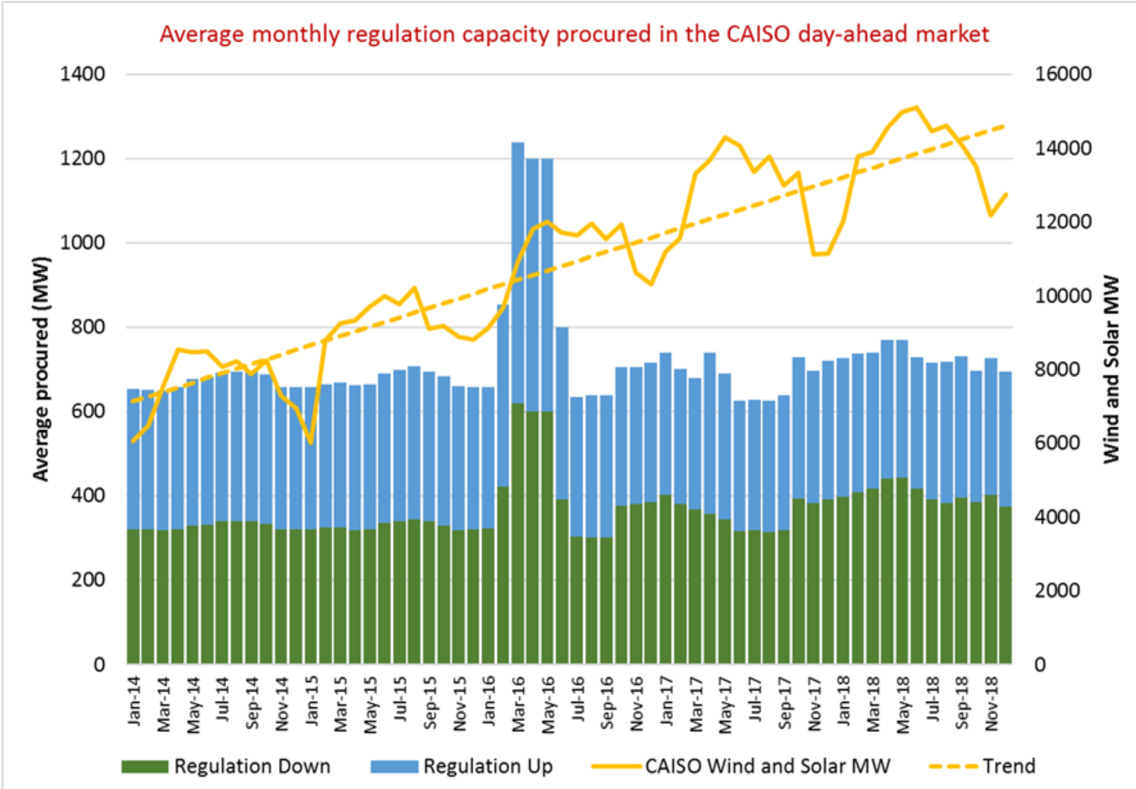
Including the EIM savings, the CAISO's ancillary service costs over the last five years have averaged 1.0% of energy market costs; this is below the long-term average (2006-2018) of 1.2% of energy market costs. Thus, there is no evidence that the high penetration of wind and solar resources that the CAISO system has integrated in recent years has increased ancillary service costs. Although the California Public Utilities Commission began a process to develop wind and solar integration charges, it has not seen the need to complete that process and permanently adopt such charges.[86]

In early 2006, the CAISO increased the amount of regulation that it purchases, from 300-400 MW to 600 MW (in both directions), due to a concern with the increasing amounts of variable wind and solar generation. This increase in regulation accounts for part of the increase in ancillary service costs in 2016 over 2015 shown in Figure 5 (the rest of that increase appears due to wetter hydro conditions). However, after a few months in 2016 the CAISO refined its algorithm for the amount of regulation that it procures, and has been able to return to the use of just 300-400 MW of regulation, even with the steady increase in wind and solar resources over the last five years. This data on the CAISO's procurement of regulation from 2014-2018 is shown in **Figure 6.**[87] This is another example of the "learning by doing" that is enabling system operators to minimize the integration costs associated with growing penetrations of renewables.

[86] The California commission has had a series of rulemaking proceedings to administer the state's Renewable Portfolio Standard (RPS) program. The rulemaking initiated in 2015 (R. 15-02-020) included as an issue the continuing development of integration cost adders (see R. 15-02-020, at p. 6), but this issue was dropped in the next RPS rulemaking initiated in 2018 (R. 18-07-003).

[87] The regulation up and down quantities are day-ahead procurement data from the CAISO's monthly market performance reports, at http://www.caiso.com/market/Pages/ReportsBulletins/Default.aspx. For example, Table 6 at page 16 or 45 of the CAISO's December 2018 monthly report is at http://www.caiso.com/Documents/MarketPerformanceReportforDecember2018.pdf. The wind and solar output data are monthly maximums of hourly CAISO wind and solar outputs (to show a measure of the amount of wind and solar capacity), from the CAISO's renewables watch output data files, which are available at http://www.caiso.com/market/Pages/ReportsBulletins/RenewablesReporting.aspx.

Figure 6



For example, the cost of regulation on the CAISO system is significantly lower than what NWE spends today for regulation.[88] NWE's *2019 ESRP* also discusses a Navigant integration study in which NWE's need for flexible capacity was reduced when 100 MW of new solar was added to an incremental 185 MW of wind.[89] This suggests that additional solar generation will not immediately result in additional integration costs.

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[88] At the CAISO's 2014-2015 market prices for regulation, NWE's current 33 MW regulation requirement would cost about $1.4 million, versus NWE's stated annual costs of $7.2 million using the combination of the Dave Gates Generating Station and NWE's hydro system. See CAISO, *2015 Annual Report on Market Issues and Performance*, at p. 135 (Figure 6.5, showing regulation costs of about $5 per MWh of regulation capacity). Available at http://www.caiso.com/Documents/May12_2016_2015AnnualReport_MarketIssues_Performance_ZZ16-4.pdf. Also see NWE's *2015 IRP*, at Figure 11-10.

[89] *2019 ESRP*, at pp. 3-8 to 3-10.

Q: Are you aware of other traditional, vertically-integrated utilities in the Pacific Northwest that have performed a series of wind or solar integration studies over time, as the penetration of wind or solar resources on their systems has increased?

A: Yes. Both PacifiCorp and Idaho Power have performed several solar or wind integration studies over time, as these utilities have added significant amounts of these renewable resources to their systems.

The following **Tables 9 and 10** summarize these studies, which generally show that integration cost estimates have declined over time, even as more renewables have been added by these neighbors of NWE.

Table 9: *PacifiCorp Integration Costs ($ per MWh)*[90]

Resource	Date of Study		
	2012	**2014**	**2017**
Wind	$2.55	$3.06	$0.44
Solar	n/a	n/a	$0.60
	Resources (MW)		
Wind	2,126	2,543	2,793
Solar	n/a	n/a	1,000

Table 10: *Idaho Power Integration Costs ($ per MWh)*[91]

Resource	Date of Study	
	2014	**2016**
Solar	0-100 MW: $0.40 0-300 MW: $1.20 0-500 MW: $1.80 0-700 MW: $2.50	0-400 MW: $0.27 0-800 MW: $0.57 0-1,200 MW: $0.69 0-1,600 MW: $0.85
	Resources (MW)	
Solar	0	325

90 The 2012 and 2014 wind integration costs are from PacifiCorp's 2015 Integrated Resource Plan (IRP), at Appendix H, Table H.3. The 2017 wind integration costs are from PacifiCorp's 2017 IRP, Volume II, at Appendix F, pp. 120-123, esp. Tables F.14 and F.16.

91 For the 2014 results, see Idaho Power, Direct Testimony of Philip B. Devol, Idaho PUC Case No. IPC-E-14-18 (July 1, 2014), at p. 5. For the 2016 solar integration costs, see Idaho Power, *Solar Integration Study Report*, (April 2016), at pp. vi and 21, esp. Tables 2 and 9.

There are a variety of factors that account for the much lower integration costs in the most recent PacifiCorp and Idaho Power studies, including (a) methodological improvements, (b) reduced market prices, and (c) the increased availability of regulation-capable gas-fired resources displaced by new renewables. Significantly, the most recent studies from both PacifiCorp and Idaho Power included review by a technical review committee of outside experts from institutions such as the National Renewable Energy Laboratory ("NREL"), the Western Renewable Energy Generation Information System ("WREGIS"), and the Utility Wind Interest Group ("UWIG").[92] I am not aware that the integration studies that NWE has conducted have received a comparable level of independent review. Idaho Power also reached a settlement with stakeholders concerning the design of its most recent integration study.[93] Finally, I note that the most recent PacifiCorp and Idaho Power studies do <u>not</u> include consideration of the intra-hour balancing savings that both PacifiCorp and Idaho Power are realizing in the western EIM, which are further reducing their intra-hour costs for the load following resources needed to integrate renewables.

Q: NWE has proposed that small QFs should pay for ancillary services under the provisions of the utility's OATT. Is this problematic?

A: Yes. System operators use ancillary services to balance the system on short time scales; they are necessary due to the inherent variability of both loads and resources. If this variability increases, the need for ancillary services increases. Adding QF generation does not change the load that must be served at the customer's meter, so the variability of loads does not increase. Whether the variability of generation resources changes when a QF is added depends on both the type of QF resource added and the generation resources that are avoided.

[92] See the 2017 PacifiCorp and 2016 Idaho Power studies referenced in footnotes 10 and 11.

[93] See the stipulation approved by the Idaho PUC in Order No. 33227 in February 2015 (Case No. IPC-E-14-18).

NWE's proposal to charge QFs for ancillary services based on the OATT fails to consider the reduction in these costs as a result of the resources that are avoided, or the savings in balancing costs that it will realize when it joins the EIM and when it builds additional flexible gas generation, as planned in the *2019 ESRP*.

Q: Has NWE previously calculated solar integration costs?

A: Yes. The utility's *2015 IRP* showed incremental regulation costs of $2.02 per MWh of solar output for 50 MW of additional solar and $4.35 per MWh for 100 MW.[94] For the reasons discussed above, it makes little sense that solar integration costs have risen to over $15 per MWh since then.

Q: You have noted above that the variability or intermittency of the output from solar or wind resources is significantly reduced for hybrid QFs because a significant share of the output can be stored and then dispatched in a controlled fashion through the battery. Should this impact any calculation of integration costs for hybrid resources?

A: Yes. Because the output of the batteries of hybrid resources can be dispatched or scheduled, this portion of the output should not require additional integration resources compared to the dispatchable resources that they displace. Thus, any integration costs adopted for QF should be reduced by the portion of the QF capacity that can be scheduled in peak periods through the storage. Thus, a small QF with a 3 MW solar field and a 1.5 MW battery should have its integration costs reduced by 50% compared to a 3 MW solar QF with no storage.

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[94] Based on the incremental regulation requirements shown in the *2015 IRP*'s Figure 11-6, assumed regulation costs of $7.2 million per year for the base 34 MW of regulation, and solar output of 2,400 MWh per MW.

V. OTHER BENEFITS OF INCREMENTAL RENEWABLE GENERATION

Q: Are there other direct, quantifiable benefits of incremental solar generation for ratepayers that are not included in the avoided cost rates in the QF-1 Tariff?

A: Yes. Incremental solar QF generation will result in other benefits for NWE ratepayers. Several these benefits can be quantified in terms of direct avoided costs for NWE that will benefit its customers, and these additional avoided costs could be included in the QF-1 tariff price. However, these are ratepayer benefits that have not been included traditionally in avoided cost prices, and it is not my recommendation that they be included at this time. Nonetheless, the Commission should consider these benefits in its deliberations, and should find that these benefits mean that ratepayers are receiving a good deal if NWE contracts for new solar generation at the QF-1(a) rates that Vote Solar has presented above. Finally, the Commission should conclude that these additional benefits exceed the costs that NWE may incur to integrate additional solar resources, such as the cost of incremental regulation capacity. This provides another reason to exclude from the QF-1 tariff the ancillary service costs that NWE has proposed to charge to small QFs.

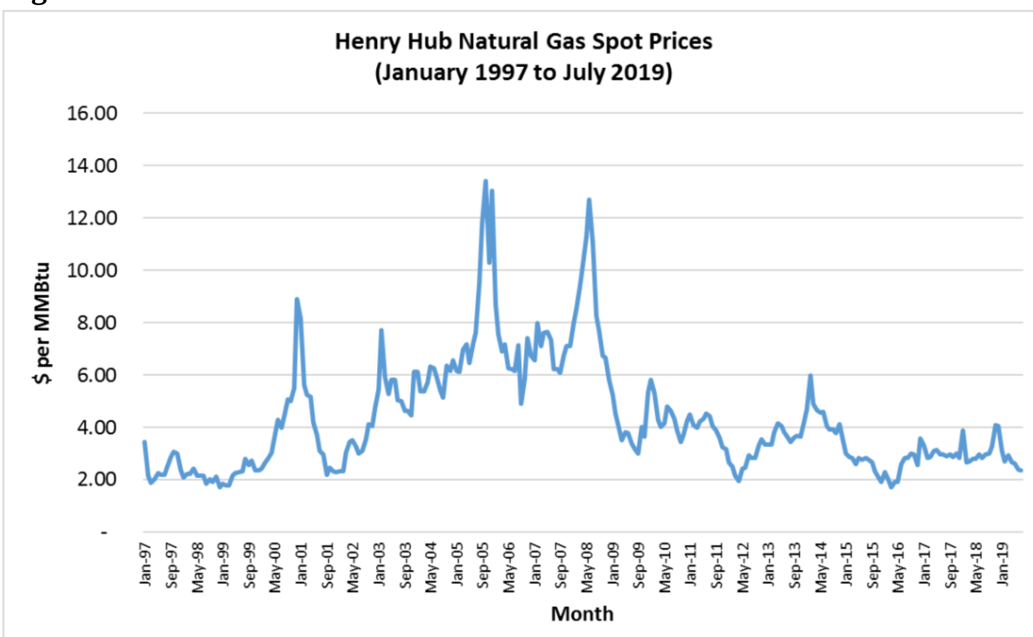
A. Hedging Benefits

Q: Do fixed-price contracts for renewable generation provide a benefit to consumers as a hedge against future uncertainty and volatility in energy and fossil fuel markets?

A: Yes, they do. As shown in NWE's *2015 IRP* and *2019 ESRP*, the alternative to the QF contracts is reliance on marginal utility fossil generation (mostly natural gas-fired) and/or market purchases, whose prices also are influenced heavily by natural gas prices. Spikes in natural gas prices have occurred regularly over the last several decades, as shown in the plot of historical benchmark Henry Hub gas prices in **Figure 7** below.[95]

Hedging against these extreme events can be very beneficial for ratepayers. Fixed prices also hedge against market dislocations or generation scarcity such as was experienced throughout the West during the California energy crisis of 2000-2001 or as occurred recently with the extreme drought in California from 2013-2015 and the long-term, drier-than-normal conditions elsewhere in the West. Obviously, there is a risk that consumers may not benefit if future prices turn out to be lower than anticipated, but, if that happens, consumers will enjoy the low prices for the portion of their needs that is not hedged.

Figure 7



The value for ratepayers of hedging this exposure is simple: fixed-price generation protects against periodic costly spikes in natural gas prices.

Renewable generation also hedges against other types of market dislocations or generation scarcity such as was experienced throughout the West during the

[95] Source for Figure 8: Chicago Mercantile Exchange data.

California energy crisis of 2000-2001 or as has occurred periodically during drought conditions in the U.S. that reduce hydroelectric output and curtail generation due to the lack of water for cooling. Renewables provide this hedge by reducing the amount of power that must be purchased at volatile short-run market prices.[96]

Q: Has this benefit been quantified?

A: Yes. A number of studies have quantified these hedging benefits. In the West, Public Service of Colorado estimated in 2013 that the long-term (20-year) hedging benefits of distributed solar resources on its system are $6.60 per MWh.[97] This study used the cost of options contracts in the gas futures market to calculate the hedging benefit.

The consultant Clean Power Research developed another approach to calculating the hedge value of renewables, as part of the Maine Public Utilities Commission's *Maine Distributed Solar Valuation Study*, released in 2015.[98] This method recognizes that natural gas prices are a primary driver of marginal energy costs, and calculates the additional costs to fix the fuel costs of a marginal gas-fired

[96] For example, in 2014 - 2015, California was fortunate that a period of rapid growth in its solar fleet occurred during a multi-year drought; in 2014, for example, the rapidly increasing output of solar projects in California covered 83% of the reduction in hydroelectric output due to the drought. This is based on Energy Information Administration data for 2014, as reported in Stephen Lacey, *As California Loses Hydro Resources to Drought, Large-Scale Solar Fills in the Gap: New solar generation made up for four-fifths of California's lost hydro production in 2014* (Greentech Media, March 31, 2015). Available at http://www.greentechmedia.com/articles/read/solar-becomes-the-second-biggest-renewable-energy-provider-in-california.

[97] Xcel Energy Services, *Costs and Benefits of Distributed Solar Generation on the Public Service Company of Colorado System: Study Report in Response to Colorado Public Utilities Commission Decision No. C09-1223* (May 2013), at pp. 6 and 43, and Table 1. This study used the cost of options contracts in the gas futures market to calculate the hedging benefit.

[98] See Maine Public Utilities Commission, *Maine Distributed Solar Valuation Study* (March 1, 2015); hereafter, "Maine Solar DG Valuation Study." Available at http://www.maine.gov/mpuc/electricity/elect_generation/documents/MainePUCVOS-ExecutiveSummary.pdf.

generator for a 25-year period, compared to purchasing gas on an "as you go" basis. To fix fuel costs for a long-term period, the money to purchase fuel in the future must be set aside today in risk-free investments. This results in higher costs because this money could otherwise be deployed to earn a higher return (assumed to be the utility's weighted average cost of capital) if it was available to be used for alternative investments. These incremental costs are what the utility who owns marginal gas generation (or who purchases such power) would have to spend to obtain the same hedging benefit that it can obtain from an identical renewable resource whose fuel costs are zero, thus eliminating the uncertainty and volatility in future fuel costs for the 25-year life of the renewable generation. These additional costs are substantial when one considers the alternative uses to which one can put the money that must be set aside upfront to fix the cost of natural gas for 25 years.

Q: Have you applied either of these methods to calculate the value for the Montana ratepayers of avoiding fuel price volatility?

A: Yes. I applied the approach from the Maine Solar DG Valuation Study to the gas commodity forecast used in NWE's QF-1 rates, using U.S. Treasuries (at current yields) as the risk-free investments, NWE's weighted average cost of capital, and a representative CCGT heat rate of 7,000 Btu per kWh. The result is the levelized hedge values shown in **Table 11** below for various QF contract terms ranging from 5 to 25 years. These numbers are comparable to those calculated by Clean Power Research for the Maine and California markets.[99]

[99] Clean Power Research, "Quantifying the Fuel Price Hedge and Energy Market Price Benefits of California's Distributed Solar PV Fleet," (October 5, 2015), at p. 18, Table 9..

Table 11: *Avoided Fuel Price Volatility*

QF Contract Term *(years)*	**Hedge Value** *($ per MWh)*
5	1.20
10	4.00
15	7.30
20	11.30
25	15.80

Q: These numbers appear to be substantial, especially for longer DER lives. Please comment on the magnitude of this benefit.

A: It is important to recognize that the market volatility and disruptions against which renewable QFs hedge do not occur often, but, when they do occur, the impacts on consumers who rely on those markets can be substantial.

I assume that small, utility-scale solar projects on NWE's system would provide a similar value in reducing the utility's exposure to volatile natural gas prices.

B. Market Price Mitigation

Q: What is the impact of adding renewable solar QF resources, which have zero variable costs, on market prices for both electricity and natural gas?

A: New solar generation will increase the electricity supplies available to NWE. The addition of this local generation will reduce the demand which the utility places on the regional markets for electricity and natural gas, producing a a corresponding reduction in the price in these markets. That price suppression benefits ratepayers by reducing the cost to buy power or natural gas in these markets. As discussed in NWE's *2015 IRP* and *2019 ESRP*, the Company has a significant short position in these markets today, and will have a similar position for many years into the future.[100] This "market price mitigation" benefit of renewable generation is widely acknowledged, has been quantified in market with

[100] NWE *2015 IRP*, at pp. 1-2 to 1-3, 1-12, 1-15, and Figures 12-1 and 12-2.

visible hourly prices such as New England and California, and has become highly visible in markets that now have significant penetrations of wind and solar resources.

Q: Please discuss how this suppression or reduction of market prices has been recognized in the calculation of avoided costs in other jurisdictions?

A: The market price suppression benefit has been analyzed extensively in the New England ISO market, where it is called the Demand Reduction Induced Price Effect (DRIPE). DRIPE is included as a benefit in the region's biennial forecasts of avoided costs used for demand-side programs.[101] Oregon includes market price reduction as one component of its resource value of solar, based in part on a recommendation that E3 made to the Oregon commission.[102] In October 2015, Clean Power Research conducted released a study on the fuel hedging and market price suppression benefits of small, distributed solar in California, finding a 20-year levelized market price response benefit in the range of $30 per MWh (SCE and SDG&E) to $38 per MWh (PG&E).[103] In an August 2018 paper, UC Davis economists also found significant reductions in hourly CAISO energy prices due to increased solar output (e.g. a $20.40 per MWh decrease in CAISO midday real-time prices from 2012 to 2016).[104]

Q: Are you aware of any modeling of this benefit elsewhere in the West?

A: Yes. The WWSIS modeling included analysis of the impact of increasing solar penetration on market prices in the West; the results for spot prices in Arizona are

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101 See Chapter 7 of the report on *Avoided Energy Supply Costs in New England*, March 27, 2015, at https://www9.nationalgridus.com/non_html/eer/ne/AESC2015%20merged%20report.pdf.

102 See Oregon PUC Order 17-357, at pp. 2-3, which outlines the 11 elements of the Oregon RVOS, including market price response.

103 Clean Power Research, "Quantifying the Fuel Price Hedge and Energy Market Price Benefits of California's Distributed Solar PV Fleet," (October 5, 2015), at p. 18, Table 9, hereafter "CPR CA Study."

104 See Bushnell & Novan, "Setting with the Sun: The Impacts of Renewable Energy on Wholesale Power Markets" (August 2018), at https://ei.haas.berkeley.edu/research/papers/WP292.pdf.

shown in **Figure 8** below.[105] The high penetration solar cases (10% to 25% penetration) in the WECC resulted in 10% to 20% reductions in spot market prices, with much of the price reductions occurring from the initial 10% solar penetration. A 15% reduction in a current forecast of the 20-year (2020-2039) levelized Mid-C market price provides a benefit of about $5.90 per MWh to NWE's ratepayers.[106]

Figure 8: *Impact of Increasing Solar Penetration on Spot Market Price*

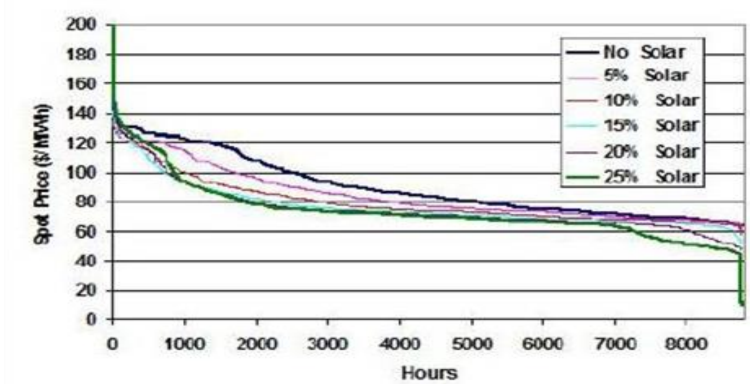

Figure 19 – Arizona Spot Price Duration Curves.

C. Local Economic Benefits

Q: Will there be local economic benefits from the development of solar QFs in NWE's Montana service territory?

A: Yes. The construction of each additional 100 MW of small QF solar generation in Montana would represent an investment of $180 million in the state, assuming a capital cost of $1,800 per kW. Not all of this money will be spent in Montana,

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[105] The high penetration solar results from the WWSIS are reported in *Impact of High Solar Penetration in the Western Interconnection* (NREL and GE Consulting, December 2010), at p. 8 and Figure 19. Note that this report assumes 100 MW of solar in Montana in the 3% solar penetration case and 500 MW of Montana solar in the 15% penetration scenario. This report, as well as all reports from the WWSIS, are available on the NREL website at http://www.nrel.gov/electricity/transmission/western_wind.html.

[106] These benefits assume equal volumes of solar and market purchases. The benefits per MWh of solar will be higher if the volume of NWE's market purchases exceeds the volume of its solar purchases.

of course, but there would be significant short-term employment benefits during construction. Additionally, there will be additional revenue to Montana from permanent employment operating and maintaining these facilities, as well as lease payments to landowners and property taxes to local communities. Significantly, because these facilities will be located in Montana, the economic benefits are more likely to accrue locally than if these were out-of-state power plants, power purchases from regional markets, or gas-fired generation whose fuel is procured out of state.

D. Conclusion

Q: Do the additional benefits you have summarized in this section more than offset any possible integration costs from QF-1 resources?

A: Yes. Any added integration costs are significantly less than the additional quantifiable benefits of solar resources, discussed above and summarized in **Table 12**, that are not included in avoided cost prices. This provides a further reason not to include a deduction for integration costs in QF-1 rates.

Table 12: *Additional Benefits and Costs of Solar Resources*

Category	**Benefits or (Costs)** *$ per MWh*
Fuel Hedging (20-year contract)	15.80
Market Price Mitigation	5.90
Integration Costs for 100 MW	(4.35)
Net Benefit	17.35

Q: Does this complete your direct testimony?

A: Yes, it does.

Exhibits to Direct Testimony of Michael Milligan
on behalf of Montana Environmental Information Center

Exhibit MM-8

Docket No. 2019.12.101

Proxy for Capacity Credit as Percent of Rated Capacity

	2018		2019		Average	
	Wind	**Solar**	**Wind**	**Solar**	**Wind**	**Solar**
Beach Method	**33.62**	**30.45**	**35.62**	**36.14**	**34.62**	**33.30**

CERTIFICATE OF SERVICE

I hereby certify that on the 25th day of September, 2020, I served the foregoing by electronic mail on the following:

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