Resource adequacy

Resource adequacy is the ability of supply-side and demand-side resources to meet the aggregate electrical demand (including losses).

Resource adequacy is quantified using loss-of-load probability (LOLP), loss of load expectation (LOLE), and expected energy not served (EENS):

- LOLE is the number of time units that the load will exceed the capacity.
- LOLP is the probability that the load will be interrupted during a given time period.
- EENS is expected energy not served during a given time period.

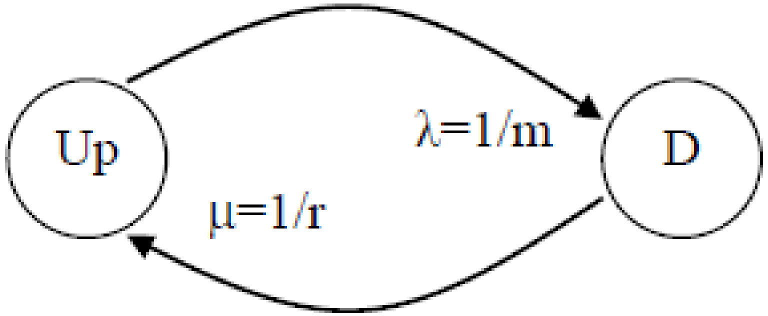
A very widely-quoted threshold (maximum) value for LOLE is “1 day in 10 years” which means that during a period of 10 years (87,600) hours, the power system is expected to interrupt load for 24 of those hours (1 day). It can also be expressed as 0.1 days per year.

There are software applications to compute LOLE for large-scale power systems, e.g., GEMARS, PRISM, SERVM; most use Monte Carlo simulation, convolution, or network flows.

Capacity markets, which exist at four RTOs (NYISO, ISONE, PJM, and MISO), are built on resource adequacy calculations. At MISO, the capacity market is called the planning resource auction (PRA).

Resource adequacy – Forced Outage Rate

A generator may be represented by a 2-state Markov model, shown below.



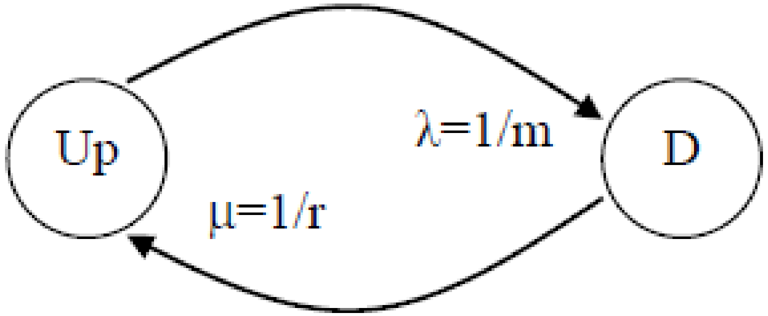
In this model, λ is the failure rate of the generator with units of number of failures per year, and μ is the repair rate with units of number of repairs per year.

These parameters may be found by computing the mean of the time to failures (MTTF) and the mean of the time to repair (MTTR), from which we obtain λ=1/MTTF and μ=1/MTTR.

More generally, λ and μ are referred to as transition rates.

The system is said to be Markov if it is memoryless, i.e., if the probability of future events depends only on information characterizing the present and not on any information characterizing the past; the amount of time it spends in each state is exponentially distributed; and the states are mutually exclusive (the process cannot reside in two or more states simultaneously).

Resource adequacy – Forced Outage Rate



We show in the notes of U16 (see section U16.5)that the long-run (steady-state) probabilities of residing in the “up” and “down” states are given by:

$$A = \frac{\mu}{\lambda + \mu}; \qquad U = \frac{\lambda}{\lambda + \mu}$$

U is also called the forced outage rate (FOR) of the generator. For a given extended period of time T in the past, it gives the percent of that time that the unit was out of service. Although it is referred to as a rate, it is treated as a probability, i.e., (assuming the statistics of the future are characterized by the statistics of the past), U=FOR gives the probability at any given time of the unit being in the down state.

Resource adequacy – Capacity Outage Probability Table (COPT)

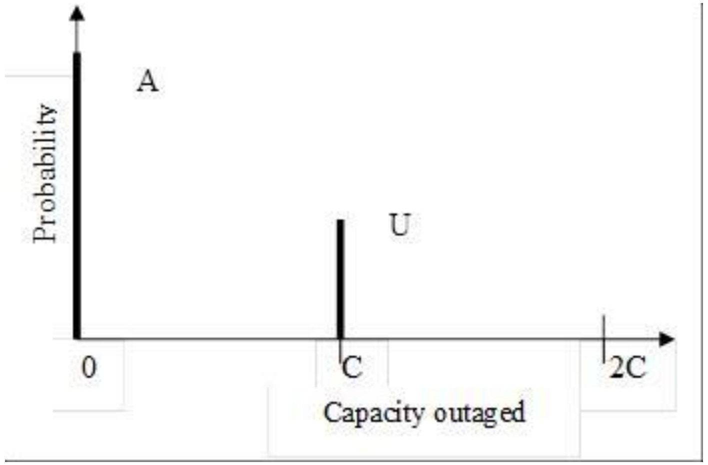
A capacity probability table is a probabilistic description of the possible capacity states of the system being evaluated. The simplest case is that of the 1 unit system, where there are two possible capacity states: 0 and C, where C is the maximum capacity of the unit. The capacity table for this case is given below.

Capacity	Probability
C	A
0	U

We may also describe this system in terms of capacity outage states. Such a description is generally given via a capacity outage probability table (COPT), shown below.

Capacity Outage	Probability
0	A
C	U

The figure below shows the probability mass function (pmf) corresponding to the capacity outage table.



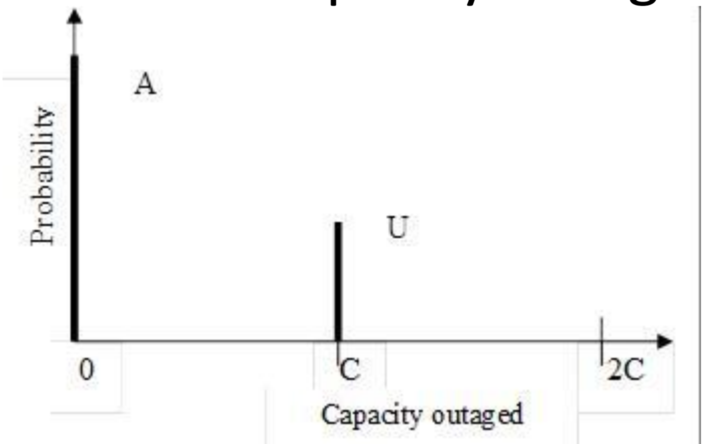
Resource adequacy – Convolution

Now consider a two unit system, with both units of capacity C. We can obtain the COPT by basic reasoning, resulting in:

Capacity Outage	Probability
0	A^2
C	AU
C	UA
2C	U^2

Capacity Outage	Probability
0	A^2
C	2AU
2C	U^2

Define X_1 as the capacity outage random variable (RV) for unit 1 and X_2 as the capacity outage RV for unit 2, with pmfs $f_{X1}(x)$ and $f_{X2}(x)$, each of which appear as the capacity outage pmf below.



We desire $f_Y(y)$, the pmf of Y, where $Y=X_1+X_2$. Recall that we can obtain $f_Y(y)$ by convolving $f_{X1}(x)$ with $f_{X2}(x)$, i.e.,

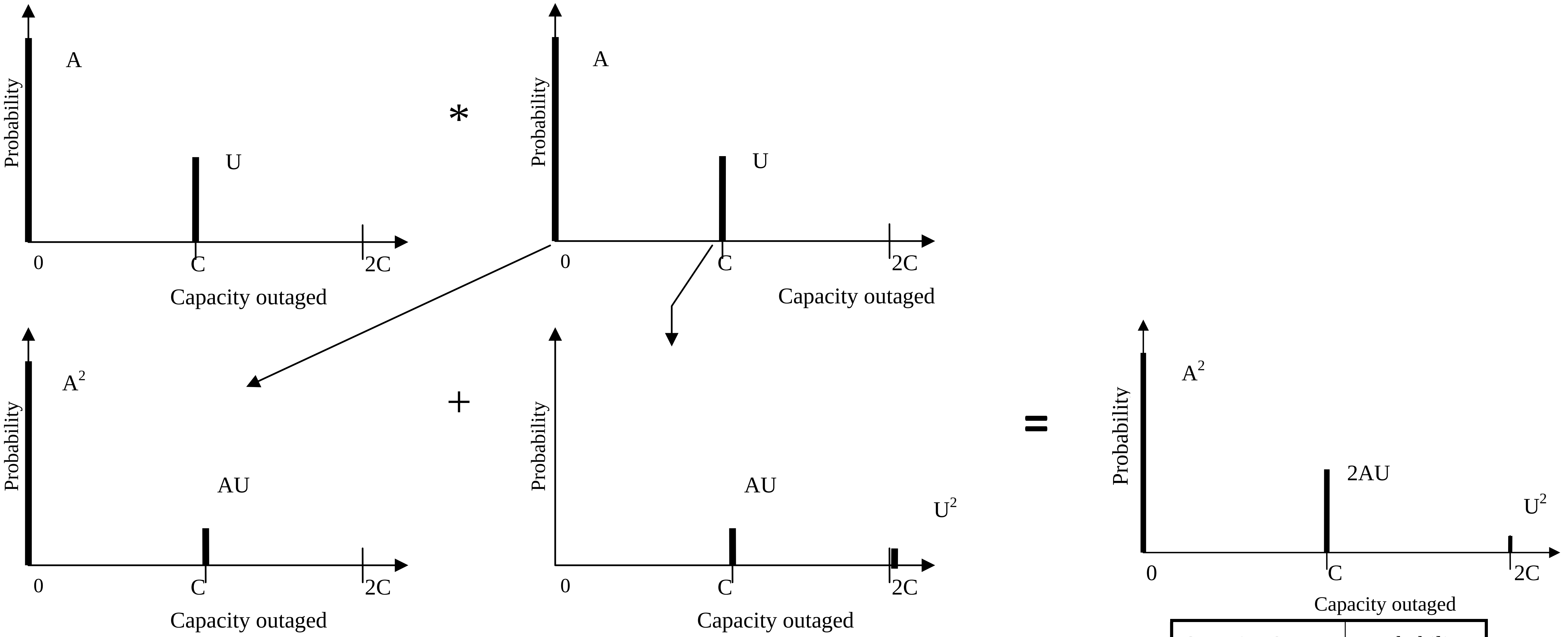
$$f_Y(y) = \int_{-\infty}^{\infty} f_{X1}(x)\, f_{X2}(y-x)dx$$

Inspection of $f_{X1}(x)$ and $f_{X2}(x)$ indicates their pmfs are comprised of impulses. Convolution of any function with an impulse function simply shifts and scales that function.

- The shift moves the origin of the original function to the location of the impulse;
- The scale is by the value of the impulse.

This enables us to perform the convolution very easily…

Resource adequacy – Convolution

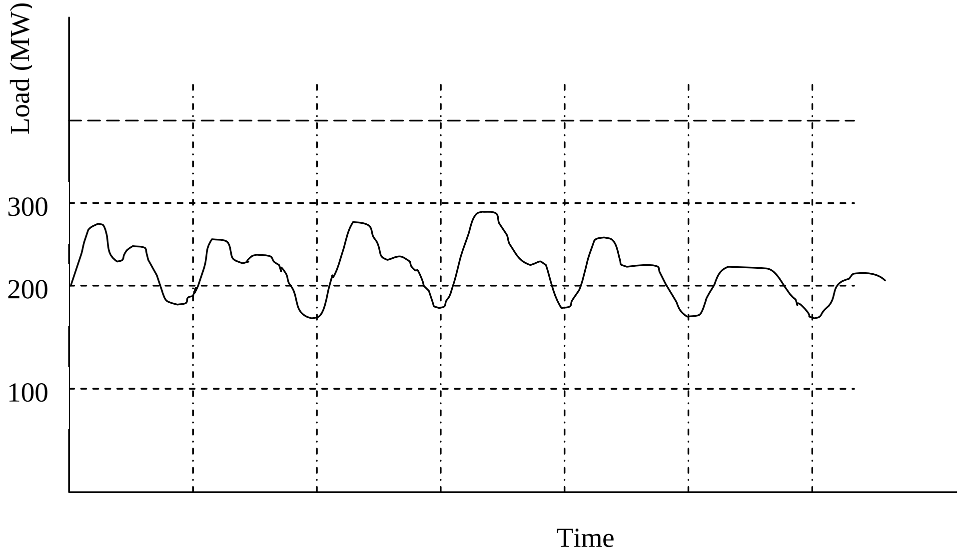


From previous slide➔

Capacity Outage	Probability
0	A^2
C	2AU
2C	U^2

Resource adequacy – Load Characterization

Consider the plot of instantaneous demand as a function of time, as below.



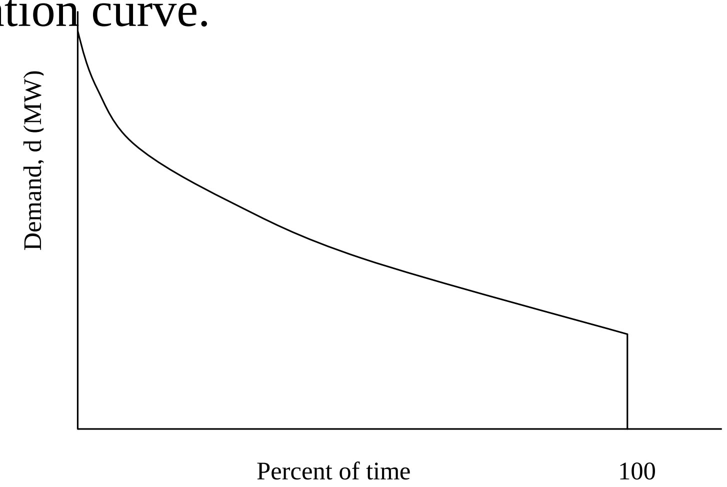
Although this curve is only illustrated for 7 days, one could easily imagine extending the curve to cover a full year.

From such a yearly curve, we may identify the % of time for which the demand exceeds a given value.

If we assume that the curve is a forecasted curve for the next year, then this percentage is equivalent to the probability that the demand will exceed the given value in that year.

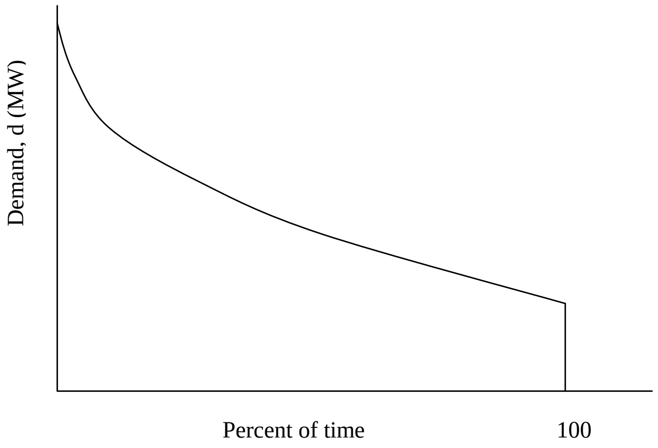
The procedure for obtaining the % of time for which the demand exceeds a given value is as follows.

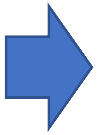
1. Discretize the curve into *N* equal time segments, so that the value of the discretized curve in each segment takes on the maximum value of the continuous curve in that segment.
2. The percentage of time the demand ***exceeds a value*** *d* is obtained by counting the number of segments having a value greater than *d* and dividing by *N*.
3. Plot the demand *d* against the percent of time the demand exceeds a value *d*. A typical such plot is illustrated below; it is called the load duration curve.

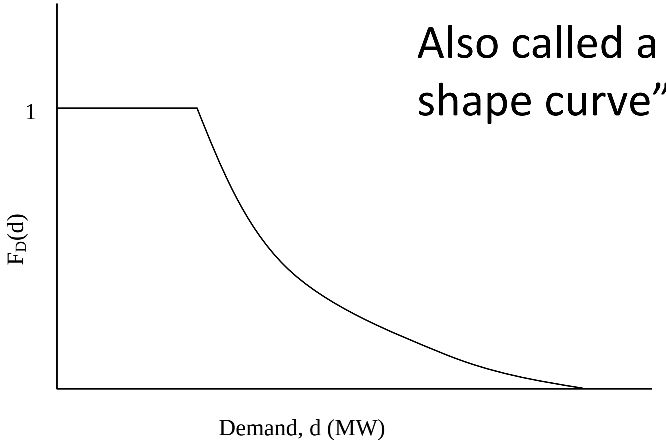


Resource adequacy – Load Characterization

We convert the load duration curve to a load model (or cumulative distribution function) by dividing abscissa values (x-axis) by 100, & switching the axes. The result is below.







Also called a "load shape curve"

The ordinate then represents the probability that the demand exceeds the corresponding value *d*. We denote this probability using the notation for a cumulative distribution function (cdf), $F_D(d)$. It is actually the complement of a true cdf, i.e.,

$$F_D(d) = P(D > d) = 1 - P(D \leq d)$$

where *D* is a random variable and *d* are values it may take.

Resource adequacy – Load Characterization

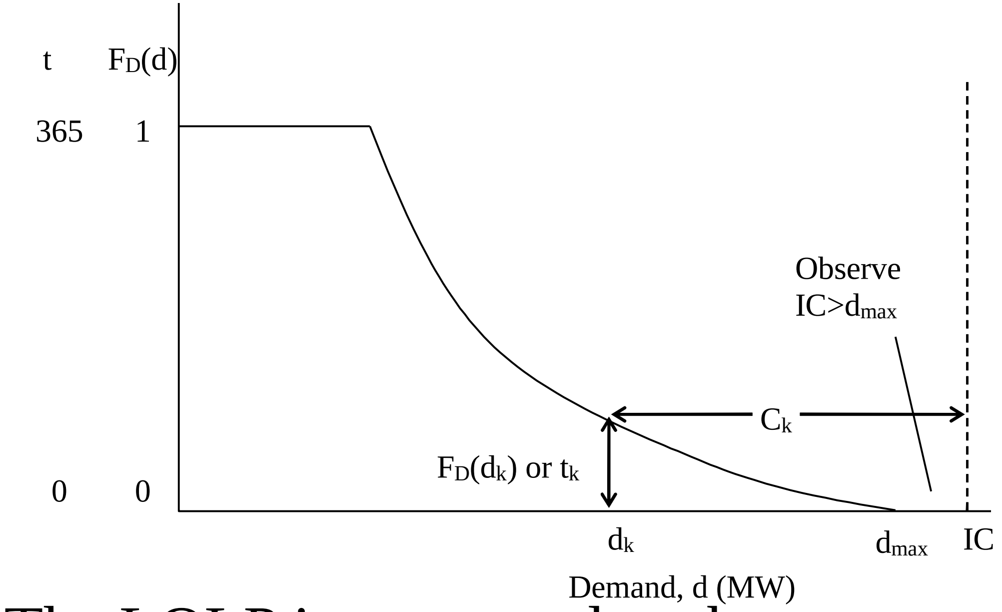
The figure to the right illustrates a typical load-capacity relationship where the load model is shown for a period of T=365 days.

The capacity outage state, C_k, is shown so that one observes that load interruption only occurs under the condition that the load exceeds the installed capacity less the capacity outage, i.e., $d > IC-C_k$. The maximum demand that avoids load interruption is $d_k=IC-C_k$, i.e., load interruption will occur for $d>d_k$.

Thus, the probability of having an outage of capacity C_k and of having the demand exceed d_k is given by the capacity outage pmf and $F_D(d_k)$, i.e.,

$$f_Y(C_k)F_D(d_k)= f_Y(C_k)F_D(IC-C_k).$$

(This assumes independence between outage events & demand).



The LOLP is computed as the sum over all capacity outage states:

$$LOLP = \sum_{k=1}^{N} f_Y(C_k)F_D(IC-C_k)$$

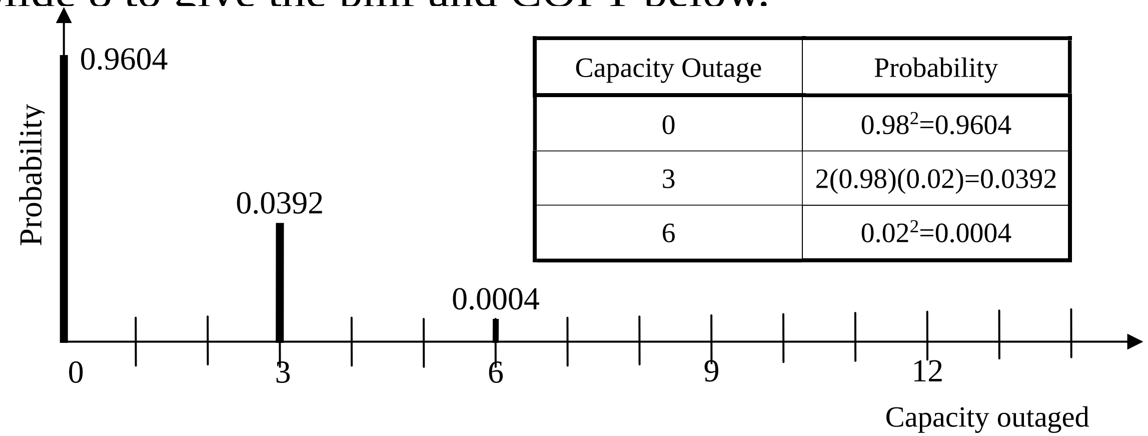
and the LOLE as:

$$LOLE = LOLP \times T = \sum_{k=1}^{N} f_Y(C_k)F_D(IC-C_k)*365 = \sum_{k=1}^{N} f_Y(C_k)t_k$$

where N is the number of capacity outage states and t_k is the amount of time the system is expected to have demand exceeding d_k (illustrated in above figure).

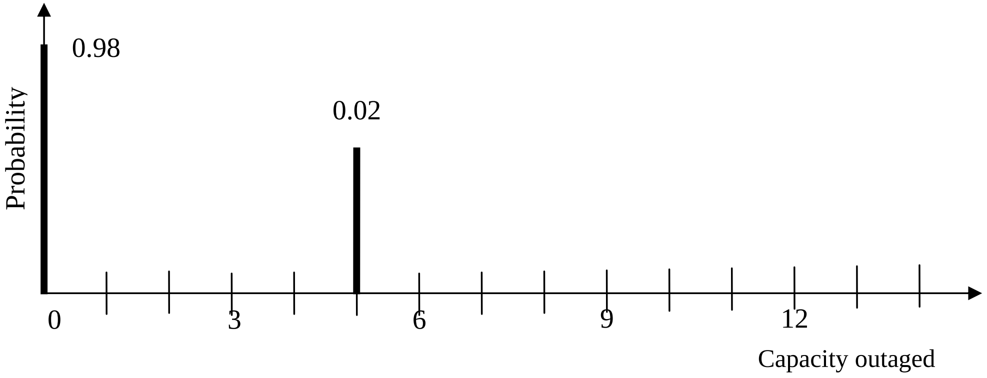
Resource adequacy – Example

Consider a system with two 3 MW units and one 5 MW unit, all of which have forced outage rates (FOR) of 0.02.
The pmfs of the two identical 3 MW units can be convolved as in Slide 8 to give the pmf and COPT below.

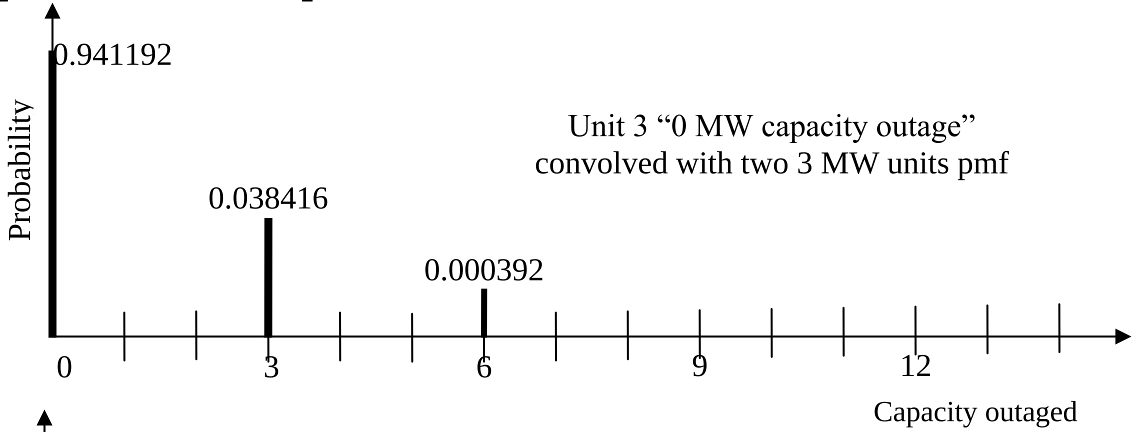


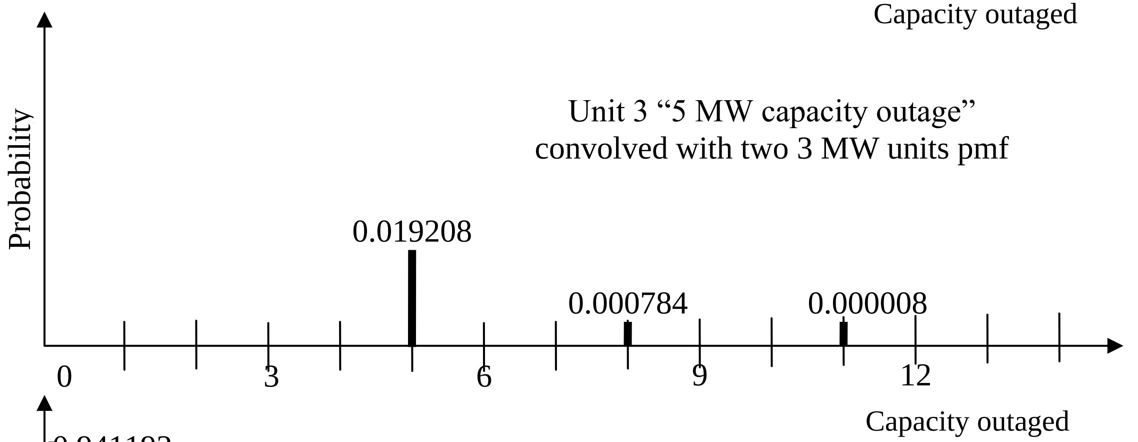
Capacity Outage	Probability
0	0.98^2=0.9604
3	2(0.98)(0.02)=0.0392
6	0.02^2=0.0004

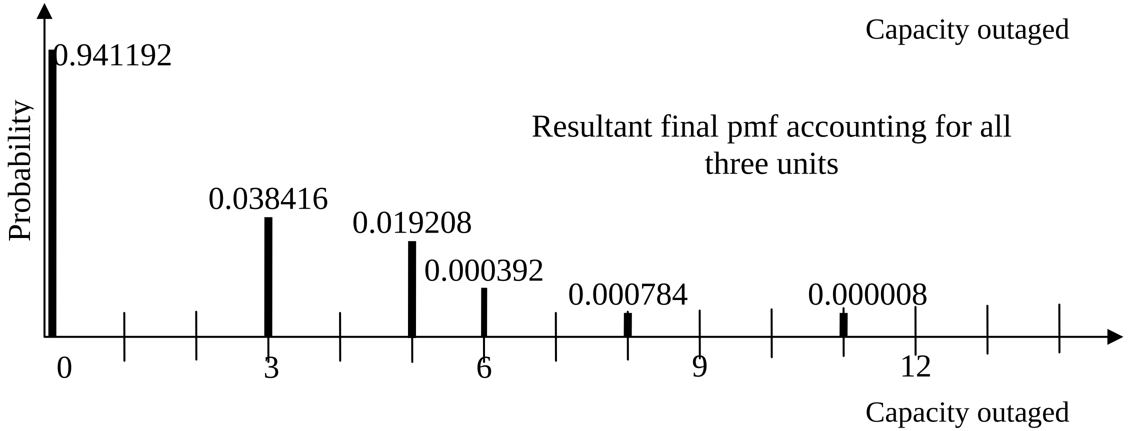
The 5 MW unit (call it “unit 3”) has a pmf as below.



Convolving the 5 MW unit’s pmf (above) with the two 3 MW units’ pmf (above top) results in the below.







The COPT for this appears on the next slide.

Resource adequacy – Example

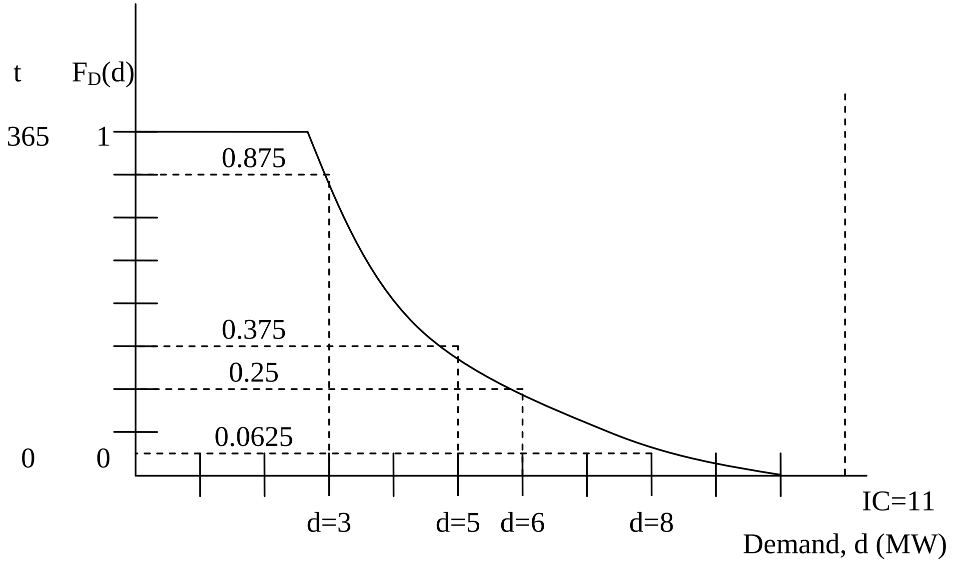
The COPT corresponding to pmf on previous slide:

Capacity Outage	Probability
0	0.98×0.9604=0.941192
3	0.98×0.0392=0.038416
5	0.02×0.9604=0.019208
6	0.98×0.0004=0.000392
8	0.02×0.0392=0.000784
11	0.02×0.0004=0.000008

This table tells us that over a given time interval, the probability that the system will have a capacity outage:

- of 0 MW is 0.941192;
- of 3 MW is 0.038416;
- of 5 MW is 0.019208;
- of 6 MW is 0.000392;
- of 8 MW is 0.000784;
- of 11 MW is 0.000008.

Now consider a system having the below load model:



Using the LOLP expression from slide 11:

$$
\begin{aligned}
LOLP &= \sum_{k=1}^{N} f_Y(C_k)F_D(IC - C_k) \\
&= f_Y(0)F_D(11) + f_Y(3)F_D(8) + f_Y(5)F_D(6) \\
&+ f_Y(6)F_D(5) + f_Y(8)F_D(3) + f_Y(11)F_D(0) = \\
&= .941192*0 + .038416*.0625 + .019208*.25 \\
&+ .000392*.375 + .000784*.875 + .000008*1 \\
&= 0.008044 / \mathit{year}
\end{aligned}
$$

We could compute LOLE using its expression on slide 11, but now that we have LOLP, it is easier to use:

$$LOLE = LOLP \times T = 0.008044 * 365\text{days} = 2.93606\text{days/year}$$

This is well-above the 0.1days/year that industry requires, and so this reliability level is unacceptable. We should add more capacity to this system. Two qualifiers:

- This LOLE is load outage time expected due to gen unavailability; it doesn't include effects of transm/dist component unavailability.
- This outage time is the long-run average of this system only if
  - all 3 units are always committed, i.e., no reserve shutdown, and there is no maintenance;
  - demand remains constant throughout each time interval

How to deal with wind & solar?

Three issues:

1. Wind and solar plants rarely outage (maybe a few turbines or panels outage at any one time), but the wind and solar production do vary greatly.
2. Viewed from a system level, we need to be able to account for the variability of the total resource.
3. In assessing resource adequacy, it is clear we should not attribute total wind and solar capacity to the wind and solar resources in a system. But what capacity should we attribute to them?

Capacity credit is the percentage of a resource's nameplate capacity that can contribute to meeting the system's resource adequacy at target reliability level. For example, MISO used a 16.3% capacity credit for wind and a 50% capacity credit for solar during the 2021-2022 planning year [1].

Effective Load Carrying Capability (ELCC) is the amount of additional load a resource, such as wind, can dependably and reliably serve [at high-risk period] while also considering the probabilistic nature of generation shortfalls and random forced outages as driving factors to load not being served [1].

$$ELCC = Capacity \times CapacityCredit$$

This concept was originally suggested in [2].

[1] MISO, "Planning year 2021-2022: Wind & Solar Capacity Credit," December 2020, https://cdn.misoenergy.org/DRAFT%202021%20Wind%20&%20Solar%20Capacity%20Credit%20Report503411.pdf.

[2] L. L. Garver, "Effective Load Carrying Capability of Generating Units," IEEE Transactions on Power Apparatus & Systems, vol. PAS-85, no. 8, pp. 910-919, Aug. 1966, doi: 10.1109/TPAS.1966.291652.

How to deal with wind & solar?

In March 2023, MISO presented the following capacity credits for 2023-2024 wind and solar [3]:

- MISO, in accordance with FERC acceptance of the Reliability Availability & Need (RAN) seasonal capacity construct (ER22-495-000), developed four unique seasonal class-average capacity values for wind for Planning Year 2023-2024, those being:
  - 18.1% for Summer 2023
  - 23.1% for Fall 2023
  - 40.3% for Winter 2023-2024
  - 23.0% for Spring 2024
- Solar default seasonal capacity credits in Planning Year 2023-2024 are 50% for all seasons, with the exception of Winter 2023-2024 for which the solar default capacity credit is 5%.

Terminology: "Capacity credit" ~ "Capacity value" ~ "Accreditation"

≠ "Capacity factor"

misoenergy.org

Observe (1) values are seasonal; (2) winter values very different from values of other seasons. Why? There are two reasons:

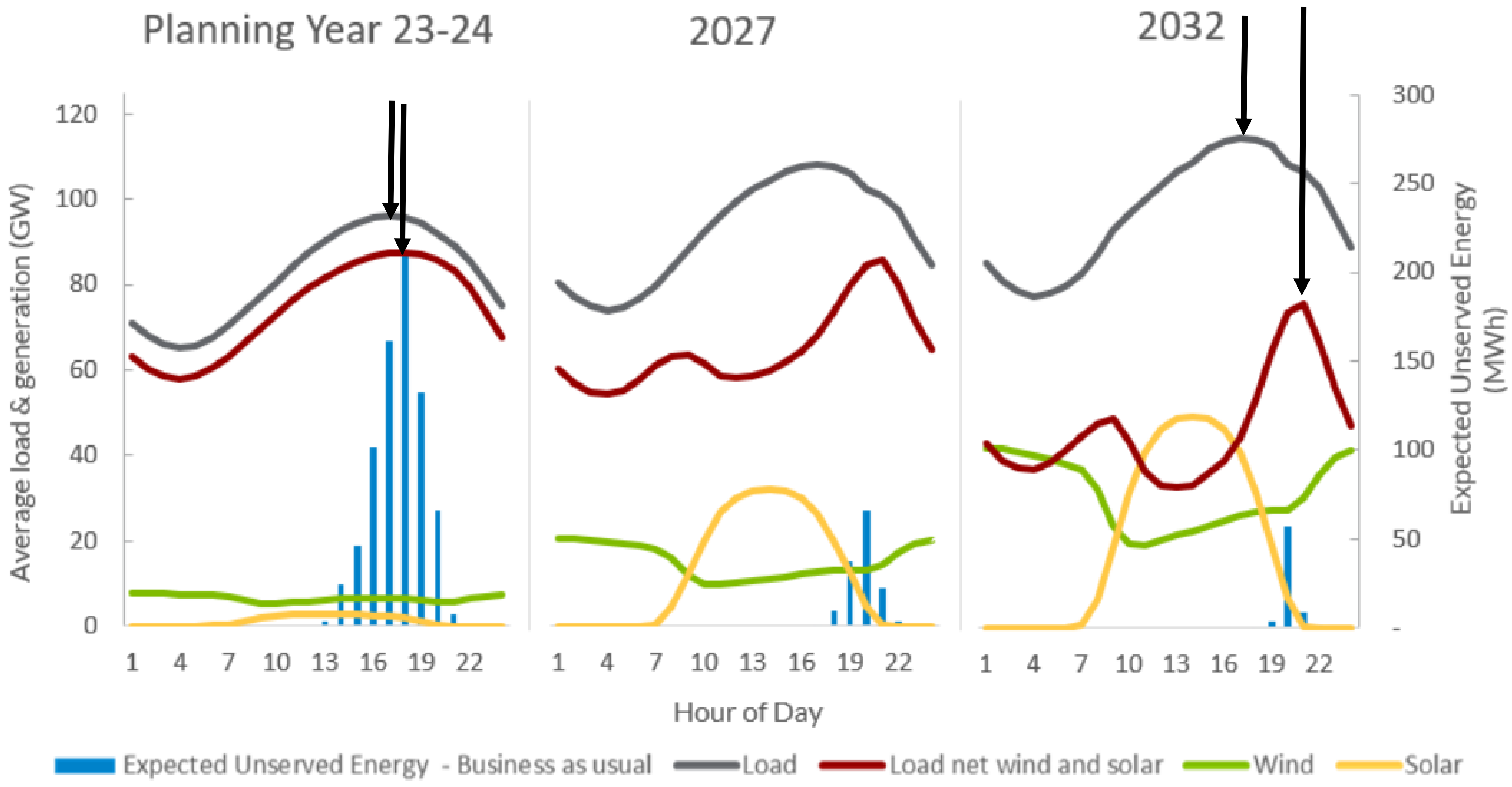
1. Avg wind/solar resources change seasonally, with winter wind & summer solar being the richest;

FACT: CC computed for highest risk condition; highest risk condition is at highest *netload* condition.

2. Highest netload condition changes with wind & solar additions (increasing solar tends to shift the netload peak later into the evening causing percentage of nameplate solar to reduce)

[3] MidContinent Independent System Operator (MISO), "Planning Year 2023-2024: Wind and Solar Capacity Credit Report," Accessed 2/22/2024, Available: https://cdn.misoenergy.org/2023%20Wind%20and%20Solar%20Capacity%20Credit%20Report628118.pdf. .

How to deal with wind & solar?



Observe: As solar grows, netload peak moves to right of load peak, resulting in a lower capacity credit for solar.

Implication: Capacity credit of a resource depends on resources coming before it!

[4] MidContinent Independent System Operator (MISO), "Attributes roadmap," Accessed 2/22/2024, Available: https://cdn.misoenergy.org/2023%20Attributes%20Roadmap631174.pdf.

How to deal with wind & solar?

Implication:

Capacity credit of a resource depends on resources coming before it!

➔This implication leads to an important question: Should resources be evaluated

- [Average approach] as a resource-type, i.e., all solar together, and all wind together (or all wind & solar together)?
- [Marginal approach] or one "plant" at a time, resulting in "incremental" or "marginal" ELCC specific to each plant?

The first efforts tended towards the Average approach (as shown two slides back). Today's efforts are tending more towards the marginal approach.

This is important because the number determines payments to the individual plant owners via the capacity market; we desire to provide market signals to obtain the capacity we want, and it makes a difference. We will address this further, but before doing so, we further investigate the calculation of ELCC.

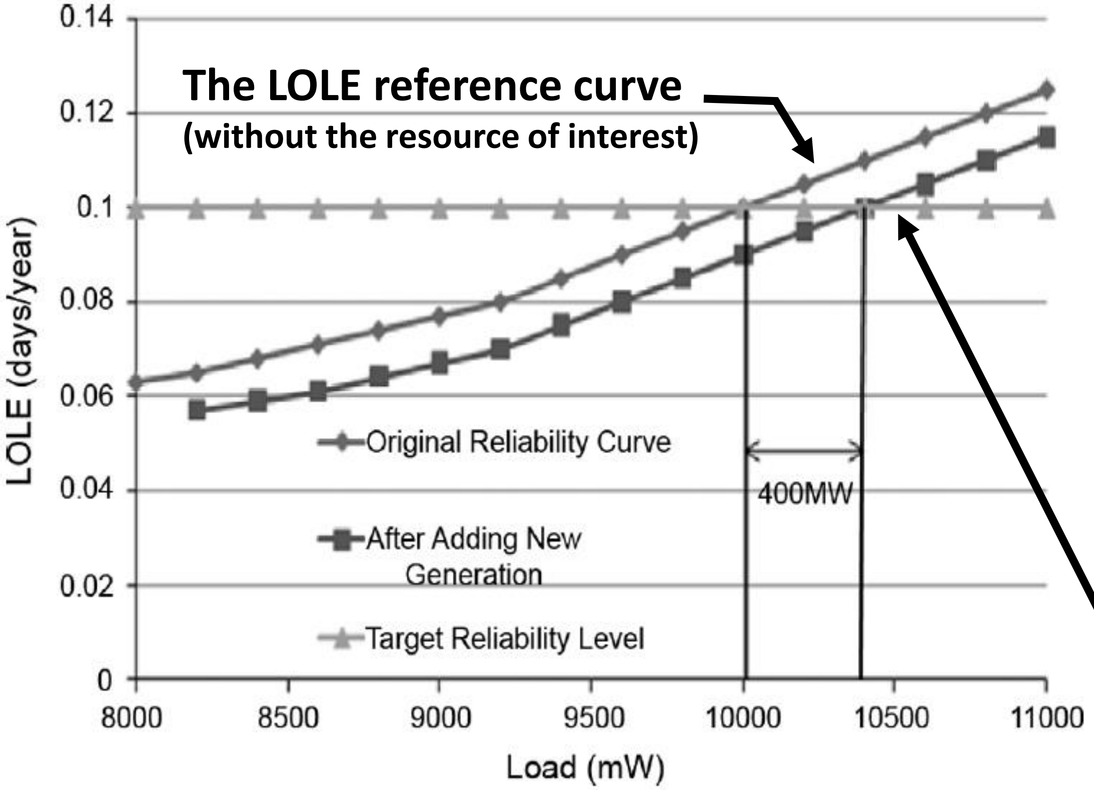
How to deal with wind & solar?

A caution:

ELCC fundamentally depends on the notion of LOLE. There has been concern that LOLE as a concept is not well-understood and is frequently misused. To this point, I refer you to the following paper:

G. Stephen, S. Tindemans, J. Fazio, C. Dent, A. Figueroa Acevedo, B. Bagen, A. Crawford, A. Klaube, D. Logan, and D. Burke, "Clarifying the Interpretation and Use of the LOLE Resource Adequacy Metric," 2022 17th International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), Manchester, United Kingdom, 2022, pp. 1-4, doi: 10.1109/PMAPS53380.2022.981061

Building the Reference LOLE Curve (*)



How is each point on that LOLE curve computed?

1. Obtain a load time series together with a gen commitment/dispatch for each time-period. Should be at each day's peak.
2. Identify the annual peak load, P_1.
3. Compute LOLE for each day.
4. Add up daily LOLE's to obtain annual LOLE. Thus we have a peak load P_1 together with the corresponding annual $LOLE_1$. This is a point on the reference plot (P_1, $LOLE_1$).
5. Scale the load data up and down to obtain other points on the LOLE curve.

The LOLE accounting for a new resource is obtained the same way, except we use:

➔ Netload time series = Load time series – Resource time series

Important observation: each point is a function of an annual time series.
The LOLE compresses the risk associated with the entire year into a single point.

[*] "Capacity Value of Wind Power," Task Force on the Capacity Value of Wind Power, IEEE Power and Energy Society, Andrew Keane, Member, IEEE, Michael Milligan, Member, IEEE, Chris J. Dent, Member, IEEE, Bernhard Hasche, Claudine D'Annunzio, Ken Dragoon, Hannele Holttinen, Nader Samaan, Lennart Söder, and Mark O'Malley, IEEE Trans on Power Systems, Vol. 26, Is 2, 2011, pp. 564-572.

How to compute ELCC? (higher-level version of the next slide)

An approach to account for low capacity factor and correlation is to set the capacity for variable generation equal to the amount of load that it enables to be added without changing the risk of a shortage in generation capacity at a targeted load level, as measured by loss of load expectation (LOLE). This is referred to as the *effective load carrying capability*, or ELCC. This concept is illustrated below [*].

➔Horizontal line is LOLE=0.1 day is satisfied for peak load less than or equal to 10000 MW.

➔LOLE function without new gen.

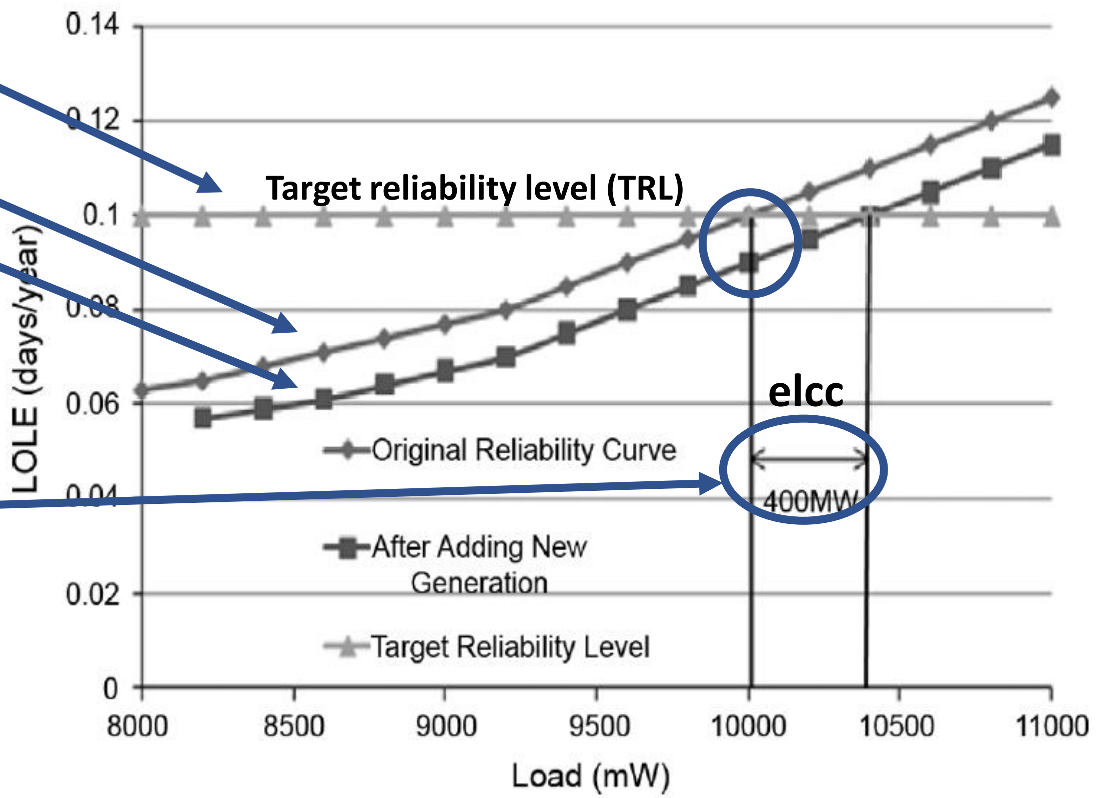
➔Addition of 2450MW new gen moves LOLE function.

➔If we required that peak load remain the same, the LOLE would go down (get better) to about 0.09.

➔Assume we want to maintain same LOLE value of 0.1→we may grow load by 400 MW! This 400 MW load growth is called ELCC of new gen.

➔ELCC of an additional gen will only be equal to capacity of that additional gen if additional gen always produces its capacity (no wind reduction, no failure).

➔Capacity credit=ELCC/CAPACITY=400/2450=.163



[*] “Capacity Value of Wind Power,” Task Force on the Capacity Value of Wind Power, IEEE Power and Energy Society, Andrew Keane, Member, IEEE, Michael Milligan, Member, IEEE, Chris J. Dent, Member, IEEE, Bernhard Hasche, Claudine D’Annunzio, Ken Dragoon, Hannele Holttinen, Nader Samaan, Lennart Söder, and Mark O’Malley, IEEE Trans on Power Systems, Vol. 26, Is 2, 2011, pp. 564-572.

How to compute ELCC? (more explicit version of previous slide)

Ref [*] provides 3-step method for computing ELCC, which depends on development of capacity outage probability table (COPT).The method is given below (quotes directly from paper).

1. **<u>Compute LOLE without NewGen</u>**: "*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 <u>wind plant.</u> 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." [We are interested in computing impact of wind (and/or solar) on the LOLE at a high risk time; not LOLE itself. So adjustment of loads is OK if the same adjusted loads are used throughout the calculation.]

   Can be total system wind/solar.

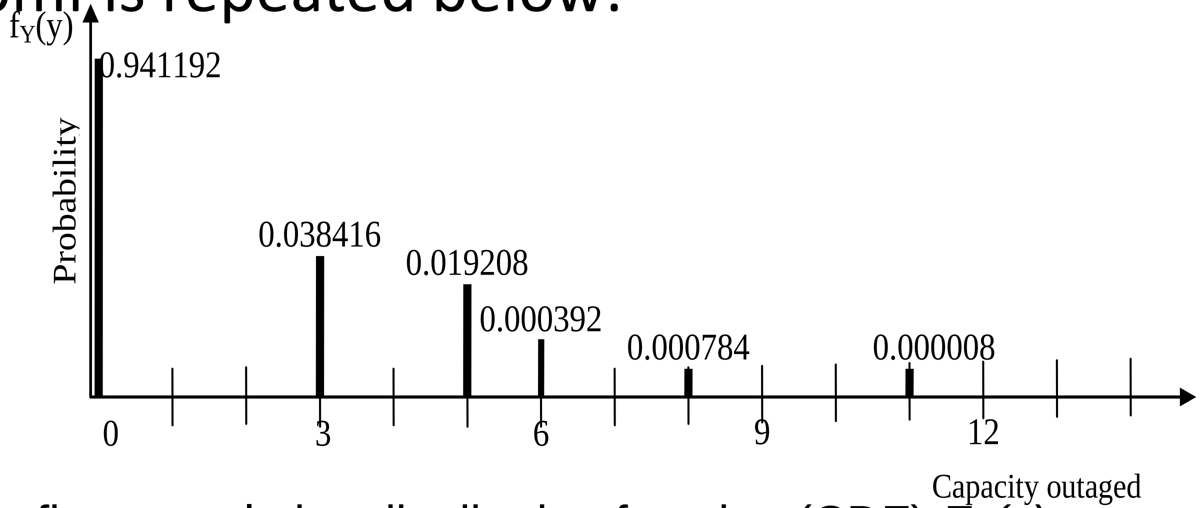
2. **<u>Compute LOLE with NewGen</u>**: "The time series for the wind plant power output is treated as negative load and is combined with the load time series, resulting in a load time series net of wind power. *In the same manner as step 1*, the LOLE is calculated. It will now be lower (therefore better) than the target LOLE in the first step."
3. **<u>Obtain ELCC by increasing load until reaching LOLE target</u>**: "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 load (sum of ΔLs) that achieves the reliability target is the ELCC or capacity value of the wind plant."

1. What is a capacity outage probability table (COPT)? We have already seen this in previous slides.
2. How to compute the COPT? We have also already seen this in previous slides. So only remaining question is #3…
3. How to do the following: "The COPT of the power system is used in conjunction with the hourly load time series to compute the hourly LOLPs" ?

[*] "Capacity Value of Wind Power," Task Force on the Capacity Value of Wind Power, IEEE Power and Energy Society, Andrew Keane, Member, IEEE, Michael Milligan, Member, IEEE, Chris J. Dent, Member, IEEE, Bernhard Hasche, Claudine D'Annunzio, Ken Dragoon, Hannele Holttinen, Nader Samaan, Lennart Söder, and Mark O'Malley, IEEE Trans on Power Systems, Vol. 26, Is 2, 2011, pp. 564-572.

How to compute ELCC? Main step: get LOLE for a single load

Using our example, the capacity outage pmf is repeated below:



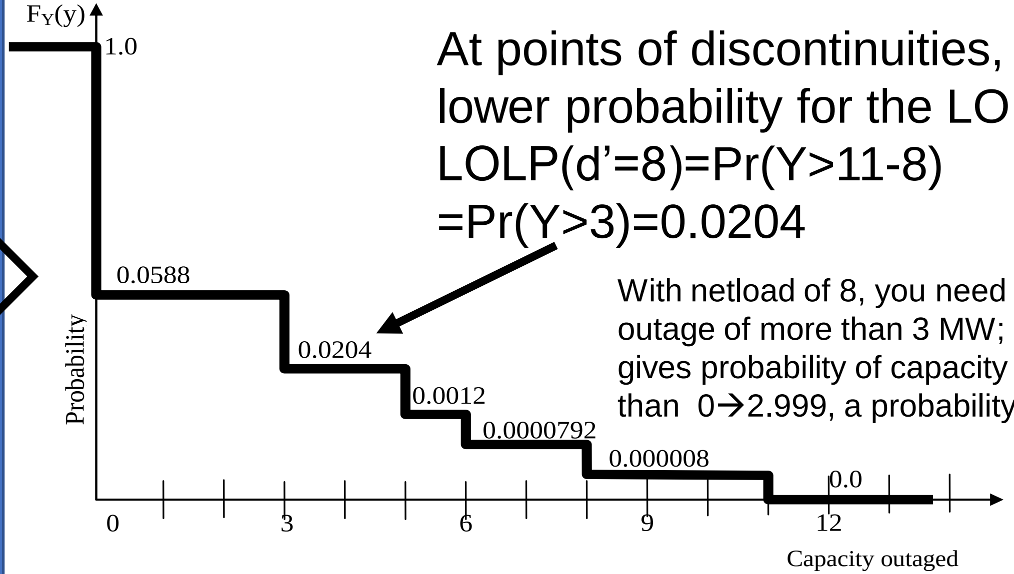
Define cumulative distribution function (CDF) $F_Y(y)$ as

$$F_Y(y) = P(Y > y) = \sum_{y_j > y} f_Y(y_j) = 1 - \sum_{y_j \le y} f_Y(y_j)$$

Cap outage state j	Capacity outage, y	Probability $f_Y(y)$	Cumulative probability $F_Y(y)$
1	0	0.941192	**0.0588**
2	3	0.038416	**0.0204**
3	5	0.019208	**0.0012**
4	6	0.000392	**.0000792**
5	8	0.000784	**0.000008**
6	**11**	**0.000008**	**0**

Once we have this table, given a certain netload *d'*, we may compute LOLP during the desired time interval, as the probability that capacity outage exceeds *IC-d'*, which is just $F_Y(y=IC-d')$, that is, $LOLP(d')=F_Y(y=IC-d')$.
Recalling *IC=11*, with netload d'=5 MW, we obtain LOLP(5)=F_Y(11-5)= $F_Y(y=6)$=0.000792.

Note that IC-d' is reserve!
So $F_Y(y)=P(Y>y)$
=P(CapOutage>Reserve)
=LOLP



At points of discontinuities, use the lower probability for the LOLP, e.g., LOLP(d'=8)=Pr(Y>11-8) =Pr(Y>3)=0.0204

With netload of 8, you need a capacity outage of more than 3 MW; use of .0588 gives probability of capacity outage of more than 0→2.999, a probability that is too high.

And we do this many times to get an LOLE curve..

The annual LOLE is obtained by summing the hourly LOLP (to get hrs/yr) or daily LOLPs (to get days/yr).

What not use Approach B?

APPROACH A: Combine entire system wind /solar output with load to obtain netload, resulting in system LOLE.

Positives: It inherently accounts for correlation between wind, solar, and load.

Negatives:

It does not account for total plant outage due to substation xfmr failure.

APPROACH B: Use some method to choose "equivalent" wind/solar plant capacities and outage probabilities (e.g., equal to that of Substation Xfmr).

Positives: Once the ELCCs are computed, it provides that a straightforward convolution approach may be used for conventional, solar, and wind plants. Units may be efficiently convolved in and convolved out.

Negatives: It does not account for correlation between wind, solar, & load; it assumes all turbines in each capacity block fail simultaneously.

"Models treating renewables as generators can be shown to introduce considerable modeling errors through the simplifying assumptions that must be made for the renewables sources as generators. These assumption errors are sidestepped by treating the renewables as load reducers and then the remaining load is served by conventional generators." [X]

[X] M. Papic, J. Ellsworth, A. V. Delgado, E. Schellenberg, G. Travis and G. Preston, "Adequacy Assessment of the Idaho Power Generation System with Integrated Variable Energy Sources," *2020 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS)*, 2020, pp. 1-6, doi: 10.1109/PMAPS47429.2020.9183653.

"Wind power cannot be adequately modeled by its capacity and FOR as wind availability is more a matter of resource availability than mechanical availability." [Y]

[Y] "Capacity Value of Wind Power," Task Force on the Capacity Value of Wind Power, IEEE Power and Energy Society, Andrew Keane, Member, IEEE, Michael Milligan, Member, IEEE, Chris J. Dent, Member, IEEE, Bernhard Hasche, Claudine D'Annunzio, Ken Dragoon, Hannele Holttinen, Nader Samaan, Lennart Söder, and Mark O'Malley, IEEE Trans on Power Systems, Vol. 26, Is 2, 2011, pp. 564-572.

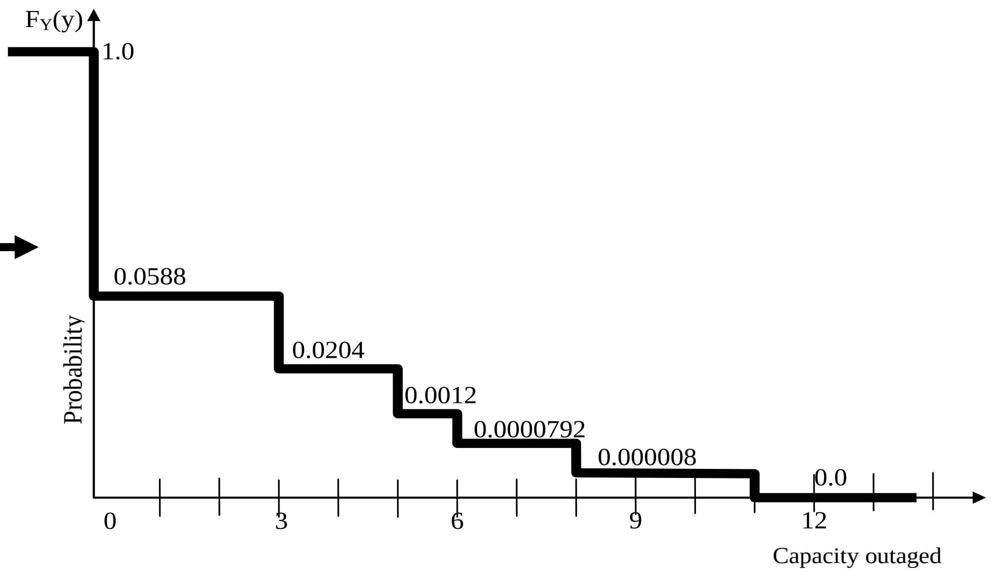
How to perform system analysis? First, compute LOLP(d)

Get the Netload *d'=d-(W+S)*

Time (hr)	Load d (MW)	Wind+Solar (MW)	Netload, d' (MW)
1	5.0	1	4.0
2	6.0	1.5	4.5
3	7.0	2	5.0
4	7.0	1.5	5.5
5	7.0	1	6.0
6	7.0	1.5	7.0
7	10.0	2	8.0
8	11.0	2	9.0
9	10.5	2	8.5
10	9.0	1.5	7.5
…	…	…	…

Use the capacity outage CDF (slide17) to obtain the LOLP as a function of netload *d'*.

repeated here



Time (hr)	Load, d (MW)	Netload d' (MW)	y= IC-d'	LOLP(d')= F_Y(y=IC-d')= Pr(Y>IC-d')
1	5.0	4.0	7.0	0.0000792
2	6.0	4.5	6.5	0.0000792
3	7.0	5.0	6.0	0.0000792
4	7.0	5.5	5.5	0.0012
5	7.0	6.0	5.0	0.0012
6	7.0	7.0	4.0	0.0204
7	10.0	8.0	3.0	0.0204
8	11.0	9.0	2.0	0.0588
9	10.5	8.5	2.5	0.0588
10	9.0	7.5	3.5	0.0204
…	…	…		

We illustrated these two on slide 17

Sums to 0.1814hrs

Resource adequacy – Other Considerations

I want to comment on seven additional resource adequacy considerations:

1. **Obtaining the LOLE curve:** How much time to use in characterizing the LOLE curve?
2. **Relation between ELCC and wind/solar gen @ CF**: Why is ELCC typically so different than wind/solar at capacity factor?
3. **Operations**: Can we assess resource adequacy for operations (as opposed to planning), and if so, what needs to change?
4. **Basic relations for LOLP, LOLE, EENS**: This are the expressions for "risk" metrics.
5. **Two illustrations**: Illustrate both approach A and approach B per slide 18.
6. **Demand response (DR)**: How does demand response play a role in resource adequacy?

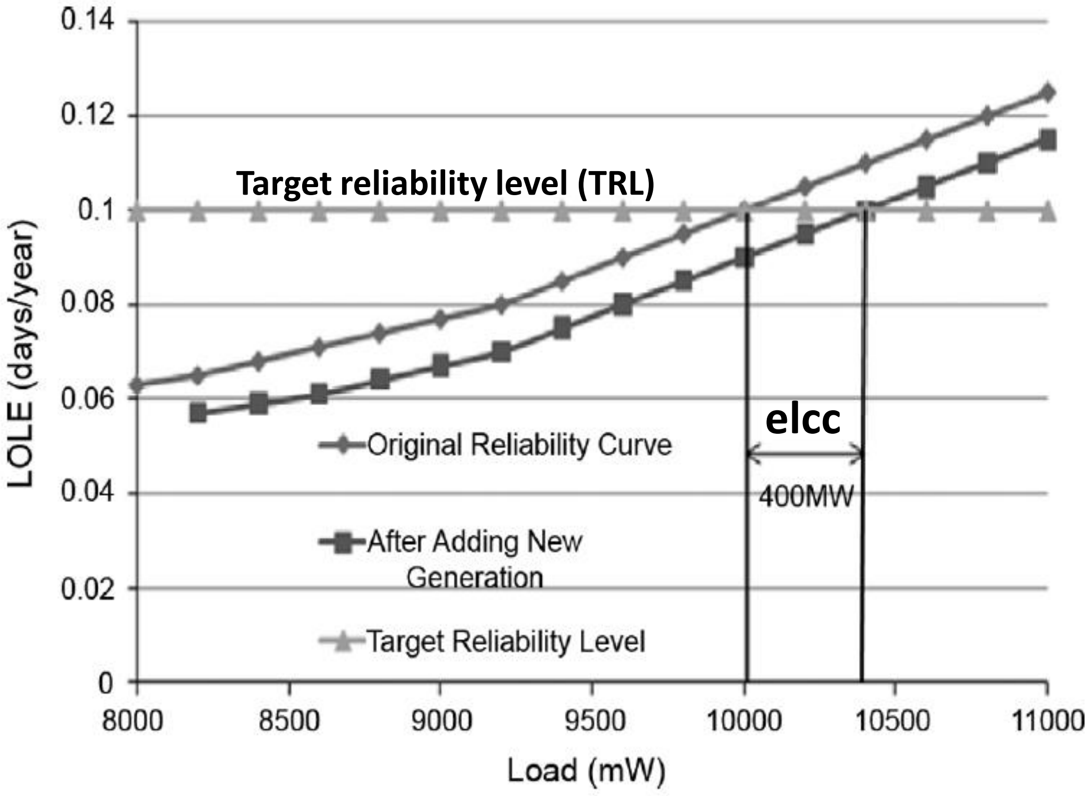
Each of these considerations can be relevant ones independent of the others, e.g., we do not have to be focused on operations in order to consider the other six.

…Let's look at each of these considerations.

Resource adequacy – Obtaining the LOLE curve

1. How much time to use in characterizing the LOLE curve? It is best to use multiple years of data, in order to capture the variation in wind/solar resources from one year to the next [*].

Reminder: Each point on the reliability curve represents the year's peak, but the LOLE is computed as a function of the entire year's hourly operating condition.



From [*], "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]."

[16] S. C. Pryor, R. J. Barthelmie, and J. T. Schoof, "Inter-annual variability of wind indices across Europe," Wind Energy, vol. 9, pp. 27–38, 2006.

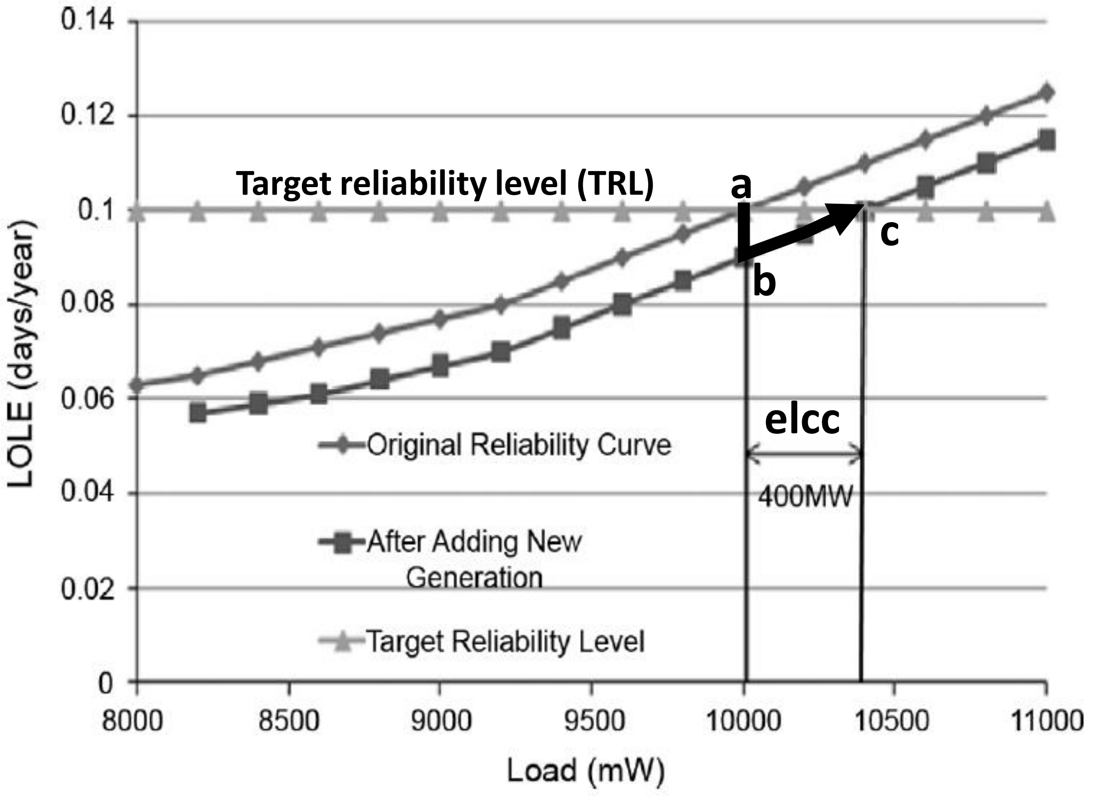
[*] "Capacity Value of Wind Power," Task Force on the Capacity Value of Wind Power, IEEE Power and Energy Society, Andrew Keane, Member, IEEE, Michael Milligan, Member, IEEE, Chris J. Dent, Member, IEEE, Bernhard Hasche, Claudine D'Annunzio, Ken Dragoon, Hannele Holttinen, Nader Samaan, Lennart Söder, and Mark O'Malley, IEEE Trans on Power Systems, Vol. 26, Is 2, 2011, pp. 564-572.

Resource adequacy – Relation between ELCC and wind/solar gen @ CF

2. Why is ELCC ≠ Wind/solar gen at @CF? Typical wind capacity factors are 30-45%, but typical capacity credit is only ~16%. Why is this?

➔The reason for this is that, whereas CF gives average percent output over a time frame, CC gives expected percent output at the high-risk time period.

➔And so we are not surprised that MISO has chosen capacity credits for solar to be as high as 50%, significantly higher than its typical 15-25% capacity factors (capacity factors are influenced by the entire 24 hour period, which includes nighttime where solar does not produce at all).



[*] "Capacity Value of Wind Power," Task Force on the Capacity Value of Wind Power, IEEE Power and Energy Society, Andrew Keane, Member, IEEE, Michael Milligan, Member, IEEE, Chris J. Dent, Member, IEEE, Bernhard Hasche, Claudine D'Annunzio, Ken Dragoon, Hannele Holttinen, Nader Samaan, Lennart Söder, and Mark O'Malley, IEEE Trans on Power Systems, Vol. 26, Is 2, 2011, pp. 564-572.

Resource adequacy – Operations

3. Can we assess resource adequacy for operations (as opposed to planning) and if so, what needs to change?

We consider calculation of reliability indices during operations. A common deterministic approach is to maintain contingency reserve equal to the capacity of the largest unit. However, this approach may be inconsistent in that it can lead to:

- over-scheduling: high reliability but very costly operations.
- under-scheduling: low-cost operation but with low reliability.

➔Compute reliability indices for operations.

In the notes U16, we show that transient conditions of the 2-state Markov model (as opposed to steady-state conditions which we have been using) result in

$$\boldsymbol{U(t)=\frac{\lambda}{\lambda+\mu}\left(1-e^{-(\lambda+\mu)t}\right)}$$

If t is small, then no repair can be done, i.e., μ=0. Then:

$$U(t)=1-e^{-\lambda t}$$

Expanding via Taylor series results in

$$U(t)=U(0)+U'(0)t+\frac{U''(0)}{2!}t^2+\frac{U'''(0)}{3!}t^3+\ldots$$

and this is

$$U(t)=0+\lambda t+\frac{(\lambda t)^2e^{-\lambda t}}{2!}+\frac{(\lambda t)^3e^{-\lambda t}}{3!}+\ldots$$

If λt is small, then higher order terms go to 0, and we have

$$U(t)=\lambda t$$

Making $t=T$, then $U=\lambda T$ (outage-replacement-rate, ORR, analogous to FOR) is the probability the unit fails during time T. In what follows, we assume T=1 hour.

4. Resource adequacy – Basic relations for LOLP, LOLE, EENS

From slide 26, we learned the first two equations below, then the 3rd and 4th follow…

How to construct cumulative distribution function from pmf

$$F_Y(y) = P(Y > y) = \sum_{y_j > y} f_Y(y_j) = 1 - \sum_{y_j \le y} f_Y(y_j)$$

Loss of load probability, as a function of load d, IC, written in terms of CDF

$$LOLP(d) = F_Y(y = IC - d) = \sum_{y_j > y} f_Y(y_j) = \sum_{y_j > (IC-d)} f_Y(y_j) = \sum_{d > (IC - y_j)} f_Y(y_j)$$

$$y_j > (IC - d) \Rightarrow d > (IC - y_j)$$

Loss of load probability, as a function of load d, IC, written in terms of pmf

$$LOLP(d) = \left[\underbrace{\sum_{j:\ d > (IC - y_j)}}_{\text{All outage states such that net load > AvailableGen}} \underbrace{f_Y(y_j)}_{\text{Probability of outage state } y_j} \right]$$

Expected energy not served, as a function of load d, IC, ΔT written in terms of pmf

$$EENS(d) = \left[\underbrace{\sum_{j:\ d > (IC - y_j)}}_{\text{All outage states such that demand > AvailableGen}} \underbrace{f_Y(y_j)}_{\text{Probability of outage state } y_j} \underbrace{\left(d - (\underbrace{IC - y_j}_{\text{AvailableGen}}) \right)}_{\text{Unserved Demand}} \right] * \Delta T$$

We use the 3rd and 4th relations in the next three slides where we illustrate how to make the computation they represent…

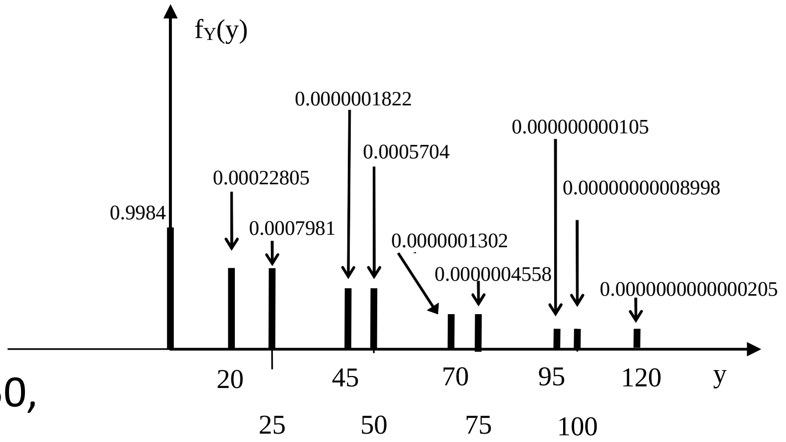
Two illustrations: Approach B
Recall this approach is not recommended.

NOTE: Using new example here…

Unit	Capacity	λ (failures/yr)	λ (failures/hour)
1 (Gen)	25	3	0.000342
2 (Gen)	25	4	0.000457
3 (Gen)	50	5	0.000571
4 (Wind)	20	2	0.0002283

For wind, the "capacity" is the generation level.

Convolution results in ⟹



Consider that load d=75 MW. Then there are 6 outage states resulting in unserved load: y_j=50, 70, 75, 95, 100, 120, because for all of these: 75>AvailableGen, or 75>(120-y_j).

$$LOLP = \left[\underbrace{\sum_{j:\, d > (120 - y_j)}}_{\text{All outage states such that net load > AvailableGen}} \underbrace{f_Y(y_j)}_{\text{Probability of outage state } y_j} \right] = \begin{bmatrix} 0.0005704+0.0000001302+0.0000004558+0.000000000105 \\ +0.00000000008998+0.0000000000000205 \end{bmatrix} = 0.0005709861005005$$

If this load level were maintained for 1yr, then LOLE=LOLP*8760hrs=5hrs/yr (as compared to the target of 0.1day/year*24hrs/day=2.4hrs/yr).

$$EENS = \left[\underbrace{\sum_{j:\, d > (120 - y_j)}}_{\text{All outage states such that demand > AvailableGen}} \underbrace{f_Y(y_j)}_{\text{Probability of outage state } y_j} \underbrace{\left(d - \underbrace{(120 - y_j)}_{\text{AvailableGen}} \right)}_{\text{Unserved Demand}} \right] * 1hr$$

$$EENS = \begin{bmatrix} 0.0005704 \times (75-(120-50)) \\ +0.0000001302 \times (75-(120-70)) \\ +0.0000004558 \times (75-(120-75)) \\ +0.000000000105 \times (75-(120-95)) \\ +0.00000000008998 \times (75-(120-100)) \\ +0.0000000000000205 \times (75-(120-120)) \end{bmatrix} \times 1hr = \begin{bmatrix} 0.0005704 \times (5) \\ +0.0000001302 \times (25) \\ +0.0000004558 \times (30) \\ +0.000000000105 \times (50) \\ +0.00000000008998 \times (55) \\ +0.0000000000000205 \times (75) \end{bmatrix} \times 1hr = \begin{bmatrix} 0.00285 \\ +0.000003255 \\ +0.000013674 \\ +0.00000000525 \\ +0.0000000049489 \\ +0.0000000000015375 \end{bmatrix} \times 1hr = 0.0028669392004375\text{MWhrs}$$

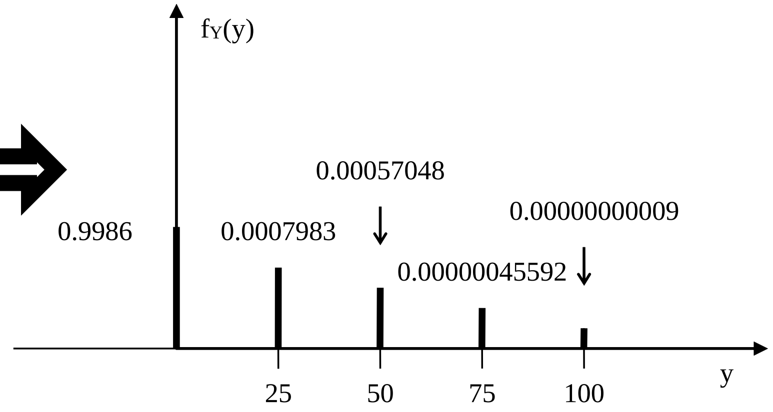
Why can't we do this?

➔We could, if we could get a meaningful evaluation of λ at each point in time. This time-dependent λ calculation would need to reflect the amount and direction of the wind/solar change as well as the tendency of individual turbines to fail. It is not easy to see how to do this, and if we can develop a method, it will need to be computationally tractable if it is to be done in operations.

Two illustrations: Approach A:
Recall this approach is recommended.

Unit	Capacity	λ (failures/yr)	λ (failures/hour)
1	25	3	0.000342
2	25	4	0.000457
3	50	5	0.000571

Convolution results in



We again assume load d=75 MW, then with 20MW of wind, the netload is d'=55 MW, and there are three outage states resulting in unserved load: y_j=50, 75, 100, because for all of these: 55>AvailableGen, or 55>(100-y_j).

$$LOLP=\left[\underbrace{\sum_{j:\, d'>(100-y_j)}}_{\substack{\text{All outage states such}\\ \text{that net load > AvailableGen}}} \underbrace{f_Y(y_j)}_{\substack{\text{Probability of}\\ \text{outage state } y_j}}\right]=0.00057048+0.00000045592+0.00000000009=0.00057093601$$

Coincidently, this result is very close to the result obtained using the Approach B (unrecommended) approach. It means that, at a 75MW load, the Approach B effect of adding a 20MW gen with 2 failures/yr is very close to the Approach A effect of having no added gen but decreasing the load by 20 MW. But there is no physical significance to the 2 failures/year (we will see individual turbines fail but almost never see the entire wind plant fail) whereas there is physical significance to the 20MW load decrease.

$$EENS=\left[\underbrace{\sum_{j:\, d'>(100-y_j)}}_{\substack{\text{All outage states such}\\ \text{that net load > AvailableGen}}} \underbrace{f_Y(y_j)}_{\substack{\text{Probability of}\\ \text{outage state } y_j}} \underbrace{\left(d'-\underbrace{(100-y_j)}_{\text{AvailableGen}}\right)}_{\text{Unserved Demand}}\right]*1hr$$

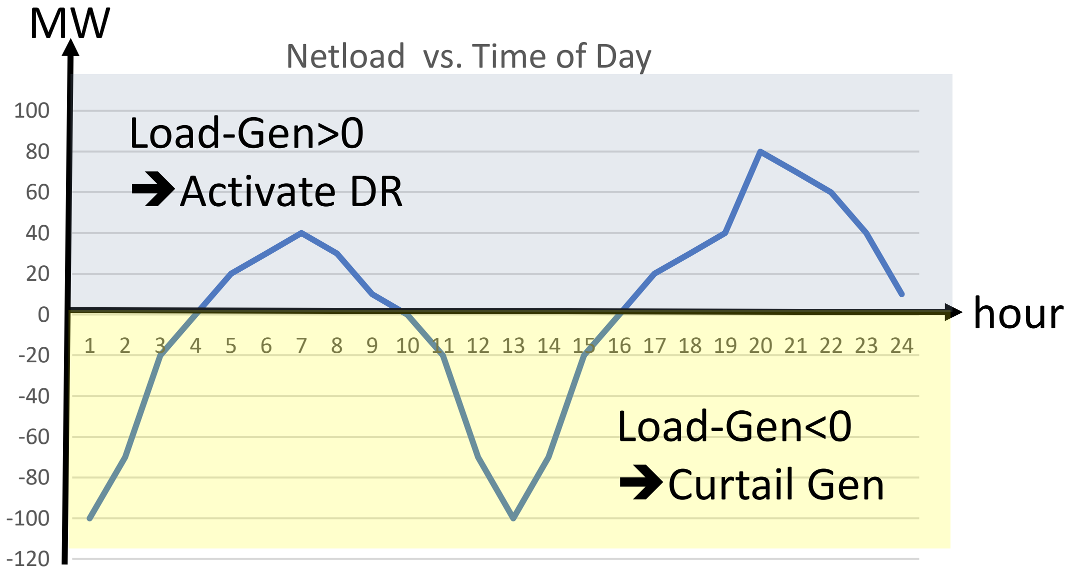
$$EENS=\begin{bmatrix}0.00057048\times(55-(100-50))\\ +0.00000045592\times(55-(100-75))\\ +0.00000000009\times(55-(100-100))\end{bmatrix}\times 1hr=\begin{bmatrix}0.00057048\times(5)\\ +0.00000045592\times(25)\\ +0.00000000009\times(55)\end{bmatrix}\times 1hr=\begin{bmatrix}0.0029\\ +0.00001398\\ +0.00000000495\end{bmatrix}\times 1hr=0.00291398495\text{MWhrs}$$

Demand response

➔We should not represent wind/solar with an EFOR but rather as negative load. This makes sense, because by doing so, the correlations between wind and solar units are "baked in" to the resulting net load time series. Then the reliability evaluation can be done using a capacity outage table developed from the conventional (non-wind/solar) units and a "net-load" duration curve.

- This certainly works when the amount of wind and solar capacity on-line at any one time is up to 50%, maybe even up to 90%
- But what happens when the amount of wind and solar capacity on-line at any one time is 100%? That is, what happens when there is no "conventional" generation on-line at all?
  1. **<u>Residual resources</u>**: One answer is that having 100% wind/solar is not going to happen because of residual resources, i.e., one or more of the following will be there: (i) hydro; (ii) natural gas-fueled CTs; (iii) storage. In this case, the "Netload approach" (previous slide) using convolution for the residual resources works fine.
  2. **<u>Demand as resource</u>**: A better answer is that if we have demand control and can curtail some loads, then this demand curtailment looks like a generator and can be modeled accordingly. In this case, the capacity outage table is built including these "negative loads" as generators. We have illustrated this approach on the next two slides.

Netload vs Time of Day for 24 hours, for a system with very high wind/solar.



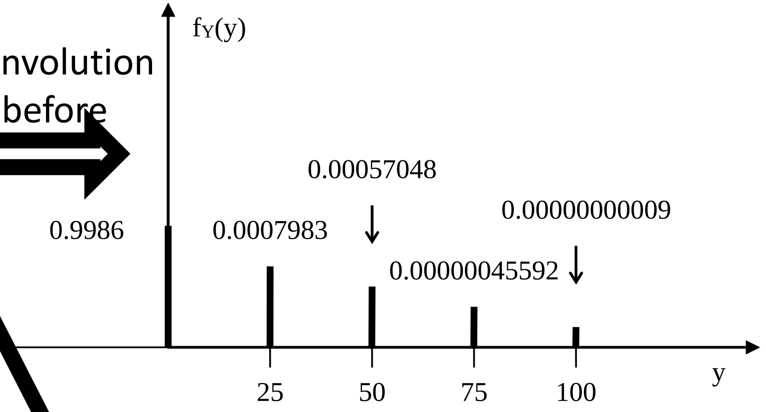
Demand response

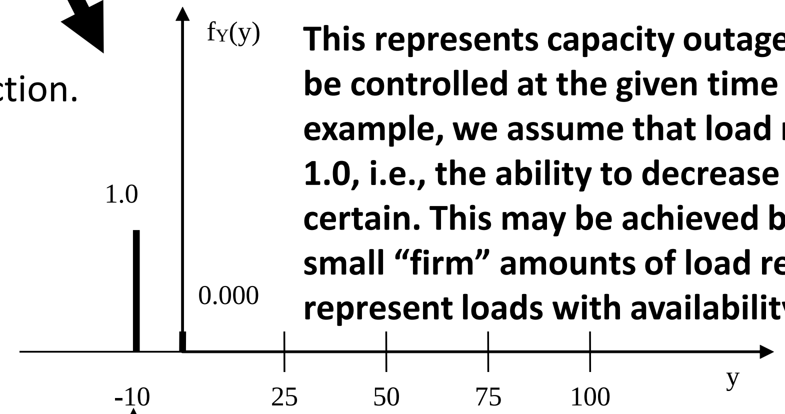
This approach may be used with a convolution method, as illustrated below:

System: 3 gens and 1 controllable load having capacities and failure rates in the below table. Let lead time be T=1 hour.

Unit	Capacity	λ (failures/yr)	λ (failures/hour)
1 (Gen)	25	3	0.000342
2 (Gen)	25	4	0.000457
3 (Gen)	50	5	0.000571
4 (Load)	-10	0	0

Convolution as before



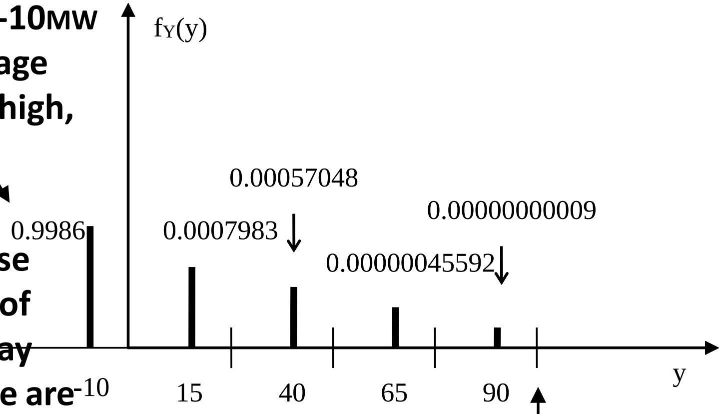


This represents capacity outage function for a load that can be controlled at the given time to reduce by 10 MW. For this example, we assume that load resource has availability of 1.0, i.e., the ability to decrease the load by 10MW is 100% certain. This may be achieved by very large loads selling small "firm" amounts of load resources. But it is possible to represent loads with availability < 1, as this figure suggests.

The "capacity outage" of -10MW is in-effect a "capacity innage" of +10MW.

Convolve in the load capacity outage function.

This says the probability of being in the -10MW capacity outage state is very high, but not 1.0.



This is because one or more of the 3 gens may fail (i.e., there are four other states with non-zero probability).

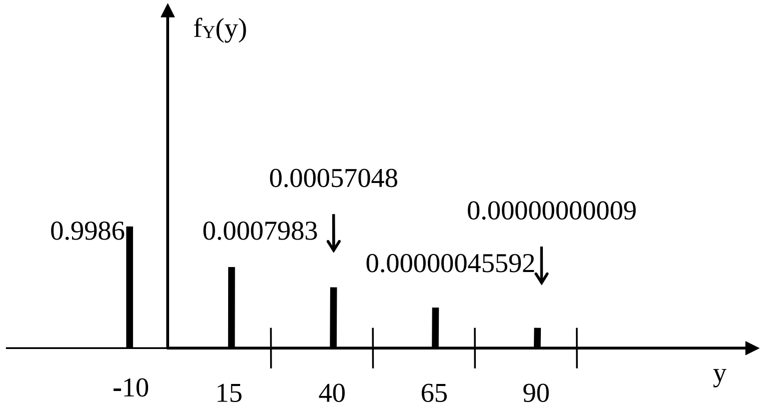
The 100MW capacity outage state is now impossible, because the -10MW controlled load has availability=1.0.

Demand response

__Netload approach__: Represent wind/solar plants in the netload curve, and then use capacity outage pmf to obtain EENS.

Unit	Capacity	λ (failures/yr)	λ (failures/hour)
1 (Gen)	25	3	0.000342
2 (Gen)	25	4	0.000457
3 (Gen)	50	5	0.000571
4 (Load)	-10	0	0

Convolution results in ⟹



$$EENS = \left[\underbrace{\sum_{j:\, d'>(90-y_j)}}_{\substack{\text{All outage states such} \\ \text{that demand > AvailableGen}}} \underbrace{f_Y(y_j)}_{\substack{\text{Probability of} \\ \text{outage state } y_j}} \underbrace{\left(d' - (\underbrace{90 - y_j}_{AvailableGen}) \right)}_{\text{Unserved Demand}} \right] * 1hr$$

For example, if demand D=75 MW, then with 20MW of wind, the netload is 55 MW, there are two outage states resulting in unserved demand: y_j=65, 90, because for both of these: 55>Reserve, or 55>(100-y_j).

------This might be wrong-----------

$$EENS = \begin{bmatrix} 0.00000045592 \times (55-(90-65)) \\ +0.00000000009 \times (55-(90-90)) \end{bmatrix} \times 1hr = \begin{bmatrix} 0.00000045592 \times (30) \\ +0.00000000009 \times (55) \end{bmatrix} \times 1hr = \begin{bmatrix} 0.0000091184 \\ +0.00000000405 \end{bmatrix} \times 1hr = 0.000009118805 \text{MWhrs}$$

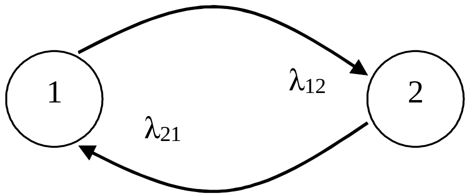
Without the 10MW load control, the EENS was ~0.0029. Load control has decreased the EENS for two reasons:

- For each outage state resulting in interrupted load, the amount of interrupted load is 10 MW less.
- One outage state, here corresponding to 40 MW (and previously corresponding to 50MW) no longer interrupts load.

This slide expands on info provided in slide 13.

Topic 1A-iii: TPL contingency probability estimation Markov Models

State 1: Up;
State 2: Down.



λ_{jk}: # of transitions per unit time from state j to state k.

λ_j: # of transitions per unit time from state j to any other state.

$$\lambda_j = \sum_{j \neq k} \lambda_{jk}$$

Transition intensity matrix: $$\underline{A} = \begin{bmatrix} -\lambda_1 & \lambda_{12} \\ \lambda_{21} & -\lambda_2 \end{bmatrix}$$

Define p(t) as the vector of state probabilities, i.e.,

$$\underline{p}(t) = \left[p_1(t) \quad p_2(t) \right]$$

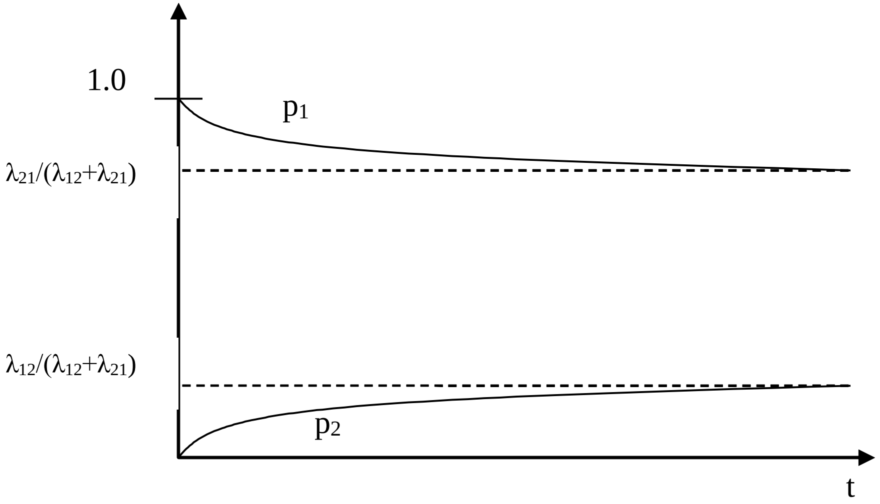
It is possible to show (see U16 notes) that

$$\dot{\underline{p}}(t) = \underline{p}(t)\underline{A}$$

The long-run (steady-state) probabilities may be found by setting the left-hand-side derivatives to 0, and (because A is singular), replacing one equation in A with the sum of all steady-state probabilities=1, in this case, $p_1+p_2=1$. This results in:

$$p_1 = \frac{\lambda_{21}}{\lambda_{12} + \lambda_{21}}; \qquad p_2 = \frac{\lambda_{12}}{\lambda_{12} + \lambda_{21}}$$

The relation of the steady-state probabilities to the general time-domain expressions is illustrated in the figure below. This figure assumes that the initial condition of the system is that it is in state 1, i.t., it is in the "up" (working) condition.



In most of our work, we will want the steady-state probabilities. For long-term planning studies, we may interpret a particular long-run state probability as the percentage of the planning horizon time that the system can be expected to reside in the corresponding state.

Topic 1A-iii: TPL contingency probability estimation
NERC TPL-001-4 Standard (shows only disturbances, i.e., performance not shown)

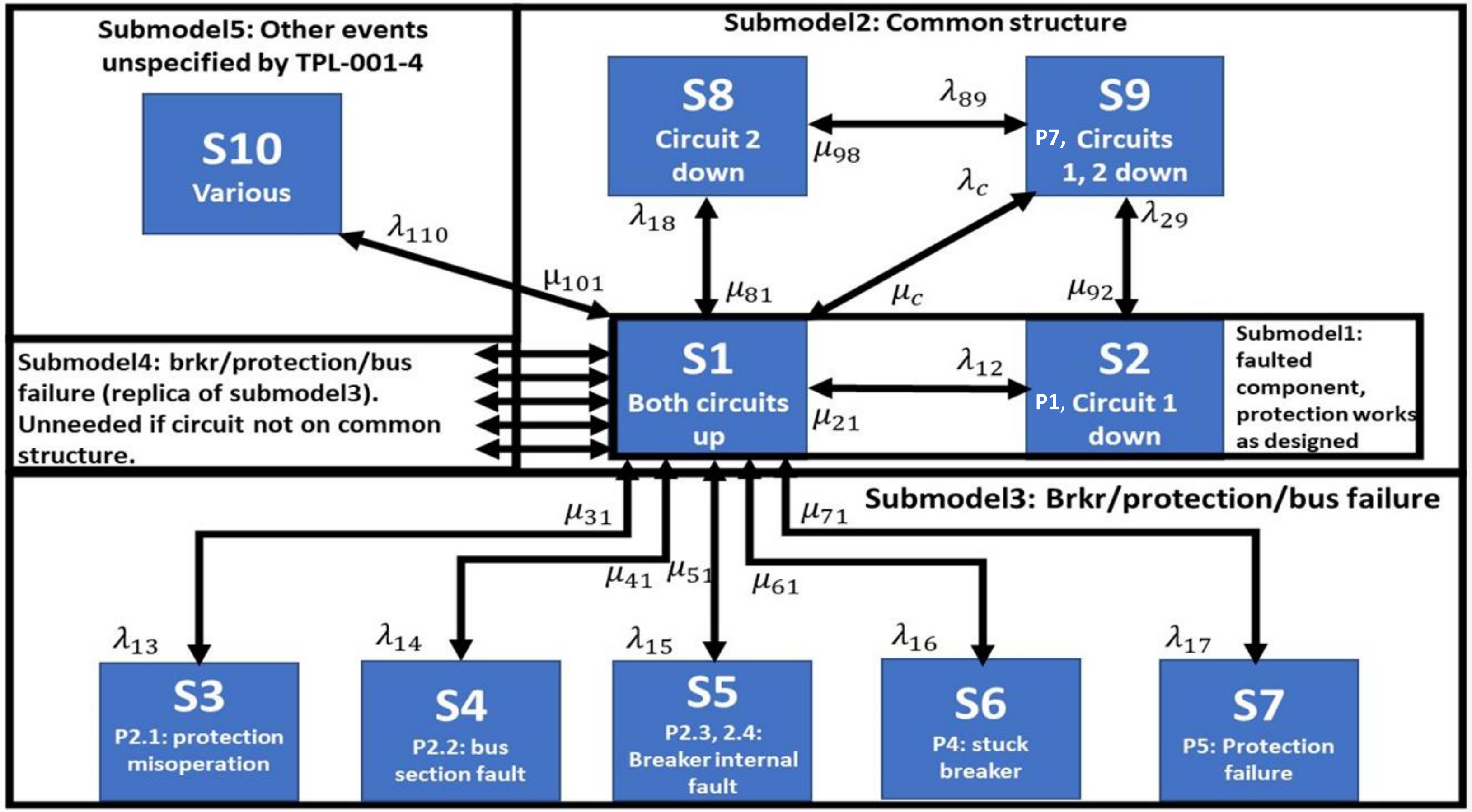
Category	Initial Condition	Event
P0	Normal System	None
P1, Single Contingency	Normal System	Loss of one of the following: 1. Generator 2. Transmission Circuit 3. Transformer 4. Shunt Device 5. Single pole of a DC line
P2, Single Contingency	Normal System	1. Opening of a line section without a fault 2. Bus section fault 3. Internal Breaker Fault (non-bus-tie breaker) 4. Internal Breaker Fault (bus-tie breaker)
P3, Multiple Contingency	Loss of generator unit followed by system adjustments	Loss of one of the following: 1. Generator 2. Transmission Circuit 3. Transformer 4. Shunt Device 5. Single pole of a DC line
P4, Multiple Contingency (Fault plus stuck breaker)	Normal System	Loss of multiple elements caused by a stuck breaker (non-bus-tie breaker) attempting to clear a fault on one of the following: 1. Generator 2. Transmission circuit 3. Transformer 4. Shunt device 5. Bus section 6. Loss of multiple elements caused by a stuck breaker (bus-tie breaker) attempting to clear a fault on the associated bus

Category	Initial Condition	Event
P5, Multiple Contingency, (Fault plus relay failure to operate)	Normal System	Delayed fault clearing due to the failure of a non-redundant relay protecting the faulted element to operate as designed, for one of the following: 1. Generator 2. Transmission Circuit 3. Transformer 4. Shunt Device 5. Bus section
P6, Multiple Contingency, (Two overlapping singles)	Loss of one of the following followed by system adjustments	Loss of one of the following:
	1. Transmission circuit	1. Transmission circuit
	2. Transformer	2. Transformer
	3. Shunt Device	3. Shunt device
	4. Single pole of a DC line	4. Single pole of a DC line
P7, Multiple Contingency, (Common structure)	Normal System	The loss of: 1. Any two adjacent (vertically or horizontally) circuits on common structure 2. Loss of bipolar DC line

This table captures 43 events; so that, when a system satisfies their specified performance requirement, the system is considered to be "reliable." But there are many more events beyond what are listed here.

Model for Branch-Related TPL Contingencies (*)

This Markov model provides the ability to compute the long run state probabilities for branch-related TPL contingencies P1, P2, P4, P5 and P7. The transition rates- λ's (failure rates) and μ's (repair rates) are required inputs.



Main Markov Model encapsulating P1, P2, P4, P5, P7 Contingency Definitions

$$\dot{\underline{p}}(t) = \underline{p}(t)\underline{A}$$

$$\underline{A} = \begin{bmatrix} -\lambda_1 & \cdots & \lambda_{1n} \\ \vdots & \ddots & \vdots \\ \lambda_{n1} & \cdots & -\lambda_n \end{bmatrix}$$

Off-diagonal elements λ_{ij} represent the transition rates between the two different states i and j.
Diagonal elements λ_i represent the state transition rates. $\lambda_j = \sum_{\substack{k=1 \\ k\neq j}}^{n} \lambda_{jk}$

For getting long-run probabilities, one row in matrix A is replaced by $\sum_{i=1}^{n} p_i = 1$ and equation is solved as,

$$0 = \underline{p}(t)\underline{A'}$$

Y. Jiang, A. Kalair, **J. McCalley**, P. Mitra, A. Gaikwad, D. Pratt, and J. Norris, "Contingency probability estimation for risk-based planning studies using NERC's outage data and Standard TPL-001-4," Proc. of the North American Power Symposium, 2021.

Probability Calculation Examples

Ex #	NERC CTNGCY TYPE	DESCRIPTION	Prob-ability
1	P1.1	N-1 of a generator (geothermal)	5.52×10^{-2}
2	P1.2	N-1 of a 30mile 100-199kV line	5.41×10^{-4}
3	P1.3	N-1 of a 100-199kV transformer	2.52×10^{-5}
4	P2.1	Opening of a 100-199kV line	4.26×10^{-6}
5	P2.2	Bus section fault terminating a 100-199kV line	3.19×10^{-6}
6	P2.3	Internal breaker fault (non bus-tie breaker)	3.70×10^{-6}
7	P3.2	N-1-1 loss of fssl-stm gen w/ sys readjstmnt, followed by loss of line	6.34×10^{-7}
8	P4.2	N-k, faulted 100-199kV line with stuck breaker	2.32×10^{-6}
9	P5.2	N-k, faulted 100-199kV line with relay failure to operate	2.85×10^{-7}
10	P6.1	N-1-1 loss of 30mile 100-199kV line w/sys readjstmnt, followed by loss of line	7.96×10^{-9}
11	P7.1	N-2 common structure 30mile 100-199kV line	1.94×10^{-6}

Risk-based planning methods

Contingency file

Identifies pool (column)

Contingency type P1

GADS and TADS

$f_{P1\text{-}1}$	$f_{P1\text{-}2}$	• • •	$f_{P1\text{-}p}$	• • •	$f_{P1\text{-}8}$

P1 estimation functions

⋮

$f_{P7\text{-}1}$	$f_{P7\text{-}2}$	• • •	$f_{P7\text{-}p}$	• • •	$f_{P7\text{-}8}$

P7 estimation functions

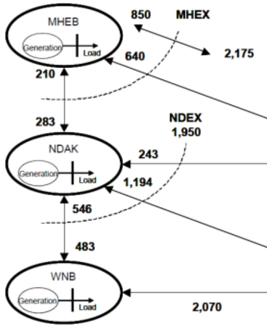
$$f_{P1-2}^{L} = \underbrace{a_1 x_1}_{\text{line length}} + \underbrace{a_2 x_2 + a_3 x_3}_{\text{Other Influences}}$$

Probability for type P1 in pool 2

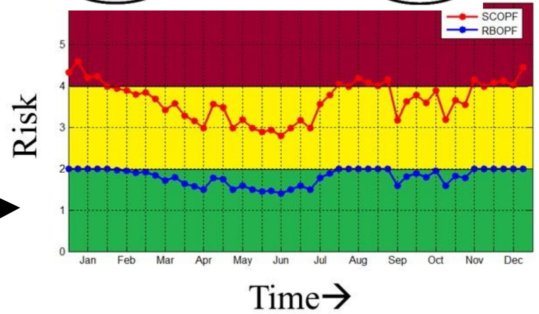
Multiarea resource adequacy evaluation

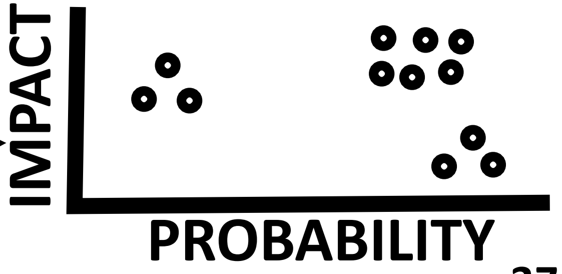
1yr hi-fidelity production simulation

Power flow contingency analysis



LOLE





Infrastructure Design Criteria

1. SUSTAINABILITY
2. INTEGRITY

- Flexibility;
- Reliability;
- Resilience;
- Adaptability.