Variable Energy Resource Capacity Contributions Consistent With Reserve Margin and Reliability

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Abstract**—** This paper presents a study case of the impact of Variable Energy Resources (VERs) on the Reserve Margin of the ERCOT region. Wind and solar are projected to provide a large contribution in generation capacity for the North American Bulk Power System (BPS). The increasing penetration of VERs makes it important to define "best practices" for quantifying the contribution of these energy-limited resources when evaluating resource adequacy. Calculating the capacity values of VERs can be challenging because they interact with each other in a nonlinear and dependent manner. The approach taken in this paper is part of a larger effort that the North American Electric Reliability Corporation (NERC) is taking to ensure reliable operation of the North American BPS. A loss of load probability model is used to determine VER capacity contributions. Over or under assigning the VER percentage capacity credits is shown to affect the reserve margin (RM) percentage needed to maintain the same level of reliability. The authors recommend a method for maintaining RM consistency.

Index Terms— Capacity Factor, Monte-Carlo, Variable Energy Resources, VER, Wind, Solar, COPT, IEEE RTS, LOLP, LOLE, LOLEV, Probability Distributions, Reserve Margin, Risk Assessment, Resource Adequacy, ERCOT, CAISO, WECC, NERC

I. Introduction

The North American Electric Reliability Corporation (NERC) is responsible for ensuring the reliability of the bulk power system in North America [1]. Anticipating the growth of VERs; NERC's effort is to ensure that the industry will have enough dependable capacity to meet future resource adequacy requirements. Not having enough planned capacity could lead to a higher Loss of Load Probability (LOLP) reliability measure. The LOLE is defined as the expected number of days per year for which the available generation capacity is insufficient to serve the daily peak demand. This is the original classic metric that is calculated using the peak load of the day (or the daily peak variation curve) and the amount of installed conventional generation capacity. The LOLP each day is a simple "lookup" from a Capacity Outage Probability Table (COPT). LOLP is calculated by convolving the capacities and forced outage rates of the generation fleet together. This results in the COPT which shows alternative levels of capacity along with their associated probabilities. A minimum LOLE of one day in ten years has been a widely used measure for many years. This historical measure is not an operating reserve but is simply a static measure of whether there is sufficient planned generation capacity. Addition of VERs complicates the LOLE calculation process.

VERs could be treated as generation or as passive load modifiers. In this study we treat VERs in an hourly sequential model as negative load to avoid the complexities of having to create VER equivalent generator models. The distribution of hourly net demand (demand minus VER) for forward looking risk calculations is the distribution of historic observations with time synchronization maintained and demand and individual VERs scaled to a future study year. The maximum daily LOLP with VERs occurs at the hour of greatest net peak demand after the hourly VER MWs have been subtracted from the hourly demands for a historical period of data spanning 2010-2015 scaled to a future test year. The traditional definition of the LOLE calculated at the peak demand hour is modified to be calculated at the hour of the maximum net peak demand each day. The LOLE=0.1 days/year is still valid.

Systems like the Electric Reliability Council of Texas (ERCOT) uses a sequential Monte Carlo program to calculate the LOLEV, loss of load events per year [2,3]. LOLEV is defined as the number of events in which some system load is not served in a given year. A LOLEV can last for one hour or for several continuous hours and can involve the loss of one or several hundred megawatts of load. This is numerically the same as the loss of load frequency (LOLF). A minimum LOLE of one day in ten years has been a widely used measure for many years. This means, that on average, there is a probability of loss of load once every ten years [4].

In Systems like ERCOT with a sharp summertime daily peak demand, loss of load events occur once per day. Numerically this leads LOLE to equal LOLEV. Other systems such as the California Independent System Operator (CAISO) has solar power that produces a demand dip in the middle of the day [5]. This results in the LOLEV being greater than the LOLE. LOLEV is a newer measure than LOLE. Other measures under consideration for adequacy testing are the LOLH (Loss of Load hours) per year, and the EUE, which is the Expected Unserved Energy. This paper uses the original LOLE measure of 0.1 days per year.

This paper discusses the ongoing evaluation of the potential impacts of new VERs on the grid. Section II presents exact calculations of reliability indices using recursive convolution method. Section III compares frequency and duration Monte Carlo (fdMC) sequential with a sequential hourly model that was used in 'exact' IEEE RTS reliability indices. Use of a COPT as was used in the RTS has been found to be in good agreement with fdMC LOLE day/year for test cases that do not include VERs. VER generator models are avoided in [6,7] and in our study by treating VERs as negative demand. Section IV discusses simulation results and section V concludes the paper and provides recommendations.

II. The IEEE RTS Exact Calculator

Allan and Billington provide an important benchmark set of "exact" calculations for reliability indices for a Reliability Test System proposed in [8] known as the IEEE 24 bus RTS [9], [11]. Hourly LOLP = $F(D)$ where F is the cumulative distribution of independent generators and D is hourly demand.

In this paper an in-house "RTS" program was written to duplicate the indices presented in [8]. Though the authors in [8] did not show their mathematical formulation, the recursive convolution in equation (1) below will reproduce the "exact" reliability indices that were given in [8].

$$\Big[F(x)^{+} = (1 - FOR_k)\cdot F(x) + FOR_k \cdot F(x - C_k)\Big] \;\forall\; x = 0, x_{max} \quad (1)$$

Where $F(x)$ is the COPT prior to adding generator k and $F(x)^{+}$ is after generator k is added. FOR_k is generator k's forced outage rate. C_k is the generator k MW capacity and $F(x\text{-}C_k)$ represents the COPT shifted to the right by C_k MW. Initially all $F(x>0)=0$ and $F(x=0)=1$. To maintain exactness in the calculations and to agree with the reference [8], the generator capacities are integers and the x MW steps are also integers. $F(x)^{+}$ is the updated table after generator k is convolved using (1). The $F(x)$ table expands to larger and larger x_{max} as more and more generators are added to $F(x)$. In the computer program x is stepped from x_{max} to 0.

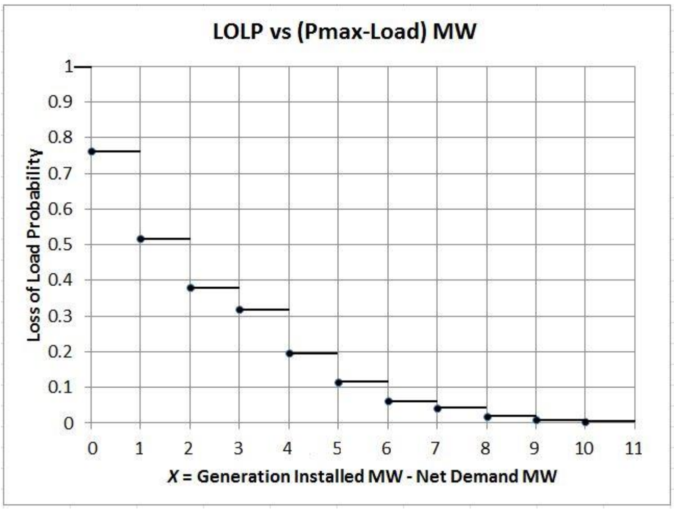

Fig. 1 RTS Program Capacity Outage Probability Table

The above figure shows how equation (1) COPT with 1 MW steps is to be used if x is not an integer since it's likely the demand is not an integer. In order to get an "exact" indices agreement with reference [8] the real value x is set to an integer x MW and then used in the COPT "lookup" table.

Maintenance is not included in this study because the objective is to review installed generation capacity. If there is a maintenance reason capacity might not be available at peak load times, the forced outage rate (FOR) could be increased.

A Monte Carlo (MC) iterative procedure can be used to generate the COPT for the same set of generators. However, a high degree of accuracy in MC will require much more computer time than the 'exact' COPT used here.

III. Modeling Sequential Events Using A COPT

A frequency and duration Monte Carlo (fdMC) model captures time dependent events such as energy constraints, weather related events, transmission constraints, and other nonlinear events. In an operating environment, the commitment and dispatch of generators is tightly coupled with what is happening before and after the hour being simulated. For example, the dispatch of hydro plants in the Pacific Northwest requires a complex sequential simulation model [12].

In reference [13], Garver linked 'sequential' to fdMC and 'analytical' to the use of load duration curves (LDC). The author correctly stated fdMC captured the loss of load frequency of events whereas the LDC analytical methods did not. Since authors of [8] on RTS did not describe the solution technique used to calculate the 'exact' indices, the solution could have been an analytical method that loses the sequential information.

The RTS program used in this study is a hybrid sequential analytical method that calculates an 'exact' LOLE in agreement with fdMC LOLE day/year for any sized system with simple RTS type data, [14,15]. The reason it maintains LOLP exactness for large systems is because earlier rounding errors are scaled down with each new generator added to the table.

A fdMC sequential model and the COPT sequential model used in this study have been tested and LOLE values are in agreement. They agree because both models use the same sequential hourly demands when there are no VERs in either model. The non VER generators have independent outages in both fdMC and in the COPT so we would expect the hourly LOLPs to be the same after there are sufficient iterations in the fdMC. The generator state transitions in fdMC are independent of each other and the demand. Therefore, the COPT hourly LOLPs are essentially the same as the fdMC LOLPs each hour. The fdMC counts of days per year 'events' divided by number of years iterated is consistent with the COPT as long as the generators are independent. A simple system has been tested using fdMC for a million iterations and it provides the same LOLE as the COPT [16].

Because some days have double peaks in the RTS, the RTS computer program tests for separate LOLP peaks in the AM and PM. These are essentially the LOLE for 12 hour periods. The 12 hour AM/PM LOLEs are reported separately to see how much loss of load is occurring in the AM and PM. These 12 hour LOLEs are summed to produce an approximate LOLEV. Other researchers should simulate the RTS using fdMC and report their findings for the LOLE, the 12 hour LOLEs, and the LOLEV.

A simple approach is used to capture the complex timing relationships between VERs and loads. Several past years of hourly VERs and load MWs are scaled to a future test year. This allows a complex fdMC model to be replaced with a simple already historically optimized set of hourly hydro dispatch MWs.

ERCOT has adopted a procedure that finds average wind during peak demand hours [17]. The averaging results in an improvement in the reliability. This is because the wind distribution within those few peak demand hours is no captured. There can be a few hours of near zero wind output within those hours causing significantly high LOLPs for those hours. If an fdMC simulation is observed to produce better LOLE results than the 'exact' RTS COPT, then the difference is probably due to VER modeling assumptions, and not to differences in fdMC sequential versus COPT sequential models.

A. *Hourly Demand and Generator Data*

Two types of ERCOT data are needed to run the RTS program, generator data by individual unit, and historical hourly wind, solar, and demand data. The ERCOT capability-demand-reserve (CDR) has the future demand forecast and all the generators that go into the generator data file, [18]. The historical hourly loads and historical wind MW are available on ERCOT reports [19]. Solar data is posted on line at several websites [20,21].

IV. Simulation Results

Five years of historical VER and demand data from 2010 to 2015 has been used. The modeling of several historical years allows us to see the variations in year to year of the reliability indices. The ERCOT GW wind and solar capacity increases are observed to increase the deviation from 0.1 days/year in the historical 2010 to 2015 period as shown in Figure 2.

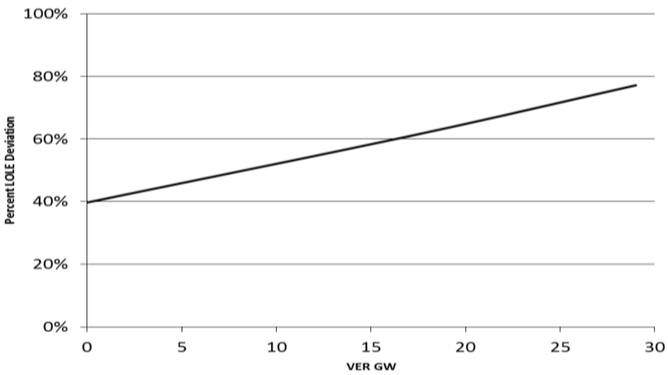

Fig. 2 Historical LOLE Deviation Increases with VER

The 0 GW case is run with 2016 data and no VERs. LOLE deviation is 40% due only to the 2010-2015 hourly load profiles. The historical profiles are normalized so each historical year has a one per unit peak demand. Then hourly MW loads are calculated by multiplying the future peak demand forecast times the per unit demand every hour. 17 GW of VER is added in 2016 to create an intermediate point in Fig 2. The right hand point at 29 GW VER in 2026 shows a larger deviation. Projecting to 30 GW of VER, the LOLE deviation is double the no VER case. VERs increase risk even when the LOLE=0.1 day/year is held constant.

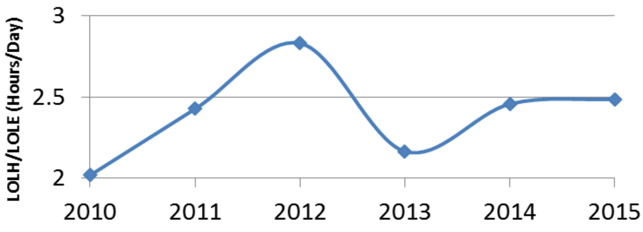

Fig. 3 Historical Years Ratio LOLH/LOLE

The LOLH is the sum of all hours' LOLPs. LOLE is the sum of daily peak LOLPs. An LOLE of 0.1 days/year is about the same level of reliability in ERCOT as 0.25 hours/year LOLH. As shown in Figure 3, the ratio of LOLH to LOLE provides, on average, loss of load hours/day measure. A 2.5 LOLH to LOLE ratio means that there is a 2.5 of loss of load hours per day, a measure that is insightful for understanding daily generation and load activities and how long the duration of generation outages could be.

With a changing generation mix, the traditional use of a Reserve Margin (RM) analysis in the US continues to be used for assessing resource adequacy. Reserve Margins measure the amount of generation capacity available to meet expected demand during the planning horizon and have been a surrogate metric for examining and planning for resource adequacy and system reliability. Based on the premise of this metric, a system should be able to supply resources to meet the projected normal weather electricity demand (given an explicit amount of reserve capacity) with a high degree of certainty that the system can manage generator outages and modest deviations from the annual demand forecast.

The RM calculation gives VERs some capacity credit. In the case of ERCOT, VER capacity contributions are estimated by averaging the VER MWs during the 20 peak demand hours of several past years [22]. In the ERCOT system, the 2016 capacity contributions are 12% for 14,727 MW noncoastal wind, 55% for 2,001 MW coastal wind, and 80% for 455 MW solar installed capacities. The 2026 VER capacities are estimated to be 23840, 2971, and 2053 MW respectively. The 2016 RM is 14.5 percent and the 2026 RM equals 14 percent.

Assuming a 3 percent LFU and a seven step approximation to the normal distribution [10], the calculated 2016 and 2026 LOLEs are 0.11 days/year and 0.30 day/year, respectively. Notice the LOLE has increased although the RM is nearly the same. This is because the capacity contributions are a bit too high. Capacity contributions from an effective load carrying capability (ELCC) analysis are a bit low.

Figure 4 shows that ERCOT would need to raise the RM to 16% in 2026 to maintain an LOLE=0.1 days/year for a no VER case of 13.8 percent RM. The RM increase in Figure 4 is needed to maintain a constant level of reliability because the VERs are being over rated.

The RM percentage dependents on the VERs capacity values. to maintain a certain level of reliability. The VERs are observed to interact with each other and in the case of solar, a point is reached in which the addition of more solar has no more capacity credit value for lowering the LOLE. This happens when the daily net peak demand peaks before sunup or after sundown; the times when solar produces no power.

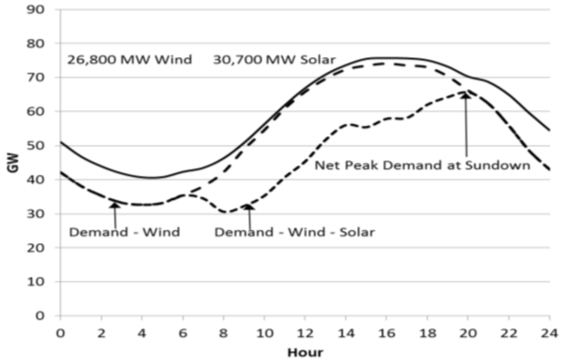

Fig. 4 Solar Shifts the Net Peak Demand to Sundown

Figure 4 shows solar scaled 15 times higher on a June peak day than the CDR forecast to illustrate how the net peak demand is shifted from about 4 to 5 PM to about 8 PM. Adding more solar will not change the net peak demand unless the solar can generate after sundown (i.e. has storage). If an ELCC calculation is performed on the case with 30 GW solar in ERCOT, the incremental capacity value is nearly 0%.

The capacity value of VER diminishes as more VER is added as shown in Figure 5. System reliability is overstated in the CDR if adjustments in the VER capacity contributions are not made. Appropriate capacity contributions can be obtained by iteratively testing various combinations of VER capacity contributions and VER capacities and observing how the LOLE and RM is affected.

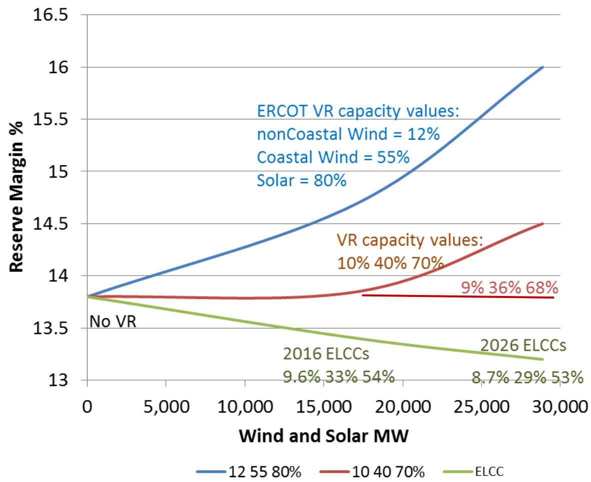

Fig. 5 ERCOT VER RM at Different Capacity Contributions.

The 2016 factors of 12%, 55%, and 80% that ERCOT is currently using could be lowered to 10%, 40%, and 70% to give a better match with holding the LOLE constant. By 2026 the additional VER capacity is less effective and the reliability findings in this paper indicate a better set of capacity contributions would be 9%, 36%, and 68% for noncoastal wind, coastal wind, and solar.

V. Conclusions and Recommendations

Variable Energy Resources are anticipated to increase substantially in the North American BPS. The importance of maintaining an adequate level of reliability therefore, becomes crucial. This paper addresses the importance of VERs modeling to BPS and distinctly showing the relationship between the assignment of different capacity credits for VERS such as wind and solar and the necessary adjustments in the reserve margin to maintain a constant level of reliability. This was done by applying a sequential hybrid direct calculation COPT rather than the use of load duration curves. The method has been chosen to model VERs in such a manner as to eliminate assumption errors.

It will be critical to provide ongoing reliability evaluation of the potential impacts of new VERs on the grid. Because prospective variable generation plants, by definition, do not already exist, obtaining data that can describe the likely behavior of future plants will be required for a number of reliability, adequacy, and integration tasks that are performed in the planning cycle. Because weather is the principle driver for load and for VER output, it is very important to maintain chronology between variable generation and load. Specific locations of future variable generation may not be known with certainty, and to evaluate the likely impacts multiple scenarios may need to be evaluated. Because of these issues, it will be necessary to develop and maintain public databases of wind, solar, and hydro historical production.

Calculating capacity value for existing variable energy resources requires chronological generation data that is synchronized with load data and other relevant system properties. Existing power system data bases can be used to track this data, which would be useful in helping to better understand variable generation performance and operational issues. NERC already collects data to inform the GADS database [23]. Although it is more data intensive than the GADS process, operational data from variable generation over the next several years will be extremely valuable in the assessment of capacity value and operational issues surrounding the use of variable generation. In this paper, a computer program is used in the study of VER capacity contributions and is benchmarked against exact six digit reliability indices published in 1986 for the IEEE RTS for conventional generators. Treating VER as hourly sequential data instead of as generators accurately captures the VER complex timing relationships with each other and with the hourly demand.

The running of a reliability analysis over a range of years is necessary in finding the load levels that can be served to meet a reliability measure such as an LOLE = 0.1 days/year, or some other measure. Once the load levels are found, then approximation means can be used to estimate VER capacity contributions to hold reserve margins constant as VERs increase in capacity. NERC and the Regions should continue facilitate the dissemination of information about how LOLP-related reliability and adequacy calculations perform and what they measure as more VERs are integrated into the system.

VI. ACKNOWLEDGMENTS

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VII. BIOGRAPHIES

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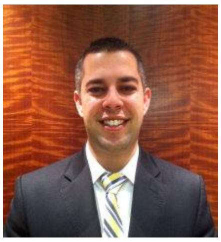

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