

Capacity Value of Photovoltaic Systems and their Impacts on Power System Reliability

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Abstract—This paper investigates the various aspects of the capacity value of photovoltaic systems (PV-systems) and the effect of their penetration levels on power system reliability. Unlike wind power, the available output power of PV-systems can be classified into two specific time periods: certainly unavailable during the night and uncertainly available during the day. In other words, during the night, the output power is zero while during the day the output power experience uncertainties due to, among others, clouds and humidity. Therefore, this mixed behavior cannot be modeled as a stochastic variable during all time periods. The output power of PV-systems is clustered into bands and convolved with the output power of the conventional generators to determine the reliability indices and the capacity value. The IEEE RTS is used to demonstrate the effects of different strategies in calculating the capacity values of PV-systems. The results not only show that the capacity value is different for the two case scenarios but also that it decreases in a semi-linear manner as the size of the PV-system increases. Sequential Monte Carlo simulation is utilized to validate the results.

Index Terms—Adequacy assessment, capacity value, PV-systems, reliability evaluation.

I. INTRODUCTION

In recent years the penetration of photovoltaic systems (PV-systems) in power grids has tremendously increased due to political, environmental, and economical incentives. Despite their environmental and economic advantages, the penetration of these sources is usually limited by technical constraints such as stability and reliability of the main grid. In other words, due to the intermittency and uncertainty of the output power of these sources, as their penetration increases, challenges of maintaining the operation and power quality aspects of the main grid becomes more evident. Therefore, determining the contribution of these sources, in terms of the capacity value, to the reliability of the main grid is of concern. The capacity value of variable energy resources (VERs) is the amount of system load that VERs can reliably support, given the variability of the input. It is usually used to measure the contribution of VERs to the available power in power system reliability assessment and planning. The evaluation process is carried out to make sure that system reliability is maintained when the intermittent sources are integrated to the power grid.

Monte Carlo simulation is usually considered as an appropriate approach for modeling the uncertainty of the output power of PV-systems. One of the advantages of Monte Carlo simulation is its ability to capture a wide range of modeling details and system dependencies. For example, Monte Carlo simulation has been used in [1] for reliability assessment of a hybrid system of wind and PV-systems. Also, in [2], reliability of wind and solar systems has been evaluated using Monte Carlo simulation technique. Further, in [3], the hourly mean solar radiation data has been used as a main input and Monte Carlo simulation technique was implemented to evaluate the system reliability. However, the solution accuracy using Monte Carlo simulation depends mainly on the number of samples that are performed to estimate the indices which is time consuming. An analytical method has been used in [4] to model the availability of the PV-systems in the reliability assessment. Also, in [5], the reliability evaluation of grid-connected PV-systems has been conducted. In the work presented in [5], a state enumeration technique was utilized to model the output power of PV-systems considering the dependency of failure rates of system components on ambient conditions. However, state enumeration based techniques are time consuming even for small systems. In [6]–[8], we developed analytical and simulation-based methods to model wind farms and PV-systems.

In general, the output power of PV-systems is modeled in power system reliability studies based on the availability of the input (solar). To evaluate the capacity value of PV-systems, a reliability index is usually utilized as a reference point. For example, the capacity value of a PV-station in Province A of northwest of China is analyzed in [9]. Also, three approaches to calculate the capacity value of PV-systems have been introduced in [10]. These approaches are based on averaging the hourly PV-systems output power during the peak load periods. However, the output power of PV-systems experience uncertainty during the day and it becomes zero during the night. For instance, Fig. 1 shows the average hourly output power of PV-system data that were taken from Santa Maria, CA region [11]. The curve in Fig. 1 is created by averaging the hourly output power of the PV-system across the year. Therefore, treating the output power of PV-systems as a

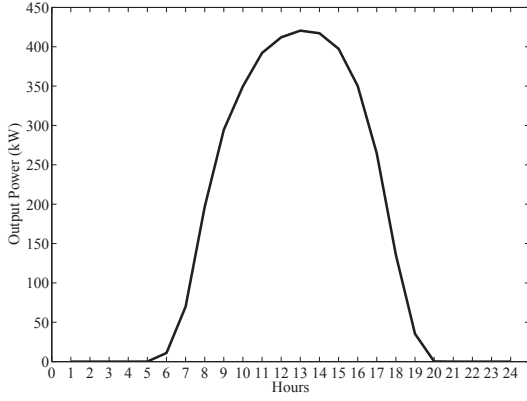


Fig. 1. Hourly PV power averaged for 24 hours during the year

stochastic variable for all time periods produces inaccuracy in determining their capacity values.

This paper investigates the various aspects of evaluating the capacity value PV-systems in power system reliability studies. Also, this paper assesses the effects of high penetration of PV-systems on their capacity values. This paper also investigates the effect of inclusion of nights (when the PV outputs are zero) in determining the capacity value of PV-systems. Further, this paper constructs a model that sorts the output power of PV-systems into clusters taking into account the time correlation with load demand. These clusters are determined using a minimum square distance based approach. The discrete convolution method is used to calculate the reliability indices and to determine the capacity value of PV-systems. Extensive case studies are performed on the IEEE RTS utilizing real PV-system data. Monte Carlo simulation is used to verify the results for possible errors due to the clustering the output power of PV-systems and load profile.

The rest of the paper is organized as follows. Section II illustrates the calculation of the output power of PV-systems. Also, section II explains the clustering procedure and the correlation between the demand and the output power of PV-systems. Section III presents the reliability evaluation in presence of PV-systems. Section IV describes the calculation of the capacity value. Section V shows a case study to demonstrate the importance of the capacity value. Section VI provides concluding remarks.

II. OUTPUT POWER OF PV SYSTEMS

The maximum output power ratings of PV-systems are provided by the manufacturers and usually are expressed in peak-watt (W_P). The current-voltage characteristics (I - V characteristics) under the standard test conditions (the radiation level of 1kW/m^2 is given for temperature of 25°C) can be calculated using the following relationship [12]:

$$I = S [I_{sc} + K_I(T_c - 25)], \quad (1)$$

$$V = V_{oc} - K_V T_c, \quad (2)$$

where S is the radiation level, I_{sc} is the short circuit current, K_I is the short circuit current temperature coefficient in $\text{A}/^\circ\text{C}$,

V_{oc} is the open circuit voltage, K_V is the open circuit voltage temperature coefficient in $\text{V}/^\circ\text{C}$, and T_c is the cell temperature in $^\circ\text{C}$ which can be expressed as follows [12].

$$T_c = T_a + S \left(\frac{T_{no} - 20}{0.8} \right), \quad (3)$$

where T_a is the ambient temperature and (T_{no}) is the nominal operating temperature of the cell ($^\circ\text{C}$).

The output power (P_{pv}) for a given radiation level, ambient temperature and the current-voltage characteristics can be calculated using the following relationships [12]:

$$P_{pv} = N \times FF \times I \times V, \quad (4)$$

where N is the number of panels and FF is the fill factor, which depends on the module characteristics, and can be expressed as follows [12].

$$FF = \frac{V_{mpp} I_{mpp}}{V_{oc} I_{sc}}, \quad (5)$$

where V_{mpp} and I_{mpp} are the current and voltage at the maximum power point respectively.

A. Clustering and Correlation between the Demand and the Output Power of PV-systems

Since PV-systems output power is used in the reliability assessment, disregarding the stage at which the solar radiation data are converted into power, the procedure starts with converting the observed radiation data into power according to (4). The values of the output power of PV-systems that correspond to the observed radiation data are clustered into several bands (states) based on their similarities. In the clustered output power, every observation belongs to one and only one band based on minimum euclidean distances between the observed data points [13]. However, before clustering the output power of PV-systems, the time correlation with the load profile should be included in the clustering process so that each band the output power of the PV-system has its corresponding (in terms of time) load band [13]–[16].

The importance of recognizing the time correlation between PV-systems output power and load can be explained in the following examples. If sequential Monte Carlo simulation is used, the chronological PV-systems output power and load data are inherently included in the simulation. However, in methods that are based on clustering load and the output power of PV-systems into different states (bands), if load chronological data are clustered independent from solar chronological data, the time correlation between these two variables will be lost. In other words, if Monte Carlo state sampling were used, the same sample would include values for PV-systems output power and load that do not chronologically occur at the same time. Since the proposed approach is based on clustering the output power of PV-systems and load chronological data into several bands, the time correlation is considered by assigning pairs of data for the output power of PV-systems and load for each point of time. During the clustering procedure, each pair of data is assigned in the same cluster level so that clusters

of PV-systems output power and load will have the same probability of occurrence. In this work, the clustering approach that is explained in [13]–[16] is used to account for the time correlation between load and PV-systems output power.

B. Clustering Procedure

The following steps are used to cluster the output of a PV farm into a finite number of bands:

- 1) Calculate the hourly output power of the PV-system.
- 2) Select initial cluster mean values M_i , where i denotes cluster $i = 1, 2, \dots, X$.
- 3) Calculate the variation distance, D_{ij} , for each hour to each cluster mean, M_i , using (6).

$$D_{ij} = |M_i - X_j|. \quad (6)$$

- 4) Group all points by assigning them to the nearest cluster and then calculate the means of the new clusters using (7).

$$M_i = \frac{\sum_{j \in K_c} X_j}{X_i}, \quad (7)$$

where X_j is the number of output power points in the i -th cluster and K_c denotes the set of the PV power points in the i -th cluster.

- 5) Repeat steps 2, 3, and 4 until the differences in all cluster means become small enough and remain unchanged between iterations.

The clustered output power is represented by a finite number of bands. The transition rate of PV-systems output power between bands is considered stationary for the time period of study.

III. RELIABILITY EVALUATION

The output power of a PV farm is represented in this paper in terms of the capacity outage probability and frequency table COPAFT. A COPAFT represents a combination of capacity levels with the probabilities of existence, cumulative probabilities and frequency of transitions to represent the probability and frequency distribution functions for each cluster (band). The COPAFT of a PV-systems and the COPAFT of the conventional generators are convolved with load levels using the discrete convolution technique to evaluate the overall system adequacy to meet the demand [6].

Various reliability indices are used to quantify system adequacy assessment after integrating PV farms. In this work, we have evaluated the most commonly indices that have been used in power system adequacy assessment to calculate the reliability indices and to determine the capacity value of PV-systems. These indices can be defined as follows.

- **Loss of Load Probability (LOLP)** is the probability of encountering one or more LOL events during a given time period where LOL is A *Loss of Load* event in which a system is unable to meet its total demand.
- **Expected Demand Not Served (EDNS)** is the expected (average) demand that the system is unable to serve as a result of LOL events during a given period. It is calculated

as the weighted sum of the demands curtailed during the LOL events; the weights being the probabilities of the corresponding LOL events. It is expressed in MW/year or GW/year.

- **Loss of Energy Expectation (LOEE)** is the expected (average) energy that the system is unable to serve as a result of LOL events during a given period. It is calculated as the weighted sum of the energies curtailed during the LOL events; the weights being the probabilities of the corresponding LOL events. It is expressed in MWh/year or GWh/year.
- **Loss of Load Expectation (LOLE)** is the expectation (average) of encountering one or more LOL events during a given time period. It is expressed in hr/year.
- **Loss of Load Frequency (LOLF)** identifying the expected frequency of encountering one or more LOL events during a given time period.
- **Loss of Load Duration (LOLD)** identifying the average duration of encountering one or more LOL events during a given time period.

A. Capacity Outage Probability and Frequency Table

The availability of the output power of a generating unit is characterized by the forced outage rate (FOR) of the generator. The failures of generating units are assumed independent events; availabilities of system components can be modeled as Markovian components with two states, “up” and “down” with known failure and repair rates.

The COPAFT can be constructed by adding new units sequentially to the table with the capacity model building approach [17]. In general, the following expressions can be used to build the COPAFT [17].

$$P(x) = \bar{P}(x)(1 - q) + \bar{P}(x - C)q, \quad (8)$$

where $P(x)$ and $\bar{P}(x)$ denote the cumulative probabilities of the capacity outage state before and after the units are added, and q is the forced outage rate. Equation (8) can be initialized as follows.

$$\bar{P}(x) = \begin{cases} 1, & \text{if } x \leq 0, \\ 0, & \text{otherwise.} \end{cases} \quad (9)$$

The cumulative probability $P(x)$ for a forced outage of X MW or greater can be in general represented by (10).

$$P(x) = \sum_i P(X_i), \quad \forall X_i \leq x, \quad (10)$$

where

$$\bar{P}(x) = 1, \quad \forall x \leq C.$$

For generating units with derated states (multi-state units), equation (8) can be modified as follows.

$$P(X) = \sum_{i=1}^n P_i \times \bar{P}(x - C_i), \quad (11)$$

where C_i is the capacity outage of derated state i , P_i is the probability of the added unit being in derated state i , and n is the number of derated states.

IV. CAPACITY VALUE OF PV-SYSTEMS

The capacity value is used to measure the contribution of adding a new PV-system to the adequacy of the generation to meet the demand. The ELCC criterion is commonly used to calculate the capacity value of PV-systems. The ELCC measures the peak load carrying capability (PLCC) of the generation system after the addition of the PV-system to the grid. The PLCC of a power system represents the peak load that the system can supply by the available generating units while maintaining a predefined reliability target [18].

The PLCC is traditionally estimated using iterative processes where the loading level of a system is linearly incremented by a certain amount, usually a constant step of load, until the targeted reliability index reaches a specified level. However, this process is computationally expensive and time consuming especially for large systems. In the process of calculating the PLCC, if PV-systems are added to the system as load modifiers, the system load model is modified but the generation model remains unchanged. On the other hand, if PV-systems are added to the system as generating units, the generation model is modified and the load model remains unchanged. However, in the adequacy assessment, both approaches produce same results. After adding PV-systems, the generation reserve margin increases which leads to improvement in system reliability.

In this paper, a direct method is used to calculate the capacity value of PV-systems using the ELCC as a criterion. The proposed method is based on the fact that the capacity value of PV-systems is bounded between 0 MW and their installed capacity (rated capacity). Also, it is assumed that the increase in system load is evenly distributed on the load profile, as has been commonly used [19]–[21]. Therefore, the capacity value can be calculated by augmenting the generation reserve margin by the maximum capacity of PV-systems. The augmented reserve margin model can be expressed in terms of generation, load, and PV-system models as follows.

$$M_{au} = M + C_V, \quad (12)$$

where M is the generation reserve margin prior to adding PV-systems and C_V is the available capacity.

The cumulative distribution function (CDF) of the augmented margin, CDF_{au} , is created in same manner as creating a CDF for the original margin. However, the range of the augmented reserve margin is from $-L$ to C_R rather than ranging from $-L$ to 0 as in the original system (prior to adding PV-systems), where C_R is the maximum capacity of the PV-system. A typical CDF of an augmented margin is shown in Fig. 2. The CDF of the generation reserve margin of the original system crosses the zero level at $P(0)$. Now, since the capacity value is defined as the amount of load increase (after adding PV-systems) that would return a reliability index to its initial value (prior to adding PV-systems), the capacity value of a PV-system can be determined by projecting $P(0)$ to the augmented margin. In other words, the capacity value of a PV-system can be directly calculated by projecting the

point at which the CDF of the augmented margin crosses the level of the required reliability index as shown in Fig. 2. Mathematically, the capacity value of PV-systems can be determined as follows.

$$\text{Capacity Value} = M_{au}\{X : CDF_{au}(X) = P(0)\}, \quad (13)$$

where $CDF_{au}(X)$ is the cumulative probability of X MW of the CDF of the augmented reserve margin.

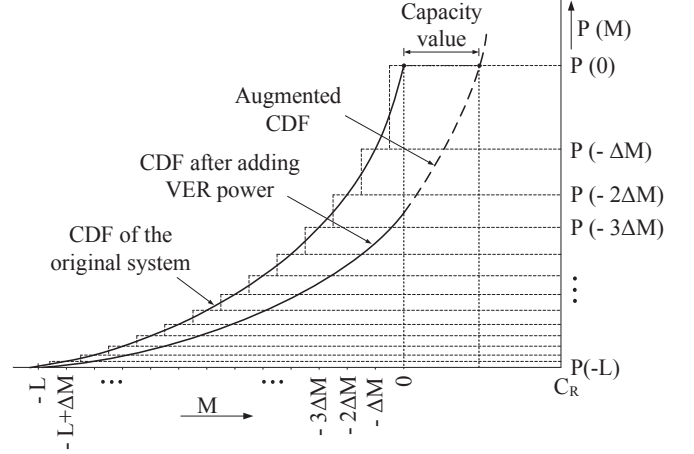


Fig. 2. Cumulative distribution function of an augmented margin before and after adding PV-systems.

V. CASE STUDY

In this paper, the size of the PV farm is assumed 100 MW. The parameters and structure of the PV farm were adopted from [4] to illustrate the proposed method. The solar radiation data for SANTA MARIA, CA region were taken from [11]. The data obtained from [11] are utilized to estimate the output power of the PV farm. Using the clustering approach, the hourly output of the PV-system is clustered into 8 bands and given in Table I.

TABLE I
PV OUTPUT BANDS AND STATE PROBABILITY

Bands	Output power (MW)	Individual Probability	Cumulative Probability
1	0.00000	0.4803	1.0000
2	4.54386	0.0421	0.5196
3	20.2848	0.0607	0.4776
4	37.7986	0.0574	0.4169
5	57.0958	0.0489	0.3595
6	75.8431	0.0618	0.3106
7	90.3725	0.0747	0.2488
8	100.000	0.1741	0.1741

The proposed formulation is applied on the IEEE RTS [22]. This system has been extensively tested for power system reliability analysis. The IEEE RTS consists of 32 generating units. The total generation of this system is 3405 MW, and total peak load is 2850 MW.

The output power bands of the PV farm are convolved with the conventional generators using the concept of the multi-state

TABLE II
RELIABILITY INDICES OF IEEE-RTS WITH 100 MW PV FARM USING
DISCRETE CONVOLUTION

	LOLP	EDNS (MW/yr)	LOLE (h/yr)	LOEE (MWh/yr)	LOLF (occ/yr)
Base Case	0.001072	0.135206	9.3681	1181.158	2.01582
Adding PV Power	0.000795	0.097248	6.9453	849.554	1.64563

TABLE III
RELIABILITY INDICES OF IEEE-RTS WITH 100 MW PV FARM USING
MONTE CARLO SIMULATION

	LOLP	EDNS (MW/yr)	LOLE (h/yr)	LOEE (MWh/yr)	LOLF (occ/yr)
Base Case	0.001070	0.135054	9.3732	1179.832	2.03671
Adding PV Power	0.000788	0.097610	6.8840	852.721	1.64863

to build a unified COPAFT [23]. The resulting COPAFT is then combined with the system load to calculate the reliability indices.

A. Reliability Indices

The reliability indices of the IEEE-RTS are calculated for the base case and with including the PV power. The reliability indices are shown in Table II. Monte Carlo simulation is used to validate the results which are given in Table III. From Table II and Table III, it can be seen that the reliability indices that are calculated using discrete convolution are close to those are calculated using Monte Carlo simulation. Also, system indices show improvement when the PV farm are added which is not surprising.

B. Capacity Value

The change in the reliability indices against the increase in system loading for considering days and nights and days only are given in Table IV and Table V respectively. The capacity values are calculated by determining the point at which the curve of the reliability index, after adding the PV power and incrementally increasing the load, matches the base case of the same index.

In the case of considering days and nights, if the LOLE index is used as an index to determine the capacity value,

TABLE IV
CHANGES IN SYSTEM INDICES DUE TO THE INCREASE IN THE DEMAND
AFTER ADDING PV POWER—CONSIDERING BOTH DAYS AND NIGHTS

Load Increase	LOLP	EDNS (MW/yr)	LOLE (h/yr)	LOEE (MWh/yr)	LOLF (occ/yr)
5 MW	0.000859	0.1099233	7.50533	960.290	1.73640
10 MW	0.000862	0.1114641	7.52635	973.375	1.76606
15 MW	0.000902	0.1133319	7.87667	990.068	1.82800
20 MW	0.000906	0.1143800	7.91500	999.293	1.86612
25 MW	0.000933	0.1188660	8.15033	1038.41	1.87539
30 MW	0.001021	0.1336816	8.92200	1167.84	2.06811
35 MW	0.001092	0.1345241	9.53971	1175.20	2.09230

TABLE V
CHANGES IN SYSTEM INDICES DUE TO THE INCREASE IN THE DEMAND
AFTER ADDING PV POWER—CONSIDERING DAYS ONLY

Load Increase	LOLP	EDNS (MW/yr)	LOLE (h/yr)	LOEE (MWh/yr)	LOLF (occ/yr)
5 MW	0.000801	0.097370	6.99367	850.624	1.64964
10 MW	0.000812	0.098380	7.09267	859.452	1.67043
15 MW	0.000838	0.099465	7.31833	868.923	1.69072
20 MW	0.000876	0.107526	7.50124	939.348	1.71285
25 MW	0.000892	0.109667	7.79602	958.055	1.73570
30 MW	0.000897	0.109992	7.83367	960.892	1.75519
35 MW	0.000910	0.111076	7.94654	970.359	1.78323
40 MW	0.000925	0.115370	8.08167	1007.87	1.82078
45 MW	0.000956	0.120554	8.35330	1053.16	1.84024
50 MW	0.000982	0.126225	8.57767	1102.70	1.91737
55 MW	0.001041	0.129906	9.09133	1134.85	2.04722
60 MW	0.001105	0.140600	9.65166	1228.28	2.08235

about 33 MW of load increase can be compensated by 100 MW of PV power. On the other hand, when considering days only, about 56 MW of load increase can be compensated by 100 MW of PV power.

In the case of considering days and nights, if the LOLF index is used as an index to determine the capacity value, about 28 MW of load increase can be compensated by 100 MW of PV power. On the other hand, when considering days only, about 53 MW of load increase can be compensated by 100 MW of PV power.

It can be seen from Table IV and Table V that including the nights in evaluating the capacity value of PV-systems produces pessimistic capacity values compared to the cases where considering days only. In other words, including both days and nights in calculating the capacity value produces lower capacity values. Also, the LOLE and LOLF indices produce different values for the capacity values of PV farms and the planner or operator has the option to consider any of them. For instance, if the concern is the expected load curtailment, the LOLE index can be used to determine the capacity value. On the other hand, if the concern is the frequency of interruptions, the LOLF can be used to determine the capacity value.

C. Capacity Value Versus Size

In order to evaluate the optimal size of the PV system, the capacity value is evaluated against the increase in system size. The PV data are utilized to calculate different nameplate capacities of the PV system. While system indices improve as the PV power penetration increases, the capacity values decreases in a semi-linear manner. The change in the capacity value as the size increases for the cases of considering days and nights and days only are shown in Fig. 3 and Fig. 4 respectively. This behavior can be attributed to the fact that the output power of PV-systems and load profile are not fully correlated. Since the proposed method can be used to evaluate both the capacity value and the corresponding system reliability improvement, it is for the planner to choose the importance of the decision variable: max capacity value or system reliability improvement.

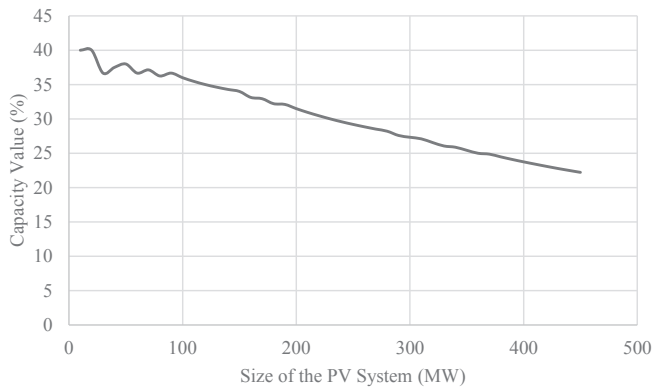


Fig. 3. The relationship between the PV system size and its capacity value for the case of considering day and night

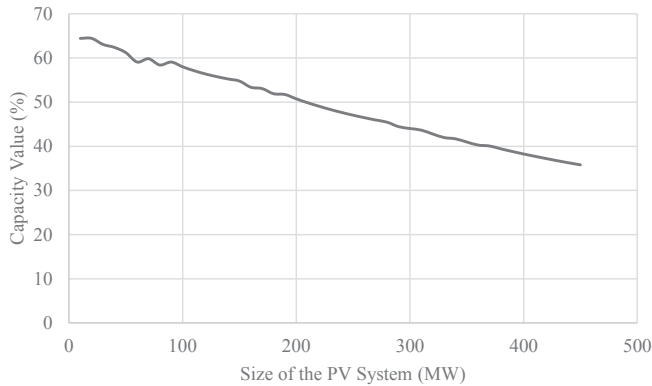


Fig. 4. The relationship between the PV system size and its capacity value for the case of considering day only

VI. CONCLUSION

This paper has evaluated the capacity value of the output power of PV-systems and their corresponding optimal sizes considering the uncertainty of the output power during days and the certainty of the unavailability of the output power during nights. Integration of renewable generation such as PV-systems into power system grids increases the necessity to develop appropriate reliability models that estimate the contribution of these resources on system reliability. A PV farm with a capacity of 100 MW is added to the IEEE-RTS to determine the capacity value of PV-systems. The results have shown that the capacity value of PV-systems in the case of considering day time periods only is approximately 1.6 times of the case of considering days and nights. Also, for the tested system and solar data, the results show that as the size of PV-systems increases, its capacity value decreases in a semi-linear manner.

REFERENCES

- [1] L. Kishore and E. Fernandez, "Reliability well-being assessment of PV-wind hybrid system using Monte Carlo simulation," in *Emerging Trends in Electrical and Computer Technology (ICETECT)*, 2011 International Conference on. IEEE, 2011, pp. 63–68.
- [2] N. Pradhan and N. R. Karki, "Probabilistic reliability evaluation of off-grid small hybrid solar PV-wind power system for the rural electrification in Nepal," in *North American Power Symposium (NAPS)*, 2012. IEEE, 2012, pp. 1–6.
- [3] R. M. Moharil and P. S. Kulkarni, "Reliability analysis of solar photovoltaic system using hourly mean solar radiation data," *Solar Energy*, vol. 84, no. 4, pp. 691–702, 2010.
- [4] A. Ghaedi, A. Abbaspour, M. Fotuhi-Friuzabad, and M. Parvania, "Incorporating large photovoltaic farms in power generation system adequacy assessment," *J. Sci. Iran*, vol. 21, no. 3, pp. 924–934, 2014.
- [5] P. Zhang, Y. Wang, W. Xiao, and W. Li, "Reliability evaluation of grid-connected photovoltaic power systems," *Sustainable Energy, IEEE Transactions on*, vol. 3, no. 3, pp. 379–389, 2012.
- [6] S. Sulaeman, M. Benidris, J. Mitra, and C. Singh, "A wind farm reliability model considering both wind variability and turbine forced outages," *IEEE Transactions on Sustainable Energy*, vol. 8, no. 2, pp. 629–637, April 2017.
- [7] S. Sulaeman, M. Benidris, and J. Mitra, "Modeling the output power of pv farms for power system adequacy assessment," in *2015 North American Power Symposium (NAPS)*, Charlotte, NC, USA, Oct. 2015, pp. 1–6.
- [8] S. Sulaeman, M. Benidris, Y. Tian, and J. Mitra, "Modeling and evaluating the capacity credit of pv solar systems using an analytical method," in *2016 IEEE/PES Transmission and Distribution Conference and Exposition (T&D)*, Dallas, TX, USA, May 2016, pp. 1–5.
- [9] Y. Huang, C. Liu, G. He, X. Xu, J. He, W. Wang, and X. Zhou, "Capacity value of PV generation and its impact on power system planning: A case study in Northwest of China," in *Asia-Pacific Power and Energy Engineering Conference (APPEEC)*, Chengdu, China, March 2010, pp. 1–4.
- [10] S. Pelland and I. Abboud, "Estimating the capacity value and peak-shaving potential of photovoltaics in Ontario: a case-study for the City of Toronto," in *17th International Photovoltaic Science and Engineering Conference*, Fukuoka, Japan, Dec. 2007, pp. 1–2.
- [11] G. d. National renewable energy laboratory (NREL), dynamic maps and analysis tools.
- [12] D. K. Khatod, V. Pant, and J. Sharma, "Analytical approach for well-being assessment of small autonomous power systems with solar and wind energy sources," *Energy Conversion, IEEE Transactions on*, vol. 25, no. 2, pp. 535–545, 2010.
- [13] C. Singh and Y. Kim, "An efficient technique for reliability analysis of power systems including time dependent sources," *IEEE Trans. Power Syst.*, vol. 3, no. 3, pp. 1090–1096, Aug. 1988.
- [14] C. Singh and A. Lago-Gonzalez, "Reliability modeling of generation systems including unconventional energy sources," *IEEE Trans. Power App. Syst.*, vol. PAS-104, no. 5, pp. 1049–1056, May 1985.
- [15] C. Singh and Q. Chen, "Generation system reliability evaluation using a cluster based load model," *IEEE Trans. Power Syst.*, vol. 4, no. 1, pp. 102–107, Feb. 1989.
- [16] S. Sulaeman, M. Benidris, and J. Mitra, "Modeling and assessment of pv solar plants for composite system reliability considering radiation variability and component availability," in *2016 Power Systems Computation Conference (PSCC)*, Genoa, Italy, June 2016, pp. 1–8.
- [17] R. Billinton, C. Wee, and G. Hamoud, "Digital computer algorithms for the calculation of generating capacity reliability indices," *Power Engineering Review, IEEE*, no. 1, pp. 34–35, 1982.
- [18] M. A. Abdullah, K. M. Muttaqi, A. P. Agalgaonkar, and D. Sutanto, "A noniterative method to estimate load carrying capability of generating units in a renewable energy rich power grid," *IEEE Transactions on Sustainable Energy*, vol. 5, no. 3, pp. 854–865, July 2014.
- [19] R. M. Castro and L. Ferreira, "A comparison between chronological and probabilistic methods to estimate wind power capacity credit," *IEEE Transactions on Power Systems*, vol. 16, no. 4, pp. 904–909, 2001.
- [20] M. Amelin, "Comparison of capacity credit calculation methods for conventional power plants and wind power," *IEEE Trans. Power Syst.*, vol. 24, no. 2, pp. 685–691, 2009.
- [21] L. Garver, "Effective load carrying capability of generating units," *IEEE Trans. Power App. Syst.*, vol. 8, no. PAS-85, pp. 910–919, 1966.
- [22] IEEE Task Force, "IEEE reliability test system," *IEEE Transactions on Power Apparatus and Systems*, pp. 2047–2054, Nov./Dec. 1979.
- [23] R. Billinton and Y. Gao, "Multistate wind energy conversion system models for adequacy assessment of generating systems incorporating wind energy," *IEEE Trans. on Energy Conv.*, vol. 23, no. 1, pp. 163–170, 2008.