

Modeling and Assessment of PV Solar Plants for Composite System Reliability Considering Radiation Variability and Component Availability

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Abstract—This paper presents a method to model the output power of large PV systems for composite system reliability assessment. Grid level PV systems are usually constructed from a large number of power electronic components and PV panels. Modeling of these systems in power system reliability is a complex task due to the dependency of the output power on the intermittent source (solar radiation) and the availability of a large number of system components. An analytical method to construct a capacity outage probability and frequency table (COPAFT) that captures both the intermittency of the input source and component failures is proposed to model PV systems. The intermittency of the input source and component availabilities are modeled separately and then convolved to construct a single COPAFT. The resulting model includes both probability and frequency distributions. The proposed method reduces the complexity of modeling and evaluating large PV systems for composite system reliability assessment. The method is demonstrated on IEEE Reliability Test System (IEEE RTS). Considering the PV farm location with a view to enhance system reliability, sensitivity study is conducted to measure the effect of the location of the PV farm on overall system reliability. The results confirm that connecting PV farms to the buses that are at a high risk enhances the overall system reliability.

Index Terms—Photovoltaic (PV) power systems, reliability of composite systems, reliability modeling of PV systems.

I. INTRODUCTION

In recent years, reliability evaluation of composite generation and transmission systems has been receiving increasing attention. This is largely because of the ongoing changes in generation portfolios and environmental constraints. Composite system reliability indices include, but are not limited to, loss of load probability (LOLP), loss of load frequency (LOLF), loss of load expectation (LOLE), expected energy not supplied (EENS), and expected demand not supplied (EDNS). These are commonly used to assess system reliability. With increasing penetration level of variable resources such as PV power plants, the reality of input uncertainty and output variability adds to the complexity of modeling these resources in planning and operation studies. The important aspects in the reliability evaluation of composite systems are the assessment of the effect of such variable resources on the reliability of the main grid.

Grid connected PV systems are usually constructed from a large number of components such as power electronic circuits and solar panels. The reliability of such components is highly dependent upon the operation and ambient conditions. Operational and environmental factors may lead to overall reduction in the output power and failure of system components [1], [2]. Modeling of these systems in power system reliability is a complex task due to the dependency of the output power on the intermittent source and the functionality of a large number of system components. From the reliability point of view, the output of PV systems is modeled based on the availability of the input and the functionality of the components.

The reliability assessment of systems that integrate PV systems and the associated technical aspects such as adequacy assessment have been amply addressed in the literature. Most of the presented work have considered the effects of power electronic components and circuits such as capacitors, IGBTs or the entire inverter to assess the reliability of PV systems [3]–[5]. Monte Carlo simulation has been used in [6] for reliability assessment of a hybrid system of wind and PV systems. A combination of deterministic and probabilistic techniques is used in reliability evaluation of these systems. In [7], the hourly mean solar radiation data were used as a main input and Monte Carlo simulation was implemented to evaluate the system reliability. In [8], an analytical method is used to model the availability of the PV systems in the reliability assessment. In [9], reliability of a wind and solar system has been evaluated using Monte Carlo simulation. In [10], a methodology for photovoltaic system reliability and economic analysis is introduced.

In this paper, a generation model for PV systems that captures the effect of the input variability and failures of system components is presented. The resultant model is added to the system. Reliability assessment of the composite systems is carried out in conjunction with the Monte Carlo simulation (state sampling method). In addition, sensitivity study is carried out to evaluate the risk (the probability of an event and the consequences or impacts of the event that lead to load curtailment) associated with allocating PV power at different buses on system reliability indices with and without

considering the effect of the availability of system components.

II. PV SYSTEM FARMS AND OUTPUT POWER

Different topologies of PV systems have been addressed in literature [11]–[14]. In general, topologies of PV systems are mainly classified based on the arrangement of PV panels and DC/DC and DC/AC converters. These arrangements are usually set up to enhance the system efficiency and reliability.

A. PV Farm Structure

In general, a PV farm is constructed from a large number of PV panels arranged in arrays. The PV arrays are constructed from PV panels which in turn are connected to the main grid through DC/AC inverters. A set of N panels in each array is called sub-array. PV panels are constructed from a large number of solar cells in series configurations. At the higher level, the output of the PV system is then connected to the grid through a power transformer [13], [15]. The amount of the output power of a PV farm at a certain location depends on the input availability (mainly solar radiation) and the availability of system components. In a PV farm, since PV panels are placed adjacent to each other, all PV panels are assumed to have the same solar radiation, and approximately experience the same operational and environmental factors that may affect the output of the farm.

B. Output Power of PV Systems

The maximum output power ratings of PV systems are provided by manufacturers on the specification sheets. The current-voltage characteristics (I-V characteristics) under the standard test conditions (the radiation level of 1 kW/m^2 is given for temperature of 25°C) can be calculated as follows [16].

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

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

where s is the normalized 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 [16].

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

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} , assuming 100% efficient maximum power point tracking (MPPT), for a given radiation level, ambient temperature and the current-voltage characteristics can be calculated using the following relationships [16].

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

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 [16].

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

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

III. RELIABILITY MODELING OF PV FARMS

For proper evaluation and modeling of the effect of system component availability and input variability on the output power of a PV farm, an analytical method is adopted to construct a generation model for PV farms. The generation model that represents the output power of a PV farm is denoted in this paper in terms of COPAFT. A COPAFT represents a combination of capacity levels with the probabilities of existence and cumulative probabilities to represent the probability distribution function of the outage states.

A. Modeling Approach

A PV system comprises a multitude of PV panels spread out over a geographic area. The operating characteristics of PV systems differ from those of traditional power plants in terms of their capability and dispatchability. PV panels on the same farm produce output power that are related to the incident input and are correlated between PV panels. Therefore, the output of individual PV panels cannot be modeled as independent random variables. This motivates the development of a method that combines a cluster of PV panels into a single equivalent multi-state unit that captures their correlation, output variability, and forced outages.

In order to build a generation model for the entire PV system that consider both the effect of input variability and system components failures, two modeling steps are taken to build a generation model for PV system: (1) modeling the dependency of the output on the variability of the solar radiation and (2) the outage due to failure of system components (failure rate). These two models are then combined to produce a single generation model that can be viewed as a single source with multi-state. The general modeling process is depicted in Fig. 1.

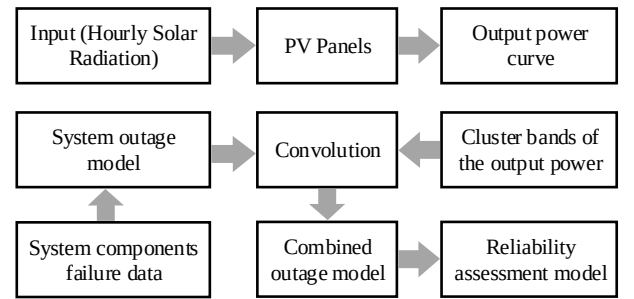


Figure 1. Modeling of PV power in power system reliability assessment

B. Attributes of PV System Components

In a PV farm, power electronic devices play an important role. Power electronic circuits deliver the output power of PV panels to the load or to the grid. Reliability assessment of power electronic circuits of large-scale grid-connected PV systems for different topologies have been addressed in [11],

[12], [17]. The major components that contribute to system failure are power electronic circuits.

In the literature, the mean time to failure (MTTF) has been used as an indicator for system unavailability; the overall reliability of the circuit is calculated by summing the failure rates (the failure rate is reciprocal of the MTTF) of the components [18]–[20]. However, this is true if a failure of a component leads to overall failure of the power electronic circuit. In some cases such as multilevel inverters, redundancy exists in power electronic topologies and their desired function is not totally affected by a component failure [21]. In this case, there are several possible different paths that can still produce an acceptable output voltage level. In such configurations, the overall failure cannot be assumed by summing the failure rates of the components. Analytical techniques can be used to estimate system reliability such as reliability network analysis, minimal cut set, minimal path set and state enumeration techniques [22]. In general, the reliability function, $R(t)$, indicates the probability that the system will operate without failures over a time interval $[0, t]$. The failure rate of system component during the useful lifetime is usually considered independent of time. The reliability of system components can be expressed as an exponential function of their constant failure rate during the useful lifetime as follows.

$$R(t) = e^{-\lambda_i t} \quad (6)$$

where λ_i is the constant failure rate.

The mean time to repair (MTTR) is often considered small enough and can be neglected [23]. This could be a valid assumption for a small system or a system with a few components where the time required to repair or replace a component is small comparing to MTTF. However, for large systems, neglecting the repair time could produce optimistic results. In this paper, the MTTR is included in modeling PV systems. System availability and unavailability as functions of MTTF and MTTR are described by (7) and (8).

$$p = \frac{\mu}{\lambda + \mu} \quad (7)$$

$$q = 1 - p = \frac{\lambda}{\lambda + \mu} \quad (8)$$

where p is the probability of component availability, q is the probability of component failure and μ is the repair rate (reciprocal of $MTTR$).

Reliability modeling of large systems such as PV systems with a large number of system components could result in a large number of system states and increase modeling complexity. Therefore, the equivalent MTTF and MTTR for subsystems are needed to drive an equivalent failure rate λ and repair rate μ . The availability of system components can be modeled as a Markovian with two states, “up” and “down” with known failure and repair rates.

The PV panels are constructed from n parallel branches; each branch is constructed by connecting m series solar cells. The equivalent failure rate of a branch can be calculated by summing the failure rates of the m series solar cells. The

failure of a solar branch leads to the failure of the PV panel. Thus, the availability and unavailability of PV panels can also be calculated using (7) and (8). In this paper, the MTTR for system wiring and fuses are considered to be small enough and don not have a significant effect on system reliability estimation. The failures of the components a PV system are assumed independent events; availabilities of system components can also be modeled as Markovian components with two states, “up” and “down”. The assessment of the availability of the system output is addressed by separately modeling the independent failures of system components and the dependency on the input availability. The equivalent availability and unavailability of system components can be estimated by calculating the equivalent failure and repair rates. For each array, the MTTF and MTTR for M components can be obtained. Each array can then be represented by equivalent MTTF and MTTR. The capacity outage probability and frequency table can be constructed for a PV farm with N arrays by adding new units sequentially to the table with the capacity model building approach explained in [24].

Based on the FOR (forced outage rate is the failure probability) of system arrays, the COPAFT of PV system can be built using the *unit addition algorithm*. This is a recursive algorithm that starts with the distribution of one unit (a PV array in this case) and successively convolves with it the distributions of the remaining units, one unit at a time. In general, when adding a new unit of capacity C , the cumulative probability and frequency of an outage state X can be determined by the following expressions [24].

$$P(X) = \bar{P}(X)(1 - q) + \bar{P}(X - C)q \quad (9)$$

where (9) is initialized as follows.

$$P(X) = \begin{cases} 1, & \text{if } X \leq 0 \\ 0, & \text{otherwise,} \end{cases}$$

where $P(X)$ and $\bar{P}(X)$ denote the cumulative probabilities of the capacity outage state before and after the units are added. 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

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

In the case of multi-state generating units, (9) can be modified as follows.

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

The cumulative frequency of capacity outage X can also be calculated using the same approach. In general it can be represented by (19).

$$F(X) = F_i(1 - q) + F_jq + (P_j - P_i)q\mu \quad (12)$$

where q and μ are respectively the probability of failure and repair rate of the new unit; P_i , P_j , F_i , and F_j are determined from the old COPAFT; i is the index of the existing capacity outage state $C_i = X$ and j is the index of existing capacity outage state C_j such that $C_j = X - C$.

C. Capacity Outage Probability and Frequency Table of a PV Farm (COPAFT)

In this work, all system components are assumed to be identical and located at the same region. All PV panels will experience the same input. Therefore, the output power of each PV panel will be approximately the same. To compensate for the input uncertainty and variation, the hourly output power of PV panels constructed from installed capacity is sorted into several clusters using the clustering approach as explained in [25], [26]. The clustered output power is represented by a finite number of bands. The transition rate of PV power between bands is considered stationary for the time period of study. The COPAFT of a PV farm considering the input uncertainty and component availability can be obtained by convolving the COPAFT over each band. The following expressions are used to construct the COPAFT of a PV farm [27].

$$M_{A(i,j)} = \frac{C_{PVCA(i)}}{C_{RPV}} \times C_{PV(j)} \quad (13)$$

where $M_{A(i,j)}$ is the modified available capacity of i^{th} state in the COPAFTT of PV panels, $C_{PVCA(i)}$ is the available capacity in state i , C_{RPV} is the rated capacity of PV panel and $C_{PV(j)}$ is the available power at state j .

$$P_{M(i)} = P_{COPAFT(i)} \times P_{PV(j)} \quad (14)$$

where $P_{M(i)}$ is the probability of being in state i and $P_{PV(j)}$ is the probability of band j .

The new outage capacity of state i of COPAFT being in band j is given by

$$C_{PVCO(i,j)} = C_{RPV} - M_{A(i,j)} \quad (15)$$

The probability of outage capacities of states i being in band j , is given by

$$P_{M(i,j)} = \sum P_{PV(j)} \times P_{COPAFT(i)} \quad (16)$$

where $P_{PV(j)}$ is the band probability and $P_{COPAFT(i)}$ is the COPAFT state outage probability.

The cumulative outage probability of an outage X can be obtained by scanning through all bands; whenever an outage state with outage capacity grater than X is encountered, its probability is accumulated as follows.

$$P(C_o \geq X) = \sum_{i=1}^n \sum_{j=1}^m P_{M(i,j)} \quad (17)$$

where n is the number of COPAFT states, and m is the number of bands.

By scanning through all bands, whenever encountering states with equal outages, their probabilities are combined and the duplicated states are eliminated. The cumulative outage

frequencies of encountering outage state with outage capacity $C_o \geq X$ due to the transition of COPAFT states between PV power bands can be calculated by (18).

$$F(C_o \geq X) = F_{(k)} + F_{PVB} \quad (18)$$

where

$$F_{PVB} = \sum P_{(k)} \times f_{COPAFT(i)} \quad (19)$$

$$F_k = \sum P_{COPAFT(i)} \times f_{(k)} \quad (20)$$

where $f_{COPAFT(i)}$ is the outage frequency of i^{th} outage state.

IV. NETWORK MODELING

In composite system reliability evaluation, operation, generation and transmission constrains are usually considered. Performing reliability assessment requires a repetitive solution of an optimization problem of minimum load curtailment. In solving power system optimization problems, power flow studies are usually carried out. In this paper, the DC power flow model was used to model the power flow in the system. At the transmission level, the DC power flow model is an appropriate model whenever fast and repeated power flow estimations are required. The formulation and incorporation of the objective function of minimum load curtailment in the linear programming problem is described in this section. The objective function is subject to the equality and inequality constraints of the power system operation limits. The equality constraints include the power balance at each bus, and the inequality constraints are the capacity limits of generating units and power carrying capabilities of transmission lines. The linear programming model of the network with DC power flow model and an objective function of minimum load curtailment is given in equation (21), which is adapted from [28].

$$\text{Loss of Load} = \min \left(\sum_{i=1}^{N_b} C_i \right) \quad (21)$$

Subject to

$$\begin{aligned} \hat{B}\delta + G + C &= D \\ G &\leq G^{max} \\ C &\leq D \\ b\hat{A}\delta &\leq F_f^{max} \\ -b\hat{A}\delta &\leq F_r^{max} \\ G, C &\geq 0 \\ \delta &\text{ unrestricted} \end{aligned} \quad (22)$$

In (21), and (22) N_b is the number of buses, b is the transmission line susceptance matrix ($N_t \times N_t$), N_t is number of transmission lines, $\hat{A}$ is the element-node incidence matrix ($N_t \times N_b$), $\hat{B}$ is the augmented node susceptance matrix ($N_b \times N_b$) (the augmented node susceptance matrix is calculated as $\hat{B} = \hat{A}^T b \hat{A}$), δ is the vector of node voltage angles ($N_b \times 1$), C is the vector of bus load curtailments ($N_b \times 1$), D is the vector of bus demand ($N_b \times 1$), G^{max} is the vector of maximum available generation ($N_b \times 1$), F_f^{max} is the vector

of forward flow capacities of lines ($N_t \times 1$), F_r^{max} is the vector of reverse flow capacities of lines ($N_t \times 1$), and G is the solution vector of the generation at buses ($N_b \times 1$). In (22) all generation availability and network constraints have been taken into consideration. Also, in order to get a feasible solution for the standard problem, it has been assumed that one of the bus angles is zero in the constraints (22).

V. CALCULATION OF RELIABILITY INDICES

This section describes the method (Monte Carlo simulation state sampling method) used for calculating the system reliability indices.

A. Calculation of Probability Indices

The estimated Loss of Load Probability (LOLP) index can be calculated using Monte Carlo state sampling method as follows.

$$\text{LOLP} = E[q] \quad (23)$$

where $E[\cdot]$ is the expectation operator and q can be evaluated as follows.

$$q = \frac{1}{N_s} \sum_{i=1}^{N_s} \pi_i \quad (24)$$

where N_s is the number of samples and π_i can be expressed as:

$$\pi_i = \begin{cases} 1, & \text{If } x_i \in X_f \\ 0, & \text{otherwise} \end{cases} \quad (25)$$

where x_i is the state of the system and X_f is the set of failure states.

The estimated Loss of Load Expectation (LOLE) index can be directly calculated from the LOLP index by multiplying by the study period.

B. Calculation of Energy Indices

In reliability assessment, commonly used energy indices are *expected demand not supplied* and *expected energy not supplied*. Let d denote the expected demand not supplied. For every tested state, if the state is a failure state, the product of the probability of this state and the amount of load curtailment is added to the d index. The expected demand not supplied is given by

$$d = \sum_{i=1}^{n_f} P\{x_i : x_i \in X_f\} \times Lc\{x_i : x_i \in X_f\} \quad (26)$$

where Lc is the amount of load curtailment of state x_i . The estimated Expected Demand Not Supplied (EDNS) index state x_i , as determined from (21) and can be calculated as follows.

$$\text{EDNS} = E[d] \quad (27)$$

where d can be evaluated as follows.

$$d = \frac{1}{N_s} \sum_{i=1}^{N_s} \psi_i \quad (28)$$

and ψ_i can be expressed as:

$$\psi_i = \begin{cases} Lc, & \text{If } x_i \in X_f \\ 0, & \text{otherwise} \end{cases} \quad (29)$$

The estimated Loss of Energy Expectation (LOEE) index can be directly calculated from the EDNS index by multiplying by the study period.

C. Calculation of Frequency and Duration Indices

Calculation of frequency and duration indices is generally more difficult than the probability and energy indices. The approach used in this work to calculate frequency and duration indices was adapted from [29], [30]. The work presented in [29], [30] was based on concepts described in [31]. We will not reproduce the rigorous derivation here; rather, the expressions will be presented for convenience.

Every failure state comprises functional components and failed components. Failure states can transit to higher states by upward transitions, and the resulting states can be success or failure states. If the resulting state is a success state, the transition is said to have crossed the boundary between success and failure states. Similarly, success states can cross the boundary and transit to failure states. The frequency of encountering success states (or failure states) is the sum of the individual frequencies associated with those transitions of the failure states (or success states) which cross the boundary.

The sum of the frequencies of the upward transitions from the failed states can be expressed as,

$$F^{(+)} = \sum_{i=1}^{n_f} \left(P\{x_i : x_i \in X_f\} \sum_{j \in Z_i} \mu_j \right) \quad (30)$$

where n_f is the number of failure states, Z_i is the set of failed components in state i , and μ_j is the repair rate of component j .

The sum of the frequencies of the downward transitions from the failed states can be expressed as,

$$F^{(-)} = \sum_{i=1}^{n_f} \left(P\{x_i : x_i \in X_f\} \sum_{k \in \bar{Z}_i} \lambda_k \right) \quad (31)$$

where $\bar{Z}_i$ is the set of functional components in state i , and λ_k is the failure rate of component k .

Some of $F^{(+)}$ transitions will cross the boundary and the others will not. Also, by the assumption that the system is coherent, none of $F^{(-)}$ will cross the boundary. As a result of frequency balance property, all those transitions included in $F^{(+)}$ which do not cross the boundary are balanced by corresponding transitions included in $F^{(-)}$. Consequently, the frequency of system success can be calculated as,

$$F_s = F^{(+)} - F^{(-)} \quad (32)$$

In the steady state, the frequency of system success and frequency of system failure will balance, that is $F_f = F_s$.

Therefore, the frequency of system failure can be calculated from failure states as follows.

$$F_f = \sum_{i=1}^{n_f} \left[P \{x_i : x_i \in X_f\} \left(\sum_{j \in Z_i} \mu_j - \sum_{k \in \bar{Z}_i} \lambda_k \right) \right] \quad (33)$$

For the multi-state components, PV power in this case, the frequency of failure is calculated based on an expression presented in [29]. This method constructs an array of “incremental transition rates,” L_j , from the cumulative frequencies of PV power as follows.

$$L_j(n) = \frac{F(n) - F(n-1)}{P(n) - P(n-1)} \quad (34)$$

where $P(n)$ is the cumulative probability of the n -state of the multi-state component, $F(n)$ is the cumulative frequency of the n -state of the multi-state component and the subscript, j , is the component index.

The estimated Loss of Load Frequency (LOLF) index can be calculated using Monte Carlo state sampling as follows.

$$\text{LOLF} = E[F_f] \quad (35)$$

where F_f can be evaluated as follows.

$$F_f = \frac{1}{N_s} \sum_{i=1}^{N_s} \phi_i \quad (36)$$

and ϕ_i can be expressed as,

$$\phi_i = \begin{cases} \sum_{j=1}^{n_c} L_j(n), & \text{If } x_i \in X_f \\ 0, & \text{otherwise} \end{cases} \quad (37)$$

where n_c is the number of components in the system.

For the two state components, if the component is in the up state, $L_j(n) = -\lambda_j$ and if the component is in the down state, $L_j(n) = \mu_j$.

VI. CASE STUDIES

In this paper, the size of the PV farm was assumed 100 MW. The parameters and structure of the PV farm were adapted from [8] to illustrate the proposed method. The PV farm is constructed from 50 arrays, each array has a capacity of 2000 kW. Each sub-array is constructed by connecting 80 panels in series. Finally, 50 arrays are connected in to the grid through a 2000 kW inverter per array. In this paper, the solar radiation data for Santa Maria, CA region was used [32]. The data obtained from [32] for one year are utilized to estimate the output power of a PV farm. In this paper, the failure rates of system components were assumed as follows: for DC/AC inverter and DC/DC converters are 0.000027 failures per hour, and for solar panels are 0.000011 failures per hour [33]. The repair rates of the DC/AC inverter and DC/DC converter were assumed 0.1 repair per hour. For the PV panel, the repair rate were assumed 0.2 repair per hour. Using the proposed method, the hourly output of solar panels is clustered into 8 bands, as shown in Table I.

TABLE I
PV OUTPUT BANDS AND STATE PROBABILITY

Bands	Output Power (MW)	Individual Probability	Cumulative Probability	Cumulative Frequency
1	0	0.4803	1	0
2	4.328	0.0421	0.5196	0.001963
3	19.318	0.0607	0.4776	0.002397
4	35.102	0.0574	0.4169	0.001712
5	54.376	0.0489	0.3595	0.001141
6	72.230	0.0618	0.3106	0.000685
7	86.062	0.0747	0.2488	0.000340
8	95.225	0.1741	0.1741	0.303650

The proposed formulation was applied on the IEEE RTS [34]. The IEEE RTS system has been extensively tested for power system reliability analysis. The selection of PV farm location depends on several factors such as solar availability, access to the grid, economic aspects, reliability enhancement of the grid, etc. In this context, the PV farm location is considered from the reliability enhancement point of view. Several studies have been conducted in the literature to identify the buses that have the highest risk from the reliability point of view, such as [35], [36]. In this work, we have studied all the possible locations and traced the correlation between the enhancement of the reliability indices and the candidate buses that have been suggested by [35], [36]. Four case studies were performed on this system. For each case study, ten scenarios were performed. Each scenario represents different location for the PV power. In other words, the system has ten generation buses which are 1, 2, 7, 13, 15, 16, 18, 21, 22, and 23, and for each scenario the PV power is connected at a different bus of the test system shown in Fig. 2. These four case studies are as follows:

- 1) Case Study I: Add PV power with no change in the system load (Ignoring components failures).
- 2) Case Study II: Add PV power with no change in the system load (Consider components failures).
- 3) Case Study III Modifying the load of the system. In this case study, the components failures of PV system is ignored. Then case studies were performed, for each case study, ten locations for PV farm were evaluated. For each case study, in each case study, the system system peak load is increased by ΔL until the LOLE Index of the system before adding PV power is reached. The peak load increase was distributed on the buses according to their percentage of the total load.
- 4) Case Study IV: In this case study, components failures of PV system is considered and LOLE index is calculated at each bus as in case study (3).

VII. DISCUSSION AND CONCLUSION

This paper presents a method to model the output power of large PV systems for composite system reliability assessment. The proposed method uses a recursive technique to build a generation model for PV system that captures both the variability of the input source and system component failures.

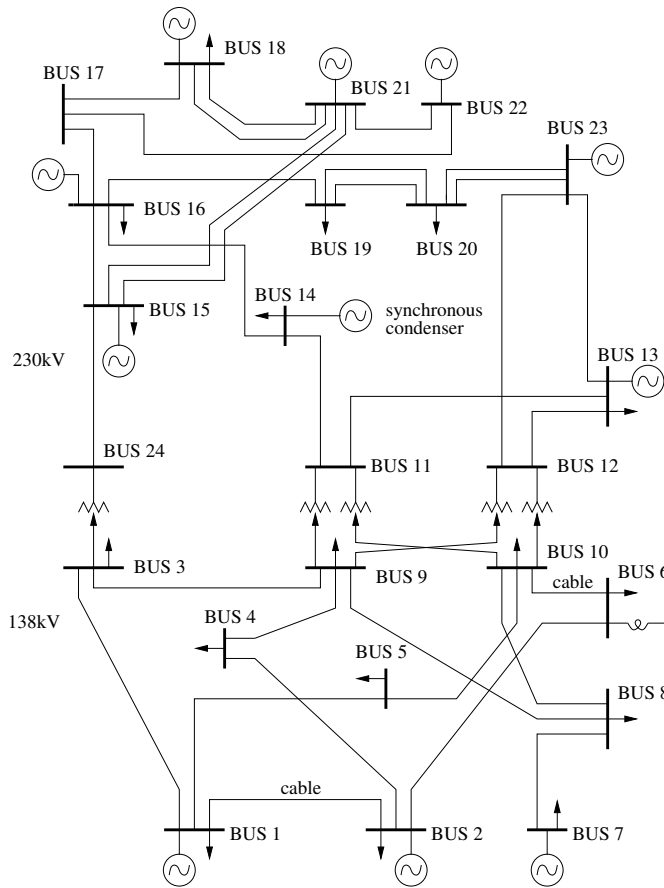


Figure 2. Single line diagram of IEEE RTS

The proposed method reduces the complexity of modeling the output of large PV system considering the failure of system components. The effectiveness of the proposed method was demonstrated on the IEEE RTS. The annualized system indices of the four case studies are shown in Tables II, III. The annualized indices were calculated at the system peak load. As a comparison between the case studies I and II, it is evident that the inclusion of components failures of PV system in the PV generation model has affected the system indices. Therefore, ignoring the effect of components failures of PV system in the PV generation model produces conservative results. The effect of the location of PV farms can be traced through the differences in the values of the reliability indices for the different PV farm locations. For example, placing a PV farm at bus 7 will not enhance the reliability of the system. This can be attributed to the fact that bus 7 has a low risk index [35], [36] and the line connecting bus 7 with the rest of the grid cannot carry the available power. Case studies III and IV were performed to examine the best location of PV farm that enhances system reliability and to evaluate the capacity value of PV power. The capacity value of PV power was evaluated with and without considering the failures of system components at different buses of the test system except bus number 7. The results of these case studies are shown in Table IV. From the reliability point of view, the best location

for the PV farm for this system is at bus 23, 2, 13, and 16, 18, as is obvious from Tables II, III and IV. Further, when PV power is allocated at these buses, the system reliability is enhanced. These observations confirm the ranking of system buses from the risk point of view, which is presented in [35]. It is also clear from the obtained results that ignoring the effect of components failures of PV system in the PV generation model and the system constraints have a significant impact on the capacity value. These analyses would provide the planner a way to allocate investment cost in enhancements.

It is appropriate to briefly discuss the role of harmonics in the above analysis. The conversion of DC from the solar panels to AC using inverters will introduce some harmonics into the system. Modern inverters and filters significantly reduce these harmonics; moreover, the extent of these harmonics introduced is subject to prevailing standards [37]. As such, these do not directly affect the reliability of the system. The only effect that may be considered, if necessary, is a suitable derating of the interfacing transformer.

TABLE II
ANNUALIZED RELIABILITY INDICES WITH PV AT DIFFERENT BUSES OF CASE STUDY I

Bus No.	LOLP	LOLF hour	EDNS MWh/yr	LOEE MWh/yr	LOLE h/yr
1	0.06238	14.51337	10.79608	94573.68044	546.4488
2	0.06238	14.56769	10.87530	95267.63584	546.4488
7	0.08334	19.47382	14.44701	126555.8624	730.0584
13	0.06302	15.16283	10.92197	95676.50309	552.0552
15	0.06256	14.76770	10.57136	92605.11846	548.0256
16	0.06292	14.74510	10.72119	93917.65180	551.1792
18	0.06348	14.94924	10.69334	93673.62330	556.0848
21	0.06286	15.23669	10.92176	95674.63748	550.6536
22	0.06110	14.79606	10.49596	91944.68074	535.2360
23	0.06242	14.96425	10.33896	90569.32802	546.7992

TABLE III
ANNUALIZED RELIABILITY INDICES WITH PV POWER AT DIFFERENT BUSES OF CASE STUDY II

Bus No.	LOLP	LOLF hour	EDNS MWh/yr	LOEE MWh/yr	LOLE h/yr
1	0.07326	17.00887	12.80134	112139.8206	641.7576
2	0.07350	17.15155	13.00607	113933.1912	643.8600
7	0.08353	19.22051	14.57872	127709.6360	731.7578
13	0.07222	17.11950	12.56997	110112.9576	632.6472
15	0.07160	16.95474	12.45556	109110.7792	627.2160
16	0.07410	17.31984	12.80797	112197.8413	649.1160
18	0.07438	17.73118	12.86709	112715.7402	651.5688
21	0.07262	16.71256	12.47330	109266.1346	636.1512
22	0.07328	17.97002	12.74643	111658.7598	641.9328
23	0.07472	17.79722	12.84269	112502.0133	654.5472

REFERENCES

- [1] S. E. Forman, "Performance of experimental terrestrial photovoltaic modules," *IEEE Trans. Rel.*, vol. 31, no. 3, pp. 235–245, 1982.
- [2] A. H. Fannay, D. B. P. Davis, M. W., D. L. King, W. E. Boyson, and J. A. Kratochvil, "Comparison of photovoltaic module performance measurements," *Journal of Solar Energy Engineering*, vol. 128, no. 2, pp. 152–159, 2006.

TABLE IV
CAPACITY VALUE BASED ON LOLE INDEX FOR RTS WITH PV POWER AT
DIFFERENT BUSES

Bus No.	Capacity Value	Equ. Cap. MW	Capacity Value	Equ. Cap. MW
PV Power Considering Sys. Failure			PV Power Only	
1	19%	19	37%	37
2	20%	20	41%	41
13	22%	22	40%	40
15	16%	16	43%	43
16	22%	22	44%	44
18	20%	20	34%	34
21	16%	16	36%	36
22	18%	18	32%	32
23	26%	26	49%	49

- [3] V. Smet, F. Forest, J. Huselstein, F. Richardeau, Z. Khatir, S. Lefebvre, and M. Berkani, "Ageing and failure modes of igbt modules in high-temperature power cycling," *IEEE Trans. Ind. Electron.*, vol. 58, no. 10, pp. 4931–4941, 2011.
- [4] J. Liu and N. Henze, "Reliability consideration of low-power grid-tied inverter for photovoltaic application," in *Proc. 24th European Photovoltaic Solar Energy Conference*, Sept. 2009, pp. 21–25.
- [5] M. Benidris, S. Elsaiah, and J. Mitra, "Sensitivity analysis of reliability performance of multi-level converters," in *Proc. North American Power Symp. (NAPS)*. IEEE, 2012, pp. 1–6.
- [6] L. Kishore and E. Fernandez, "Reliability well-being assessment of pv-wind hybrid system using monte carlo simulation," in *Proc. Int. Conf. of Emerging Trends in Elect. and Comput. Technol.* IEEE, 23–24 March 2011, pp. 63–68.
- [7] 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.
- [8] A. A. Ghaedi, A. 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.
- [9] 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 *Proc. North American Power Symp. (NAPS)*, pp. 1–6.
- [10] H. W. R. Stember, L. H. and M. S. Bridgman, "A methodology for photovoltaic system reliability & economic analysis," *IEEE Trans. Rel.*, vol. 31, no. 3, pp. 296–303, 1982.
- [11] P. Zhang, W. Li, S. Li, Y. Wang, and W. Xiao, "Reliability assessment of photovoltaic power systems: review of current status and future perspectives," *Applied Energy*, vol. 104, pp. 822–833, 2013.
- [12] R. Carbone and A. Tomaselli, "Recent advances on ac pv-modules for grid-connected photovoltaic plants," in *Proc. Clean Electrical Power (ICCEP)*. IEEE, 14–16 June 2011, pp. 124–129.
- [13] D. Picault, B. Raison, and S. Bacha, "Guidelines for evaluating grid connected pv system topologies," in *Proc. Industrial Technology*. IEEE, 10–13 Feb. 2009, pp. 1–5.
- [14] Y. Wang, P. Zhang, W. Li, and N. H. Kan'an, "Comparative analysis of the reliability of grid-connected photovoltaic power systems," in *Proc. Power and Energy Society General Meeting, 2012 IEEE*, July 2012, pp. 1–8.
- [15] W. Xiao, N. Ozog, and W. G. Dunford, "Topology study of photovoltaic interface for maximum power point tracking," *IEEE Trans. Ind. Electron.*, vol. 54, no. 3, pp. 1696–1704, 2007.
- [16] 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," *IEEE Trans. Energy Convers.*, vol. 25, no. 2, pp. 535–545, 2010.
- [17] C. R. S. Reinoso, D. H. Milone, and R. H. Buitrago, "Simulation of photovoltaic centrals with dynamic shading," *Applied Energy*, vol. 103, pp. 278–289, 2013.
- [18] U. De Pra, D. Baert, and H. Kuyken, "Analysis of the degree of reliability of a redundant modular inverter structure," in *Proc. INTELEC*. San Francisco, CA: Telecommunications Energy Conference, 1998., 1998, pp. 543–548.
- [19] H. Calleja, F. Chan, and I. Uribe, "Reliability-oriented assessment of a dc/dc converter for photovoltaic applications," in *Proc. Power Electronics Specialists Conference*. IEEE, 2007, pp. 1522–1527.
- [20] F. Chan and H. Calleja, "Reliability estimation of three single-phase topologies in grid-connected pv systems," *IEEE Trans. Ind. Electron.*, vol. 58, no. 7, pp. 2683–2689, 2011.
- [21] M. Benidris, S. Elsaiah, and J. Mitra, "Sensitivity analysis of reliability performance of multi-level converters," in *Proc. North American Power Symp. (NAPS)*. IEEE, 9–11 Sept. 2012, pp. 1–6.
- [22] R. Ramakumar, *Engineering reliability: fundamentals and applications*. Prentice Hall, 1993.
- [23] R. Ramakumar, *Engineering reliability: fundamentals and applications*. Prentice Hall, 1993.
- [24] R. Billinton, C. L. Wee, and G. Hamoud, "Digital computer algorithms for the calculation of generating capacity reliability indices," *IEEE Power Eng. Rev.*, no. 1, pp. 34–35, 1982.
- [25] W. Li et al., *Reliability assessment of electrical power systems using Monte Carlo methods*. Springer Science & Business Media, 1994.
- [26] 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, 1989.
- [27] S. Sulaeman, M. Benidris, and J. Mitra, "Modeling the output power of pv farms for power system adequacy assessment," in *Proc. North American Power Symp. (NAPS)*. IEEE, Oct 2015, pp. 1–6.
- [28] J. Mitra and C. Singh, "Incorporating the dc load flow model in the decomposition-simulation method of multi-area reliability evaluation," *IEEE Trans. Power Syst.*, vol. 11, no. 3, pp. 1245–1254, 1996.
- [29] J. Mitra and C. Singh, "Pruning and simulation for determination of frequency and duration indices of composite power systems," *IEEE Trans. Power Syst.*, vol. 14, no. 3, pp. 899–905, 1999.
- [30] A. C. G. Melo, M. V. F. Pereira et al., "A conditional probability approach to the calculation of frequency and duration indices in composite reliability evaluation," *IEEE Trans. Power Syst.*, vol. 8, no. 3, pp. 1118–1125, 1993.
- [31] C. Singh, "Calculating the time-specific frequency of system failure," *IEEE Trans. Rel.*, vol. 2, pp. 124–126, 1979.
- [32] National Renewable Energy Laboratory (NREL). Dynamic Maps, GIS Data, and Analysis Tools. [Online]. Available: <http://www.nrel.gov/gis/solar.html>
- [33] A. Garro and F. Barrara, "Reliability analysis of residential photovoltaic systems," in *Proc. Int. Conf. Renewable Energies Power Quality*, vol. 11, 13–14 April 2010.
- [34] IEEE Task Force, "IEEE reliability test system," *IEEE Trans. Power App. Sys.*, pp. 2047–2054, Nov/Dec. 1979.
- [35] M. Benidris, S. Elsaiah, and J. Mitra, "Sensitivity analysis in composite system reliability using weighted shadow prices," in *Proc. Power and Energy Society General Meeting*. IEEE, 2011, pp. 1–6.
- [36] M. Benidris and J. Mitra, "Reliability and sensitivity analysis of composite power systems under emission constraints," *IEEE Trans. Power Syst.*, vol. 29, no. 1, pp. 404–412, 2014.
- [37] C. K. Duffey and R. P. Stratford, "Update of harmonic standard IEEE-519: IEEE recommended practices and requirements for harmonic control in electric power systems," *IEEE Trans. Ind. Appl.*, vol. 25, no. 6, pp. 1025–1034, Nov 1989.