

Analytical Assessment of Time-Varying Reliability and Penetration Limit of PV-Integrated Systems

Dilip Pandit, *Student Member, IEEE*, Nga Nguyen, *Member, IEEE*, Salem Elsaiah, *Member, IEEE*, and Joydeep Mitra, *Fellow, IEEE*

Abstract—This paper presents a discrete convolution-based method for reliability evaluation of a grid-connected photovoltaic (PV) system, where special consideration is given to the variable availability of PV array components. Along with the negative impacts of variable solar irradiance and ambient temperature on the PV power generation, they affect the reliability of PV system power electronic components. A variable availability model based on the power loss in the semiconductors of PV system components is needed to account for this effect in the reliability analysis. The paper proposes a three-dimensional capacity outage model of a PV farm that accounts for the variable availability and the redundancies associated with the topologically complex multi-string PV arrays. The outage model is used to construct a PV capacity outage probability and frequency table (COPAF), which along with conventional generation COPAF, is convolved with the distribution of load to determine system reliability. An integration limit assessment tool is also developed within the proposed framework, ensuring that the PV power integration does not violate the system frequency stability. Simulations on the modified IEEE RTS-79 system demonstrate the efficacy of the proposed method.

Index Terms—Availability, discrete convolution, frequency stability, outage, photo voltaic, reliability.

NOMENCLATURE

ΔT_{IGBT}	Temperature rise in IGBT
ΔT_{diode}	Temperature rise in diode
$\mathcal{P}_{IGBT}$	Power dissipation in IGBT
$\mathcal{P}_{diode}$	Power dissipation in diode
θ_{11}, θ_{22}	Thermal resistance of IGBT and diode
θ_{12}, θ_{21}	Coupling coefficient of IGBT and diode
T_{junc}	Junction temperature for IGBT/diode
T_a	Ambient temperature
θ_a	Thermal resistance from case to ambient
$\mathcal{P}_l$	Power dissipated by additional components
λ_{IGBT}, r_{IGBT}	Failure rate and repair time for IGBT
λ_{0th}	Base IGBT failure rate due to thermal stress
γ_{th}	Accelerating factor for λ_{0th}
V_{app}	Applied voltage
V_r	Rated reverse voltage of IGBT/diode
$\lambda_{diode}, r_{diode}$	Failure rate and repair time for diode
λ_b	Base failure rate for diode
γ_T, γ_S	Thermal and stress accelerating factors
$\lambda_{cap}, \lambda_{ind}$	Failure rate for capacitor and inductor
$\mathcal{L}_{base}$	Base life at maximum temperature T_{max}
T_c	Capacitor core temperature
θ_c	Capacitor to ambient thermal resistance
$\mathcal{P}_{cap}$	Applied power to the capacitor terminals
V_{DC}	Input DC voltage to the capacitor

R_s	Equivalent series resistance of capacitor
T_{ind}	Operating temperature of inductor
$\mathcal{P}_{ind, loss}$	Core and winding loss of inductor
$\mathcal{P}_n, V_n$	Nominal rated power and voltage
A_{ind}	Inductor radiating surface area
L_{ind}	Inductance of the output line filter inductor
λ_{b_ind}	Base failure rate for inductor
$\lambda_{inv,k}, \lambda_{conv,k}$	Failure rate of inverter and DC-DC converter at state k , respectively
$r_{inv,k}, r_{conv,k}$	Repair time of inverter and DC-DC converter at state k , respectively
$\mu_{inv,k}, \mu_{conv,k}$	Repair rate of inverter and DC-DC converter at state k , respectively
l	Total number of inductors in output filter
$\rho_{i,j}$	Transition rate between states i and j
$n_{i,j}$	Total transitions between states i and j
N	Total number of irradiance states
D_i	Duration of state i
P_i	Probability of state i
$P_{a,j}$	Availability of one PV array at irradiance band j
$P_{inv,j}, P_{conv,j}$	Availability of inverter and DC-DC converter, respectively
m	Total number of inverters in a PV farm
n	Total number of DC-DC converters in one array
$P_{i,j,k}$	Probability of a capacity outage level
$P_{pv,i}$	Probability of PV array in state i
$P_{r,j}$	Probability of irradiance in state j
$P_{c,k}$	Probability of DC-DC converters in state k
β_j	Transition rate to lower irradiance states
$f_{i,j,k}$	Frequency of moving to lower outage levels
$\beta_{i,j,k}^+$	Transition rate to lower outage levels
$P_o(X)$	Equivalent probability for outage level X
$\lambda_o(X)$	Equivalent transition rate to lower levels for outage level X
C_i	Aggregated capacity outage for i^{th} state
$P(C \geq X)$	Cumulative probability for outage level X
$F(C \geq X)$	Cumulative frequency for outage level X
H	System equivalent inertia
D	System equivalent damping
K_{LFC}	System LFC controller
R	Equivalent regulation constant
T_R	Equivalent governor constant
F_H	Fraction of power from HP turbines
n_m	Total number of machines in the system
ζ	System Damping Constant

ω_n	System Natural Frequency
$\frac{df}{dt}$	System RoCoF
Δf_{max}	System frequency nadir
Δf_{ss}	Steady state frequency
β	PV integration factor
β_{cv}	Conventional generation inertia reduction factor
Δf_s	Frequency deviation safe limit
$ \frac{df}{dt} _{lim}$	ROCOF safe limit
$\Delta f_{ss,min}$	Steady state frequency safe limit
P_{IR}	ESS power rating for inertia support
H_{IR}	Inertia support provided by ESS
f_r	Rated system frequency
$\frac{df}{dt}$	Estimated maximum system RoCoF
T_{IR}	Time rating of the ESS

I. INTRODUCTION

The inherent advantages of unlimited supply, no fuel cost, and negligible emissions have promoted the integration of solar photovoltaic (PV) generation worldwide. The projection for the PV integration to reach the sustainable development scenario level by 2030 requires the electricity generation from PV to increase 15% annually, from 720 TWh in 2019 to almost 3300 TWh in 2030 [1]. With the projected increase in PV integration, an essential aspect of PV composite systems is assessing their effect on the grid's reliability. One of the significant components of reliability, system generation adequacy, is affected by the intermittent nature of PV generation. Generation adequacy of a power system is a measure of the ability of a power system to supply the load in all the steady states in which the power system may exist considering standards conditions [2]. In addition to intermittency, the multi-component nature of PV power introduces an additional level of complexity to adequacy assessment compared to the two-state conventional generation [3]. Since inclusive reliability models are paramount to planning and operation studies, there is still a need for comprehensive reliability models for PV-integrated systems.

PV farm topology presents a major concern in developing reliability assessment models. Past research works have presented the impacts of PV farm topology on the reliability of PV integrated systems. Authors in [4], [5] have incorporated the effects of common PV topologies such as the central inverter, string, and micro-inverter topologies into their reliability models for system adequacy assessment. Similarly, research in [6], [7] present PV system reliability models based on Monte Carlo simulation, and authors in [8]–[10] analyze PV inverter reliability with an emphasis on component failures. The works mentioned above propose models that deploy a DC-AC cascaded topology for PV farms. Despite their wide usage, the cascaded DC-AC topologies have a problem of series redundancy due to the series inverter-converter structure. In addition to the inverters, the increasing deployment of DC-DC converters for MPPT indicates that they must be included in the reliability assessment [11], [12]. With the increasing inverter and converter power ratings, a failure in any component in the cascaded topology can result in a large

capacity reduction. As a solution, multi-string topologies have been studied extensively in recent research [13]–[15]. Authors in [14] propose a Markov-chain-based analytical reliability model for repair rate estimation. However, the reliability assessment method in [14] cannot be integrated into a composite system since it only considers the design optimization of components within an array. The review of existing works on multi-string topology suggests that there is still a need for an analytical reliability assessment tool for multi-string PV integrated systems.

In addition to the PV farm topologies, the major factors associated with the modeling of PV-integrated systems in reliability studies are the random output of PV farms, load variation, and the forced outage rate of the system components. Authors in [16], [17] propose analytical models of PV farms considering the solar irradiance variability and component availability. Research in [18]–[21] account for geographical and environmental factors such as cloud shading and climate change in their reliability model. Even though these works have considered various factors in their PV reliability models, they have used a constant failure rate for all the PV components. The failure of components within large-scale photovoltaic systems plays a key role in the overall reliability of PV integrated systems. Recent works focus on the potential effects of smaller component failures on the reliability of large PV systems [22], [23]. Research in [24] has shown that the varying solar radiation input contributes to varying failure rates in the power electronic components. The analytical model in [25] and MCS-based methods in [7], [26] have considered varying failure rate in their PV reliability models. However, as indicated by [27], the state enumeration technique used in [25] can pose significant problems with a larger PV-integrated system. Furthermore, [25] is only applicable to the central inverter topology of PV farm and has not considered the outage levels caused by DC-DC converter comprised string failure, which renders the model not useful for multi-string topology. Thus, there is a need for a general analytical model that accounts for redundancies associated with the multi-string topology, considers varying string and array availability, and applies to a large system with multiple generator types.

Another critical topic overlooked in the reliability analysis for systems with high renewable energy penetration is the possibility of frequency instability due to their unmitigated integration, displacing conventional generators with high inertia [28]. Incorporating this property in the reliability assessment of wind integrated systems by limiting the integration of wind power is a major focus in [29], [30]. Since the PV systems also provide negligible inertia and have associated generation intermittency, their integration must be limited so that the frequency security constraints are not violated. The frequency security constraint employed in [29], [30] only considers the system frequency nadir as the controlling variable. However, the system rate of change of frequency (RoCoF) and steady-state frequency are also affected by the integration of zero-inertia intermittent generation [31]. These factors must be considered while enforcing the frequency security constraints to determine the PV integration limit.

In this paper, a discrete convolution-based reliability model

of PV integrated systems is constructed with a thermal power-loss model to accompany the time-varying availability of the PV array components. The proposed three-dimensional PV outage model is used to construct the capacity outage probability and frequency table (COPAF). The COPAF captures the intermittency of the input irradiance and varying availability of the power converters and inverters. In addition, this paper develops an analytical model to determine the PV integration limit to satisfy the frequency security constraints of frequency nadir, maximum RoCoF, and maximum steady state frequency deviation. The discrete convolution model with the PV integration limit assesses the effect of limited PV integration for frequency security on system reliability. The major contributions of the paper are as follows:

- 1) The proposed model is a multi-layered approach that combines the redundancies associated with the multi-string topology with the variable availability of PV system components. The resulting PV farm reliability model is comprehensive and accounts for multiple factors resulting in capacity outages.
- 2) The proposed discrete convolution framework ensures the PV farm reliability model is accurately interfaced with the conventional generation and load, thus improving the reliability of composite systems. Existing literature has primarily focused on intra-PV farm reliability compared to the impacts of PV system components on the overall system reliability.
- 3) The developed analytical PV power integration limit model ensures frequency stability by limiting the displacement of conventional sources. The integration limit model ensures the prevention of optimistic reliability assessment with unmitigated PV power integration, a major in currently available methods.
- 4) The models presented in this paper require low computation time as they do not require Monte-Carlo simulation or optimization for assessment of reliability and PV integration limit.

The paper is organized as follows. Section II presents the multi-string topology considered in this paper. Section III presents the thermal power-loss model to develop a time-varying reliability model of the converter and inverter. Section IV presents the discrete Markov model for irradiance and the reliability model of a PV array. Section V presents the discrete convolution-based reliability model of a PV farm. The PV power integration limit model based on a load frequency controller (LFC) is developed in section VI. Section VII presents the simulation results and discussion.

II. MULTI-STRING PV FARM TOPOLOGY

In this paper, the proposed reliability model considers the multi-string topology of PV farms. Figure 1 illustrates the base topology of a single-phase unit of one PV array. As seen from the figure, a series of PV modules are connected to a DC-DC converter circuit which makes one string of a PV array. Each string of an array has a maximum power point tracking (MPPT) module. A series of strings are connected to one inverter of an array using the DC-combiners. An LCL output

filter is connected to the output of the single-phase inverter before interfacing with the AC bus. Three single-phase units comprise one PV array, a combination of which makes an array group. A PV-farm will have multiple array-groups.

This widely-used PV farm topology has parallel redundancy in two ways. The failure of one array does not lead to a complete failure of an array group, instead causes the PV farm to have a capacity reduction. Similarly, string failures also introduce parallel redundancy since the inverter can still be operational despite string failures. There is no parallel redundancy in the single-phase inverters, i.e., failure of one single-phase inverter will lead to a complete failure of one PV array. The presence of series and parallel redundancies, in addition to the intermittency associated with solar irradiance, causes the PV farm to encounter multiple outage states.

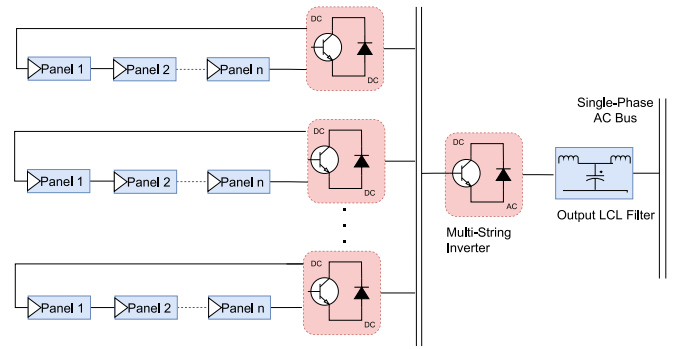


Fig. 1: Multi-String Topology of a Single Phase Component of One PV Array.

III. THERMAL POWER-LOSS MODEL OF PV COMPONENTS

The overall methodology of the proposed work is presented in Fig. 2. As seen in the figure, one of the major steps in the proposed algorithm is to obtain the PV array's variable failure and repair rates based on the clustered irradiance and temperature levels. The failure rate of DC-DC converters and inverters significantly impacts the reliability of PV power integrated systems. The converters and inverters handle a large amount of power, thus incurring higher energy losses in power diodes, switches, and capacitors. The energy losses, dependent on the power flow, change with the input solar irradiance and ambient temperature. Since the losses are proportional to the junction temperature rise, continuous operation under temperature degrades the component reliability. Hence, a thermal model must be included in the PV system reliability assessment that accounts for the impact of varying solar irradiance and ambient temperature rise on the component failure. The thermal power-loss model is developed as follows:

A. Failure Rate of IGBT and Diode

Given the power losses, the temperature rise in IGBT and diode can be calculated as [25]:

$$\Delta T_{IGBT} = \theta_{11} \mathcal{P}_{IGBT} + \theta_{12} \mathcal{P}_{diode} \quad (1)$$

$$\Delta T_{diode} = \theta_{21} \mathcal{P}_{IGBT} + \theta_{22} \mathcal{P}_{diode} \quad (2)$$

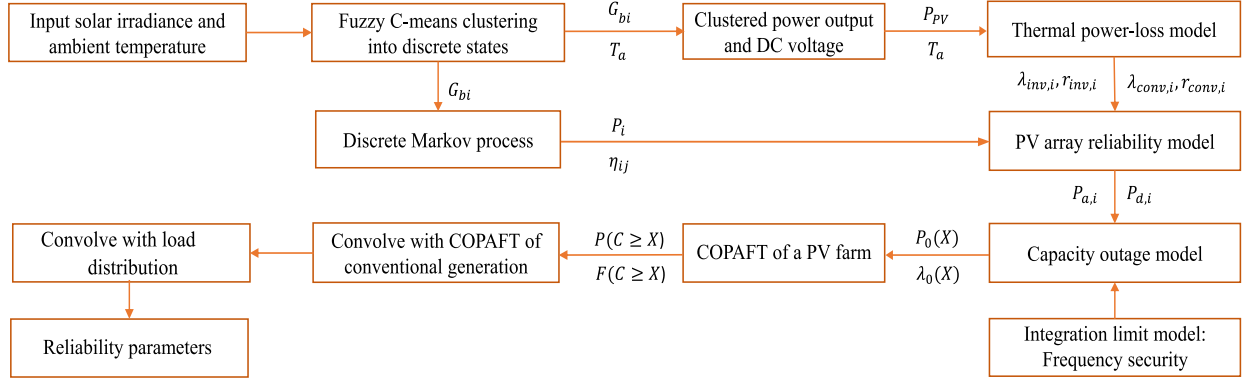


Fig. 2: Proposed Discrete Convolution-based Reliability Model of PV integrated Systems.

The junction temperature for IGBT/diode is calculated as [25]:

$$T_{junc} = T_a + \theta_a (\mathcal{P}_{IGBT} + \mathcal{P}_{diode} + \mathcal{P}_l) + \Delta T_{IGBT/diode} \quad (3)$$

The power dissipation in IGBT and diode are evaluated using the expressions in [32]. Using the expressions for power loss and junction temperature, the failure rate for IGBT is obtained as follows [33]:

$$\lambda_{IGBT} = (\lambda_{0th}\gamma_{th} + \lambda_{cy_case}\gamma_{cy_case} + \lambda_{SJ}\gamma_{SJ} + \lambda_{0RH}\gamma_{RH} + \lambda_{0M}\gamma_M)\gamma_{ind}\gamma_{PM}\gamma_{Process} \quad (4)$$

The stress factors except γ_{th} are not crucial to our problem and hence only their base values are considered. The thermal accelerating factor γ_{th} is given as follows:

$$\gamma_{th} = \gamma_{ei} \times e^{11604 \times 0.7 [1/293 - 1/(T_{junc} + 273)]} \quad (5)$$

and,

$$\gamma_{ei} = \begin{cases} (V_{app}/V_r)^{2.4}, & \text{if } (V_{app}/V_r) > 0.3 \\ 0.056, & \text{if } (V_{app}/V_r) \leq 0.3 \end{cases} \quad (6)$$

Similarly, for diode, the failure rate is expressed as [34]:

$$\lambda_{diode} = \lambda_b \gamma_T \gamma_S \gamma_c \gamma_Q \gamma_E \quad (7)$$

Again, the important accelerating factors are:

$$\gamma_T = e^{-3091(1/(T_{junc} + 273) - 1/298)} \quad (8)$$

$$\gamma_S = \begin{cases} (V_{app}/V_r)^{2.4}, & \text{if } 0.3 < (V_{app}/V_r) < 1 \\ 0.054, & \text{if } (V_{app}/V_r) \leq 0.3 \end{cases} \quad (9)$$

Other accelerating factors can be obtained from [34].

B. Failure Rate of Capacitors and Inductors

The commonly accepted formula is used for capacitor failure rate, which is expressed as follows [25]:

$$\lambda_{cap} = \frac{1}{L_{base} \times 2^{(T_{max} - T_c)/10}} \quad (10)$$

The capacitor core temperature can be calculated as [25]:

$$T_c = T_a + \theta_c \left[\left(\frac{\mathcal{P}_{cap}}{\sqrt{2}V_{DC}} \right)^2 R_s \right] \quad (11)$$

The inductors are a crucial part of the PV system as they are used in the DC-DC converter and the output line filter circuit. The operating temperature of the inductor is given by [34]:

$$T_{ind} = T_a + 137.5 \times \mathcal{P}_{ind_loss} \frac{V_n}{A_{ind} L_{ind} \mathcal{P}_n} \quad (12)$$

The failure rate for inductors is given by [34]:

$$\lambda_{ind} = \lambda_{b_ind} \gamma_T \gamma_Q \gamma_E \quad (13)$$

The thermal accelerating factor is given as follows:

$$\gamma_T = e^{-1276.54(1/(T_{ind} + 273) - 1/298)} \quad (14)$$

C. Reliability Model of DC-DC Converter and Inverter

The reliability model of the DC-DC converter and inverter can be modeled separately as series networks since there are no parallel redundancies in both components. Let us define a state $k = (G_{bi}, T, V_{DC})$ with irradiance G_{bi} , atmospheric temperature T , and the MPPT assigned DC-voltage V_{DC} . The equivalent failure rate and repair rate for the DC-DC converter at state k are given as follows:

$$\lambda_{conv,k} = \lambda_{pv} + \lambda_{cap}(k) + \lambda_{ind}(k) + \sum_i (\lambda_{diode,i}(k) + \lambda_{IGBT,i}(k)) \quad (15)$$

$$r_{conv,k} = \frac{1}{\mu_{conv,k}} = \frac{1}{\lambda_{conv,k}} [\lambda_{pv} r_{pv} + \lambda_{cap}(k) r_{cap} + \lambda_{ind}(k) r_{ind} + \sum_i (\lambda_{diode,i}(k) r_{diode} + \lambda_{IGBT,i}(k) r_{IGBT})] \quad (16)$$

Similarly, the inverter failure and repair rates are as follows:

$$\lambda_{inv,k} = \lambda_{dc} + \lambda_{ac} + \lambda_{cap}(k) + \sum_l \lambda_{ind,l}(k) + \sum_j (\lambda_{diode,j}(k) + \lambda_{IGBT,j}(k)) \quad (17)$$

$$r_{inv,k} = \frac{1}{\mu_{inv,k}} = \frac{1}{\lambda_{inv,k}} [\lambda_{dc} r_{dc} + \lambda_{ac} r_{ac} + \lambda_{cap}(k) r_{cap} + \sum_l \lambda_{ind,l}(k) r_{ind} + \sum_j (\lambda_{diode,j}(k) r_{diode} + \lambda_{IGBT,j}(k) r_{IGBT})] \quad (18)$$

where, i, j are the number of diodes/switches in DC-DC converter and inverter respectively, subscript pv denotes the aggregated PV modules in a string, subscript dc denotes the aggregated model of DC-combiner and DC-disconnect, and ac denotes the AC sub-panel.

IV. MULTI-COMPONENT SOLAR ARRAY RELIABILITY MODEL

The previous section developed a thermal power-loss model that quantifies the impact of variable irradiance and temperature on the DC-DC converter and inverter failure rates. The following sections will develop an analytical PV farm reliability model based on the discrete convolution method.

A. Solar Irradiance Model using Discrete Markov Process

The solar irradiance time-series fuzzy clustered data is modeled using a discrete Markov chain [35]. A Markov chain can capture the probability and frequency of each solar irradiance level. A limited number of clustered irradiance levels are chosen as states in a Markov chain, with each state having a probability and frequency of transition to other states. As the transition of irradiance from one state to another is random, transition among all the states is possible. With a sufficient number of samples, the transition rate between any states is evaluated using the frequency balance between the states. The transition rate between any two states and state probability is determined as follows [36]:

$$\rho_{i,j} = \frac{n_{ij}}{D_i} \quad (19)$$

$$P_i = \frac{\sum_{j=1}^N n_{ij}}{\sum_{k=1}^N \sum_{j=1}^N n_{kj}} \quad (20)$$

B. Reliability model of an Array

From the topology of a multi-string PV array, it can be seen that only the failure of inverter and line filter components leads to a complete failure of the array. This paper aggregates the failures of PV modules in a string and adds to the DC-DC converter failure rate. So, the DC-DC converter failure rate also represents the string failure. Hence, a PV array can have derated states due to the DC-DC converter failure and the change in solar irradiance. The availability of one PV array is expressed as:

$$P_{a,j} = P_{inv,j} \sum_{i=1}^n \binom{n}{i} P_{conv,j}^i (1 - P_{conv,j})^{n-i} \quad (21)$$

The availability of the inverter and DC-DC converter can be expressed as:

$$P_{inv,j} = \frac{\mu_{inv,j}}{\lambda_{inv,j} + \mu_{inv,j}}, \quad P_{conv,j} = \frac{\mu_{conv,j}}{\lambda_{conv,j} + \mu_{conv,j}} \quad (22)$$

The failure and repair rates for any irradiance state j are calculated using (15)-(18).

V. MODELING OF PV FARM CAPACITY OUTAGE

A. PV Farm Capacity Outage Model

This paper presents an improved model for the PV-farm capacity outage. Past works have focused on implementing the unit addition algorithm to one PV array at a time [16], [37] assuming a constant availability of strings and a central inverter topology. While the model can be computationally feasible, it suffers in accuracy as the outage states due to the partially and fully operational arrays cannot be modeled accurately. This paper models the capacity outage states of the PV array group (PV farm has multiple array groups) as a three-dimensional tensor. Each state will have a probability and frequency of jumping to lower capacity states.

Let, $i = 1, 2, \dots, m$ be the number of PV arrays in one array group, $k = 1, 2, \dots, n$ be the number of DC-DC converters in one array, and G_j be the output of one DC-DC converter in radiation level j , where $j = 1, 2, \dots, J$. Any state in the capacity outage matrix will have an outage value equal to:

$$C_{i,j,k} = mnG_J - ((m-i)n + k)G_j \quad (23)$$

The probability of any state in the tensor is given by:

$$P_{i,j,k} = P_{pv,i} \times P_{r,j} \times P_{c,k} \quad (24)$$

where, $P_{pv,i}$ = Probability of the PV array in i -state, given by:

$$P_{pv,i} = \binom{m}{i} P_{a,j}^i (1 - P_{a,j})^{m-i} \quad (25)$$

where $P_{a,j}$, $P_{d,j}$ are obtained from (21). $P_{r,j}$ in (24) is obtained from (20) and,

$$P_{c,k} = \binom{n}{k} P_{conv,j}^k (1 - P_{conv,j})^{n-k} \quad (26)$$

As discussed previously, any outage state can move to a higher capacity outage in multiple ways due to the intermittency and component failures. We will consider the transition to lower capacity outage levels instead of higher capacity outage levels due to the associated computation efficiency and frequency balance of the system [30]. Generally, for an outage state, the transition rates to lower outage levels with the highest occurring probability are as follows:

- Transition of solar radiation to a higher level $\sum_{i=j+1}^N \beta_i$.
- Repair of a DC-DC converter $\mu_{conv,j}$.
- Repair of inverter of a fully operational array $\mu_{inv,j}$.
- Repair of inverter of a partially operational array $\mu_{inv,j}$.

It should be considered that the transition rates will be different in the extreme regions of the tensor. For example, state $C_{m,k,j}$ cannot make a $\mu_{inv,j}$ transition since all the arrays are available. Mathematically, frequency of moving to the lower capacity outages of one state is given by:

$$f_{i,j,k} = P_{i,j,k} \times \sum \beta_{i,j,k}^+ \quad (27)$$

where $\beta_{i,j,k}^+$ is the sum of aforementioned transition levels. Since there are multiple overlapping outage states, they will

be aggregated to one state with a probability and transition rate. The resulting expressions are as follows:

$$P_o(X) = \sum_{i,j,k} P_{i,j,k}(X) \quad (28)$$

$$\lambda_o(X) = \frac{\sum f_{i,j,k}(X)}{P_o(X)} \quad (29)$$

The outage state probabilities and frequencies of PV array groups are used to build a Capacity Outage Probability and Frequency Table (COPAFT) for a PV farm. The PV farm COPAFTs are then convolved with the conventional generator COPAFT and load levels to estimate the reliability indices.

B. Formation of Capacity Outage and Frequency Table

A PV farm is considered a multi-state generator due to varying input radiation and component failures. Each capacity outage level has a probability and frequency of transition to lower outage levels. The unit addition algorithm with discrete convolution is used to develop a COPAFT. For a conventional generator, the cumulative probability and transition frequency to lower capacity outage states for an outage of X MW can be calculated as follows [38]:

$$\begin{aligned} F(C \geq X) &= \sum_{i=1}^2 (F'(X - C_i) p_{cv,i}) + \\ &\quad (P'(X - C_2) - P'(X)) p_{cv,2} \mu_{cv} \\ P(C \geq X) &= \sum_{i=1}^2 P'(X - C_i) p_{cv,i} \end{aligned} \quad (30)$$

where, $p_{cv,i}$ is the probability of a conventional generator to have a capacity outage of C_i , and μ_{cv} is the repair rate of the generator. The P' and F' denote the probability and frequency of the old COPAFT table, respectively. Using the unit addition algorithm, the addition of new generator results in the formation of a new COPAFT. Since a PV array can be considered a conventional generator with multiple outage states, the cumulative frequency and probability for a PV array are expressed as follows:

$$P(C \geq X) = \sum_{i=1}^N (P'(X - C_i) \times P_o(C_i)) \quad (31)$$

$$F(C \geq X) = F_1 + F_2 + F_3 \quad (32)$$

where,

$$F_1 = \sum_{i=1}^N ((F'(X - C_i) \times P_o(C_i)) \quad (33)$$

$$F_2 = \sum_{i=1}^N [(P'(X - C_{i+1}) - P'(X - C_i)) P_o(C_{i+1}) \lambda_o(C_{i+1})] \quad (34)$$

$$F_3 = (P'(X - C_N) - P'(X - C_1)) P_o(C_N) \lambda_o(C_N) \quad (35)$$

In above expressions, F_1 and F_2 result from the changes in states of units other than the added unit, while F_3 results from a change in the state of the added unit.

VI. ESTIMATION OF PV POWER INTEGRATION LIMIT

The system model is represented by a low-order LFC multi-machine model [39]. If the load disturbance is assumed to be

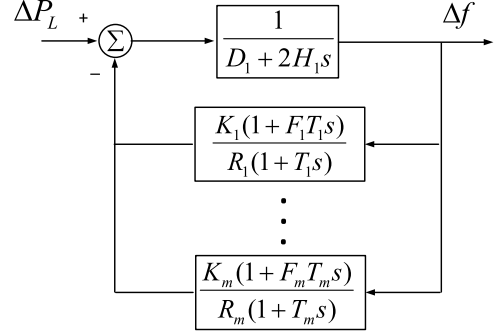


Fig. 3: LFC model for a multi-machine system [40].

a step function ΔP_L , the frequency deviation is given by [39]:

$$\Delta f = \frac{\Delta P_L}{D + 2Hs + \sum_{i=1}^{n_m} \frac{K_{LFC,i}(1 + F_i T_R s)}{(1 + T_R s)}} \quad (36)$$

Considering equivalent T_R for all the generators in the system, the frequency deviation can be expressed as follows:

$$\Delta f = \frac{\Delta P_L}{2HT_R} \frac{1 + T_R s}{s(s^2 + 2\zeta\omega_n s + \omega_n^2)} \quad (37)$$

Rewriting,

$$\Delta f = \frac{\Delta P_L}{2HT_R} \frac{1}{s(s^2 + 2\zeta\omega_n s + \omega_n^2)} + \frac{\Delta P_L}{2H} \frac{1}{(s^2 + 2\zeta\omega_n s + \omega_n^2)} \quad (38)$$

Applying Laplace transformation to (38), the time-domain frequency deviation is given by:

$$\begin{aligned} \Delta f &= \frac{\Delta P_L}{2HT_R\omega_n^2} \left(1 - \frac{1}{\sqrt{1 - \zeta^2}} e^{-\zeta\omega_n t} \cos(\omega_n \sqrt{1 - \zeta^2} t - \phi) \right) \\ &\quad + \frac{\Delta P_L}{2H\omega_n \sqrt{1 - \zeta^2}} e^{-\zeta\omega_n t} \cos(\omega_n \sqrt{1 - \zeta^2} t) \end{aligned} \quad (39)$$

where,

$$\begin{aligned} R_T &= \sum_{i \in n} \frac{K_{LFC,i}}{R_i}, \quad F_T = \sum_{i \in n} \frac{K_{LFC,i} F_i}{R_i}, \\ \zeta &= 0.5 \times \frac{2H + T_R(D + F_T)}{\sqrt{2HT_R(D + R_T)}}, \quad \omega_n = \sqrt{\frac{D + R_T}{2HT_R}} \end{aligned}$$

Similarly, the instantaneous RoCoF can be expressed as:

$$\begin{aligned} \frac{df}{dt} &= s\Delta f = \frac{\Delta P_L}{2HT_R} \frac{1}{(s^2 + 2\zeta\omega_n s + \omega_n^2)} \\ &\quad + \frac{\Delta P_L}{2H} \frac{s}{(s^2 + 2\zeta\omega_n s + \omega_n^2)} \end{aligned} \quad (40)$$

Expressing the RoCoF in time domain, we get:

$$\begin{aligned} \frac{df}{dt} &= \frac{\Delta P_L}{2HT_R\omega_n \sqrt{1 - \zeta^2}} e^{-\zeta\omega_n t} \sin(\omega_n \sqrt{1 - \zeta^2} t) \\ &\quad + \frac{\Delta P_L}{2H\sqrt{1 - \zeta^2}} e^{-\zeta\omega_n t} \cos(\omega_n \sqrt{1 - \zeta^2} t + \phi) \end{aligned} \quad (41)$$

The maximum frequency deviation (nadir) can be estimated by equating (40) to zero. The frequency nadir can then be expressed as:

$$\Delta f_{max} = \frac{\Delta P_L}{R_T + D} \left(1 + e^{-\zeta \omega_n t_{max}} \sqrt{\frac{T_R(R_T - F_T)}{2H}} \right) \quad (42)$$

Since the delay of the RoCoF relay is not considered in this work, the system is assumed to attain maximum RoCoF at $t = 0$. The maximum RoCoF can be expressed as follows:

$$\left| \frac{df}{dt} \right|_{max} = \left| \frac{df}{dt} \right|_{t=0} = \frac{\Delta P_L}{2H\sqrt{1-\zeta^2}} \cos(\phi) \quad (43)$$

Using the final value theorem, the steady state frequency can be estimated. The settling time can be estimated using the second order approximation for a step disturbance. They are expressed as follows:

$$\Delta f_{ss} = \lim_{s \rightarrow 0} s \Delta f = \frac{\Delta P_L}{2HT_R\omega_n^2} \quad (44)$$

As the low inertia PV farms replace the conventional generators, total system inertia decreases and the equivalent system regulation increases. This effect is modeled using a PV integration factor β which can be expressed as follows:

$$\beta = 1 - \beta_{cv} \quad (45)$$

It is assumed that the PV farms provide zero inertia support. Hence, the system equivalent reduced inertia is given by $H = \beta H$ and increased frequency regulation constant is given by $R = R/\beta$. Consequently, the new values due to the change in H and R with PV integration are calculated as follows:

$$R_T = \sum_{i \in n} \beta \frac{K_i}{R_i}, \quad F_T = \sum_{i \in n} \beta \frac{K_i F_i}{R_i}$$

$$\zeta_{pv} = 0.5 \times \frac{2\beta H + T_R(D + \beta F_T)}{\sqrt{2\beta H T_R(D + \beta R_T)}}, \quad \omega_{n,pv} = \sqrt{\frac{D + \beta R_T}{2\beta H T_R}}$$

The value of β changes with the integration level of RERs which consequently changes the system frequency response. According to the sensitivity analysis in [29], the effect of load damping D can be ignored and the values can be approximated as $\zeta_{pv} = \zeta$ and $\omega_{n,pv} = \omega_n$. Consequently, the maximum value of β can be obtained as follows:

$$\beta_{max} = \max[\beta_{max,1}, \beta_{max,2}, \beta_{max,3}] \quad (46)$$

where,

$$\beta_{max,1} = \frac{\Delta P}{\Delta f_s R_T} \left(1 + e^{-\zeta \omega_n t_{max}} \sqrt{\frac{T_R(R_T - F_T)}{2H}} \right) \quad (47)$$

$$\beta_{max,2} = \frac{\Delta P_L}{2H \left| \frac{df}{dt} \right|_{lim} \sqrt{1-\zeta^2}} \cos(\phi) \quad (48)$$

$$\beta_{max,3} = \frac{\Delta P_L}{2f_{ss,min} H T_R \omega_n^2} \quad (49)$$

The values of (47)-(49) can be termed as the frequency security parameters. The vector of parameters $[\beta_{max,1}, \beta_{max,2}, \beta_{max,3}]$ correspond to the values of Δf_s , $\left| \frac{df}{dt} \right|_{max}$, and $f_{ss,min}$ respectively. Using the value of β_{max} in (45), β_{cv} can be estimated,

which is further used to find the maximum integration power of PV farms. Consideration of these frequency security parameters to obtain the PV power integration limit is among the major contributions of this paper.

VII. SIMULATION AND RESULTS

The proposed method is implemented on the IEEE RTS-79 system with MATLAB as the simulation platform. The original IEEE RTS-79 system includes 32 conventional generators with a total capacity of 3405 MW. The 400 MW generator is displaced by PV farms of varying capacity for all simulation scenarios. All the other generators, their failure and repair rates, and the load levels have been kept the same as in the standard IEEE-RTS system [41]. The major reason for the generator replacement by PV farms is to ensure the frequency stability studies are performed on a slightly reduced inertia system. The annual peak load of the system is 2850 MW. Also, comparing the reliability results with the base case in [41], the modified system illustrates the change in system reliability when a large conventional generator is replaced by PV farms, which is pertinent to the recent changes in real-world power generation. The system is modified with varying penetration of PV farms of capacity 140 MW each. Each PV farm has 8 array groups, where each array group has 50 PV arrays. Each array has a rated power capacity of 350 kW with three single-phase inverters. Each PV array consists of 50 strings with a 7 kW DC-DC converter in each string. The three-year solar radiation data from 2018-20 is extracted using the NSRDB database provided by the National Renewable Energy Laboratory (NREL) [42] and mean-clustered into one-hour intervals. Then, fuzzy C-means clustering is applied to divide the irradiation into 8 states. The transition rate matrix of the clustered states is evaluated using (19) and presented in Table II. The values of clustered radiation, associated MPPT voltage, and state probabilities are shown in Table III.

TABLE I: Modified RTS System Inertia Data.

Generator Name	G_{12}	G_{20}	G_{50}	G_{76}	G_{100}	G_{155}	G_{197}	G_{350}	G_{400}
Number of Generators	5	4	6	4	3	4	3	1	1
Power (MW)	12	20	50	76	100	155	197	350	400
Inertia (s)	0.34	0.56	1.75	2.28	2.8	4.65	5.52	10.5	20

TABLE II: Transition Rates Between Solar Irradiance States

State	1	2	3	4	5	6	7	8
1	0.922	0.045	0.033	0	0	0	0	0
2	0.523	0.078	0.232	0.161	0.006	0	0	0
3	0.139	0.336	0.058	0.335	0.126	0.003	0.002	0
4	0	0.149	0.290	0.067	0.296	0.193	0.003	0
5	0	0.007	0.182	0.275	0.224	0.238	0.073	0.001
6	0	0.002	0.006	0.104	0.340	0.232	0.312	0.003
7	0	0	0.002	0.003	0.055	0.339	0.303	0.296
8	0	0	0	0	0.005	0.023	0.290	0.681

TABLE III: Fuzzy C-means Clustered Irradiance Levels, Ambient Temperature, Associated State Probabilities and DC Voltage.

State	1	2	3	4	5	6	7	8
$G_{bi}(W/m^2)$	2.733	119.2	260.4	411.8	551.6	687.6	837.8	988.9
$T_a(^{\circ}C)$	3.174	7.803	12.33	16.87	21.56	26.32	31.56	37.20
P_i	0.543	0.062	0.068	0.064	0.071	0.068	0.063	0.060
$V_{dc}(V)$	216.7	258.1	265.7	269.2	271.0	272.2	271.8	273.6

A. PV Farm Variable Availability Assessment

The clustered irradiance and ambient temperature data for an arbitrary day are presented in Fig. 4 and the variation in the junction temperatures of the components of converters and inverters for that particular day is illustrated in Fig. 5. This variation in junction temperature is dependent on the irradiance and ambient temperature. It can be noted that the junction temperature of DC-DC converter components in Fig. 5a is more correlated with the ambient temperature in Fig. 4b. In contrast, Fig. 5b is more correlated with the irradiance level in Fig. 4a. The temperature increase in the DC-DC converter is more dependent on the ambient temperature than the component power loss (due to the smaller current in the strings). In contrast, the inverter components incur a much larger current. Figure 6 shows the variation in the availability of inverters and converters for a day. Since the variation in irradiance and temperature affects both the failure and repair rates of the components, there is a considerable variation in the availability, especially the inverter availability. Including the time-varying failure and repair rates in the reliability model helps to capture this correlation between the component availability and environmental conditions, which is often ignored in the constant availability-based analysis.

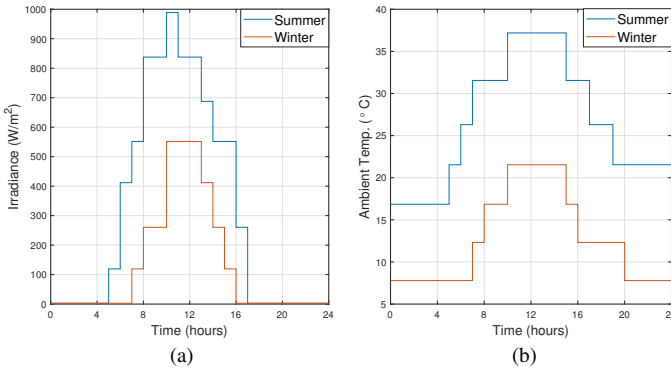


Fig. 4: a) Solar Irradiance b) Ambient Temperature in an Arbitrary Day.

B. Reliability Assessment Simulation Scenarios

In order to demonstrate the impacts of varying availability of inverters and converters and the frequency security consideration, simulations are performed under various scenarios as described below:

- *Scenario I-I, and Scenario I-II*: In Scenario I-I, three solar farms are integrated into the system with total PV power

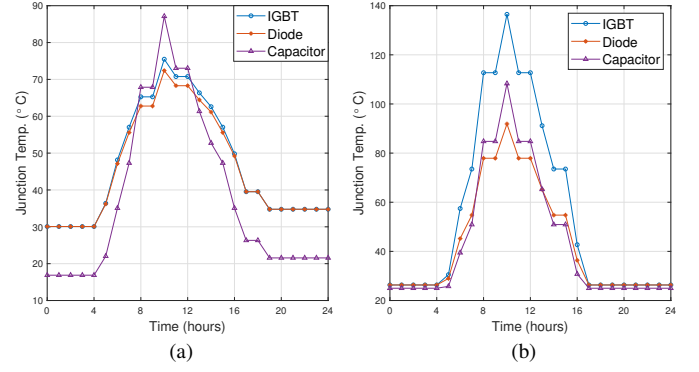


Fig. 5: Junction Temperature of a) Converter b) Inverter Components in a Summer Day.

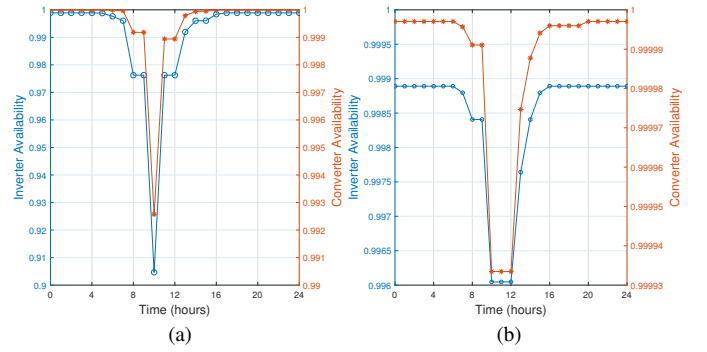


Fig. 6: Availability of Inverters and Converters on an Arbitrary Day. a) Summer b) Winter Day.

of 420 MW. Both the variable availability model and the integration limit model are ignored. In Scenario I-II, the variable availability is aggregated to the discrete convolution model while ignoring the integration limit model. These scenarios will illustrate the effects of time-varying component availability on system reliability.

- *Scenario II-I, and Scenario II-II*: In Scenario II-I, six solar farms are integrated into the system with total PV power of 840 MW, and the reliability is evaluated without variable availability and integration limit models. In Scenario II-II, the variable availability is aggregated to the discrete convolution model without considering the integration limit model. These scenarios investigate the effect of PV power increase and how the variable availability of components can affect the system reliability under high PV penetration.
- *Scenario III-I and Scenario III-II*: In scenario III-I, the PV power integration limit model is integrated into the system in scenario II-I while ignoring the variable availability model. Scenario III-II considers both models in the reliability analysis. The integration limit can be obtained using the procedure described in Section VI. For the RTS system without the 400 MW generator, the frequency security limits are chosen as: $\Delta f_s = 0.25$, $|df/dt|_{lim} = 0.5$, and $\Delta f_{ss,min} = 0.1$. The corresponding value for $\beta_{max} = [0.8085, 0.7335, 0.7464]$ and $\beta_{cv} = 0.1915$. Hence, the maximum inertia that can be displaced is $H_{pv} = 18.6903$ s. The best combination of conventional generators for the

TABLE IV: Cumulative Outage Probability and Frequency for a Single PV Array Group

Outage Level (X) (MW)	Scenario I-I		Scenario I-II		Scenario III-I		Scenario III-II	
	$P(C \geq X)$	$F(C \geq X)$	$P(C \geq X)$	$F(C \geq X)$	$P(C \geq X)$	$F(C \geq X)$	$P(C \geq X)$	$F(C \geq X)$
0	1	0	1	0	1	0	1	0
1	0.94018	0.04360	0.99205	0.04225	0.94011	0.04346	0.98488	0.04224
2	0.94003	0.04360	0.96048	0.04225	0.94003	0.04345	0.95066	0.04223
3	0.89163	0.04660	0.92367	0.04224	0.87675	0.04347	0.88174	0.04315
4	0.87668	0.04360	0.87902	0.04224	0.87667	0.04345	0.87671	0.04222
5	0.87667	0.05617	0.87668	0.04224	0.80853	0.04348	0.80872	0.04222
6	0.80861	0.04364	0.80896	0.04224	0.80844	0.04345	0.80844	0.04222
7	0.80844	0.04360	0.80844	0.04224	0.73767	0.04346	0.73766	0.04223
8	0.75437	0.04713	0.75038	0.04586	0.73766	0.06288	0.73766	0.07090
9	0.73766	0.04360	0.73766	0.04224	0.67366	0.04345	0.67366	0.07208
1	0.73766	0.06201	0.73766	0.07025	0.67366	0.06306	0.67366	0.07208
11	0.67366	0.04360	0.67366	0.04224	0.60554	0.06294	0.60554	0.06590
12	0.67366	0.06217	0.67366	0.07162	0.60554	0.06294	0.60554	0.06590
13	0.62162	0.04867	0.61076	0.04460	0.54321	0.08691	0.54321	0.08445
14	0.60554	0.06206	0.60554	0.06563				
15	0.60554	0.06206	0.60554	0.06563				
16	0.54321	0.04360	0.54321	0.04224				
17	0.54321	0.08719	0.54321	0.08448				

displacement is obtained to be $1 \times G_{350}$, $2 \times G_{100}$, $1 \times G_{76}$, and $1 \times G_{12}$, resulting in total power that can be displaced to be 638 MW. Despite the total available PV power being 840 MW, only 638 MW can be integrated into the system to ensure frequency security. It can also be noted that the integration limit was not applied to scenarios I-I and I-II because the total available PV power of 480 MW was less than the integration limit of 638 MW. These scenarios illustrate how the need to maintain frequency security can negatively impact system reliability.

C. Frequency Security Analysis

Frequency security analysis for the reliability assessment scenarios is performed using the Monte-Carlo simulation. Since the conventional generator parameters are extracted in a uniform distribution within limits specified in [40], the simulation results are averaged over 10^4 Monte-Carlo trials for each scenario to ensure consistency. The variable availability model is not considered in this simulation as they do not have any impact on the system inertia. The Monte-Carlo simulation-based frequency security assessment results have been summarized in Table V.

TABLE V: Frequency Security Indices of Simulation Scenarios (averaged over trials).

Index	H s	Δf_{max} Hz	$ \frac{df}{dt} _{max}$ Hz/s	Δf_{ss} Hz	Violation?
Scenario I-I	84.808	0.2172	0.3529	0.0768	No
Scenario II-I	72.148	0.2522	0.4145	0.0890	Yes
Scenario III-I	76.928	0.2416	0.3891	0.0856	No

As seen in Table V, the frequency security limit is violated in scenario II-I as the frequency nadir exceeds the predefined limit of 0.25 Hz. It can be attributed to the fact that to integrate

a large amount of PV power (840 MW), more conventional generators need to be displaced, thus reducing the system equivalent inertia as seen in Table V. In scenario III-I, by incorporating the integration limit model, the total PV power integration is reduced to 648 MW, and the frequency security constraints are satisfied.

D. Reliability Assessment Results

The proposed discrete convolution-based method is implemented on the modified RTS system under various simulation scenarios. The reliability assessment results are summarized in Table VI. Based on the simulation results, the following observations can be made:

- 1) The effect of incorporating the variable availability model into the base discrete convolution model can be seen in the COPAFT for a single PV sub-array in Table IV. The cumulative probability for lower outage levels is much higher in scenario I-II compared to scenario I-I. For example, considering the outage level of 1 MW, the probability for a PV sub-array in scenario I-I to have an outage of 1 MW or higher is 0.94018, whereas, in scenario I-II, the probability is much larger at 0.99205. This indicates that the PV array has a greater outage probability at smaller outage levels when the variable availability model is integrated. The reliability indices for scenarios I-I and I-II are presented in Table VI. From the table, it can be seen that the indices degrade when the variable availability model is added in scenario I-II.
- 2) From Table VI, in scenarios II-I and II-II, the reliability indices improve compared to scenarios I-I and I-II since an additional 420 MW of PV power is integrated into the system. It can also be noted that, in scenario II-II, when the varying availability model is integrated into II-I, the indices worsen slightly more compared to the difference between scenarios I-I and I-II. It is because as the PV power

integration increases, the impact of the variable failure rate becomes more significant.

- 3) In scenario III, the PV power integration is limited to 638 MW due to the integration limit for frequency security. As expected, the reliability indices in Table VI degrade compared to scenarios II-I and II-II as the available PV power is curtailed to maintain frequency security. The COPAFT in Table IV for a single PV array-group also changes due to the power curtailment. As seen in the table, the maximum outage level for the array group is limited to 13 MW due to the integration limit constraint. The LOLP and LOLE for the cases when the system load exceeds the generation are presented in Fig. 7 and Fig. 8 respectively.

TABLE VI: Reliability Indices of PV Integrated IEEE-RTS

Index	LOLP	HOLE h/yr	LOLE f/yr	EDNS MW/yr	EUEE MWh/yr
Scenario I-I	0.00315	27.542	10.158	0.3847	3360.9
Scenario I-II	0.00318	27.788	10.276	0.3910	3423.7
Scenario II-I	0.00133	11.579	6.5303	0.1492	1298.5
Scenario II-II	0.00138	12.011	6.8394	0.1654	1380.5
Scenario III-I	0.00183	16.008	7.6985	0.2128	1858.9
Scenario III-II	0.00188	16.440	8.0468	0.2201	1922.7

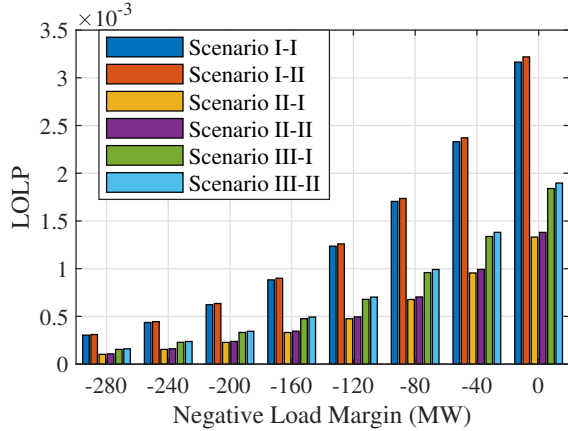


Fig. 7: LOLP for Negative Load Margins ($P_{Gen} < P_{Load}$).

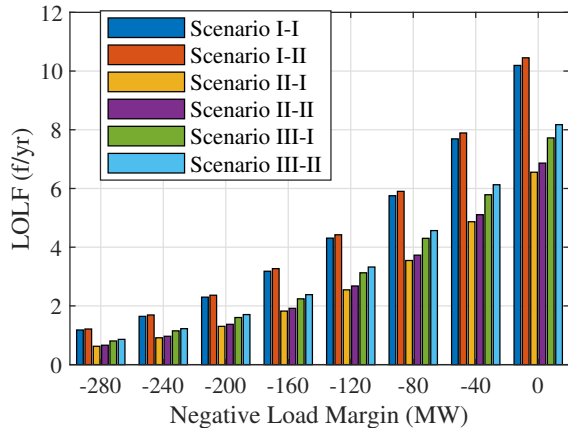


Fig. 8: LOLE for Negative Load Margins ($P_{Gen} < P_{Load}$).

Additional Scenario: The frequency security simulation results show that the PV integration must be limited in scenario II-I to ensure system frequency security. However, with the growing need for renewable power and the associated costs, curtailment of available PV power cannot be a feasible option for the generation authorities and system operators. As a result, the energy storage system (ESSs) can be deployed to provide inertia support to the grid so that the integration of PV power can be maximized. For scenario II, where the frequency security is violated, the ESS can be sized as follows:

The real power required to be injected by the ESS for inertia support, P_{IR} , is expressed as follows [31]:

$$P_{IR} = \frac{2H_{IR}}{f_r} \frac{df}{dt} \quad (50)$$

The integration limit model showed that 202 MW of PV power must be curtailed in scenario II to ensure frequency security. In this scenario, instead of curtailing the PV power, ESS are deployed to compensate for the loss of inertia caused by the displacement of conventional generators by PV farms. The generator combination for the 202 MW displacement is chosen to be $1 \times G_{155}, 1 \times G_{50}$, resulting in the inertia support required from the ESS to be $H_{IR} = 6.4$ s. The required ESS power P_{IR} is thus obtained to be 10.67 MW. Also, the energy capacity of the ESS for inertia support can be obtained as follows:

$$S_{IR} = P_{IR} T_{IR} \quad (51)$$

Since the ESS is assumed to provide inertia support for the duration of the disturbance, the ESS time rating (T_{IR}) can be estimated to be the settling time for a step disturbance. Using the second order approximation:

$$T_{IR} = \frac{0.02\sqrt{1-\zeta^2}}{\zeta\omega_n} \quad (52)$$

The total capacity of the ESS deployed to ensure frequency security is thus obtained to be $P_{IR} = 10.67$ MW and, $S_{IR} = 74.69$ kWh. Fig. 9 and Fig. 10 present the system frequency response with the integration of ESS. From Fig. 9, it can be seen that the inertia response provided by the ESS ensures that the frequency deviation limit is not violated even when all 840 MW of available PV power is integrated in the system. With the integration of ESS for inertia support, the reliability benefits of additional PV farms is retained while keeping the frequency security parameters within limits.

The results show that the discrete convolution-based reliability model successfully captures the time-varying nature of component availability in PV arrays which cannot be modeled accurately with constant failure and repair rates. The proposed method successfully formulated and integrated this effect into the reliability assessment problem. In addition, the proposed integration limit model for PV power presents a constraint in the unmitigated integration of PV power while displacing the conventional generators with large inertia. These two constraints in the proposed model prevent optimistic reliability assessment in PV integrated systems. The results also show that with an appropriate fast-acting ESS, the integration of PV power can be increased as the ESS can provide the necessary inertia support. The proposed model can be helpful

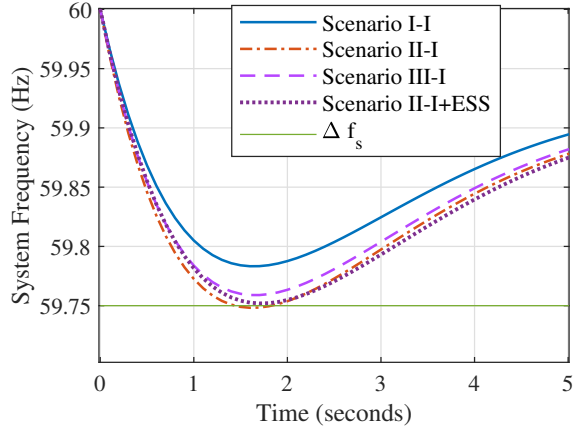


Fig. 9: Frequency Deviation for Step Disturbance of 100 MW (averaged over trials).

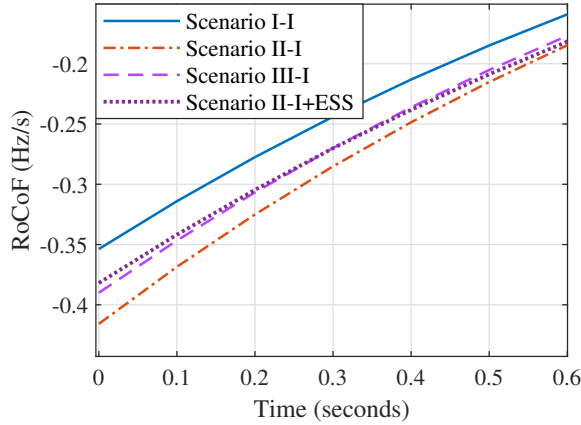


Fig. 10: System RoCoF for Step Disturbance of 100 MW (averaged over trials).

for adequacy assessment during the system planning studies, particularly for the optimal sizing and siting estimation of PV farms. Since the model is computationally inexpensive and thus suitable for many trials, it can be deployed to capture the effects of geographical conditions on the PV component and overall system availability (optimal placement). One of the practical limitations of the proposed method is the data available for the implementation. The failure and repair rates of all power electronic components are not always available, and they can vary based on manufacturer design specifications and operating conditions. With the lack of accurate failure and repair rates from the manufacturers, the use of estimated failure and repair rates can induce minor inaccuracies within the proposed variable availability model.

VIII. CONCLUSION

The growing integration of PV power in power grids demands an accurate reliability assessment technique for PV-integrated systems. This paper proposes an analytical reliability model based on discrete convolution for PV-integrated systems. In addition to considering the impacts of variable irradiance and ambient temperature on general reliability, the

proposed model incorporates their impact on the availability of inverters and converters using a thermal power-loss model. In addition, the reliability model is developed to account for redundancies associated with a multi-string topology of high complexity, thus making the model generalizable to standard central inverter and string topologies. An integration limit assessment tool is also developed within the proposed framework, ensuring that the PV power integration does not violate the system frequency stability. The simulation results show that the proposed reliability model integrates these impacts to ensure a non-optimistic reliability assessment. The proposed method can benefit power systems operation and planning studies, especially with the increasing integration of PV farms.

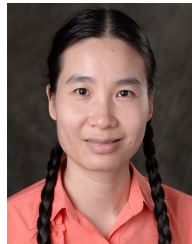
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Dilip Pandit (S'19) received the bachelor's degree in electrical engineering from Tribhuvan University, Nepal in 2016 and Master's degree in electrical and computer engineering from the University of Wyoming, Laramie, WY, USA in 2022. He is currently a PhD student at the University of Wyoming. His research interests include power system reliability and frequency stability in the presence of renewable power and storage systems.



Nga Nguyen (S'11–M'18) received the bachelor's and master's degrees from the Hanoi University of Science and Technology, Hanoi, Vietnam, and the Ph.D. degree from Michigan State University, East Lansing, MI, USA, all in electrical engineering. She is currently an Assistant Professor with the University of Wyoming, Laramie, WY, USA. Her research interests include stability, reliability, and control of power systems in the presence of renewable energy



operation and planning, microgrids, and hybrid electric systems. Dr. Elsaiah is the recipient of the several awards including the best paper award at the North American Power Symposium, North Dakota (2018).

Salem Elsaiah (S'09–M'16) is within the John R. Post School of Engineering at Alvernia University. He received his B.S. and M.S. in electrical engineering from Benghazi University and his Ph.D in electrical engineering from Michigan State University, East Lansing, MI in 2015. He taught numerous introductory and core electrical engineering courses. He worked as a Post-Doctoral Associate at the Energy Reliability and Security Research Lab at Michigan State University, where he was involved in developing methods for optimal power systems



operation and planning, microgrids, and hybrid electric systems. Dr. Elsaiah is the recipient of the several awards including the best paper award at the North American Power Symposium, North Dakota (2018).

Joydeep Mitra (S'94–M'97–SM'02–F'19) received the B.Tech.(Hons.) degree from the Indian Institute of Technology, Kharagpur, India, and the Ph.D. degree from Texas A&M University, College Station, TX, USA, both in electrical engineering. He currently holds the title of MSU Foundation Professor of electrical engineering at Michigan State University, East Lansing, MI, USA. He is the Director of the Energy Reliability and Security Laboratory and a Senior Faculty Associate with the Institute of Public Utilities. He is a coauthor of the book *Electric Power Grid Reliability Evaluation: Models and Methods* and of IEEE Standard 762. His research interests include reliability, planning, stability, and control of power systems. He was a recipient of the 2019 IEEE-PES Roy Billinton Power System Reliability Award and the 2020 Merit Award from the International Society for Probabilistic Methods Applied to Power Systems (PMAPS).