

A New Method for Estimating the Longevity and Degradation of Photovoltaic Systems Considering Weather States

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Abstract The power output of solar photovoltaic (PV) systems is affected by solar radiation and ambient temperature. The commonly used evaluation techniques usually overlook the four weather states which are clear, cloudy, foggy, and rainy. In this paper, an novel analytical model of the four weather conditions based on the Markov chain is proposed. The Markov method is well suited to estimate the reliability and availability of systems based on a continuous stochastic process. The proposed method is generic enough to be applied to reliability evaluation of PV systems and even other applications. Further aspects investigated include the new degradation model for reliability predication of PV modules. The results indicate that the PV module degradation over years, failures, and solar radiation must be considered in choosing an efficient PV system with an optimal design to achieve the maximum benefit of the PV system. For each aspect, a method is proposed, and the complete focusing methodology is expounded and validated using simulated point targets. The results also demonstrate the feasibility and applicability of the proposed method for effective modeling of the chronological aspects and stochastic characteristics of solar cells as well as the optimal configuration and sizing of large PV plants in terms of cost and reliability.

Keywords photovoltaic (PV) systems, solar cell, Markov model, weather effects

1 Introduction

Similar to other power system components, photovoltaic (PV) systems may fail because of different weather conditions, momentary events or aging failures in their components. In addition, the reliability of grid-connected PV systems is influenced by the failures which may lead to system interruptions and cause a huge amount of economical losses [1–6]. A more serious issue is that in order to optimize decisions in installation, construction, service, performance, and procurement, the operator should be able to assess the reliability of the system [7–9].

PV modules are some of the most critical components in a PV system [10]. A typical PV module can convert 4%–17% of the solar radiation into suitable electricity [11]. However, the temperature of PV modules, solar radiation intensity, weather state, and environment around PV modules affect the reliability and failure rate of modules as well as the overall reliability of PV systems. For instance, in a rainy weather state, the failure rate of PV modules is drastically larger than in a clear sky weather state. In addition, the solar radiation intensities in a rainy weather are smaller than those in a clear sky state. Thus, the nominal output power of a PV system is fluctuated due to different radiation intensities.

The present paper intends to improve and extend the methods developed in Ref. [10] which has analyzed the reliability of large-scale, grid-connected PV systems based on the fault tree analysis (FTA) to find the critical components. It has been revealed that PV modules are some of the most critical components in a PV system. An important aspect of this paper, not emphasized by Ref. [10], is that the effects of the weather must be considered in reliability assessment in order to enhance the performance decisions about a PV system. First, this paper recapitulates the reliability modeling of large-scale, grid-connected PV

systems using the FTA method and minimal cut sets. However, the present model is more efficient and accurate than the assumptions used Ref. [10]. Second, this paper proposes a novel approach for modeling the four weather states (cloudy, foggy, sunny, and rainy) based on the Markov process. The proposed method not only can be used for the reliability evaluation of PV systems, but also can be used for the reliability analysis of other electric systems like electric distribution systems. Third, this paper focuses on solar cells incorporating the four weather states in order to optimize the installation and service decisions as well as investment costs and economical benefits. Finally, this paper estimates the reliability of PV systems considering the four weather states. This is significant since the output power of PV systems is drastically influenced by different weather states. It is necessary to point out the repair time of the components which have been ignored because it has been assumed that the repair time is less than a critical value and the loads could be incorporated with the distribution system during failure. However, the proposed method is applicable when the repair and the common-cause degradation are considered [12].

2 Literature review

The stochastic behavior of PV systems is caused by the intermittent solar radiation as well as the failures in their components. On the other hand, quantifying the reliability of PV systems and solar cells considering weather effects is crucial. The existing literature mainly investigated the reliability of PV systems [13], and discussed the reliability of PV system components [14]. The reliability of small-scale PV systems was investigated [15], and the electrical architecture of large-scale, grid-connected PV systems was proposed [10]. Various simulation and modeling methods were also studied [16]. For instance, a method for the assessment of the reliability of a photovoltaic system was proposed based on the Markov chain method [17]. However, all the currently available methods neglected the four weather conditions. For instance, reliability evaluation methods incorporating two and three weather conditions using the Markov model were investigated [18]. However, the focus was solely on the electrical distribution systems. In some literature, evaluating the reliability of solar PV based on weather effects was of great interest. For example, the adverse effects of PV systems on the utility grid was investigated [19]. A method based on sequential Monte-Carlo for the reliability evaluation of PV systems incorporating the influence of two weather conditions was proposed [20], and a method to forecast the output power of PV systems based on weather conditions and support vector machines was presented [21]. Besides, the model and parameters for the solar cells but without considering

weather effects were also addressed [22], and several techniques were also developed to enhance the PV performance based on solar cells over the past decade [23–30]. Furthermore, the reliability estimation of PV modules in different types of degradation and failure modes of PV modules was also conducted [31]. However, evaluation methods related to PV systems incorporating the four weather effects have not been addressed. Further consideration incorporating the four weather conditions are required in order to develop all methods and tools related to PV system analysis. Therefore, this paper mainly contributes to the evaluation of system reliability.

3 Reliability model based on FTA and minimal cut sets

The fault tree method (FTA) is a widely accepted method to achieve the probability of system failure in reliability evaluation. The approach presented in Ref. [10] was used to evaluate the reliability of the system based on the FTA method. FTA provides a diagrammatic description based on logic diagrams which show the state and behavior of the system in order to predict the system failures. The top event is also used in FTA in order to define the terms of failure mode of the whole system. After defining the fault tree of the system, the failures should be formulated based on the tree which is incorporated with the top event. The process of converting fault trees into Boolean models and mathematical equations is called generation of minimal cut sets. The minimal cut set involves obtaining the various combinations of events which cause system failure. If all components in a minimal cut set are unavailable, the top event will occur. If all components are available, the top event will not occur. However, it is worth noting that the important characteristic of a minimal cut set is that even if one component of a minimal cut set is available, the top event will not occur. The minimal cut set for any fault tree is finite and can be achieved easily. For instance, three component minimal cut sets indicate that all three components must fail in order for the top event to occur. For an n component minimal cut set, all n components must be unavailable. The pictorial chart for the proposed reliability algorithm based on FTA is depicted in Fig.1.

4 Proposed method for PV reliability assessment

A new mathematical model based on the Markov method and analytical model is proposed to study the impact of the four weather states on the reliability of PV systems. The methods used for modeling and evaluation of the reliability of power systems can be categorized into three kinds, analytical [32], Monte Carlo simulation [33], and combi-

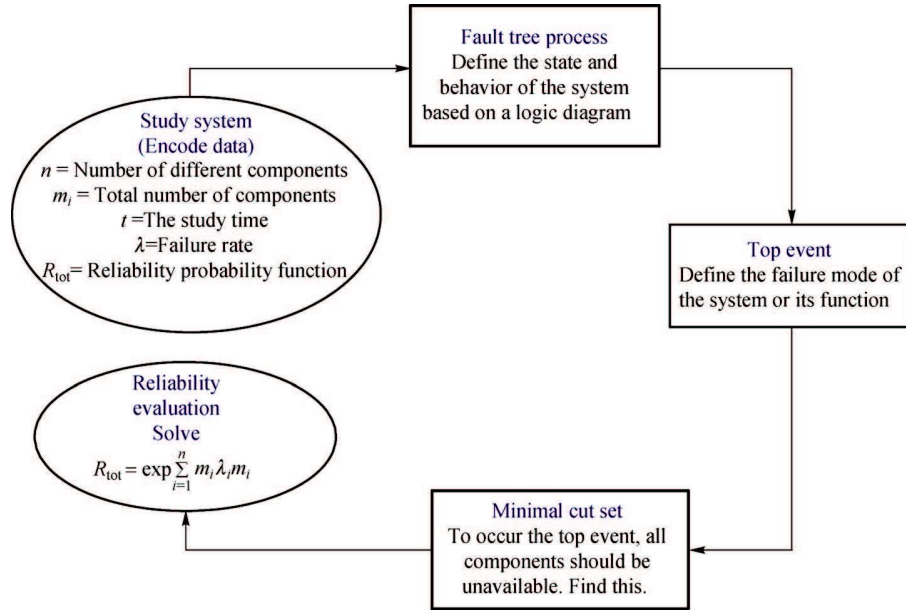


Fig. 1 Pictorial chart of reliability evaluation based on FTA

nations [34] of simulation and analytical techniques. The reliability parameters used in analytical techniques are usually assumed to be constant. In addition, mean times to failure (MTTF) and the mean times to repair (MTTR) are parameters of exponential distributions. The first concept of different weather effects on the reliability of power systems could be obtained from the approximate and analytical models. The Markov model serves as an applicable tool to simply demonstrate system states and behaviors and transition between these states based on two assumptions. The first assumption is that the system does not have any long or short term memory. This means that the future probability of events is only a function of the existing condition of the current system state and does not depend on the prior state of the system. The second assumption is that the system states do not vary with time, which means that transition probabilities between states are constant and the system state is in a permanent state [35]. The Markov state space models was used to evaluate the reliability a power system with two or three weather state model [36]; however, the four weather states associated with PV systems are proposed in the present paper. The type of weather states which may cause component failure in an electric power system or PV system significantly can be described by an adequate Markov model. The Markov model serves to deduce a state-space diagram for system conditions. A detailed explanation of the Markov process could be found in Ref. [18]. The transition rates from state to state are denoted by the first letter of the current state and the next state, e.g., n_c is the transition rate from normal to cloudy weather state; λ , λ_c , λ_f and λ_r are the failure rates of the normal, cloudy, foggy and rainy weather conditions, and μ is the repair rate of the normal weather condition.

The transitional probability with the four weather states for the system is shown in Fig. 2.

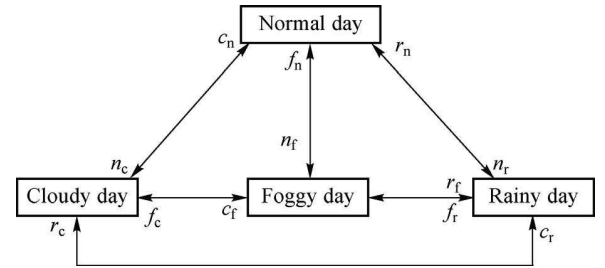


Fig. 2 Four weather state models

The frequency balance approach [18,37,38] used to estimate the probabilities between weather states shown in Fig. 2 can be expressed as

$$P_n \times N_t = P_c \times c_n + P_f \times f_n + P_r \times r_n, \quad (1)$$

$$P_c \times C_t = P_n \times n_c + P_f \times f_c + P_r \times r_c, \quad (2)$$

$$P_r \times R_t = P_n \times n_r + P_f \times f_r + P_c \times c_r, \quad (3)$$

$$P_n \times P_c + P_f + P_r = 1, \quad (4)$$

where $N_t = n_f + n_c + n_r$, $C_t = c_n + c_f + c_r$ and $R_t = r_n + r_f + r_c$. Also, P_n , P_c , P_f , and P_r are the probability of normal, cloudy, foggy, and rainy states, respectively.

In order to deduce an adequate and practical analysis considering the four weather states, the following transition rates (occ/h) were considered [39]: $n_c = 1/6000$, $n_f =$

$1/7000$, $n_r = 1/5000$, $r_n = r_c = r_f = 1/2000$, $c_n = c_f = c_r = 1/1000$ and $f_n = f_c = f_r = 1/800$. Therefore, the average duration of weather states (hours) will be $N = 1/(n_r + n_f + n_c) = 1962.6$, $R = 1/(r_n + r_f + r_c) = 666.6$, $C = 1/(c_n + c_f + c_r) = 333.3$ and $F = 1/(f_n + f_f + f_c) = 266.6$, where N , R , C and F are the average duration of clear sky, rainy weather, cloudy weather and foggy weather, respectively. Further, the steady state probability of the four weather states using Eqs. (1)–(4) can be obtained as $P_n = 0.6045$, $P_c = 0.1022$, $P_f = 0.0789$ and $P_r = 0.2145$.

The failure rates for the proposed weather conditions incorporated with PV modules can be obtained as

$$\lambda_k = \frac{\lambda_n \times F_k}{P_k}, \quad (5)$$

where λ_n and λ_k are probability of failure rate in normal weather per calendar year and per year of the k th weather state, respectively. F_k is the fraction of total failures occurring in the k th state (i.e., foggy, rainy, and cloudy). P_k represents the probability regarding the foggy, rainy, and cloudy weather. Based on this equation, and assuming $\lambda_n = 0.0152 \times 10^{-6}$ failures/hour and 70% of the outages occurred in normal weather, 5% of the outages occurred in rainy weather, 15% of the outages occurred in cloudy weather, and 10% of the outages occurred in foggy weather, the failure rates in different weather conditions for PV modules using Eq. (5) can be obtained as ($\times 10^{-6}$ failures/hour): $\lambda_n = 0.0152$, $\lambda_c = 0.02230$, $\lambda_f = 0.01926$ and $\lambda_r = 0.0354$. For example, the failure rate of the cloudy weather is calculated using Eq. (5) as $\lambda_c = \frac{0.0152 \times 0.15}{0.1022} = 0.02230$.

5 Numerical studies

The proposed reliability evaluation algorithms are tested on a real large-scale, grid-connected PV system [10], which is illustrated in Fig. 3. The system consists of seven PV systems, with a nominal output power from 100 kW to 2500 kW. The data for the PV module and inverter

characteristics are available in Ref. [10]. The number of components in each PV system is given in Table 1 and the reliability data are presented in Table 2. The inverters are protected from lightning by surge protection devices (SPDs). The reliability results for SPDs are not listed because the open, and closed states during lightning does not have an effect on the reliability of the system. Therefore, the failure rate of SPDs is neglected in this paper. Additionally, PV system degradation is considered to be the material degradation of the components (due to ageing and stress factors such as thermal cycling, mechanical loading, UV exposure, humidity, voltages stress, etc.), leading to a drop in the maximum power of the modules measured under standard conditions (1000 W/m^2 , 25°C , AM 1.5), or visual defects (such as yellowing, burn marks), or component failures (glass breakage, diode failure, solar cell fractures, etc.).

5.1 Case study 1: clear sky

The total component reliability for the PV system over one year and over 20 years of operation in the clear sky state was calculated based on the FTA method. The results are demonstrated in Figs. 4 and 5 which show the highest unavailability of the system in upper years. From Figs. 4 and 5, it can be inferred that the increase in the number of components and powers required for the system corresponding to a decrease in the PV output power show almost a linear relationship. In addition, a probability of 0% means that there is at least one component that deduces the top event and the failure of the overall PV system [10]. The unavailability analysis was performed to interpret the above results. The unavailability of the system can be calculated as [10]

$$\text{Unavailability} = \left[1 - \exp\left(-\sum_{i=1}^n m_i \lambda_i t_i\right) \right], \quad (6)$$

where all the parameters are explained in Fig. 1. The procedures are plotted in Figs. 6 and 7 for one year and for 20 years of operation, which indicate that the component

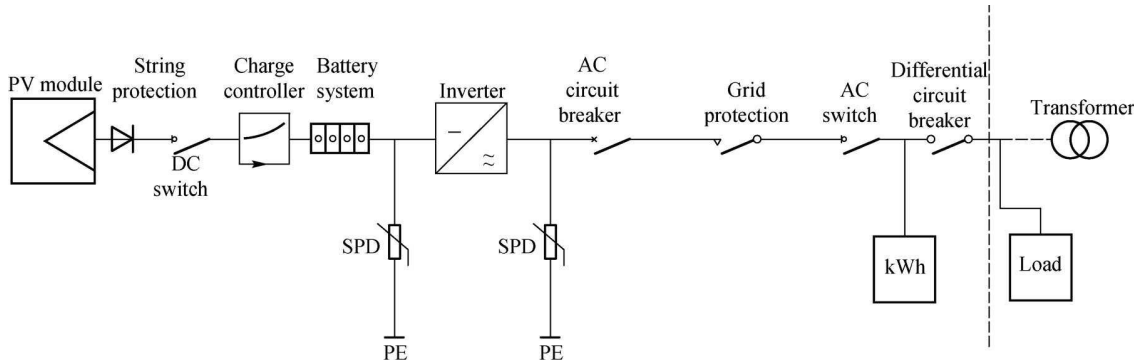


Fig. 3 Online diagram of large-scale PV systems [10]

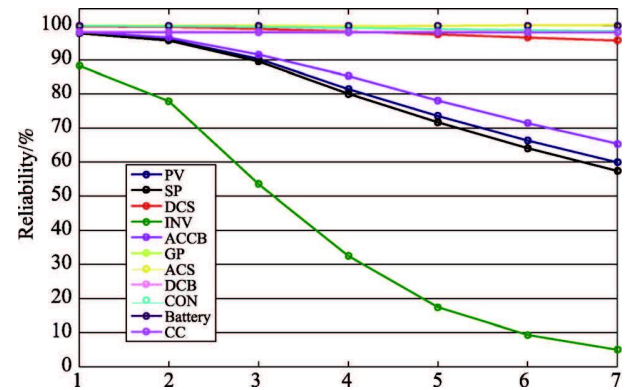
Table 1 Number of components per each PV system [10]

Power/kW	PV modules	DC switch	AC switch	Inverter	Connector	SP	DCB	BS	ACCB	GP	CC
100	437	3	1	1	874	23	1	16	1	1	1
200	874	6	1	2	1748	46	1	30	2	1	1
500	2166	15	1	5	4332	114	1	76	5	1	1
1000	4351	27	1	9	8702	229	1	150	9	1	1
1500	6517	42	1	14	13034	343	1	224	14	1	1
2000	8702	57	1	19	17404	458	1	298	19	1	1
2500	10868	72	1	24	21736	572	1	372	24	1	1

Notes: SP—String protection, DCB—Differential circuit breaker, BS—Battery system, ACCB—AC circuit breaker, GP—Grid protection, CC—Charge controller

Table 2 Failure rate of component [10]

Component	Failure rate/(10^{-1} failures $\cdot$ h $^{-1}$)
PV modules	0.0152
String protection	0.313
DC switch	0.2
Inverter	40.29
AC circuit breaker	5.712
Grid protection	5.712
AC switch	0.034
Differential circuit breaker	5.712
Connector (couple)	0.00024
Battery system	12.89
Charge controller	6.44

**Fig. 4** Reliability of total component after one year of operation (in percentage)

unavailability increased as the nominal output power of the system. The seven PV systems are numbered 1 to 7.

5.2 Case study 2: incorporating weather effects

The impact of four weather conditions on the reliability of PV power system is estimated. Using the steady state probabilities and failure rates of the four weather states deduced from the Markov method, the reliability of the PV module can be estimated. Tables 3 and 4 list the reliability of the PV module associated with the four weather states for one year and 20 years of operation. The reliability of the overall system for one year and for 20 years of

operation considering different weather conditions is also presented in Tables 5 and 6. Figures 8 and 9 show the unavailability of PV modules associated with the weather effects. The results for the unavailability of the overall system for one year and for 20 years of operation are displayed in Figs. 10 and 11.

The following discussion is restricted to case 2 which is the main case study. As expected, a comparison of case 1 and case 2 indicates that the system unavailability is increased in case 2, due to the incorporation of the reliability deficits associated with different weather states.

As shown in Tables 3–6, the system is not reliable because of its lower performance and efficiency. Therefore,

Table 3 Reliability of PV module for a period of one year (Unit: %)

Power/kW	Normal	Rainy	Cloudy	Foggy
100	97.96	95.31	97.02	97.42
200	95.96	90.84	94.13	94.91
500	90.28	78.82	86.08	87.85
1000	81.44	62.01	74.00	77.10
1500	73.54	48.88	63.70	67.74
2000	66.34	38.45	54.76	59.45
2500	59.89	30.31	47.14	52.23

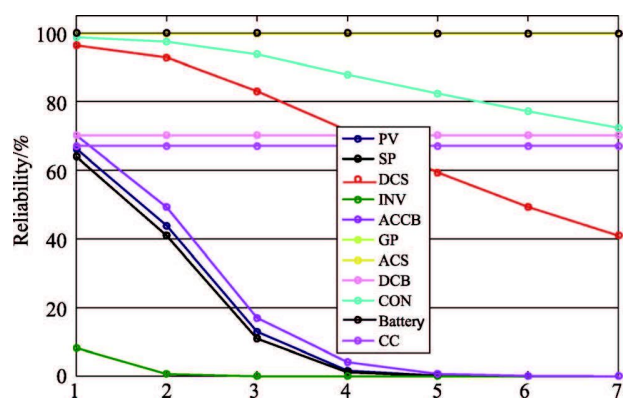


Fig. 5 Reliability of total component after 20 years of operation (in percentage)

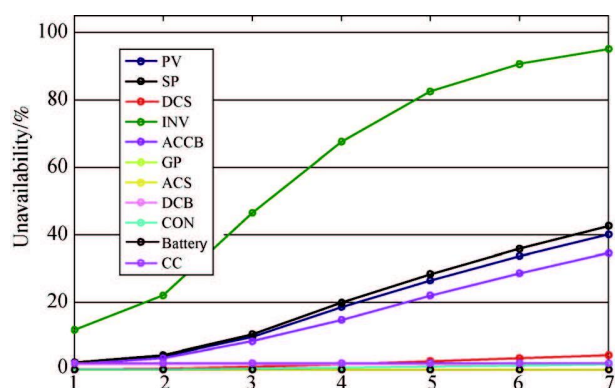


Fig. 6 Unavailability for a period of one year

Table 4 Reliability of PV module for a period of 20 years (Unit: %)

Power/kW	Normal	Rainy	Cloudy	Foggy
100	66.22	38.29	54.62	59.31
200	43.85	14.66	29.83	35.18
500	12.96	0.85	4.99	7.51
1000	1.65	0.0071	0.24	0.55
1500	0.2141	0.0001	0.01	0.04
2000	0.02	0	0.0006	0.003
2500	0.0035	0	0	0.0002

Table 5 Reliability of overall system for a period of one year (Unit: %)

Power/kW	Normal	Rainy	Cloudy	Foggy
100	78.37	76.25	77.62	77.94
200	64.92	61.46	63.69	64.21
500	36.98	32.29	35.26	35.99
1000	16.68	12.70	15.15	15.79
1500	6.52	4.33	5.65	6.0088
2000	2.54	4.33	2.10	2.28
2500	0.99	0.50	0.78	0.86

Table 6 Overall system's reliability for a period of 20 years (Unit: %)

Power/kW	Normal	Rainy	Cloudy	Foggy
100	0.7641	0.4419	0.6303	0.6845
200	0	0	0	0
500	0	0	0	0
1000	0	0	0	0
1500	0	0	0	0
2000	0	0	0	0
2500	0	0	0	0

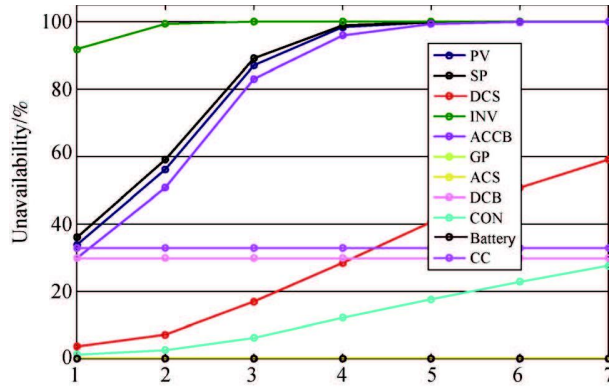


Fig. 7 Unavailability for a period of 20 years

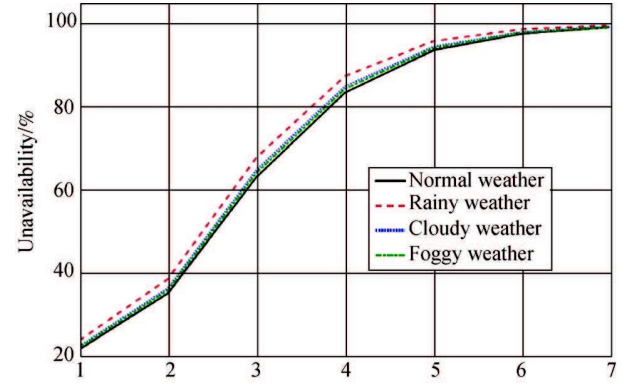


Fig. 10 Reliability of overall system for a period of one year of operation

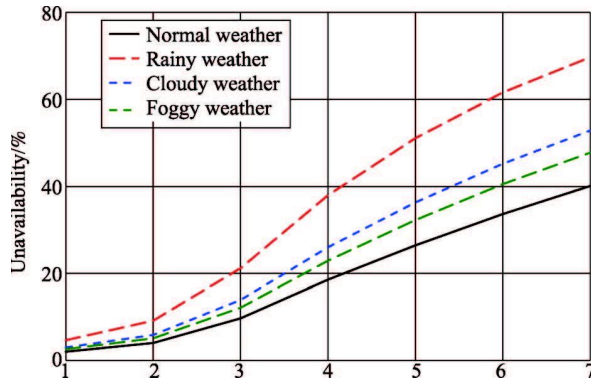


Fig. 8 Reliability of PV modules for a period of one year of operation considering weather effects

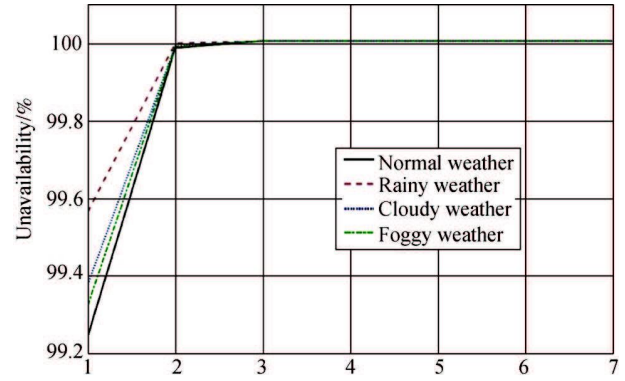


Fig. 11 Reliability of overall system for a period of 20 years of operation

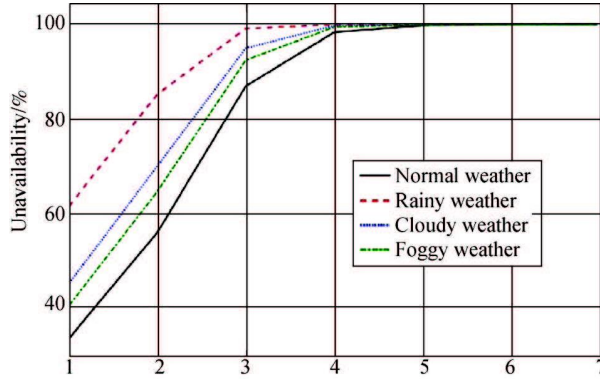


Fig. 9 Reliability of PV modules for a period of 20 years of operation considering weather effects

it cannot produce the expected energy output. The changes in the reliability of the system considering both weather effects and failures are presented in Tables 3–6. It can be also seen that the weather effects are much more sensitive than the failures, and that the reliability of the system affects the energy availability of the PV system. The results

of Figs. 8–11 indicate the severe influence of the weather on the reliability parameters of PV modules and the reliability of the system. It can be intuitively observed from the implementations that, as expected, the system becomes more unreliable because of the effect of the weather. In addition, a comparison of the values in Tables 3–6 demonstrates that the rainy weather has a significant impact on the reliability of the PV modules and the overall system. It is intuitively observed clearly from Figs. 8–11, that the PV modules are very critical components due to the unavailability derived from severe weathers.

6 Concluding remarks

In this paper, an ovel analytical approach has been proposed to evaluate the reliability performance of large-scale, grid-connected PV systems incorporating different weather states. The main contributions consist of the reliability evaluation method for the reliability of PV modules and the overall system considering weather states. Further, a new four weather state model incorporating the PV systems has been introduced. For modeling the PV

components exposed to different weather environment, the consideration of weather conditions is an important factor for evaluating the reliability of the system. The Markov method has been used to simply demonstrate system states and behaviors and the transition between these states. An ovel approach for the reliability assessment of large-scale, grid-connected PV systems incorporated with the four weather conditions using the Markov method and approximate equations has been investigated. Based on studies using seven large-scale, grid-connected PV systems, the effectiveness of the proposed algorithm has been revealed. The methods developed in this paper are useful for choosing an efficient PV system design based on an optimal planning model, and will result in the maximum benefits of the PV system. The proposed method can also be tailored to other applications such as modeling the chronological aspects and stochastic characteristics of solar cells and the optimal size of PV systems in terms of cost and reliability.

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