Reliability Analysis of Photovoltaic Module based on Measured Data

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Abstract. This paper analyzes the reliability of photovoltaic modules based on the electrical data of photovoltaic modules collected by photovoltaic power stations. Traditional module life depends on equipment calibration and lacks consideration of the actual use of modules. The experimental data in this article comes from modules with different service hours in the real power plant environment. The extended β model with four free variables is used to model the power data of the modules to obtain the expected output power of the modules in each service time. The power generated by the module is used as a measure of the reliability of the module, and the reliability index is used to obtain indicators such as the failure rate and the average life of the module.

1. Introduction

After the photovoltaic module is tested and calibrated in the laboratory, various problems will still be found during outdoor field operation. Only the laboratory test results cannot reflect the operation of the photovoltaic system under various climate types. The actual outdoor monitoring data is important for supplementing the laboratory test results.

At present, the commonly used photovoltaic module reliability evaluation methods are mainly based on a large number of life data or model formulas obtained from experience. The factory standards for photovoltaic modules usually require a module life of more than 25 years[1][2]. In actual analysis and application, it is usually difficult to obtain complete data on a long-term span of a certain module, and photovoltaic modules usually do not reach such a long service time, and it is difficult to determine the failure time.

In addition, traditional reliability analysis labels have only two types: normal and failure. The actual failure situation is a process of degradation and accumulation, and only recording its failure time is not sufficient for reliability analysis. The main failure mechanisms that affect the reliability of photovoltaic modules[3][4] are:

- Alternation of ambient temperature and humidity intrusion: leading to failure of the sealing material, cracking of the battery sheet, separation of the backplane from the EVA, etc;
- Light radiation [5]: UV light breaks the main chain of EVA, causing degradation and yellowing of the bonding material EVA;
- Mechanical damage: impact and pull by external forces such as strong wind, earthquake, hail, and thick snow;
- Chemical corrosion [6]: rust of aluminum frame, failure of grounding impedance, etc.
In order to overcome the "normal-failure bipolarity" in the above-mentioned traditional reliability methods, the 1:1 life span of a long time span is difficult to collect, etc.

A type of reliability assessment method based on performance degradation has been paid attention. The main difference is that it does not require a long-term failure mark, and does not depend on the critical point of life from normal to failure. A performance degradation model is established based on the power attenuation curve of the module under test, and the reliability of the module is evaluated accordingly.

Based on the monitoring data of the outdoor actual measurement base, it is possible to track the power attenuation indicators of various types of modules within a certain period of time, and provide strong data support for the above-mentioned reliability evaluation methods based on performance degradation.

2. Reliability analysis of photovoltaic modules

2.1. Reliability characteristics
The reliability characteristics of photovoltaic modules mainly include reliability, failure rate, failure probability density, average life[7], etc. The definitions are as follows:

\[ R(t) = P(T > t) \]  \hspace{1cm} (1)
\[ F(t) = 1 - R(t) \]  \hspace{1cm} (2)
\[ f(t) = \frac{dF(t)}{dt} = F'(t) \]  \hspace{1cm} (3)
\[ \theta = \int_0^{+\infty} R'(t) dt \]  \hspace{1cm} (4)

T is the time of module failure, R(t) is the reliability rate, F(t) is the failure rate, f(t) is the failure probability density, \( \theta \) is the average life.

2.2. Experimental data source
The following content is the long-term monitoring of the photovoltaic module power data of the selected photovoltaic power station actual measurement platform. The failure probability model of photovoltaic modules is established from the perspective of performance degradation, and the failure probability analysis between various types of modules is performed. Table 1 shows the measured output power of a certain manufacturer's monocrystalline silicon module. Each data has been cleaned before calibration, and the actual environmental parameters are converted into STC standard environmental conditions.

| Module Number | Service time / year |
|---------------|---------------------|
|               | 12  | 13  | 14  | 15  | 16  | 17  |
| 1             | 287.65 | 286.46 | 281.54 | 279.56 | 276.00 | 275.27 |
| 2             | 282.74 | 279.19 | 273.68 | 270.55 | 265.58 | 267.17 |
| 3             | 284.99 | 283.47 | 276.40 | 273.76 | 269.37 | 269.22 |
| 4             | 286.39 | 283.95 | 277.87 | 277.13 | 271.79 | 271.03 |
| 5             | 286.61 | 285.34 | 278.12 | 277.18 | 273.39 | 272.95 |
| 6             | 286.85 | 285.40 | 279.85 | 278.03 | 274.05 | 273.45 |
| 7             | 290.62 | 291.17 | 287.81 | 284.16 | 281.66 | 279.74 |
| 8             | 286.94 | 285.87 | 280.16 | 278.87 | 274.13 | 274.08 |
Calculate the fourth-order moment of the matrix of each year's data column of each module: mean, variance, skewness, kurtosis. Take the data column for 12 years of service as an example:

| Year | Data     |
|------|----------|
| 9    | 287.56   |
| 10   | 290.04   |
| 11   | 289.01   |
| 12   | 284.42   |
| 13   | 289.10   |
| 14   | 289.26   |
| 15   | 286.23   |
| 16   | 289.43   |

\[ a_1 = \bar{X} = 287.365 \]  
\[ a_2 = \sigma^2 = 4.401 \]  
\[ a_3 = \sum_{i=1}^{16} (X_i - \bar{X})^3 / 16\sigma^3 = -0.42 \]  
\[ a_4 = \sum_{i=1}^{16} (X_i - \bar{X})^4 / 16\sigma^4 = 2.513 \]

2.3. Data modeling

Introducing the β distribution, which is a density function as the conjugate prior distribution of the Bernoulli distribution and the binomial distribution. The domain of β distribution is \([0, 1]\). Its probability density function is

\[ f(x; \alpha, \beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1} \]  
\[ \Gamma(x) = \int_0^\infty t^{x-1} e^{-t} dt \]

Therefore, the β distribution has two free quantities \(\alpha\) and \(\beta\). Translate and stretch its domain to extend to the interval \([k, k+k+w]\).

\[ f(x; \alpha, \beta, k, w) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} (kx+w)^{\alpha-1} (1-kx-w)^{\beta-1} \]

From this we have obtained an extended distribution model with 4 degrees of freedom. The characteristic quantities of the distribution model are as follows:

\[ \mu = k\mu + w = k\frac{\alpha}{\alpha+\beta} + w \]  
\[ \text{var} = k^2 \text{var}' = \frac{k^2 \alpha \beta}{(\alpha+\beta)^2(\alpha+\beta+1)} \]

Skewness and kurtosis will not change due to scaling, so their formulas are consistent with the beta distribution follows:

\[ \text{skew} = \frac{2(\beta-\alpha)\sqrt{\beta+\alpha+1}}{(\beta+\alpha+2)\sqrt{\alpha+\beta}} \]
Then, we have obtained the formula of the fourth-order central moment of the distribution model, and the statistical feature quantity corresponding to the module data. Substitute the aforementioned fourth-order moment statistics into the above formula. The classical Gauss-Newton will fall into a local extremum on this system of equations and converge slowly. Use Levenberg-Marquardt algorithm to solve this nonlinear equation. The four parameters of the extended $\beta$ distribution are

$$k = 14.317$$

$$w = 280.034$$

$$\alpha = 1.612$$

$$\beta = 1.412$$

For the data columns from 13 to 17 years, the same distribution model parameters are determined. The fourth-order moment feature quantities of each data column are shown in Table 2.

| Service time / year | Statistical feature |
|---------------------|---------------------|
|                     | Mean    | Variance | skewness | kurtosis |
| 12                  | 287.365 | 4.401    | -0.42    | 2.513    |
| 13                  | 286.009 | 10.783   | -0.424   | 2.499    |
| 14                  | 280.673 | 14.951   | 0.023    | 2.066    |
| 15                  | 278.413 | 15.11    | -0.396   | 2.366    |
| 16                  | 274.678 | 20.41    | -0.278   | 2.252    |
| 17                  | 273.136 | 13.52    | -0.183   | 2.640    |

From the feature statistics and the model feature quantity formula, solve the nonlinear equations to obtain the model parameters shown in the following Table 3:

| Service time / year | Model parameter |
|---------------------|-----------------|
|                     | $\alpha$ | $\beta$ | $k$    | $w$    |
| 12                  | 3.934   | 2.324   | 11.696 | 280.01 |
| 13                  | 3.704   | 2.162   | 17.837 | 274.75 |
| 14                  | 1.682   | 1.737   | 16.259 | 272.67 |
| 15                  | 2.582   | 1.502   | 18.176 | 266.92 |
| 16                  | 2.409   | 1.655   | 20.692 | 262.41 |
| 17                  | 7.177   | 5.855   | 27.690 | 257.89 |

2.4. Module reliability analysis

According to the $\beta$ distribution model parameters obtained in Table 3, the output power probability density curve of each service time module is visualized, as shown in Figure 1:
Combined with the measured values, the module failure is defined as the module output power lower than 280W. The nominal power of this type of module is 320W, that is, the output power is lower than 87.5% as the degradation boundary[7]. According to different actual application backgrounds, this failure boundary can be customized according to the purpose of reliability evaluation[8]. Integrate the obtained β probability distribution model in the interval of [280,320) to obtain Table 4, which shows the proportion of samples whose module power in each service time is not lower than the self-defined failure limit.

Table 4. Reliability rate of each service time module

| Service time / year | Reliability rate / % |
|---------------------|----------------------|
| 12                  | 100                  |
| 13                  | 95.46                |
| 14                  | 55.44                |
| 15                  | 39.48                |
| 16                  | 13.18                |
| 17                  | 2.5                  |

Fitting the reliability data to the Weibull distribution, the best fitting result of the module degradation curve is shown in Figure 2.
This paper analyzes the method ideas and experiments for evaluating the reliability of modules from the perspective of performance degradation based on the measured data of photovoltaic modules at different service times. This method uses four-parameter β distribution to fit the distribution of the measured data samples. In the β distribution model fitting, the problem that the amount of data is small and the power distribution probability cannot be directly fitted is solved. First, calculate the statistical characteristics of a small number of samples, and then use the Levenberg-Marquardt method to solve the nonlinear equations based on the statistical characteristics. The fourth-order statistical characteristics of the sample are retained to fit the sample distribution to the greatest extent.

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