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Application of gamma process model to estimate the lifetime of photovoltaic modules

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ABSTRACT

The analysis of long term data for degradation of PV modules suffers from volatility and uncertainty due to intrinsic and extrinsic factors. The low rate of degradation causes analysis complexity and ambiguity. In this study, methods used to estimate the PV module lifetimes were reviewed in terms of degradation of power output with time. Under the assumption that degradation is continuous, gradual, and monotonic, the gamma process model can explain the sampling and temporal uncertainties of lifetime data. Examples are provided to demonstrate the use of gamma process model for long term and accelerated lifetime test (ALT) data. Three types of lifetime estimation method were compared for long term operation data. Although they all gave similar estimated lifetime, the gamma process model gave the most applicable results to determine warranty life. The gamma process model can also express the condition variation at inspection and the lifetime variation at failure level as probability distributions. A method to determine warranty life is proposed using an age based replacement policy. For ALT data, we estimated the lifetime from degradation data using the Arrhenius equation for standard environmental conditions and applied the gamma process model to obtain time varying probability distributions for condition and lifetime. Service life was estimated as the median, while warranty life was estimated as the minimum rate of increase of optimal replacement time.

1. Introduction

Photovoltaic (PV) modules are solid-state devices that convert sunlight directly into electricity without requiring heat engines or rotating equipment. When the semiconducting material is exposed to light, electrical charges are generated. The electrical output from a single cell is small, so multiple cells are connected and encapsulated to form a module. Although PV systems have environmental advantages, low efficiency and high cost of manufacturing the sheets of semiconductor materials are significant drawbacks. Efficiency improvements of the panels and manufacturing methods have steadily reduced the costs and PV systems have become of great interest worldwide (Kalogirou, 2014).

The Annual Energy Outlook for 2015 from the Energy Information Administration of the US Department of Energy states that fossil fuel, including natural gas, coal, petroleum and other liquids, accounts for 78% of total energy consumption, while renewables constitute just 8% (Energy Information Administration , 2015). However, in the context of present energy crisis and the consequences of fossil fuels on our environment, the development and use of renewable energy sources has become very important. Solar PV technology is one of the most important renewable sources of energy generation (Gaur and Tiwari, 2013). PV power generation takes a leading role in the renewable energy market and has received great attention in developing countries as an appropriate technology with rapid growth over the last few decades (Panyakeow, 1984; Ahmad et al., 2010).

The useful lifetime of PV modules is an important factor determining the cost per unit of generated electricity and estimating this lifetime is just as important as determining the power output or efficiency of a module (Ossenbrink and Sample, 2003). In 1993, the International Electrochemical Commission (IEC) developed the IEC 61215 standard to guarantee PV module lifetimes of 15–20 years in moderate climates and has applied it to qualification testing (IEC 61215, 1993). The IEC Module Type Approval tests have effectively addressed commercial module design problems well (Ossenbrink and Sample, 2003). However, the tested stress level limited and quality approval does not guarantee long term performance, but only confirms satisfaction of the required specification. It is difficult to clearly identify the predominant failure

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mechanism(s) of long term operation (Osterwald and McMahon, 2009), since long term data collection to confirm PV module degradation pathways and lifetimes is difficult due to the low rate of performance degradation. Therefore, it is necessary to study reliability directly, such as failure mechanism(s), degradation rate, and develop suitable models to estimate remaining useful lifetime, etc.

Performance evaluation of 192 PV modules installed at SERC in 1990 showed that average maximum power output degraded 4.39% over 11 years from discoloration, browning, and ethylene–vinyl acetate copolymer (EVA) delamination and the variance significantly increased (Reis et al., 2002). Corrosion and cell or interconnection-breaks accounted for 86% of the failure modes with failures related workmanship, process control, and system problems comprising the balance (Wohlgemuth et al., 2005). Environmental factors contributing to failure were solar (particularly UV) radiation, humidity, wind, snow, rain, hail, high or low temperatures, salt, sand, dust, gas, etc. (Ndiaye et al., 2013; Phinikarides et al., 2014; Bhattacharya et al., 2014). These factors produce temporal uncertainty of degradation and broad variation because of compounding effects on the PV modules by mechanical, chemical, and thermal stresses.

There are two failure types: functional failure, where the module fails to provide the intended function; and conditional failure, where the module degrades below a predefined level in the prescribed operational environment. Factors leading to conditional failure are divided into internal and external factors. Internal factors are related to inhomogeneity or material imperfections, and external factors are related to environmental stresses (Ferrara and Philipp, 2012; Park and Kim, 2016). These effects compound on PV module performance, and the power output degrades to some predefined failure level. Internal factors suffer from sampling uncertainty resulting in variation of degradation rate in the same operational environment. On the other hand, external factors suffer from temporal uncertainty resulting in non-linearity of the degradation path for the same material. Therefore, the volatile and ambiguous characteristics of power output degradation with time should be modelled stochastically to estimate PV module lifetimes with reliability (Park and Kim, 2016).

Stochastic model has been applied previously to deal with lifetime data that displays temporal uncertainty of degradation. The gamma process model, in particular, is suitable to model gradual, monotonic, and continuous degradation phenomena but it has not previously been applied to estimate PV module lifetimes. Therefore, we focus on the gamma process model, comparing the outcomes to other lifetime estimation models, such as deterministic and statistical model, for analyzing long term degradation data. We estimate the variation of probability distribution for failure and lifetime with operational time using the gamma process model and develop a method to estimate PV module lifetime based on long term operation and accelerated life test (ALT) data. The proposed method to determine warranty life based on an age replacement policy is presented using the estimated lifetime probability distribution from the gamma process model.

2. Lifetime estimation for long term data

2.1. Long term data and failure criteria

To compare the lifetime estimation models, we used the long term data from Kuitche (Kuitche, 2010), as shown in Fig. 1. and we applied deterministic, statistical, and stochastic models to these data. Fig. 1 shows the fraction of initial power output measured each year between 1998 and 2009 for four monocrystalline PV modules. The degradation rate increases rapidly after 2000 days of operation. The individual or system performance degrades gradually with time, but still affects performance above the threshold level. PV modules are usually guaranteed to perform to 80% of the initial power for 20–25 years (Wohlgemuth et al., 2005; Ndiaye et al., 2013; Carr and Pryor, 2004). This paper considers power output decrease time in outdoor use over long periods with 20% power loss as the critical threshold level or failure level for conditional failure.

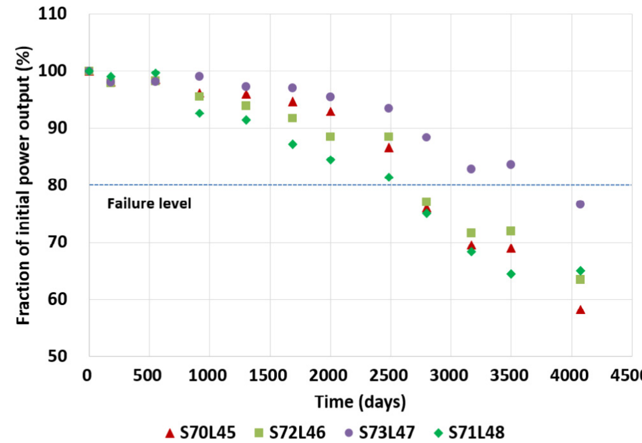

Fig. 1. Normalized power output degradation with time.

Fig. 2 shows the degradation path model with operational time. PV module power output degrades from some initial state, r_0, to the failure state, s. Let $X(t_i)$ be the cumulative degradation at some inspection time. In the early stages, PV module power output is relatively stable. However, the power output degrades and the rate of degradation increases with time, then levels off somewhat. Fig. 2 also shows the variation at inspection (condition distribution), as well as at the failure level (lifetime distribution). Although the data fits various non-linear regression equations well, the power output for any inspection time may drop unexpectedly and this drop may be expected to be continued for subsequent inspections. Thus, the long term degradation data appears as a staircase.

2.2. Long term data characteristics

We live in a volatile, uncertain, complex, and ambiguous (VUCA) world. The phrase was introduced by the U.S. Army War College to describe the multilateral world resulting from the end of the Cold War, and VUCA has mainly been used for strategic leadership in the area of business management, as shown in Fig. 3 (Lawrence, 2013; Davies, 2015). We apply the VUCA approach to describe long term data characteristics from Fig. 2. Volatility and uncertainty are related to the nature of degradation and complexity and ambiguity to test & analysis methods.

- *Volatility:* the rate and amount of performance degradation vary in a volatile manner under the influence of environmental circumstances and interaction between parts. A great deal of long term data would be required to identify the volatile driving factors, but gathering such long term data is time consuming and costly.
- *Uncertainty:* the degradation path is not invariant or expected. The uncertainty originates from time varying, compounding environmental stresses (temporal uncertainty) and material inhomogeneity of either individual parts or the system (sampling uncertainty). Therefore, the Markovian property exists