

IEA PVPS Task 13 - Performance, Operation and Reliability of Photovoltaic Systems

Service Life Estimation for Photovoltaic Modules

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Executive Summary

The economic success of photovoltaic (PV) power plants depends crucially on their lifetime energy yield. Degradation effects and the total lifetime directly influence the produced electricity and therefore the cash flow, which also impacts the levelized costs of energy (LCOE) and therefore the profitability of the power plant. In most cases, the lifetimes and degradation rates that are used to estimate the system performance are not system-specific but are based on average values from the evaluations of older systems or data sheets. So, these values unfortunately have no direct correlation with the specific location. Also, the mathematical models used for calculating the expected power output typically expect linear degradation rates which are not in line with real degradation processes found in the field, which are typically non-linear.

This report gives an overview on empirical degradation modelling and service life prediction of PV modules since they are the major components of PV systems that are subject to the effects of degradation. For other components no comparable scientific data is available. The structure of the document addresses different stakeholders with different backgrounds. Chapter 1 begins with a short introduction including a condensed overview of the state of the art.

Chapter 2 follows with the definition of relevant terms and definitions. Since especially in discussions on lifetime and degradation different terms are not used coherently in industry or science, the authors try to improve the situation with this dedicated glossary. In addition, the extremely relevant term "end-of-life" is discussed with different definitions, depending on the point of view and perspective of the user and the typical factors impacting the PV module or PV system. For this "end-of-life" term, no definition which is generally applicable in all situations can be given. Since the definition is crucial for the calculated service life, yield, and all related parameters, through to LCOE it is important to be aware of this when evaluating power plants and PV investments.

Climatic factors play a major role in degradation and are by nature location specific. It is pre-condition for the creation of meaningful service life prediction or degradation data to know about the relevant (climatic) stressors. Therefore Chapter 3 introduces the different relevant climatic stressors as well as classification schemes and methodologies to handle and analyse them. The chapter also describes differences and relations of the so called macro-climatic stressors, describing the climatic conditions in the ambience of the modules, and the situation at material level, the so called micro-climatic stressors. The latter describes the relevant parameters for degradation processes and so also the mathematical models addressing module degradation and service life prediction. The ambient macro-climatic conditions at specific locations can be estimated using data for the climatic regions or adapted climatic maps and so be classified using climatic classification schemes which exist also specified for PV purpose like e.g. the Köppen-Geiger PV scheme. For the determination of microclimatic loads - which are typically input parameters for degradation models, further calculations are necessary. The re-port presents possible ways to determine the necessary data for the most important micro-climatic parameters which are temperature and humidity. This data is also very important for the definition of accelerated tests, which can deliver module specific parameters for the service life and degradation prediction. Chapter 3 also describes basic accelerated ageing tests, as described in the respective IEC

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standards, and how they can support degradation and service life prediction and modelling as well as their limitations.

Chapter 4 addresses general degradation and service-life modelling approaches including related issues. It starts in section 4.1 with general issues of empirical modelling one has to be aware of when working on mathematical modelling solutions for service life and degradation prediction and interpreting results. There are very different approaches for empirical modelling of the lifetime performance prediction and service life of products such as PV modules empirical statistical modelling, and empirical physical modelling. Physical empirical models are those that utilize analytic or numerical forms to represent the fundamental physics and chemistry of the phenomena. Statistical models, often referred to as data driven models, use mathematical forms which are able to fit the (measured) data without direct relation to physical or chemical processes. Both approaches use empirical (measured) data to determinate parameters which can be used for predicting future behaviour.

Section 4.2 introduces on one hand models for specific degradation modes or phenomena of modules (e.g., backsheet or cell cracking or electrochemical corrosion). On the other hand, modelling approaches for degradation effects of components and materials are presented. A special focus is here on degradation of polymeric materials since these materials are known to be sensitive to degradation effects causes by typical climatic stressors like high temperature, humidity and UV radiation. The modelling approaches using predictive models and inferential mechanistic models are presented using polyethyleneterephtalate (PET) degradation as catchable example. It is shown that different modelling approaches are necessary to describe all degradation effects. Weak points of modules can be identified and focussed optimization of products can be supported.

Performance degradation models are addressed in Section 4.3 which are the core models for the prediction of degradation of modules over time for specific types and locations. Combined with defined end-of-life conditions, these models can be used for service life prediction. Different approaches which have been specifically developed for PV modules are presented. Starting with an approach focusing on physical and chemical processes and the specific application. An approach to develop performance loss rate (PLR) models following the statistical methodology is presented as well including the processes to determine the relevant parameters from field data.

The modelling approaches are presented including the methodological approach to the problem the used input data, and parameters related to specific module types or local climatic conditions, down to calculations of degradation rates over time or remaining useful lifetime (RUL) or total expected lifetime. The latest scientific work shows that service lifetime and degradation models for PV modules are of specific use if they combine different modelling approaches and include know-how and modelling parameters of the most relevant degradation effects. Such models can differentiate between the behaviour of different module types and to include the situation at different service locations. For some modules, it is also necessary to use multi-step modelling approaches to enable meaningful results.

Advanced approaches of data analysis and modelling also enable the determination of degradation signatures which can be related to specific degradation effects. This approach is expected to be very helpful in future work to identify failures based on operational data.

Since uncertainties of input parameters can have significant impact on the results but are often not totally avoidable, these topics are addressed in Chapter 4.3.