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AI-BASED RELIABILITY ASSESSMENT OF POWER ELECTRONIC SYSTEMS

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ABSTRACT

One of the most important elements for market acceptance of new technologies is ensuring reliability. Nowhere is this truer than in the shift from well characterized fossil fuel technologies to newer renewable and sustainable energy technologies. The key enabling technology driving these shifts is the development of power converters and inverters. Conventional approaches to assess reliability of these devices have severe drawbacks. Frequent redesigns, often with new parts having no historical data, limit the usefulness of methods based on historical data. Conversely, physics-of-failure approaches often do not capture the most relevant failure mechanisms, including those related to operationally induced electrical overstress and software. In this paper, we will discuss a revolutionary new reliability assessment approach that utilizes advancements in artificial intelligence (AI), machine learning, and data analytics, along with new techniques for characterizing and modeling failure mechanisms to improve power electronics reliability.

The reliability assessment method combines AI and machine learning algorithms for analyzing field failure data, with top down models that translate the impacts of grid-connected and grid-parallel mode dynamics and mode-transition dynamics on power systems, and reliability physics degradation models for key failure mechanisms that simulate the effects of both electrical and environmental degradation under field operational stresses. These models can be embedded in digital twins created specifically to replicate the design of current and new inverters. The output of these digital twins reflects the effects of aging and component degradation on system performance and will be transferable to multiple power electronic systems and platforms.

Keywords: AI, Digital Twin, Inverter, Solar Energy, Reliability

NOMENCLATURE

PV	Photovoltaic
PoF	Physics of Failure
RUL	Remaining Useful Life

1. INTRODUCTION

The development of Photovoltaic (PV) systems that have a lifetime of 20-25 years with minimal maintenance is necessary for widespread penetration of solar power. This combined with the significant impact of PV systems on distribution grid reliability makes it critical to have a dependable method to assess reliability and durability of all components in a PV system. Figure 1 shows the results of a study [1] of the long-term reliability of PV systems analyzed for a duration of 20 years, with the probable states defined using the continuous Markov process, and the condition of each state discussed. Failures are significant after a few years of operation, with the reliability gradually decreasing to 81% percent in 20 years. The study provides insight into the degradation of component performance in PV systems. One of the highlighted issues in the context of the reliability of PV systems was failure of the inverter. Inverters are the most critical and complex components of PV systems, and failures in the inverter lead to compete loss of production during downtime. Golnas [2] found inverters to have the highest failure rate and contributed the greatest production loss in PV systems. According to a more recent study by Jordan et. al. [3], inverters still fail more than other components in PV systems, although the resulting production loss has decreased.

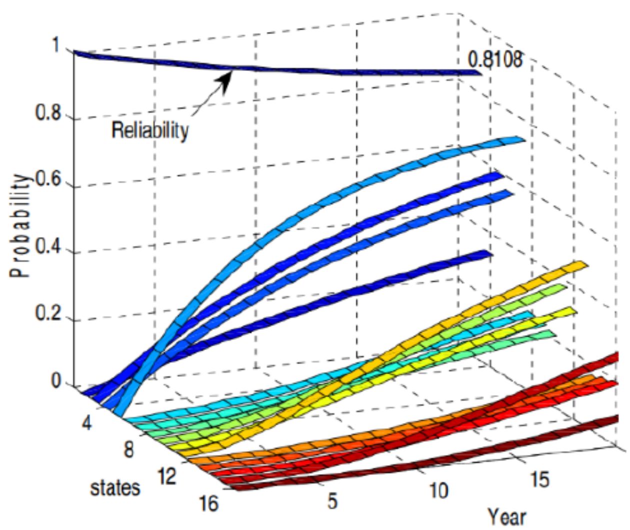

FIGURE 1: THE PROBABILITY OF EACH STATE IN 20 YEAR LIFETIME OF PV SYSTEM [1]

Despite the critical importance of the inverter to the PV system, current approaches to determine PV reliability have significant limitations. One common approach is to use the Failures in Time (FIT) of individual components to estimate the reliability of the system as a whole. This approach relies on significant historical field data to make predictions, which is infeasible when component selection and topology design are evolving at a rapid pace. New components inherently lack the field data required to accurately estimate the FIT rate, and the purely empirical nature of the approach invalidates attempts to predict reliability under new conditions.

Another popular approach is to assess reliability through Physics of Failure (PoF). PoF assesses reliability based on the fundamental mechanisms that cause degradation and precipitate failure [4]. The benefit of this approach is that it includes causality in assessing reliability, so resulting models can be applied to new operating conditions to an extent. However, PoF alone is limited by its complexity. Individual components are subject to multiple competing failure mechanisms, and determining the dominant mechanism and parameters unique to each component for a full system yields a model that is infeasibly complex. Liivik et. al. [5] and Hacke et. al. [6] developed PoF models that were based solely on the switching devices in the inverter. These models considered temperature and irradiance, but were forced to assume a dominant failure mechanism to make the assessment, and they did not account for grid interactions. Shen et. al. [7] presented a model for a PV microinverter that used PoF to assess the reliability of the switches and the DC-link capacitors. While this model was able to estimate the reliability of the system considering multiple components and 3 different capacitor selections, it was still limited to applying PoF to just the switches and DC-link capacitors.

Another key drawback of current PoF models is that they only consider the lifetime of the components without acknowledging the effect that physical degradation has on electrical performance. In essence, current PoF models only address the start and end points; they do not address the degradation in between, nor do they address how that intermediate degradation affects the system's performance or accelerates the degradation of other components, and thus the system as a whole.

Because understanding degradation is so critical to accurately assessing system reliability, it is not enough to use existing PoF models to predict component life. Testing to end of life with electrical measurements at a sufficient sampling frequency is needed to build a PoF model that correlates a failure mechanism with the electrical degradation that the mechanism precipitates prior to end of life.

This study will develop an integrated approach to assessing the reliability of electronic components in PV systems based on the development of physics-informed degradation models embedded in digital twins and validated with accelerated life testing and field data. This integrated approach, depicted in Figure 2, merges the information collection, analysis, and anomaly detection capabilities of a data driven approach with prognostic capabilities of a PoF approach.

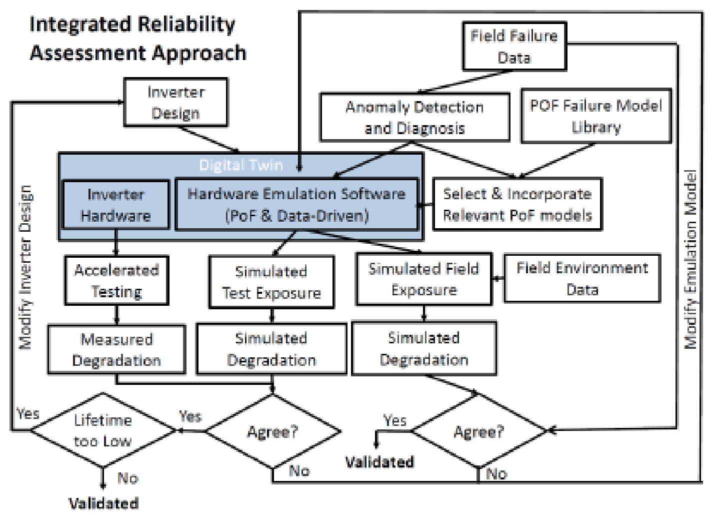

FIGURE 2: INTEGRATED RELIABILITY ASSESSMENT FLOWCHART

2. RELIABILITY APPROACH AND METHODS

Each element of the integrated approach has an important role to play. Fundamental reliability physics provides the basis for an intelligent machine-learning framework that can be used to screen historical data and accelerate analysis, allowing accurate degradation predictions from smaller datasets. It also provides the ability to assess the reliability of new designs and components that have insufficient field history. Conversely, the analysis of historical data allows a system-wide perspective that permits the identification of components critical to reliability, and dominant failure modes and mechanisms. This limits the number of components, failure mechanisms, and circuit configurations that need to be fundamentally modeled, significantly reducing the complexity of a bottom-up modeling approach. Furthermore, the engineering knowledge gained from both the historical data and reliability physics analyses can guide the selection of components and system signals for condition monitoring, thus limiting the number of sensors needed.

2.1 Data Mining and Analysis

The first step in this study will be to collect data from a range of inverter types in a variety of environments that will be mined to determine the most commonly failed components and dominant failure modes. In addition, a physics-based top-down modeling approach will be created that translates the impacts of grid-connected and grid-parallel mode dynamics and mode-transition (e.g., islanding, blackstart) dynamics on the most vulnerable PV-inverter components in terms of electrical, thermal, and humidity-based stress parameters.

In the top-down approach, several stress-producing factors are analyzed. The different data that are sourced in chronological AI analysis are from forty-six grid-following three phase inverters of Florida International University's microgrid. The five years of historical data consist of DC voltage and DC current on the input side, and three-phase AC voltage, three-phase AC current, frequency, and power on the output side. The output data is analyzed by statistical and multiple machine learning algorithms to detect anomalous outputs over time. Two techniques which are suitable for identifying anomalies in the inverters are isolation forest and decision tree algorithms. Isolation forests are unsupervised learning algorithms, and therefore do not need any labels or target variables prior to classifying anomalous data. Regression analysis can also provide outliers in DC and AC current for weather parameters like temperature and irradiance.

Anomaly-related timestamps are vital to correlate the stresses on the inverters to alerts or warnings, and narrow down the number of critically related alerts. Stress also comes from thermal cycling and power cycling on a daily basis as the inverter powers off at night. The intermittencies in the irradiance due to cloud coverage are another factor to add to these external stress producers, and will be analyzed with a decision tree algorithm in this work to further narrow down the degradation-related failures. The findings from this top-down data mining and classification approach are further strengthened by feeding in the actual maintenance service records information of inverter failures either from components, a circuit board, or the entire inverter. The maintenance records are a vital source of information as they present the historical health of the inverters and assist in pinpointing the malfunctioning inverter and its state at the time of failure. Going deeper, the validation of the machine learning approach is fine-tuned to get desired control algorithm parameters by utilizing the above information.

This information will then be used alongside a bottom-up component-level PoF reliability tool to ascertain a probability-of-failure matrix and acceleration factors for these vulnerable solar inverter components and the inverter as a whole when subjected to different operating conditions. This will be done using the embedded physics-informed degradation models, which are accessed from the generated database of PoF models. These models may be straightforward differential/algebraic analytical models representing the fundamental aspects of the degradation, but, in cases with limited PoF data, they can also employ pattern recognition and machine learning tools applied to field data.

2.2 Accelerated Environmental Testing

This study will include environmental stress testing similar to that of previous studies, but the tests will not be terminated early based on a semi-arbitrary failure threshold. This is in part because it is necessary to observe the final stages of degradation for the devices under test to build an accurate model. But even more importantly, the threshold for failure is unique to the system in which the device is deployed, not just to the device itself. One way in which this study differs from previous studies is that the test results will not be used to curve-fit a standard PoF model to the data so that others can estimate their lifetime based on different usage conditions. Instead this model will be correlated to the electrical performance of the devices along the electrical degradation curve. Between these two, the relationship between physical damage and electrical degradation can be derived, and this relationship can be used to understand the extent of physical degradation from the electrical test data, from which point one can extrapolate the RUL. The benefit of this approach is that it builds the foundation for other digital twins to be built with reduced testing requirements. The model for the electrical degradation varies significantly based on the test conditions, as is shown in Figure 3 [8], and purely data-based modeling does not allow for a translation between conditions. This means that a lot of testing would be necessary to build the twin without a PoF foundation. In this regard, the PoF approach reduces the amount of testing required because data from previous tests can be translated more readily for use in future digital twins.

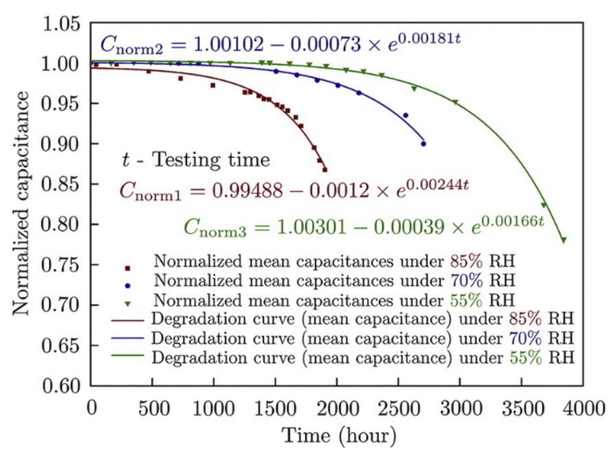

FIGURE 3: ELECTRICAL DEGRADATION CURVES OF FILM CAPACITORS UNDER DIFFERENT TEST CONDITIONS

2.3 Combining Data and Testing in the Digital Twin

The PoF-informed models generated from the environmental stress tests will be fed into the digital emulation model that forms the simulated half of the digital twin. Following component-level testing to build the degradation models, a scaled-power prototype inverter will be developed and assembled as the hardware half of the digital twin. Figure 4 shows the flowchart for this digital twin process.

Essentially, the hardware comprises a programmable dc source that emulates the photovoltaic energy source, which in turn, feeds a two (or single) stage inverter. The inverter feeds an application load that emulates to the extent possible application scenario. The operation of the inverter switches that controls the energy flow from the source to the load is achieved using an embedded controller (e.g., DSP/FPGA) based on the feedback or sensing of the inverter states.

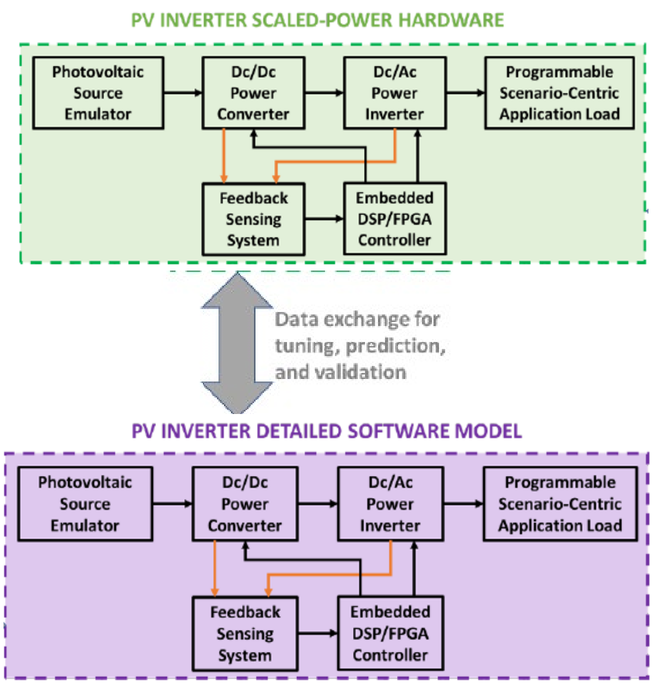

FIGURE 4: A TWIN EXPERIMENTATION/MODELING APPROACH TO RELIABILITY ANALYSIS OF THE INVERTER

Now, to realize the digital twin, the control input fed to the physical inverter hardware is also fed to the software model and this process is continued until the responses of the model and the inverter are close enough, thereby yielding the digital twin. Such a software model could be physics based, data based, or a hybrid combination of the two. A key advantage of the physics-based model is reduced convergence time while the data based (e.g., machine learning or AI) approach is more generalizable at the cost of enhanced need for computational and data overhead. The surrogate approach leverages the proven physics-based model and uses machine learning or AI based approach to reduce model structural uncertainty and reduce computational overhead. The inverter prototype will be subjected to performance characterization before, during, and after accelerated testing. The results from these tests will be used alongside field data on deployed inverters to validate the digital half of the twin, which will then be incorporated into software that manufacturers can use to make better informed reliability assessments for PV inverters.

3. CONCLUSION

In this paper the limitations of current techniques to assess reliability of PV inverters was discussed, and a solution was proposed. The proposed approach combines physics-based modeling, which maintains causality in the model and allows for accurate translation between test and use conditions, with advanced data mining to allow for reduced complexity in the model. The end result is a digital twin model that evaluates performance, durability, and lifetime.

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