INTRODUCTION & BACKGROUND

Warranties of 25 years are the norm in the solar industry, yet physical data to support designing to meet this reliability requirement are typically not fully integrated into a complete physical model. In this paper we report results of an integrated model that not only solves the coupled electro-thermal equations that predict panel performance for a given set of weather conditions, but also incorporates physical sub-models for key degradation modes and failure modes that govern panel lifetime performance.

Inputs to the model include a weather file and cell-level electrical and thermal parameters. For each hour of a module’s life, the model independently computes the incident spectrum, electrical operating point and temperature of each individual cell. Based on computed electrical state and temperature, the incremental degradation during each timestep is computed using multiple physical sub-models. Degradation modes, such as UV-induced cell degradation, encapsulant browning, are computed using models based on test data. Failure probabilities due to binary "end of life" events are also calculated. The model is back-tested against lab data and field data obtained from various SunPower product monitoring efforts.

In addition to being able to predict performance degradation over 25+ years, the model is able to explore effects of potentially coupled degradation modes in the design phase, including exploring unstable positive feedback loops. For example, the model can explore a hypothetical situation of an initially “weak” cell within a string that, while not reverse-biased, is warmer than its neighbors due to its current being forced to a higher value than MPP. This “warm” cell could potentially have faster degradation, leading to an even weaker, and eventually hotter cell; eventually this feedback mechanism could lead to a reverse-biased cell. The model also helps understand the degradation “budget” – that is, how much degradation is attributable to which modes – and this allows one to quantitatively target areas for improvement and set priorities for module design.

EXPERIMENTAL & THEORETICAL RESULTS

Electrical/Thermal Model

We recently described a 1-diode model [1], which offers accurate results but has implicit temperature dependence that requires a substantial amount of computational time. The electrical model has recently been upgraded to a 2-diode model with explicit temperature dependence, which retains accuracy but reduces computation time substantially [2].

To confirm the validity of this approach, 2-diode cell parameters (I_{sat1}, I_{sat2}, R_s and R_{sh}) were obtained using I-V characteristics obtained from the Sandia-model characterization of a panel [3], and from this temperature and irradiance dependent 2-diode cell parameter curves were generated. According to theory [2] and as shown in Fig. 1, data for multiple values of irradiance (E) can be collapsed onto a single curve in temperature (T) with very good accuracy. Therefore the 2-diode cell parameters can be explicitly expressed as a single function of temperature for all irradiances and levels of degradation. This explicit temperature dependence creates an opportunity for substantial computational speed improvement and allows field dependent degradation modes, such as potential-induced degradation, to be predicted for the entire PV system in a reasonable amount of simulation time.

Degradation Modes

The full paper will discuss recent improvements in understanding of key degradation modes, including UV degradation, encapsulant browning, and potential-induced degradation, which are key degradation modes for all solar panels.

For example, we have recently obtained substantial data for the yellowing of certain formulations of EVA at various temperatures and various intensities of UV radiation produced by various types of accelerated test lamps. As shown in Figure 2, we have also been able to closely match the results of these experiments using a new encapsulant browning model that uses simplified kinetics to two independent chemical reactions, plus an integrated form of Beer’s Law for absorption. The first kinetics step is photo-bleaching of the absorber A, which is modeled as a 1-step reaction:

\[ A + h\nu \rightarrow A^* \]

where B is the photobleached absorber. The second step is a first-order reaction for the conversion of a polymer moiety R to a yellow chromophore Y:

\[ R + h\nu \rightarrow Y \]

This is a completely independent kinetic step, however, the two are coupled by the spectrum of incident light which is strongly attenuated by the concentration of absorber A along the light path. Thus it is necessary to also take into account the absorption of UV light by the absorber.
Figure 1. \( I_{\text{sat1}}(T) \) and \( I_{\text{sat2}}(T) \) collapsed to single curves via polynomial fits in temperature \( T \) and irradiance \( E \).

Figure 2. Transmittance data for EVA as a function of time of high-intensity UV exposure at elevated temperatures \( T \) for various visible wavelengths. Note the initial period showing no degradation while UV absorbers are being photo-bleached. 2-step kinetic model results are shown in corresponding solid lines.

throughout the thickness of the material, which changes as the absorber is depleted. An analytical solution to the model for constant irradiance and temperature demonstrates the essential mechanism, and numerical solutions are used within PVLiFE for arbitrary irradiance/temperature inputs.

As another example, we are currently developing cell-level stress models using fundamental results derived from a quarter-cell geometry finite element analysis (FEA) model on ANSYS multi-physics. This has been developed to simulate the cell-level response on thermo-mechanical stress. For example, setting the cell with frictionless contact and no flatness constraints, the model was raised from 30°C to 55°C. Z-deflection of the Si (due to coefficient of thermal expansion mismatch between the Silicon and the copper backside) was captured at 55°C. Simulation results (as shown in Figure 3) were validated with the z-deflection measurements obtained on actual devices at the specified temperatures.

Field validation

Field validation of the model has been performed using multiple methods. One method (that will be described in more detail in the full paper) derives estimated degradation versus time for entire systems. Following Jordan and Kurtz [4], it begins by computing the ratio of AC output to modeled output using a degradation-free simulation model.

The current method uses a custom performance model that virtually eliminates seasonal variation, with the exception of soiling. A typical result for a site with low summer rainfall is shown below in Figure 4. The green datapoints show summertime periods of significant soiling.
losses, with rapid recovery after the first rainfall each autumn.

This type of data is post-processed to decouple low power due to soiling and cloudy weather and therefore reveal the true system degradation rate. For example, one filter eliminates cloudy (unstable irradiance) days, while another filter only keeps data for days after significant rainfall.

After filtering, the data can be fitted to straight lines to determine system degradation rate, and can also be fitted to more complicated functions to estimate local soiling rates for the site (see black line in Figure 3 below). The algorithms for normalizing and fitting the data will be described in more detail in the full paper. Results of a detailed uncertainty analysis in the use of this technique will also be presented.

Last but not least, 25-year simulations incorporating these significant updates and field validation compared to our previously-reported results [1] and compared with actual site data will also be presented.

Figure 3. Quarter cell Z-deflection results from ANSYS simulation at temperature = 55°C.

Figure 4. Field data normalized by model (green), with data points passing various filters shown in blue and red. Rainfall data are red dotted lines, shown against scale on right-side axis.

REFERENCES


