Statistical Modeling for Service Life Prediction of PV Materials and Laminates

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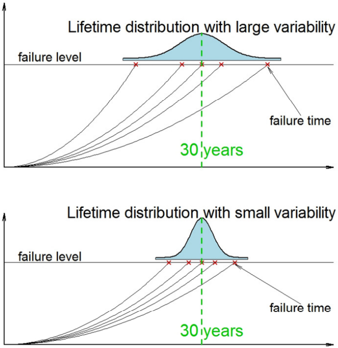
Overview

- Objectives and general strategy
- Data for building predictive model
- Statistical predictive model
- Analysis of degradation data
- Concluding remarks

Objective

- The overall objective is to make service life predictions for polymeric components in PV systems.
- Degradation models provide tools for service life prediction.
- One major step is to build a predictive model for the degradation path.



General Strategy

- Use the accelerated test data and knowledge of the physics and chemistry of the degradation process to help identify the functional forms for the experimental variables as they relate to the degradation path model.
- Use the identified functional forms and the accelerated test data to build a degradation path model linking the sample degradation paths and the experimental variables.
- Use the identified model to generate predictions of degradation for given covariate histories.
- To verify the effectiveness of the accelerated test methodology, compare predictions, based on the accelerated test degradation data and model, with observed degradation paths for outdoor-exposed specimens.

Data for Building Predictive Model

- A Laminated Glass/EVA/PPE System is used as the studying material.
- The yellowing index is used as the degradation index.
- Experimental variables: UV spectrum, UV intensity, temperature, and RH.
- Spectra study (four filters): 306 nm ($\pm$3), 326 nm ($\pm$6), 353 nm ($\pm$19), and 452 nm($\pm$80).
- Reciprocity law study (four intensity filters): 40%, 60%, 80%, 100% (nominal percentages).
- Temperature: 45C, 65C, and 85C.
- RH: 0%, 30%, and 60%,

NIST Datasets

- NIST datasets are used as training datasets to build the predictive model.
- Two sets of data were collected based on two slightly different material compositions.
- The first dataset contains 80 test samples. Data from 72 samples were used for training the predictive model and 8 samples were set aside for testing the model.
- The second dataset contains 32 test samples. Data from 28 samples were used for training the predictive model and 4 samples were set aside for testing the model.

Experiment Configuration for Dataset 1

SET 1				
	ND	ID	BP	ID
45C/0%RH	40%	6,12	306	11,17
	60%	9,15	324	10,16
	100%	2,3,4,5	354	8,14
			383	7,13
65C/0%RH	40%	6,12	306	11,17
	60%	9,15	324	10,16
	100%	2,3,4,5	354	8,14
			383	7,13
85C/0%RH Reciprocity (RE)	40%	2,8,12,16		
	60%	5,7,11,15		
	80%	4,6,10,14		
	100%	3,9,13,17		
85C/0%RH Wavelength (WA)			306	2,8,12,16
			324	5,7,11,15
			354	4,6,10,14
			383	3,9,13,17
85C/60%RH	40%	2,8,12,16		
	60%	5,7,11,15		
	80%	4,6,10,14		
	100%	3,9,13,17		

- IDs marked with red were used as testing samples.

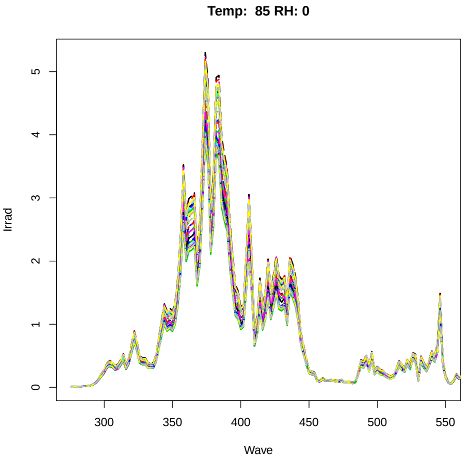
Experiment Configuration for Dataset 2

SET 2				
	ND	ID	BP	ID
Repeated 85C/0%RH	100%	2,3,4,5	306	7,11,15
			324	6,10,14
			354	9,13,17
			383	8,12,16
85C/30%RH	100%	2,3,4,5	306	9,13,17
			324	8,12,16
			354	7,11,15
			383	6,10,14

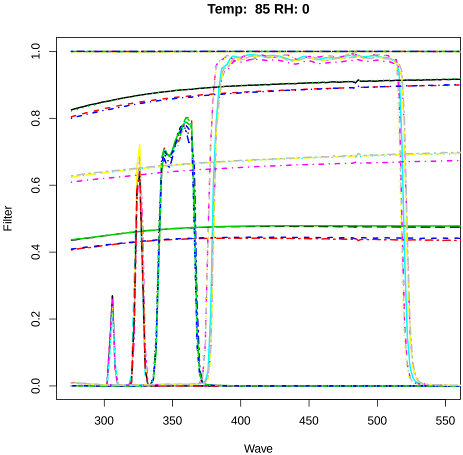
- IDs marked with red were used as testing samples.

Lamp Spectral Irradiance

- The lamp irradiance is denoted by $E(\lambda)$.



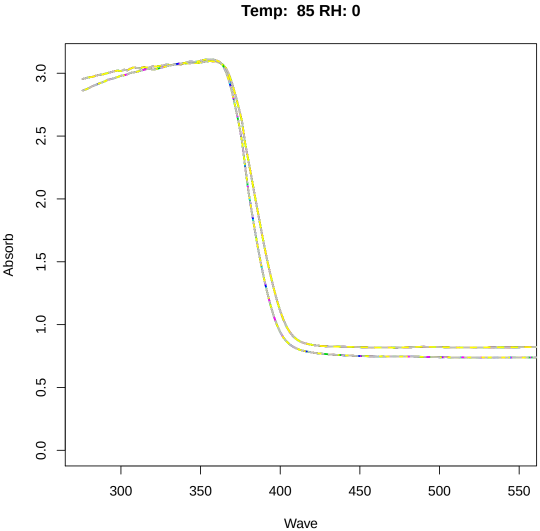
Bandpass and Neutral Density Filters



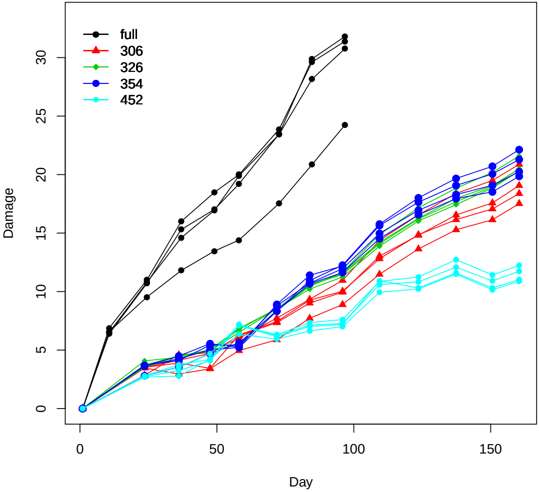
- Bandpass filters, denoted by $B(\lambda)$, 306nm, 326nm, 354nm, and 452nm
- Intensity filters, denoted by $F(\lambda)$, 40%, 60%, 80%, and 100%

Absorbance Spectrum

- The absorbance spectrum is denoted by $A(\lambda)$.



Sample Degradation Paths



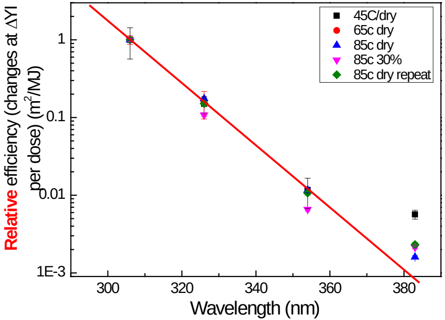
Degradation Characteristics

- Degradation is increasing and “nearly” linear over time.
- Dosage with smaller wavelength tends cause more damage (higher degradation).
- The degradation rate under the full spectrum seems to be slower than the sum of the rates under the four filtered spectrum.
- We also observe higher temperature causes higher rate; higher intensity causes higher rate, and higher humidity causes higher rate.

Degradation Path Modeling

- We model the degradation path under experimental condition x as
$$D(t; x) = \alpha(x) \cdot t^{\gamma}.$$
- The acceleration factor $\alpha(x)$ depends on UV spectrum and intensity, temperature, and RH
- The Arrhenius relationship is used to describe the acceleration factor of temperature, $\exp\left(\beta_t \cdot \mathrm{Temp}\right)$.
- $\mathrm{Temp} = \frac{11605}{\mathrm{TempC}+273.15} - \frac{11605}{85+273.15}$.
- Based on preliminary data analysis, the RH effect is modeled as linear, $(1 + q \cdot \mathrm{RH})$.

Wavelength Effect



- Wavelength effect is modeled by log linear plus some adjustment for 383nm,
  $\phi(\lambda) = \exp[\beta(\lambda - 354)] + \exp(\beta_0 + \beta_{0t} \cdot \mathrm{TEMP})$.

Wavelength Specific Intensity Effect

- The wavelength specific intensity effect is modeled by the power law relationship,

$$[F(\lambda)]^{p\cdot\exp(p_t\cdot\mathrm{TEMP})},$$

which is also adjusted by temperature.

- We observe that degradation rate under the full spectrum seems to be slower than the sum of the rates under the four filtered spectrum, which could be related to bleaching effect.

- We introduce a term for full wavelength adjustment, $\exp[1_{\mathrm{full}}\cdot(\xi+\xi_t\cdot\mathrm{TEMP})]$.

Model Summary

- In summary, the acceleration factor is modeled as,

$$\alpha(x) = \left(\int_{\lambda} E(\lambda)B(\lambda)[F(\lambda)]^{p \cdot \exp(p_t \cdot \mathrm{TEMP})} \{1 - \exp[-A(\lambda)]\} \phi(\lambda) d\lambda \right)$$
$$\times \exp[1_{\mathrm{full}} \cdot (\xi + \xi_t \cdot \mathrm{TEMP})] \times \exp\left(\beta_t \cdot \mathrm{Temp}\right)$$
$$\times (1 + q \cdot \mathrm{RH}) \times \exp(\mu)$$

- Here $\phi(\lambda) = \exp[\beta(\lambda - 354)] + \exp(\beta_0 + \beta_{0t} \cdot \mathrm{TEMP})$, and μ is a baseline constant.

Statistical Model for Degradation Path

- The model for degradation measurements is

$$y_{ij} = D_i(t_{ij}) + \epsilon_{ij}$$

  for unit i at time t_{ij}.

- Here ϵ_{ij} is the deviation that can not be captured by $D_i(t_{ij})$.

- Also,

$$D_i(t) = \alpha(x_i) \cdot t^{\gamma},$$

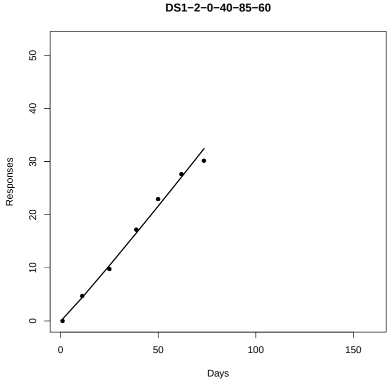
  which are determined by unknown parameters.

Model Fitting

- Let θ denote all unknown parameters in $D(t)$ (e.g., $\beta, p, \cdots$).
- We need to find the θ to minimize the sum of squares of the errors.
- That is to minimize

$$\sum_{ij} [y_{ij} - D_i(t_{ij})]^2.$$

Illustration of Model Fitting

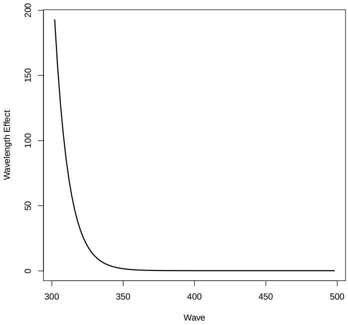


- Find the curve, $D_i(t)$, to minimize the sum of the squares of the vertical distances.
- $D_i(t)$ is determined by experimental conditions and parameters in the model (e.g., $\beta, p, \ldots$).

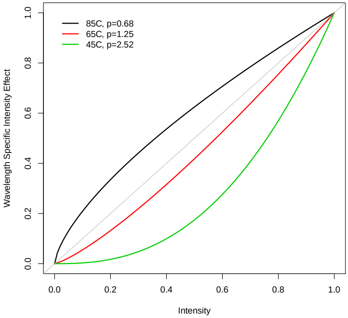
Analysis of Dataset 1: Parameter Estimates

Parameter	Interpretation	Value
β	wavelength effect	-0.101
p	wave. specific intensity effect	0.679
p_t	intensity by temperature	0.322
β_t	temperature effect	-0.473
q	RH effect	2.430
γ	shape parameter	1.058
μ	baseline constant	-3.619
β_0	383nm adjustment	-1.621
β_{0t}	383nm adjustment by temp.	-0.262
ξ	full wavelength adjustment	-2.554
ξ_t	full wavelength adj. by temp.	0.008

Plot of Variable Effects

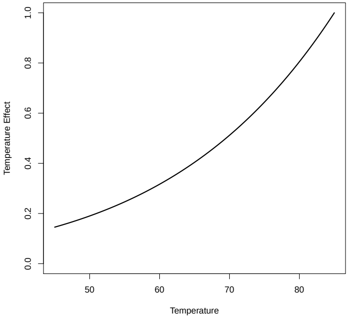


(a) BP Effect

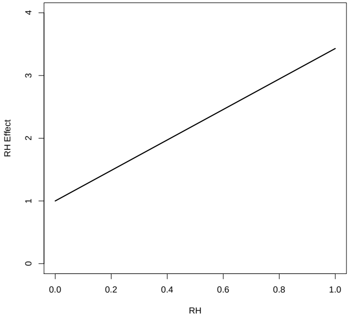


(b) Intensity Effect

Plot of Variable Effects

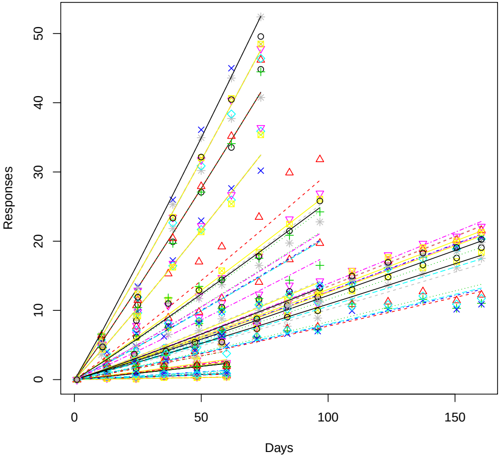


(c) Temperature Effect

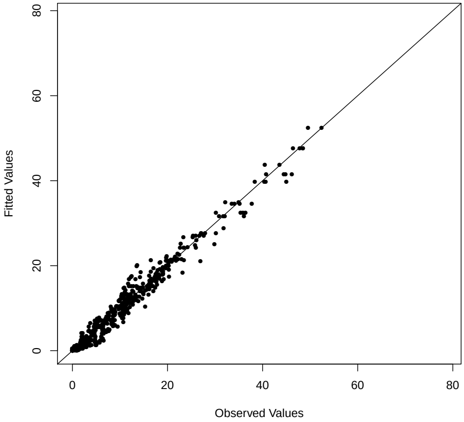


(d) RH Effect

Plot of Fitted Paths

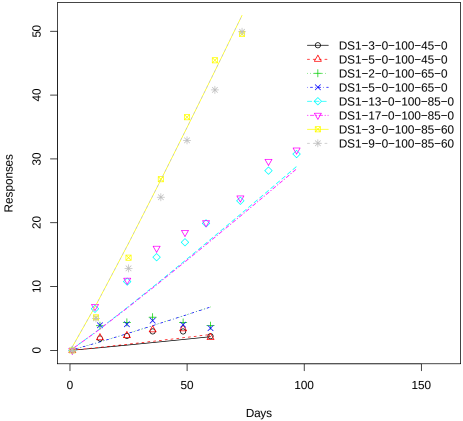


Fitted vs Observed



- Overall, the model can fit the data well.

Out of Sample Prediction

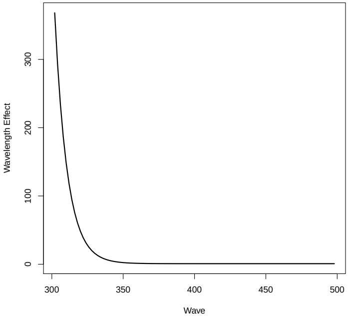


- Overall, the model can predict the test sample well.

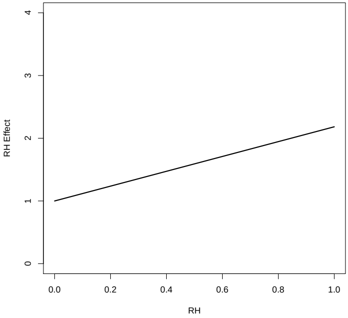
Analysis of Dataset 2: Parameter Estimates

Parameter	Interpretation	Value
β	wavelength effect	-0.114
q	RH effect	1.183
γ	shape parameter	0.566
μ	baseline constant	-2.530
β_0	383nm adjustment	-0.196
ξ	full wavelength adjustment	-2.928

Plot of Variable Effects

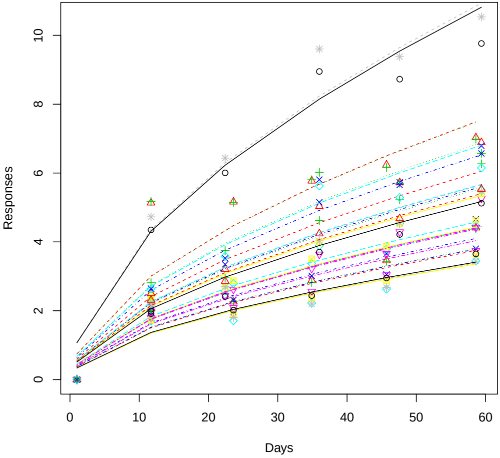


(a) Wavelength Effect

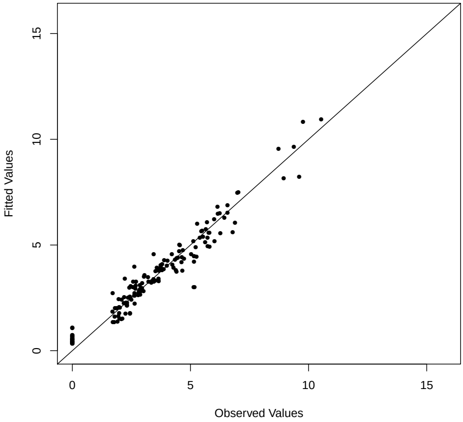


(b) RH Effect

Plot of Sample Fitted Path

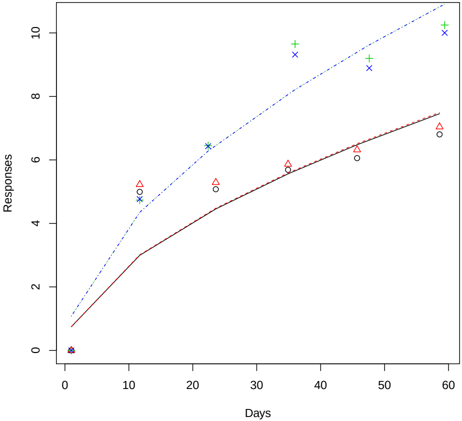


Fitted vs Observed



- Overall, the model can fit the data well.

Out of Sample Prediction



- Overall, the model can predict the test sample well.

Concluding Remarks

- We developed a statistical predictive model for degradation model, which can be used for service life prediction.
- The statistical models for covariates are based on physical/chemical mechanisms.
- The statistical model can fit and prediction the degradation well, and it can be applied to different datasets.