Statistical Modeling for Service Life Prediction of PV Materials

Yili Hong

Department of Statistics
Virginia Tech
Blacksburg, VA

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Overview

- General strategy and data for building predictive model
- Statistical predictive model
- Modeling and analysis of yellowing data
- Prediction for indoor tested units from NIST and several companies
- Prediction of outdoor tested units with environmental data
- Concluding remarks

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 a 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

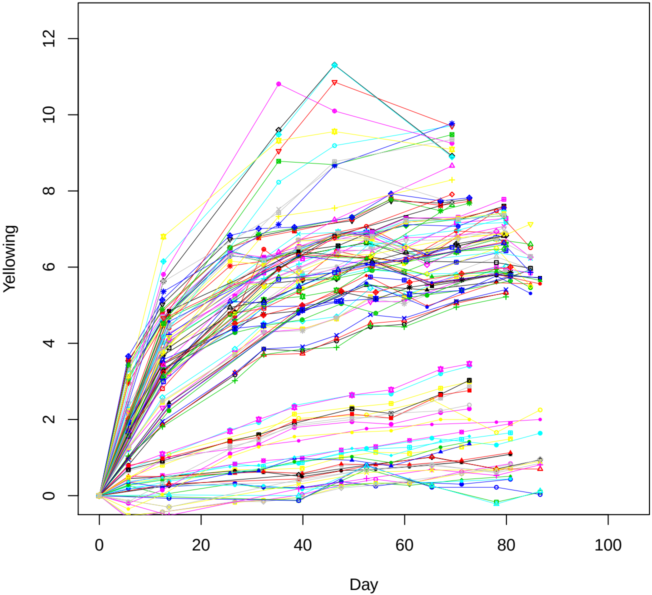
- PPE is used as the studying material.
- The chemical damage (1475/1410, 1715/1410, 1245/1410, and 1685/1715), and discoloration are used as the degradation indices.
- Experimental variables: UV spectrum, UV intensity, temperature, and RH.
- Spectra study (four filters): 306 nm ($\pm$3), 326 nm ($\pm$6), 353 nm ($\pm$19), and 452 nm($\pm$80).
- Reciprocity law study (four intensity filters): 40%, 60%, 80%, 100% (nominal percentages).
- Temperature: 45C, 65C, 75C, and 85C.
- RH: 0% and 60%.

Experiment Configuration for Yellowing

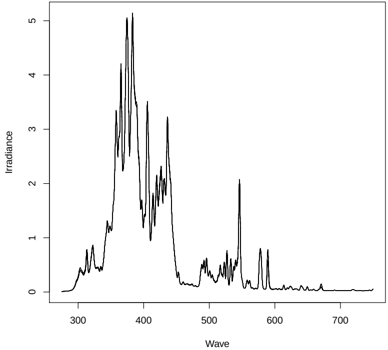
EXP_ID	TEMP	RH	DEN	SAMPLE	BP	SAMPLE	EXP_ID	TEMP	RH	DEN	SAMPLE	BP	SAMPLE
45_0_R	45	0	40%	8, 11, 14, 17	-	-	75_0_W	75	0	100%	2, 3, 4, 5	-	-
	45	0	60%	7, 10, 13, 16	-	-		75	0	-	-	306	8, 12, 16
	45	0	80%	6, 9, 12, 15	-	-		75	0	-	-	326	9, 13, 17
	45	0	100%	2, 3, 4, 5	-	-		75	0	-	-	354	6, 10, 14
								75	0	-	-	389	7, 11, 15
65_0_R	65	0	40%	2, 8, 12, 16	-	-							
	65	0	60%	3, 9, 13, 17	-	-	85_0_W	85	0	100%	2, 3, 4, 5	-	-
	65	0	80%	4, 6, 10, 14	-	-		85	0	-	-	306	8, 12, 16
	65	0	100%	5, 7, 11, 15	-	-		85	0	-	-	326	9, 13, 17
								85	0	-	-	354	6, 10, 14
65_0_W	65	0	100%	2, 3, 4, 5	-	-				-	-	389	7, 11, 15
	65	0	-	-	306	8, 12, 16							
	65	0	-	-	326	9, 13, 17	85_60_R	85	60	40%	2, 8, 12, 1	-	-
	65	0	-	-	354	6, 10, 14		85	60	60%	3, 9, 13, 1	-	-
	65	0	-	-	389	7, 11, 15		85	60	80%	4, 6, 10, 1	-	-
								85	60	100%	5, 7, 11, 1	-	-
75_0_R	75	0	40%	8, 11, 14, 17	-	-							
	75	0	60%	7, 10, 13, 16	-	-							
	75	0	80%	6, 9, 12, 15	-	-							
	75	0	100%	2, 3, 4, 5	-	-							

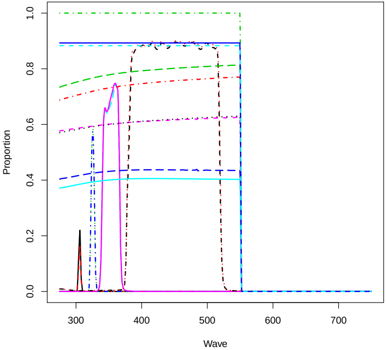
- The total sample is 112 under 7 experiments. 98 used for model training, 14 used for model testing (marked by red).

Plot of Degradation Data for Yellowing



Lamp Spectral Irradiance and Filters





- The lamp irradiance is denoted by $E(\lambda)$.
- Filters, denoted by $F(\lambda)$: bandpass 306nm, 326nm, 354nm, and 452nm; intensity: 40%, 60%, 80%, and 100%

Building Predictive Model - Effective Dosage Model

- The wavelength-specific intensity is $I(\lambda) = E(\lambda) \times F(\lambda)$.
- To incorporate the effect of wavelength and intensity, we introduce the idea of effective dosage.
- The usual dosage is computed as $d(t) = \int_0^t \int_\lambda I(\lambda) d\lambda d\tau$.
- The effective dosage is modeled as

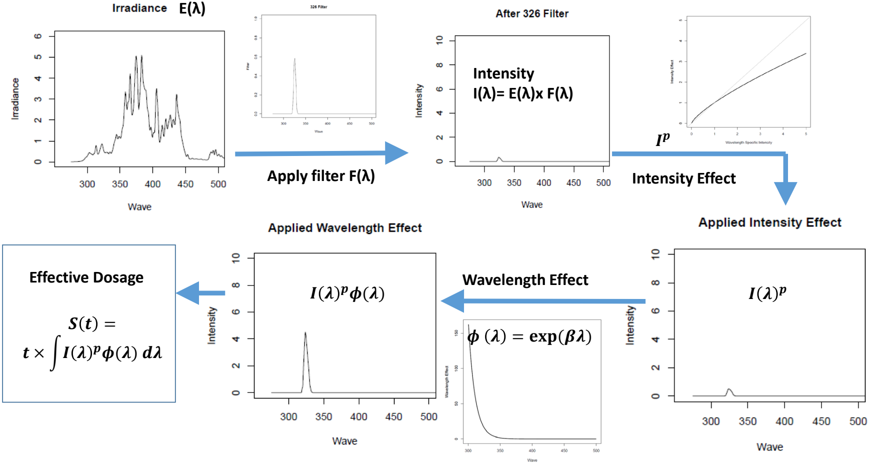
$$s(t) = \int_0^t \int_\lambda [I(\lambda)]^p \phi(\lambda) d\lambda d\tau = t \times \int_\lambda [I(\lambda)]^p \phi(\lambda) d\lambda$$

- The effect of wavelength is $\phi(\lambda) = \exp[\beta(\lambda - 354)]$, log-linear relationship. Here, we use the 354nm as the baseline. That is the acceleration factor at 354nm is one.
- The effect of intensity is $[I(\lambda)]^p$, power law relationship.

Summary of Variable Effects

- Wavelength effect is modeled by log linear model.
- The intensity effect is modeled by the power law relationship.
- The Arrhenius relationship is used to describe the acceleration factor of temperature: $\exp\left(\frac{\beta_t \cdot 11605}{\mathrm{TempC}+273.15}\right)$.
- The RH effect is updated as $(1 + \mathrm{RH})^{\beta_r}$.

Illustration of Effective Dosage Computing



Statistical Model for Degradation Path

- The model for degradation measurements is

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

- $\epsilon_{ij} \sim \mathrm{N}(0, \sigma_\epsilon^2)$ is the error that can not be captured by $D(t_{ij})$.
- The model used for an increasing degradation path is

$$D(t) = \frac{A}{1 + \exp\left\{-\frac{\log[s(t)] - \mu - \beta_t \frac{11605}{\mathrm{TempC}+273.15} - \beta_r \log(1+\mathrm{RH})}{\sigma}\right\}}$$

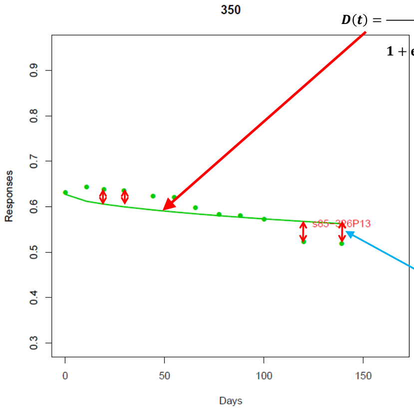
$$s(t) = t \times \int_\lambda [I(\lambda)]^p \phi(\lambda) d\lambda$$

$$\phi(\lambda) = \exp[\beta(\lambda - 354)].$$

Parameter Interpretation

- A is initial degradation.
- Let $\eta = \exp(\mu)$ and $\gamma = 1/\sigma$.
- η is the half-degradation effective dose. That is the amount effective dose needed for the degradation to reach $0.5A$.
- γ is related to the steepness of the damage curve. For example, the slope at $s(t) = \eta$ is $\frac{A}{4\eta}\gamma$. So the larger the γ, the steeper the curve.

Illustration of Predictive Model



$$D(t) = \frac{A}{1 + \exp\left\{\frac{\log[S(t)] - \mu - \beta_t \frac{11605}{\text{TempC} + 273.15} - \beta_r \log(1 + \text{RH})}{\sigma}\right\}}$$

$$S(t) = t \times \int I(\lambda)^p \phi(\lambda)\, d\lambda$$

$$\phi(\lambda) = \exp(\beta\lambda)$$

Find the curve to minimize the sum of the squares of the vertical distances.

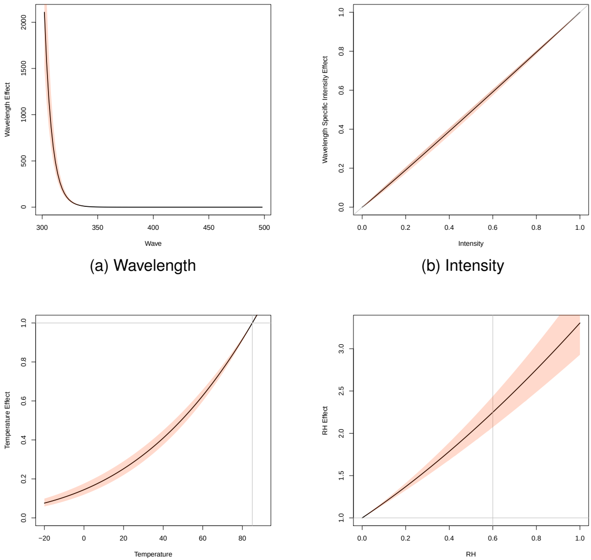
- The curve depends on parameters $A, \mu, \sigma, \beta, p, \beta_t$, and β_r.
- Parameter estimate are obtained by finding values of $A, \mu, \sigma, \beta, p, \beta_t$, and β_r which minimize the sum of the squares of the vertical distance over the 98 units in the training set.

Indoor Model Summary for Yellowing

- Parameter estimates

Parameter	Interpretation	Value
A	ultimate degradation	16.297
$\eta = \exp(\mu)$	half-degradation dose	310.132
$\gamma = 1/\sigma$	steepness	0.458
β	wavelength effect	-0.147
p	intensity effect	1.03
β_t	temperature effect	0.192
β_r	RH effect	-1.724
σ_ϵ^2	error variance	0.390

Plot of Variable Effect



(a) Wavelength

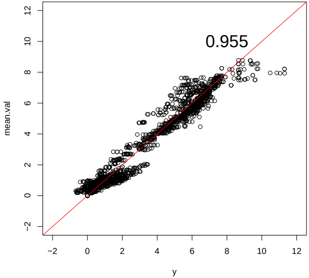
(b) Intensity

(c) Temperature

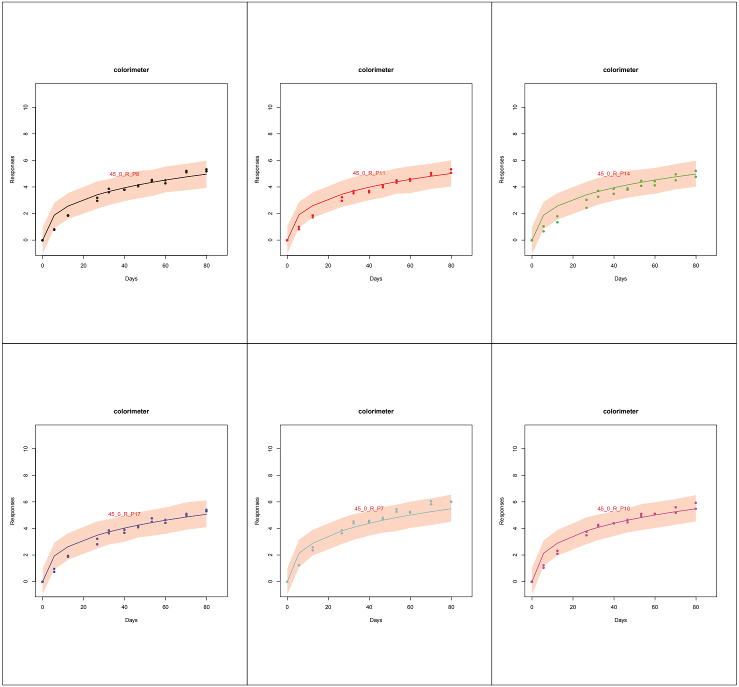
(d) RH

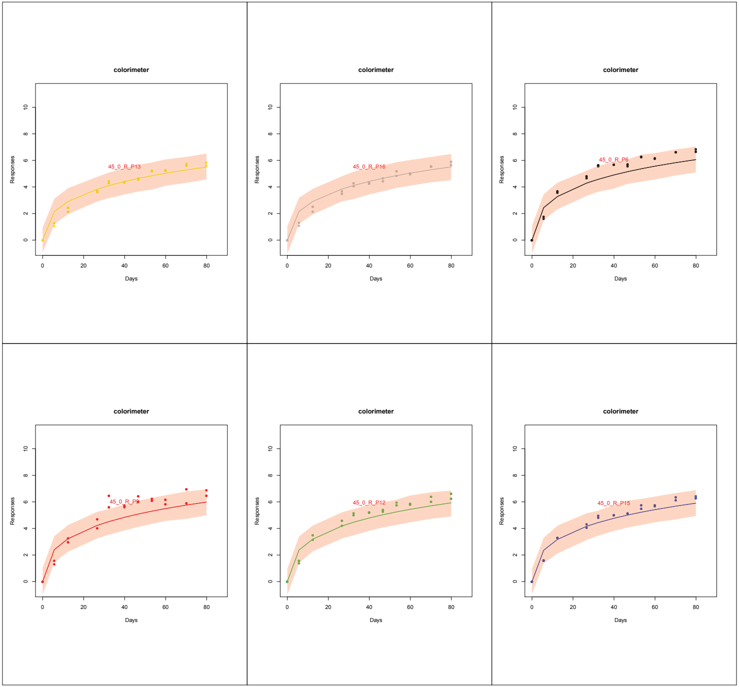
Plot of Fitted Paths for Colorimeter

- The overall R^2 is 95.5%.
- The x-axis is the observed degradation and the y-axis is the predicted degradation from the model.



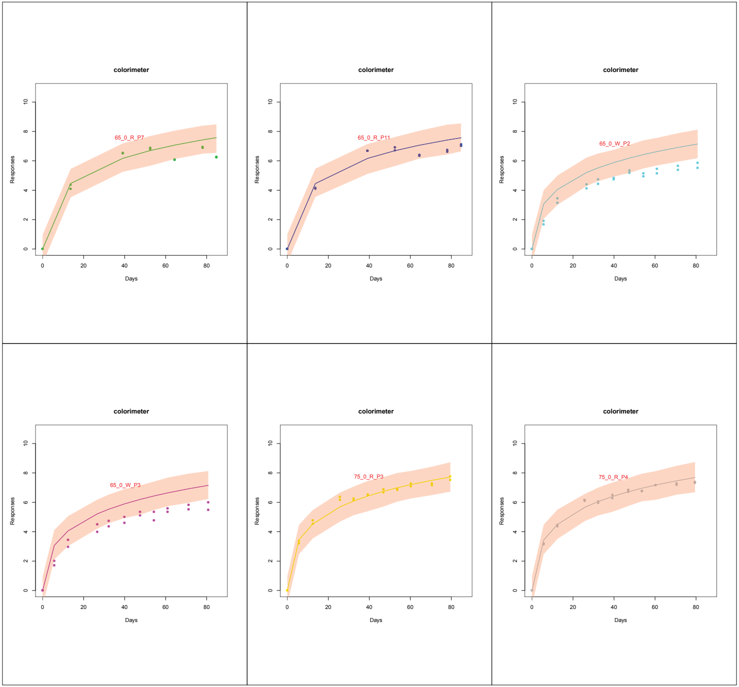
- The fitting for individual samples is shown in the following slides for a subset of units in the training set.
- The shaded area shows the 90% statistical interval for uncertainty quantification.


colorimeter
45_0_R_P8
colorimeter
45_0_R_P11
colorimeter
45_0_R_P14
colorimeter
45_0_R_P17
colorimeter
45_0_R_P7
colorimeter
45_0_R_P10
Responses
Days
0
2
4
6
8
10
0
20
40
60
80

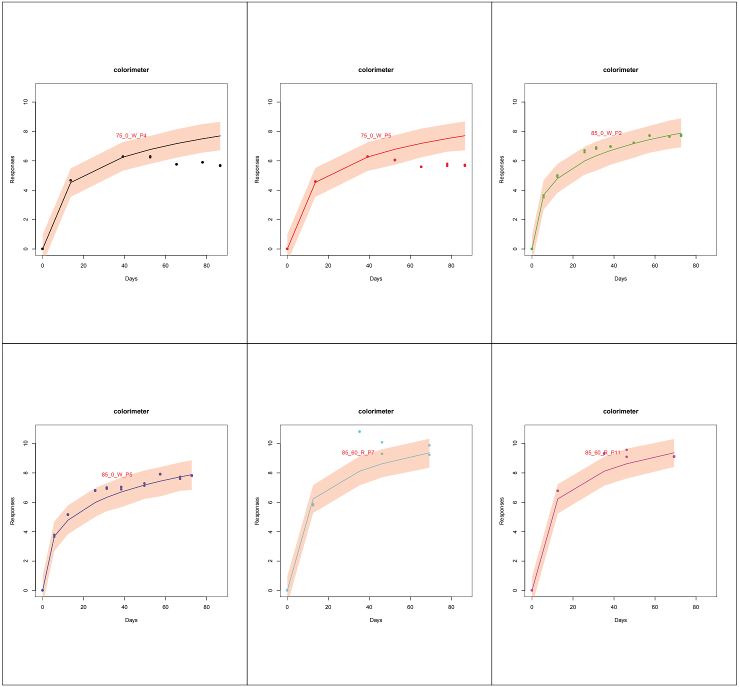

colorimeter
45_0_R_P13
45_0_R_P16
45_0_R_P6
45_0_R_P12
45_0_R_P15
Responses
Days

Out of Sample Prediction for NIST Data

- Use the fitted model to predict the test samples in NIST data (14 samples in total).
- The prediction for individual samples is shown as follows.
- Overall, the out of sample test works quite well for the NIST data.

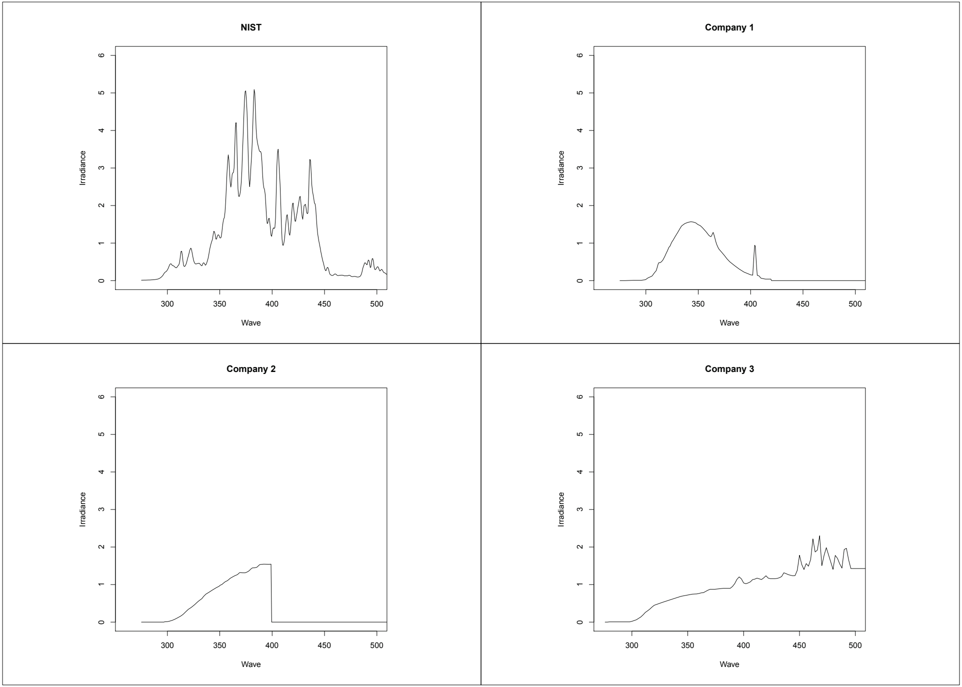


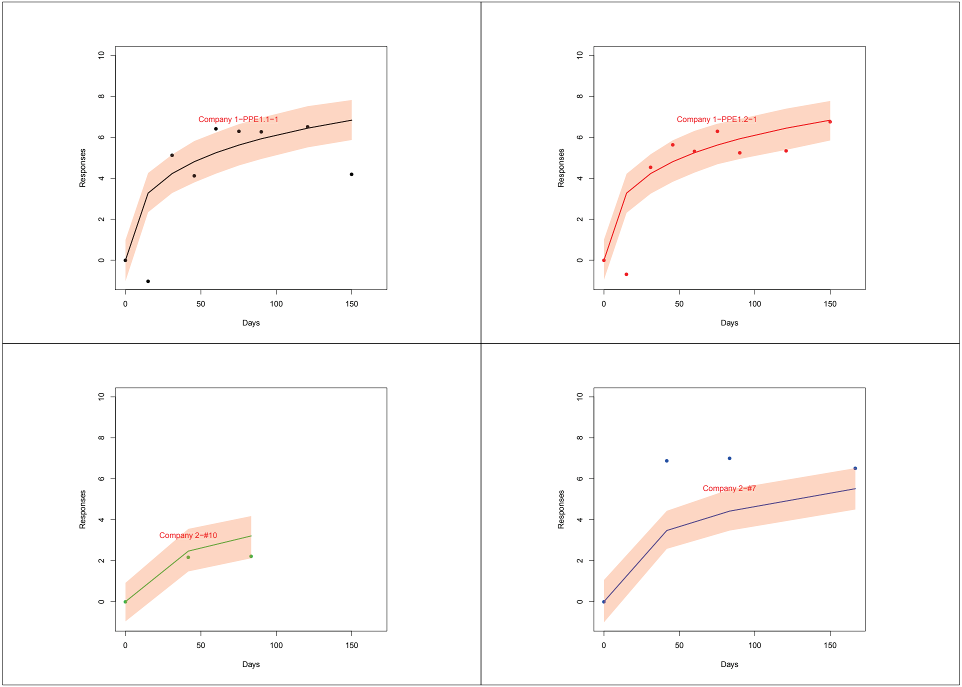
colorimeter
65_0_R_P7
Responses
Days
colorimeter
65_0_R_P11
Responses
Days
colorimeter
65_0_W_P2
Responses
Days
colorimeter
65_0_W_P3
Responses
Days
colorimeter
75_0_R_P3
Responses
Days
colorimeter
75_0_R_P4
Responses
Days

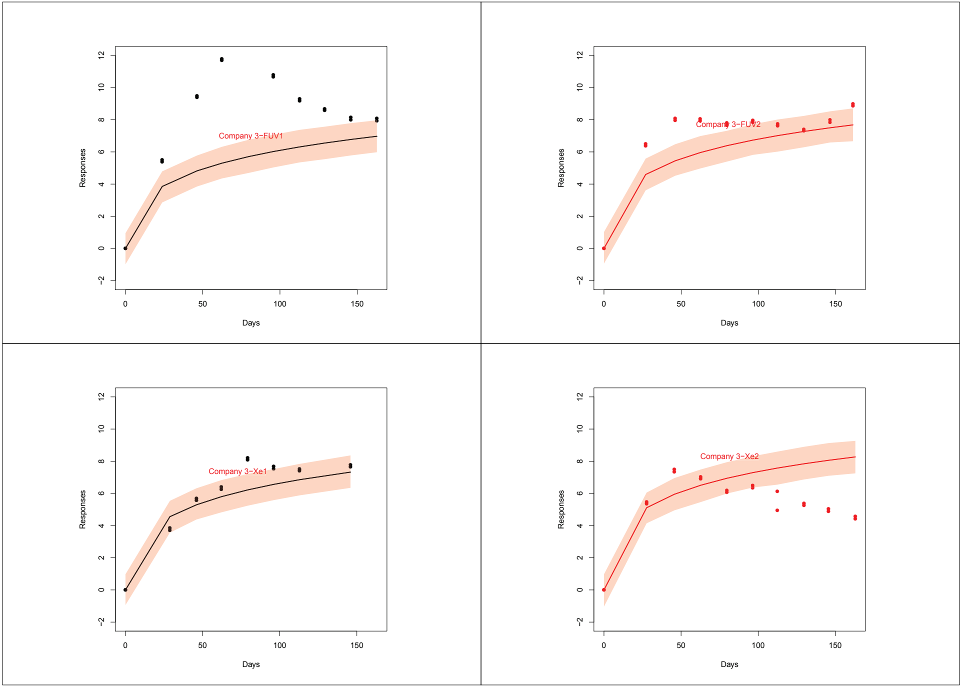

colorimeter
75_0_W_P4
colorimeter
75_0_W_P5
colorimeter
85_0_W_P2
colorimeter
85_0_W_P5
colorimeter
85_60_R_P7
colorimeter
85_60_R_P11
Responses
Days
0 2 4 6 8 10
0 20 40 60 80

Test Datasets from Company

- Use the predictive model to predict the degradation for samples tested at industrial labs.
- Three sources of datasets:
  - Company 1: 2 samples: 65C RH uncontrolled, full wavelength
  - Company 2: 2 samples: BPT 70C RH 50%, full wavelength
  - Company 3: 4 samples: BPT 50C, 50C, 70C, 90C; RH uncontrolled, 30%, full wavelength
- The following plots show four different lamp spectral irradiances and model testing results.

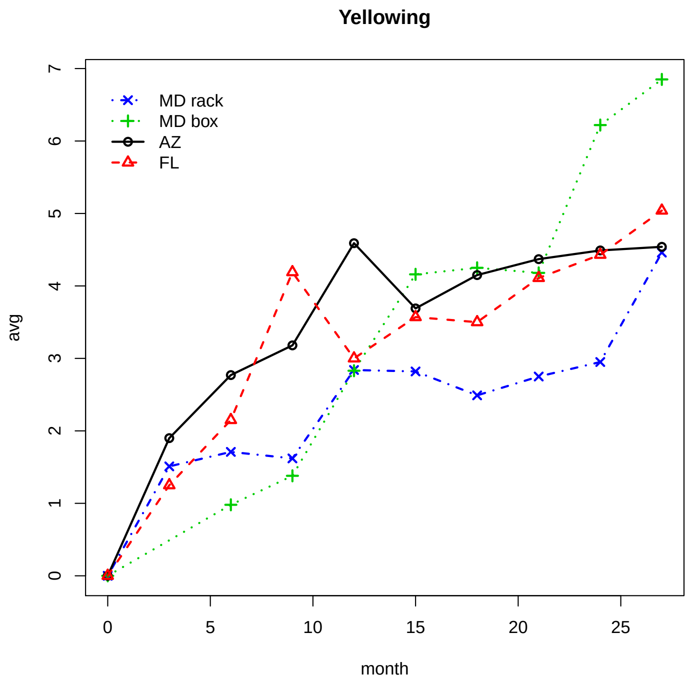

NIST
Company 1
Company 2
Company 3
Irradiance
Wave


Company 1−PPE1.1−1
Company 1−PPE1.2−1
Company 2−#10
Company 2−#7
Responses
Days

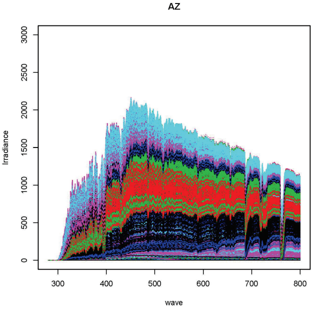

Company 3−FUV1
Company 3−FUV2
Company 3−Xe1
Company 3−Xe2
Responses
Days
−2
0
2
4
6
8
10
12
0
50
100
150

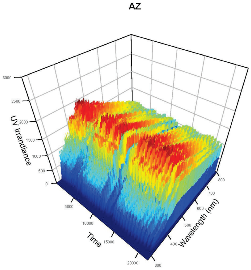
Outdoor Data

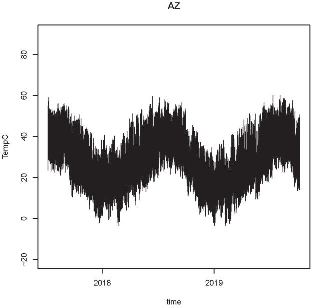
- The outdoor experiments are carried out at three locations with four different settings.
- The settings are Arizona, Florida, Maryland rack, and Maryland box.
- The outdoor units are measured every three months. So far ten measurements are available.
- Outdoor sun irradiance, temperature, and RH are also available as functions of time.
- The following slides show the outdoor degradation and time-varying covariates.

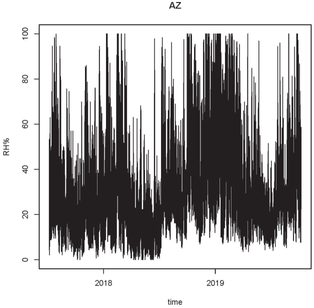


Yellowing
MD rack
MD box
AZ
FL
avg
month
0
1
2
3
4
5
6
7
0
5
10
15
20
25


AZ
Irradiance
wave
0
500
1000
1500
2000
2500
3000
300
400
500
600
700
800


AZ
UV Irradiance
Time
Wavelength (nm)


AZ
TempC
time
-20
0
20
40
60
80
2018
2019


AZ
RH%
time
0
20
40
60
80
100
2018
2019

Effective Dosage for Time-Varying Covariates

- To incorporate time-varying environmental variables for outdoor degradation, the effective dosage model is extended as

$$s(t) = \int_0^t \exp\left[\frac{\beta_t \cdot 11605}{\mathrm{TempK}(\tau)}\right] [1 + \mathrm{RH}(\tau)]^{\beta_r} \int_\lambda [E(\lambda, \tau)]^p \phi(\lambda) d\lambda d\tau$$

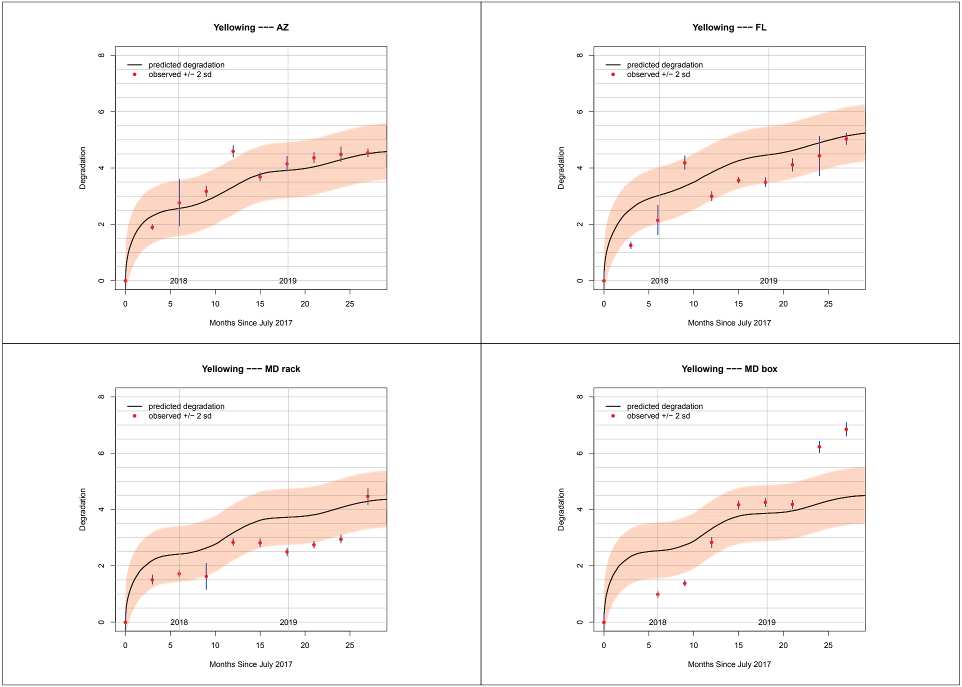
- The effect of wavelength is $\phi(\lambda) = \exp[\beta(\lambda - 354)]$.
- The effect of intensity is $[E(\lambda, \tau)]^p$.
- The temperature effect is modeled as $\exp\left[\frac{\beta_t \cdot 11605}{\mathrm{TempC}(\tau) + 273.15}\right]$.
- The RH effect is modeled as $[1 + \mathrm{RH}(\tau)]^{\beta_r}$.

Outdoor Prediction Model

- The input for the effective dosage model is the data for outdoor irradiance, temperature, and RH as functions of time and the model parameters estimated from indoor data.
- The effective dosage $s(t)$ can be computed as a function of time.
- With the effective dosage, the outdoor degradation can be computed as

$$D(t) = \frac{A}{1 + \exp\left\{-\frac{\log[s(t)]-\mu}{\sigma}\right\}}.$$

- The following slide shows the predicted degradation for the four settings at three locations, along with 90% prediction intervals.


Yellowing --- AZ
Yellowing --- FL
Yellowing --- MD rack
Yellowing --- MD box
predicted degradation
observed +/− 2 sd
Degradation
Months Since July 2017
2018
2019
0
2
4
6
8
0
5
10
15
20
25

Concluding Remarks

- We developed a statistical predictive model for degradation model, which can be used for service life prediction.
- The statistical model can fit and predict the degradation path reasonably well, and it can be applied to different datasets collected from different companies under different testing conditions.
- We can generate prediction for outdoor tested samples.
- The modeling framework can be applied to other degradation indexes, such as chemical changes, although the yellowing data is used for illustration.
- Toward SLP, we still need to know how to correlate degradation and failures.
- Develop software for the developed methodology.