Low Creep / Low Relaxation Polymer Composites for Deployable Structures

Machine Learning Methods for Determining Viscoelastic Properties of Polymer Composites

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Problem

Key Term – Stress Relaxation: the time-dependent decrease in stress of a viscoelastic material held under constant strain

- Deployable structures spend up to 1 or 2 years in stowage before deployment
  - Can result in loss of structural integrity if significant relaxation occurs
- Need to mitigate stress relaxation within ultralightweight carbon fiber / polymer composites
- Current investigations rely on experimental results of material testing
  - This process is time-consuming and requires in-person lab access

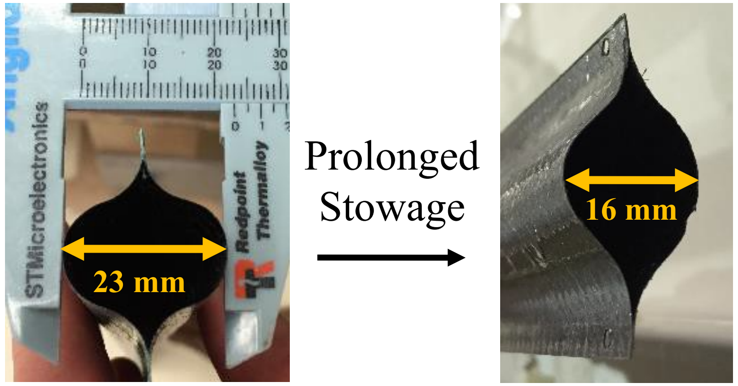


Fig. 1. About 50% loss in buckling strength due to stress relaxation [1]. Image credit: NASA

[1] J. M. Fernandez et al., “An Advanced Composites-Based Solar Sail System for Interplanetary Small Satellite Missions,” in 2018 AIAA Spacecraft Structures Conference, Kissimmee, Florida, 2018, doi: 10.2514/6.2018-1437.

Objectives

Driving Question: How can the stress relaxation modulus of polymer composites be determined without physically testing candidate materials?

- Assess candidate algorithms for use in determining stress relaxation modulus
- Create a program that will learn from existing stress relaxation database to predict stress relaxation behavior in polymer composites
- Validate model and improve mean squared error (MSE)

Approach

- Developed model for validation with experimental data:
  - Gaussian Process Regression (GPR) Algorithm
    - Implicit determination of influencing factors using covariance matrix
      - Where *X* is an array of *m* elements and *E* denotes the expected value of *X*
    - Experimental data obtained consisted of 11 influencing factors (parameters)
      - Time, Temperature, Relaxation Modulus, Stress, Strain Recovery, Decay Time, Strain, Displacement, Length, Static Force, Stiffness
- Analysis Comparison utilized Time-Temperature Superposition (TTS)
  - Time-dependent mechanical properties (relaxation) can be mathematically approximated in time using high temperature experiments
    - i.e. the relaxation of a polymer over 1,000,000 minutes at room temperature can be approximated by the relaxation of the same polymer over 60 minutes at 100

Results

- GPR Mean Squared Error (MSE): 9.8976
  - Range of values is 10^4,
    - Scaled MSE: 0.045%
  - Dataset Length: 703
  - Number of Parameters: 11

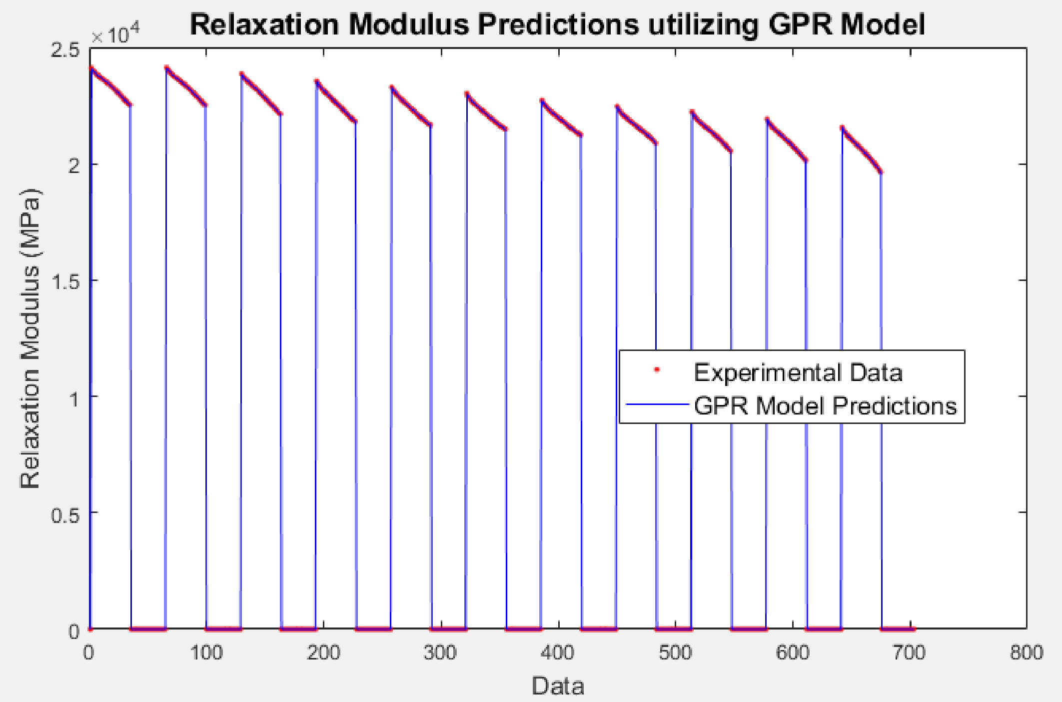


Fig. 2. Overlay of Experimental Data on GPR Model Predictions of Stress Relaxation Modulus for a Carbon Fiber-Reinforced Polymer Composite over entire experimental domain

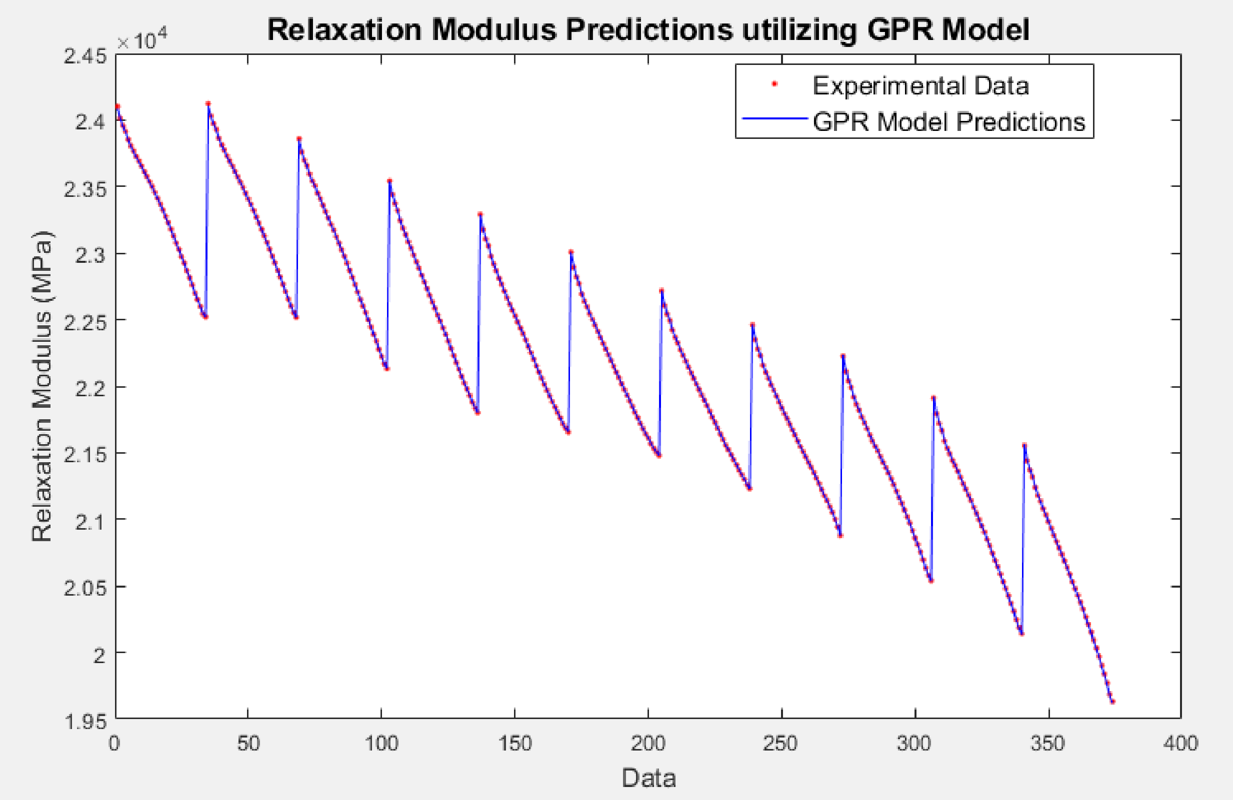
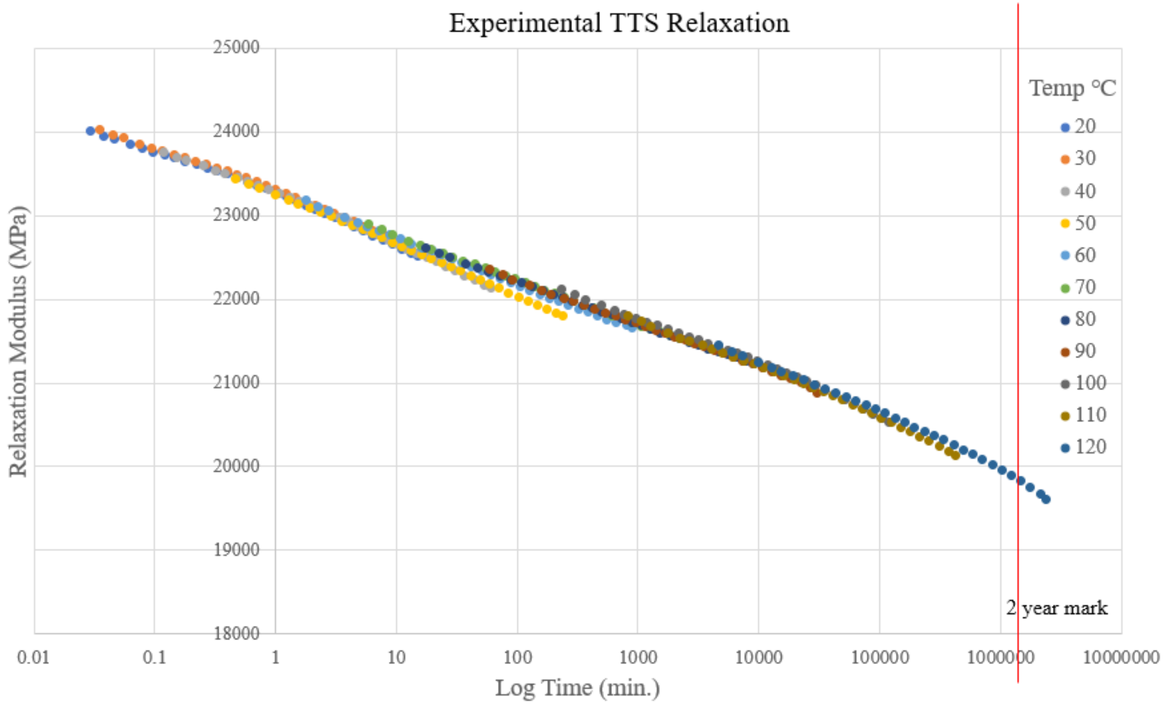


Fig. 3. Overlay of Experimental Data on GPR Model Predictions of Stress Relaxation Modulus for a Carbon Fiber-Reinforced Polymer Composite over domain of interest

Analysis



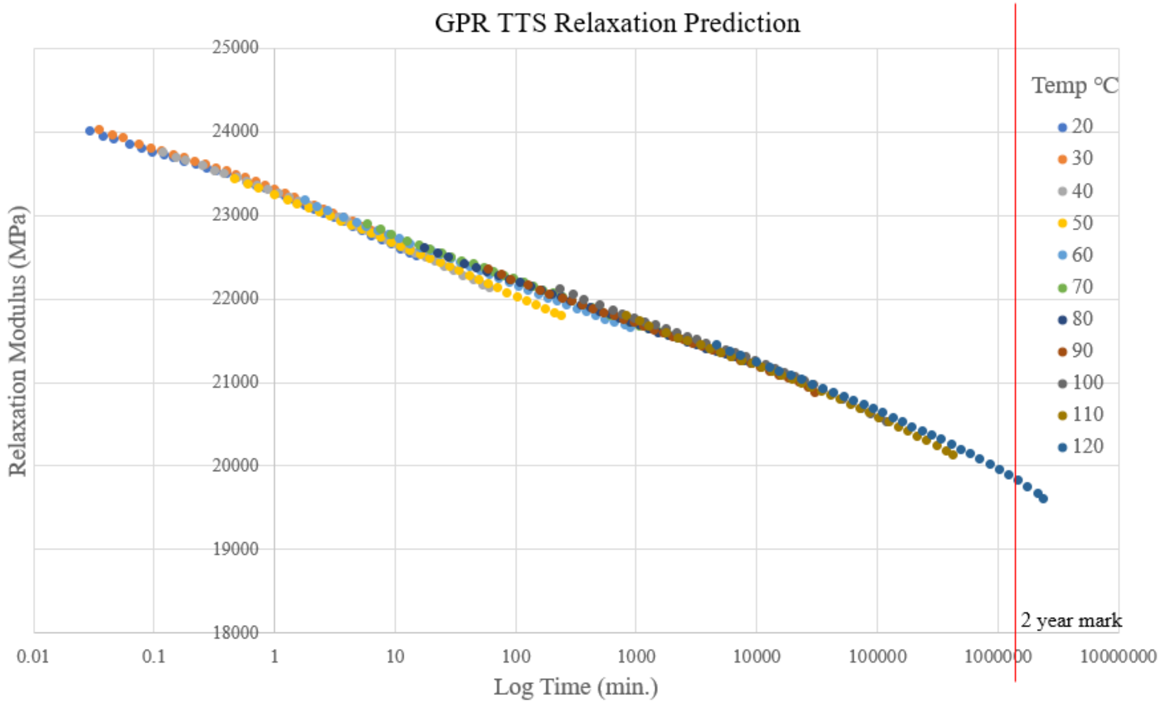


Fig. 4 & 5. Comparison of experimental (left) and modeled (right) stress relaxation behavior for carbon fiber polymer composite after time-temperature superposition post-processing analysis

- Experimental Results:16.87% reduction in relaxation modulus after 2 years of stowage
- GPR Prediction Results:16.86% reduction in relaxation modulus after 2 years of stowage
- 0.059% difference between experimental and modeled results
- Suggests that majority of regression loss (mean squared error) is due to viscoelastic modeled region of composite
- Validated model is highly accurate

Next Steps

- Developing a focused algorithm utilizing transfer learning
  - Limited dataset of stress relaxation
  - Transfer learning can accurately predict complex relationships using limited data
- Highly versatile project
  - Constructed models can learn and predict material properties beyond stress relaxation
    - Thermoelectric properties
    - Mechanical properties
    - Optical properties

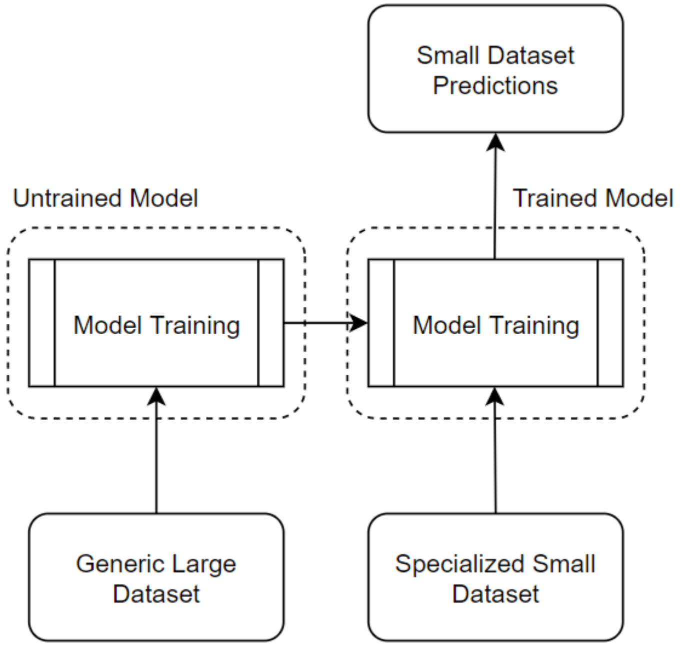


Fig. 6. Transfer Learning schematic for small dataset predictions.

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