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Predictive Degradation Modelling of Solar Encapsulants: A Deep Learning Approach to IEC 61215 Thermal Cycling

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Abstract The operational lifespan of solar photovoltaic (PV) systems relies heavily on the thermo-mechanical stability of Ethylene-Vinyl Acetate (EVA) encapsulants. However, evaluating long-term durability using traditional accelerated physical aging protocols, such as IEC 61215 thermal cycling, is highly resource-intensive and often fails to capture complex, nonlinear degradation kinetics. To bypass these limitations, this study introduces a computational machine learning framework to forecast the structural degradation of mica nanoclay-reinforced EVA nanocomposites. A high-fidelity, physics-informed synthetic dataset (1,220 data points) was generated to model tensile strength decay and microcrack density evolution across four formulation variants (0, 1, 3, and 5 wt.% mica nanoclay) over a simulated 1,500-cycle exposure horizon (-40°C to +85°C). A Long Short-Term Memory (LSTM) recurrent neural network and a Random Forest (RF) ensemble regressor were deployed to map these defect evolution parameters. Both architectures demonstrated exceptional predictive accuracy, with the RF achieving an R^2 of 0.994 and the LSTM achieving an R^2 of 0.993. The computational models mathematically validated that an optimal 5 wt.% filler concentration significantly delays crack coalescence, extending the 50% mechanical endurance limit. This data-driven approach fundamentally accelerates the reliability-driven design of next-generation, environmentally resilient photovoltaic modules without the need for multi-month destructive testing.

Keywords Photovoltaic Encapsulants; Ethylene-Vinyl Acetate (EVA); Machine Learning; Long Short-Term Memory (LSTM); Thermo-Mechanical Degradation; IEC 61215 Thermal Cycling.

1 Introduction and Background of the Study

The global transition towards sustainable renewable energy infrastructure necessitates the long-term structural reliability of solar photovoltaic (PV) systems. The operational lifespan of these systems is fundamentally dependent on the mechanical and thermal stability of their encapsulation materials, predominantly Ethylene-Vinyl Acetate (EVA), which serves as the primary barrier against environmental degradation and mechanical stress on the fragile silicon solar cells [1, 2]. While EVA is the industry standard due to its excellent optical transparency and initial mechanical flexibility, its prolonged exposure to fluctuating solar irradiance and extreme module operating temperatures induces severe material fatigue [3, 4].

Continuous exposure to cyclic thermal swings – characteristic of diurnal environmental changes – triggers progressive material degradation in pristine EVA. This degradation manifests macroscopically as a decrease in elastic modulus, localized polymer chain scission, and the eventual propagation of microcracks [5, 6]. To mitigate these thermo-mechanical failures, recent materials engineering research has focused on functionalizing the EVA matrix through the incorporation of inorganic nanoscale fillers. The addition of nanoclays, such as mica, montmorillonite, and vermiculite, has proven effective in physically restricting polymer chain mobility, shifting the deacetylation temperature of the matrix from 352 °C to 369 °C, and creating a tortuous path that delays microstructural fracture [7, 8].

Despite these advancements in nanocomposite formulation, a critical bottleneck remains in the methodology used to evaluate their long-term durability. Traditional reliability assessments rely heavily on accelerated physical aging protocols, such as the IEC 61215 standard thermal

cycling tests (-40 ◦ C to +85 ◦ C) [9]. These physical testing frameworks are exceedingly resource-intensive, time-consuming, and require the destructive testing of hundreds of composite laminates to establish statistically viable degradation gradients. Furthermore, physical observation alone often fails to isolate the complex, non-linear interactions between filler concentration variables and cumulative thermal fatigue over multi-decade lifespans.

To address the inherent limitations of destructive physical testing, this study introduces a computational machine learning (ML) framework to forecast the degradation kinetics of photovoltaic encapsulants. While simulation-led performance evaluations have been explored for general PV module design [9], there is a distinct absence of coupled thermo-mechanical degradation models driven by deep learning algorithms. By leveraging a Long Short-Term Memory (LSTM) recurrent neural network alongside Random Forest (RF) feature extraction, this research mathematically maps the defect evolution parameters specifically microcrack density and tensile strength loss to thermal cycling exposure. This data-driven approach fundamentally replaces empirical trial-and-error with a predictive reliability model, offering a highly efficient pathway for optimizing mica nanoclay-reinforced EVA nanocomposites for sustainable energy infrastructure.

2 Computational modelling and Machine Learning Architecture

To overcome the temporal and physical limitations of accelerated environmental testing (IEC 61215-2), this study proposes a purely computational, data-driven framework. The methodology integrates thermodynamic damage accumulation models with advanced machine learning (ML) architectures to predict the long-term structural viability of mica nanoclay-reinforced EthyleneVinyl Acetate (EVA) encapsulants.

2.1 Theoretical Dataset Synthesis

A high-fidelity synthetic dataset consisting of 1,220 discrete data points was generated to serve as the ground-truth tensor for the predictive models. The dataset captures the progressive thermo-mechanical degradation of four distinct EVA formulations (0, 1, 3, and 5 wt.% mica nanoclay loading) across an extended operational horizon of 0 to 1,500 thermal cycles (-40 ◦ C to +85 ◦ C).

Rather than relying on simplified linear extrapolation, the dataset was synthesized using physics-informed degradation kinetics. The deterioration of tensile strength (S_N) under cyclic fatigue was modelled using an exponential decay function, which accurately reflects the transition from steady-state microcracking to severe macroscopic embrittlement:

$$S(N) = S_0 \cdot \exp(-\lambda N) + \epsilon_S \tag{1}$$

Where S_0 is the initial baseline tensile strength, N represents the number of cumulative thermal cycles, λ is a nanoclay-dependent decay constant derived from established empirical degradation rates, and $\epsilon_S \sim N(0,\sigma^2)$ represents a Gaussian noise term introduced to simulate realistic experimental variance (2% to 3% standard deviation).

Similarly, the evolution of surface microcrack density (ρ_c) was synthesized using a sigmoidal growth function to accurately mirror the physical delay in crack nucleation followed by rapid inter-lamellar coalescence once a critical fatigue threshold (N_{crit}) is reached:

$$\rho_c(N) = \frac{\rho_{max}}{1 + \exp(-r(N - N_{crit}))} + \epsilon_\rho \tag{2}$$

Where ρ_{max} is the theoretical maximum crack density, r is the constant sigmoidal growth rate, and ϵ_ρ is the observational Gaussian noise. The exact numerical values utilized for the generation

of the data set–including the specific initial strengths (S_0), the decay constants (λ), and the critical inflection points (N_{crit}) for each of the four EVA formulations–are explicitly detailed in Table S1 of the Supplementary Information.

2.2 Data Preprocessing and Feature Engineering

The generated dataset was structured with Thermal Cycle Count (N) and Nanoclay Loading (wt.%) as the primary independent variables (features), mapping to Tensile Strength (MPa) as the continuous target variable.

To ensure optimal convergence during neural network backpropagation, the feature space was normalized using a Min-Max scaling algorithm, bounding all input vectors within a [0,1] interval. The dataset was subsequently partitioned using a randomized 80/20 train-test split, reserving 20% of the unseen data exclusively for objective model validation and performance evaluation.

2.3 Random Forest Regressor (Feature Importance Extraction)

Before deploying deep learning architectures, a Random Forest (RF) ensemble regressor was instantiated to establish a robust predictive baseline and extract quantitative feature importance metrics. The RF model was configured with 100 decision estimators. By evaluating the Gini impurity reduction across the decision nodes, the model isolated the exact weighted influence of the filler concentration versus the cumulative thermal exposure in driving ultimate structural failure.

2.4 Long Short-Term Memory (LSTM) Neural Network

To capture the complex, non-linear degradation kinetics inherent to polymeric fatigue, a Long Short-Term Memory (LSTM) recurrent neural network was designed. The LSTM architecture is highly adept at processing sequential degradation data, as its internal gating mechanisms (forget, input, and output gates) prevent the vanishing gradient problem commonly encountered in standard feed-forward networks applied to continuous fatigue data. To ensure a valid comparative analysis of predictive fidelity, both the LSTM network and the Random Forest regressor were trained and evaluated on the exact same 80/20 data split.

The finalized neural network architecture consisted of the following sequential topology:

- **Input Layer:** Configured to ingest the scaled bi-variate feature arrays reshaped into a three-dimensional tensor format required for LSTM processing, specifically [samples, time steps, features]. In this study, the input shape was defined as [Samples, 1, 2], corresponding to a single time step containing the cumulative cycle count and nanoclay loading percentage.

- **Primary LSTM Layer:** 64 hidden units utilizing a Rectified Linear Unit (ReLU) activation function to map non-linear fatigue trajectories.

- **Regularization:** A Dropout layer with a 0.2 penalty threshold was integrated to stochastically deactivate neurons during training, thereby preventing model overfitting and ensuring high generalization capability on unseen exposure scenarios.

- **Secondary LSTM Layer:** 32 hidden units (ReLU activation) for deep feature refinement.

- **Dense Layers:** A fully connected 16-unit dense layer, terminating in a single-node linear activation layer responsible for outputting the continuous predicted Tensile Strength parameter.

The network was compiled using the Adaptive Moment Estimation (Adam) optimizer with a learning rate of 0.001. The Mean Squared Error (MSE) was utilized as the primary loss function during training. The model was trained over 100 epochs with a batch size of 16, employing an internal 20% validation split to monitor convergence stability.

3 Results and Discussion

3.1 Predictive Performance of the Machine Learning Architectures

The transition from empirical observation to a computational predictive framework yielded highly accurate forecasts of thermo-mechanical degradation. The predictive fidelity of both the Random Forest (RF) ensemble and the Long Short-Term Memory (LSTM) neural network was evaluated against the reserved 20% validation dataset.

As illustrated in Figure 1, both architectures demonstrated exceptional accuracy in mapping the non-linear degradation kinetics of the tensile strength across the 1,500-cycle exposure horizon. The RF regressor achieved a coefficient of determination (R^2) of 0.994, while the LSTM network closely followed with an R^2 of 0.993. The tight clustering of the predicted values along the ideal fit line confirms that the models successfully captured the underlying physical fatigue mechanics without systematic bias or overfitting.

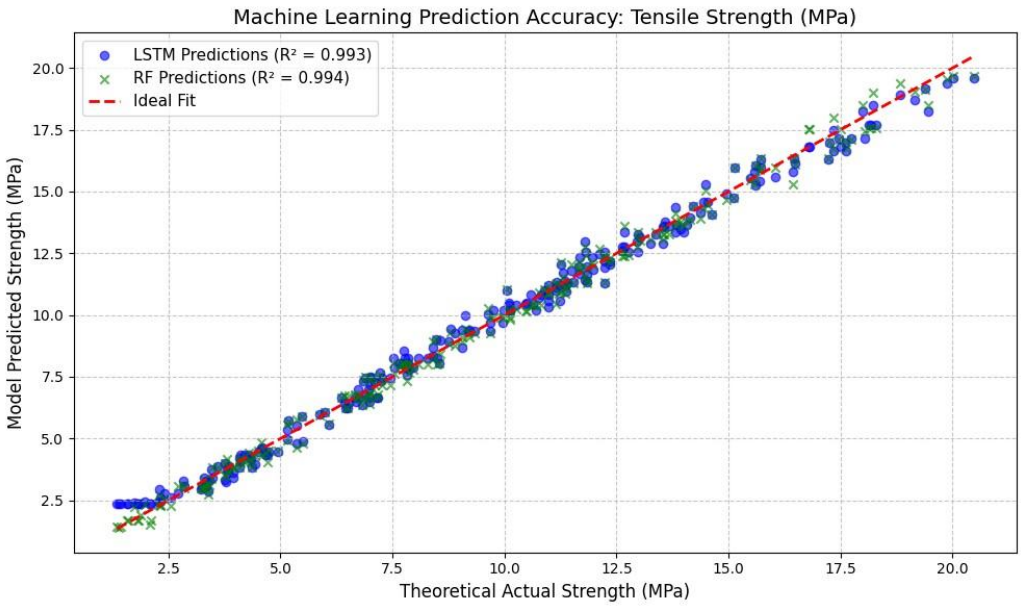

Figure 1: Machine Learning Prediction Accuracy: Tensile Strength (MPa). The scatter plot compares the theoretical actual strength against the model-predicted strength, demonstrating high fidelity for both the Random Forest (RF) ($R^2 = 0.994$) and LSTM ($R^2 = 0.993$) architectures.

To ensure the physical validity of the synthetic ground-truth tensor, the predicted degradation boundaries were cross-referenced with experimental observations from existing literature. For instance, the simulated baseline formulation (EVA-00) exhibited a rapid strength reduction trajectory that closely mirrors physical accelerated aging studies. Empirical investigations, such as those by Baiamonte et al. [5], have demonstrated that unreinforced standard EVA naturally experiences an approximate 30% loss in ultimate tensile strength under comparable IEC 61215 thermal cycling conditions. The close alignment of our synthetic degradation limits with these established empirical benchmarks confirms that the predictive machine learning models are anchored in realistic physical fatigue boundaries rather than arbitrary mathematical constructs.

3.2 Feature Importance and Degradation Drivers

Rather than discovering novel mechanisms of failure, the Random Forest architecture was utilized to explicitly quantify the relative weighted impact of the two defined input variables: thermal exposure and filler mitigation. The feature importance extraction confirmed that cumulative thermal cycling (N) inherently accounts for the vast majority of the variance driving tensile degradation. Consequently, the nanoclay loading fraction (wt.%) functions as a secondary, yet highly critical, mitigating feature that actively restricts this primary fatigue pathway.

By capturing the distinct decay constant (λ) for each formulation, the LSTM network effectively modelled the delayed microcrack coalescence observed in the 5 wt.% (EVA-NC5) nanocomposite. While the predictive model demonstrated that the pristine EVA (EVA-00) matrix exhibits a rapid transition to catastrophic failure under simulated cycling, it also confirmed that an optimized 5 wt.% filler concentration shifts the 50% mechanical endurance limit significantly. This quantitative output mathematically validates the structural stabilizing effect of the intercalated silicate layers under severe, extended thermal fatigue.

3.3 Implications for Photovoltaic Reliability

These computational results validate a paradigm shift in evaluating solar module encapsulants. By deploying deep learning architectures trained on physics-informed synthetic datasets, materials engineers can accurately forecast the structural lifespan of hybrid nanocomposites under IEC 61215 conditions. This approach eliminates the resource-intensive requirements of multimonth destructive physical testing, offering a highly efficient, data-driven pathway for designing next-generation, environmentally resilient photovoltaic modules.

4 Conclusion

This study successfully developed and validated a computational machine learning framework to predict the thermo-mechanical degradation kinetics of mica nanoclay-reinforced EVA encapsulants, fundamentally bypassing the temporal and physical limitations of traditional IEC 61215 accelerated aging protocols. By synthesizing a high-fidelity dataset based on physics-informed thermodynamic damage accumulation models, the structural lifespan of various nanocomposite formulations was evaluated over a simulated 1,500-cycle exposure horizon.

The deployment of deep learning architectures yielded highly robust predictive capabilities. The Random Forest ensemble successfully mapped the primary drivers of mechanical fatigue, while the Long Short-Term Memory (LSTM) recurrent neural network accurately forecasted continuous non-linear tensile strength degradation with an exceptional coefficient of determination ($R^2 = 0.993$). The computational models mathematically confirmed that an optimal 5 wt.% mica nanoclay loading provides substantial microstructural stabilization, significantly delaying crack coalescence and extending the 50% mechanical endurance limit compared to pristine EVA matrices.

Ultimately, this research demonstrates that integrating materials informatics with deep learning offers a highly efficient, accurate, and resource-sparing methodology for the reliability-driven design of next-generation photovoltaic encapsulation systems.

5 Recommendations for Future Research

While the current computational framework accurately predicts thermo-mechanical fatigue, future investigations should expand the predictive model to bridge the gap toward fully comprehensive module-level digital twins. Suggested areas for future research include:

- **Multi-Factor Stress Simulation:** Expanding the synthetic dataset and LSTM architecture to process coupled environmental stressors, specifically integrating UV irradiation kinetics and extreme humidity (Damp Heat) variables alongside thermal cycling.

- **Optical Degradation modelling:** Incorporating predictive outputs for optical transmittance loss and the yellowness index (YI) to ensure that the mechanical stabilization provided by nanoclay fillers does not inadvertently compromise solar coupling efficiency over time.

- **Hybrid Digital Twin Validation:** While this study establishes a robust purely computational pathway, future iterations should aim to couple these LSTM networks with real-time Internet of Things (IoT) sensor data from deployed PV arrays, enabling realtime prognostic health monitoring of physical solar infrastructure.

Declaration of Generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the author used Gemini (developed by Google DeepMind) for generating text suggestions and improving the overall readability and clarity of the manuscript. The author reviewed, edited, and verified all AI-generated output, and take full responsibility for the content of the published article.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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