Supporting Material Reuse in Drone Production

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Abstract

This paper, part of the European Horizon project Plooto, details an end-to-end, data-driven framework for reusing expired carbon-fiber prepregs in drone production. First, 19 batches of expired prepregs were tested, revealing that most remained usable within the first year after expiration. Machine learning models were then developed to predict material usability pre-production and product quality post-production, using manufacturing data and time-series features. To facilitate this process, a dedicated data pipeline and an interactive Product Quality Explorer tool were created to support explainable model development and integration with industrial partners. This framework demonstrates how combining material requalification with data-driven predictions can lower costs and support circularity in drone production.

Keywords

circular economy, digital product passport, machine learning, product quality

1 Introduction

The growing demand for lightweight, high-performance materials is driving the increased use of carbon fiber reinforced polymers (CFRPs) in industries such as aerospace, automotive, and drones. However, this rapid adoption also creates challenges, particularly with the accumulation of expired materials. While much research has focused on recycling fully cured CFRPs, less attention has been given to the reuse of uncured prepregs, which, despite expiring during storage, can still retain valuable properties [5]. Addressing this challenge is crucial for advancing circular economy principles in high-tech manufacturing.

This paper presents research from the European Horizon project Plooto, focusing on the reuse of expired prepregs in sustainable drone production. Our work contributes in three key areas: (1) a comprehensive evaluation of the effects of aging on expired prepregs through thermal, chemical, and mechanical testing to establish requalification thresholds [1], (2) the development of machine learning models to predict the usability of expired prepregs before production, and (3) the application of predictive models to assess the quality of final products after production, specifically for sandwich panels made from recycled prepregs. By combining experimental testing with data-driven methods, our findings highlight the potential to reduce waste and enhance sustainability in drone manufacturing.

By integrating machine learning models to predict the usability of expired prepregs and assessing the quality of final products, we provide industrial partners with actionable insights that directly enhance operational decision-making. The combination of material requalification and predictive analysis supports the sustainability goals of the drone production process.

2 Data and Methods

2.1 Materials and experimental techniques used for prepreg usability assessment

Expired rolls of epoxy prepregs from HP Composites S.p.A were used for this study. A total of 19 prepreg batches were investigated, comprising four different resin systems (ER450, IMP509, X1, ER431), with reinforcement varying according to supplier availability. Usability is assessed through periodic chemical-physical and mechanical testing after the expiration date, to monitor property changes in materials stored at -18°C. Differential Scanning Calorimetry (DSC) tests were performed with Mettler Toledo DSC 823e on uncured prepreg samples by applying a dynamic heating from -40°C to 250°C at 20°C/min under a nitrogen atmosphere. DSC analysis provides two key parameters: the glass transition temperature of the uncured system (T_{g0}), related to the initial crosslink density, and the residual cure degree (α), calculated from the polymerization enthalpies values. Composite plates for physical and mechanical testing were manufactured by draping a variable number of prepreg plies at 0°, depending on reinforcement type, to obtain cured laminates of $\approx$ 3 mm. The prepreg plies were stacked on a flat mold surface over a peel ply. The plates were then covered with an additional peel ply, a release film, and a breather layer. The self-adhesive seal and the vacuum bag were used to create a sealed vacuum during the entire process. Plates curing was carried out in a hot press according to the curing cycle recommended by the supplier in the material datasheet, as reported in the table 1. The void content (V_c) was measured on five specimens through a digestion procedure according to standard ASTM D3171 Method A. [3] The interlaminar shear strength (ILSS) tests were performed with a 3-point bending system on MTS Insight machine according to the standard test ASTM D2344 [2] on five different specimens for each prepreg batch. These experimental results, including DSC data, ILSS, and void content (V_c) measurements, provide essential features for the machine learning models discussed in Section 2.2. The values of key properties such as the glass transition temperature (T_{g0}), residual cure degree (α), and interlaminar shear strength (ILSS) are directly used to predict the usability of the

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expired prepregs and to assess the quality of the final products after manufacturing.

Material	Temperature (°C)	Time (h)	Pressure (bar)
ER 450	135°C	2h	6 bar
IMP 509	140°C	1.5h	4 bar
X1 120	130°C	1.5h	6 bar
ER 431	125°C	1h	5 bar

Table 1: Curing cycle parameters for the plates recommended in the material datasheet.

2.2 Predicting the usability and key parameters of prepreg using machine learning methods

The results from the DSC tests, along with other experimental data such as ILSS and void content (V_c) collected in Section 2.1, were systematically organized and used as input features for the machine learning models to predict prepreg usability and key process parameters. Each row represents one checkpoint on an expired roll and includes: test date, month code, prepreg code and lot, type (expired roll), stocking temperature (−18 °C), original expiry date, α (%), $T_{g,\text{onset}}$ (°C), ILSS (MPa), V_c (°C; curing temperature), Usable (Y/N), and, when redefinition is applied, pressure (bar), temperature (°C), time (min), and the redefined expiry date. For the correct operation of machine-learning methods, a *days-after-expiry* feature was introduced and computed as `test_date − original_expiry_date`.

The study addresses two predictive tasks: a classification problem for *Usable* (three classes: Y, Y/N, N) and regression problems for process/quality parameters (ILSS, $T_{g,\text{onset}}$, V_c, α). Analysis proceeds in two stages. First, a per-material stage fits separate models for each prepreg system (ER450, IMP509, ER431, X1) to resolve material-specific issues observed during preliminary inspection. Second, a pooled stage trains a unified model over all records to evaluate cross-material generalisation.

Predictors are restricted to pre-test covariates: days-after-expiry, material identity, normalised lot descriptors, month code, storage conditions, and other metadata available at decision time, while measured targets are excluded from inputs to prevent label leakage. Random-forest classifiers and regressors (scikit-learn) parameterised as $n_{\text{estimators}}$=100, max $\_depth$=3, random_state=42 serve as the base models and enable inspection of feature importances.

Performance estimation relies on leave-one-out cross-validation (LOO-CV) [6] in both stages. For the classification task, overall accuracy is reported to evaluate the model's performance in predicting prepreg usability. For the regression tasks, R^2, MAE, and RMSE are used to assess the model's ability to predict continuous process parameters. R^2 measures the proportion of variance explained, while MAE provides the average error magnitude, and RMSE emphasizes larger errors. Feature-importance profiles are examined to identify the dominant drivers of re-usability and variation in process parameters across materials and in the pooled setting.

2.3 Machine Learning for Post-Production Quality Prediction

This part of the pilot addressed the prediction of production quality in sandwich panel manufacturing, with the aim of supporting drone production after re-qualification.

The dataset combined two types of information. The first component consisted of production metadata, which described the context of each cycle. These attributes included the date of the cycle, the operator responsible for production, the specific prepreg batch (identified by lot number), and the number of days between when the prepreg was made and used in production. Tool-related information was also provided, such as which tool was used and how many cycles had passed since its last maintenance. Each cycle was associated with a measurement curve identifier, a quality result (labelled as either fully compliant, minor defect, or scrap), and, in cases of non-compliance, the reported reason for failure.

The second component of the dataset consisted of time-series data collected during the manufacturing process. For each cycle, approximately 1,300 measurements were recorded at ten-second intervals. These measurements included the chamber's target temperature (setpoint), the actual chamber temperature, the temperature of the piece being moulded, and the vacuum setpoint. Together, these readings captured the thermal and pressure dynamics that govern the curing of composite materials.

To make this information usable for machine learning models, feature extraction was required. Temperature curves were divided into intervals based on their inflection points—that is, the points where the curve transitioned from stable plateaus to rising or falling slopes. Each interval was then summarised using statistical properties such as average, minimum, maximum, variance, and trend. In addition to these aggregated features, new variables were engineered to capture deviations from expected behaviour. For example, the vacuum difference quantified the gap between the measured and target pressure, while the temperature difference measured the offset between chamber setpoints and the actual values recorded. These derived variables provided indicators of process deviations that might affect the final product quality.

The analysis followed the CRISP-DM methodology, beginning with data fusion and preparation, followed by feature selection and model training. Metadata and time-series features were combined into a single dataset, from which irrelevant or redundant variables were removed.

For predictive modelling, several classification algorithms were evaluated to balance interpretability and performance. Logistic regression and decision trees offered transparent decision boundaries, while ensemble methods such as random forests and gradient boosting provided stronger predictive power by aggregating multiple weak learners. Multi-layer perceptrons (MLP) were also considered to capture non-linear patterns in the data.

To integrate the methodology into the production workflow, a dedicated service was implemented. Metadata was provided in an Excel (.xlsx) file, while the process data was provided in .rdb formats by the industrial partner. A pipeline was developed to automatically download these files from a shared Dropbox folder provided by the industrial partner, parse the .rdb data, and convert the files into structured JSON files. The JSON files were enriched with derived variables and unique identifiers, then uploaded to the Plooto platform via its API. This ensured seamless integration of raw production data with machine learning models, enabling continuous prediction of product quality.

As part of this work, we developed a tool called Product Quality Explorer to support domain experts in analyzing production data and assessing product quality [4]. Its primary goal is to facilitate the creation of explainable machine learning models. The tool helps users understand factors influencing quality outcomes and make informed adjustments to the manufacturing process. The tool provides a summary of descriptive statistics (count, mean, standard deviation, minimum, quartiles, and maximum) and allows users to visualize selected columns through histograms and boxplots. Finally, it generates a heatmap of all columns to provide an overview of relationships within the data.

In the next step, the user selects the features to include in the machine learning model. This step is necessary both to define the target variable for prediction and to exclude irrelevant columns such as IDs, dates, or textual data. The tool also provides several options for handling missing values. The user can choose the approach that best suits the dataset: leaving missing values unchanged (which may prevent some algorithms from functioning properly), removing features with missing values, removing rows containing missing values, or imputing missing values using the column mean.

The next step provides the option to generate new attributes. This can be done through techniques such as one-hot encoding, polynomial feature generation, or logarithmic transformations. After creating new attributes, the user selects the features to be used in the machine learning process. This selection can be performed manually or automatically with the assistance of genetic algorithms.

Finally, the user can select which machine learning models to apply. Once training is complete, the results are presented in a summary table containing performance metrics such as precision, recall, F1-score, and accuracy, along with a confusion matrix visualization. The tool also provides a comparative overview of model performance across all metrics (precision, recall, F1-score, accuracy).

In addition to evaluation, the system integrates explainability techniques. Global explanations are generated using SHAP to show how features influence model decisions across the entire dataset, while local explanations are provided using SHAP and LIME to illustrate how the model arrived at a prediction for a specific datapoint. These explanations are supported by interactive visualizations, which enable users to better understand both the overall model behavior and individual predictions.

3 Results

3.1 Results of usability assessment

Ageing trends from DSC. Differential scanning calorimetry (DSC) on the selected prepreg rolls (grouped by resin system) shows that T_{g0} increases progressively over time after expiration. This behaviour is consistent with *i)* increasing molecular weight and *ii)* higher crosslink density of the polymer network due to ongoing polymerization. The measured α values align with the T_{g0} trend, indicating a time-dependent decrease in the residual degree of cure; notably, within the first two years after expiration, the reduction remains limited to <15%.

Mechanical strength and porosity evolution. Across all batches, interlaminar shear strength (ILSS) exhibits a time-dependent decline: reductions generally do not exceed 15% within the first 12 months after expiration, whereas more pronounced decreases of 25–30% occur in the 12–24 month interval. Consistent with this mechanical trend, the void content V_c remains below 10% during the first 12 months after expiration and increases thereafter, often exceeding 15% in later months.

3.2 Predictive modeling results for prepreg reuse

We analysed $N = 81$ inspection records with a two–stage workflow: global model across all prepregs and material-specific models were trained and estimated using leave-one-out cross-validation (LOO-CV). Table 2 summarizes the results of all experiments, including classification and regression performance for global and material-specific models.

Type	Usability	Metrics	α	T_{g0}	ILSS	V_c
All types	Acc=0.91	**AggR²** =	0.83	0.77	0.7	0.77
		MAE =	1.22	1.05	4.49	1.52
		RMSE =	1.59	1.33	5.93	1.98
ER450	Acc=0.96	**AggR²** =	0.86	0.88	0.92	0.94
		MAE =	1.25	0.54	2.75	0.87
		RMSE =	1.51	0.77	4.05	1.15
IMP509	Acc=0.87	**AggR²** =	0.76	0.6	0.82	0.8
		MAE =	1.44	1.23	2.5	1.35
		RMSE =	1.9	1.58	3.01	1.75
X1	Acc=0.96	**AggR²** =	0.82	0.79	0.79	0.43
		MAE =	1.12	0.98	2.41	1.77
		RMSE =	1.44	1.12	3.09	2.32
ER431	Acc=1	**AggR²** =	0.97	0.88	0.94	0.87
		MAE =	0.57	0.89	1.43	1.06
		RMSE =	0.76	1.15	1.93	1.64

Table 2: LOO-CV performance across prepregs for regression and classification

As we can see from the presented results, the global multi-class classifier achieved 0.91 accuracy under LOO-CV on an imbalanced set (54 Y / 14 Y-N / 13 N), indicating that a simple pre-production screen is feasible from routine metadata. Per-material classifiers were even higher (often ≥0.96), but these figures are almost certainly optimistic given tiny per-material sample sizes and class imbalance. A detailed classification report, including precision, recall, and F1 scores, can be provided upon request.

A consistent trend across the regression tasks is the superior performance of models trained on a single prepreg type compared to the global model trained on all data.[1] For instance, the global model predicted ILSS with an aggregate R^2 of 0.70, whereas the material-specific models for ER450 and ER431 achieved much higher scores of 0.92 and 0.94, respectively. This suggests that ageing and curing behaviours are highly specific to the resin system, and tailored models better capture these characteristics. However, this is not a universal rule; the prediction of V_c for the X1 prepreg (aggregate R^2=0.43) was notably worse than the global model (aggregate R^2=0.77), indicating that in cases of very limited data or less distinct features, the global model can be more robust.

Feature importance analysis performed during the experiments revealed the most influential factors in predicting key parameters in Table 2. The Days_Since_Expiry was consistently one of the most critical predictors across both global and material-specific models, confirming its fundamental role in tracking material degradation. Furthermore, the analysis revealed strong intercorrelations between the measured properties themselves. For example, the degree of cure (α) and T_{g0} were often the most

[1]The dataset is modest and unevenly distributed across resins (ER450 n=28, X1 n=22, IMP509 n=15, ER431 n=14). Consequently, per-material models are trained on few observations and LOO-CV performance is likely optimistic.

important features for predicting ILSS and V_c, indicating that these thermal and chemical properties are highly interdependent. Batch identifiers (prepreg code/lot) were generally minor, although *lot* occasionally ranked higher for ILSS, indicating possible batch effects.

Taken together, these patterns suggest that compact, physics-aligned feature sets explain most of the variance, and that ageing/α consistently drive both regression and classification. Nevertheless, limited data—especially for IMP509 and ER431—and the optimism of LOO-CV preclude production use without further data collection and validation across broader process conditions.

3.3 Evaluation of Post-Production Classification Models

The predictive modelling was applied to production cycles from sandwich panel manufacturing provided by the Italian pilot partners. We also used the aforementioned Product Quality Explorer tool after we had already transformed the data and created new features. The objective was to assess whether production quality outcomes could be predicted from a combination of metadata and process-derived time-series features. This is particularly important for supporting drone production after re-qualification, as early detection of potential quality issues can prevent defective panels from progressing further in the manufacturing chain. Moreover, it can save manufacturers time, energy, and personnel costs, as each panel must currently be manually inspected and tested.

The dataset comprised 294 production cycles, the majority of which were compliant, with only a small fraction classified as non-compliant. This strong imbalance reflects real-world conditions, where defects are rare but critical, yet it also creates difficulties for machine learning approaches. Most algorithms tend to favour the majority class, which can lead to high overall accuracy but poor detection of defective cases.

Several classification algorithms were tested. Overall accuracy values appeared relatively high (between 0.77 and 0.85) this was largely driven by the correct classification of compliant cases. Performance on the minority (non-compliant) class was weaker, as reflected by modest recall and F1-scores. This indicates that while the models are well-suited to reproducing the majority outcome, their ability to identify rare defective panels is more limited.

These findings suggest that machine learning can provide useful insights into production quality trends, but further progress requires additional data, particularly more defective cases. A larger dataset would allow models to better distinguish between compliant and non-compliant cycles, thereby increasing their value as a decision-support tool in quality assurance.

The detailed performance of each tested classifier is reported in Table 3.

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.846	0.838	0.838	0.838
Decision Tree	0.769	0.764	0.738	0.745
Random Forest	0.808	0.797	0.806	0.800
XGBoost	0.808	0.797	0.806	0.800
LightGBM	0.846	0.838	0.838	0.838
Support Vector Machine (SVM)	0.808	0.801	0.788	0.793
Multi-layer Perceptron (MLP)	0.808	0.801	0.788	0.793

Table 3: Performance of machine learning models on the Italian pilot sandwich panel dataset.

4 Conclusion

This study demonstrates an end-to-end approach that integrates material science and machine learning to enhance the reuse of expired prepregs in drone production. By evaluating and requalifying expired materials, we have shown that they remain serviceable within the first year after expiry, with gradual performance decline, particularly in interlaminar shear strength and curing behavior. This underscores the effectiveness of resin-specific reuse gates and modified processing windows to extend material lifetimes.

Machine learning models were employed to support both pre-production and post-production processes. The pre-production models classified expired prepregs for reuse, while the post-production models predicted the quality of sandwich panels based on combined metadata and process features. Despite challenges related to data imbalance, the results demonstrate the potential for predictive quality monitoring in manufacturing, contributing to more sustainable production practices.

The integration of machine learning with material science not only optimizes requalification processes and reduces waste, but also supports cost reduction and environmental sustainability in high-performance manufacturing. Future work should focus on expanding datasets, refining resin-specific criteria, and exploring the broader applicability of the models in other composite manufacturing contexts, further advancing circular economy principles.

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