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Learning to Repair Through AI-Driven Geometry Reconstruction for Sustainable Manufacturing

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ABSTRACT

Remanufacturing plays a vital role in advancing circular economy strategies by extending product lifecycles and reducing energy consumption. However, the variability in part condition and lack of predictive tools often hinder efficient repair planning and sustainable decision-making. This paper presents the Eco-Remanufacturing Architect, an AI-driven solution designed to reconstruct degraded geometries and support informed decision-making in additive remanufacturing processes. The tool integrates edge-based contour extraction and Fourier descriptor encoding to capture degraded component geometries, which are then predicted from process parameters using a pair of Random Forest Regressors. To enhance generalization across diverse repair scenarios, the training dataset is augmented using a Variational Autoencoder. The reconstructed curves are evaluated using both descriptor-based and spatial metrics, confirming the model's ability to capture both global shape and local detail with high accuracy. Beyond geometric feasibility, the system estimates key environmental indicators—such as energy consumption, material use, and carbon footprint—enabling multi-criteria evaluation of repair strategies. The proposed pipeline demonstrates how digital intelligence can empower more sustainable and cost-effective remanufacturing workflows by enabling accurate part assessment and resource-aware repair planning.

Keywords: Artificial intelligence, Smart remanufacturing, Sustainable design

INTRODUCTION

Remanufacturing is increasingly recognized as a key enabler of circular economy, offering substantial environmental and economic benefits by restoring end-of-life products to like-new condition. It reduces raw material demands, limits waste generation, and lowers energy consumption when compared to traditional manufacturing. However, the effectiveness of remanufacturing processes is often constrained by limited digitalization (González-Val, Precker & Muíños-Landín, 2022), lack of predictive tools, and the inherent variability in the condition of returned parts (Kerin & Pham, 2020). These factors make it difficult to evaluate whether a component is suitable for repair, what level of intervention is required, and what the expected outcome—in terms of functionality and sustainability—might be.

Recent advances in artificial intelligence and computer vision have opened up new possibilities for addressing these limitations. Emerging frameworks increasingly incorporate machine learning to automate condition assessment, optimize repair strategies, and quantify sustainability metrics (De Simone et al., 2024). Specifically, techniques such as contour-based geometry analysis, Fourier descriptors for shape encoding, and data augmentation through generative models have gained attraction in industrial applications requiring robust design and repair automation (Romero-González et al., 2020; Liu, Tian & Kan, 2022; Ekwaro-Osire et al., 2025).

The **Eco-Remanufacturing Architect** is an AI-driven solution designed to overcome these challenges by enabling data-driven decision-making in the context of additive repair. The tool enables the prediction of remanufacturing outcomes and associated energy costs based solely on additive manufacturing parameters. During the dataset creation phase, geometries of titanium repaired regions are extracted from metallographic images using a pipeline based on Holistically Nested Edge Detection (HED) and Fourier descriptors, converting physical repair contours into structured shape representations. These Fourier descriptors serve as ground truth to train a pair of Random Forest regression models that learn to map process settings (e.g., power, feed speed). At inference time, the trained regressors directly predict the expected repair geometry without requiring image data, enabling fast and interpretable shape estimation from parameter inputs alone. To improve model generalization and performance in low-data conditions, the pipeline incorporates Variational Autoencoders (VAEs) to generate synthetic manufacturing parameter sets for training augmentation. Through this combination of computer vision, shape modelling, regression, and generative AI techniques, the Eco-Remanufacturing Architect provides a comprehensive framework for predicting AM repair outcomes and assessing their environmental impact in the industry.

The rest of the paper is structured as follows. Section 2 presents the related work on AI for remanufacturing. Section 3 describes the methodologies and technical details of the proposed tool. Section 4 includes the experimental setup and evaluation results. Section 5 discusses the implications for industrial practice and smart remanufacturing. Finally, Section 6 outlines future research directions and concludes the work.

RELATED WORK

When it comes to remanufacturing, the use of machine learning has focused primarily on predictive maintenance and anomaly detection. Nonetheless, recent works have begun to leverage shape descriptors and regression models to restore or replicate worn component geometries. In (Romero-González et al., 2020), machine learning algorithms are investigated for the prediction of dimensional deviations in additively manufactured components. More recently, (Teresa García-Ordás et al., 2024) proposed a method that combines shape and contour descriptors to improve tool wear classification in milling processes. In parallel, recent works have revisited the use of Fourier descriptors for classifying shape deformations (Se, 2016), highlighting their value in characterizing complex geometries in industrial settings.

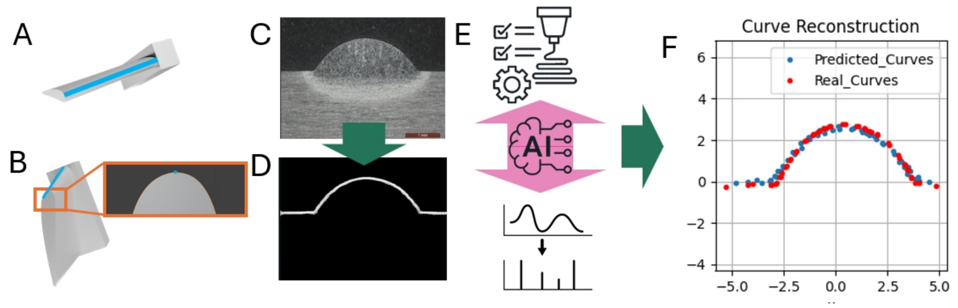

Figure 1: Pipeline of the eco remanufacturing training process. (A) A component with surface degradation targeted for additive manufacturing (AM)-based repair, with the affected region highlighted in blue. B) The damaged area is modelled as a geometric deviation represented by a curve. C) A metallographic image one slice of a titanium sample manufactured to evaluate the reparation process with its corresponding set of manufacturing parameters. D) Extracted contour of the repaired region using computer vision techniques. E) AI-based model correlates AM process parameters with the fourier descriptors of the extracted curve. F) Curve reconstruction comparing predicted and actual profiles, demonstrating model accuracy (axis show spatial dimensions in the range of mm).

While remanufacturing plays a central role in circular economy strategies, the application of AI to support sustainable decision-making in this domain is still emerging (Acerbi, Forterre & Taisch, 2021). Most existing approaches rely on rule-based or heuristic methods, with limited integration of data-driven models that account for environmental trade-offs (Okorie et al., 2018). By predicting key geometric and energy-related indicators using Random Forest models, eco-Remanufacturing Architect supports more circular, efficient, and transparent decision-making in additive repair contexts. Paving the way to an effective sustainable design of products and its consequent potential in a broad spectrum of manufacturing frameworks, considering aspects from material optimization (Gregores Coto et al., 2023) or selection (Couñago et al., 2025) to digitalized product lifecycle management strategies (Martínez et al., 2024) and collaborative lifecycle management (Gonzalez-Val & Muinos-Landin, 2020).

METHODOLOGY

Overview. The Eco-Remanufacturing Architect is an AI-driven tool designed to support circular manufacturing strategies by predicting the outcome of additive manufacturing (AM) repair processes. It correlates manufacturing settings (e.g., power, feed speed) with the resulting reconstructed geometry, allowing users to anticipate the effectiveness of a repair and estimate its associated energy cost on early-stage process planning. By bridging process data and sustainability indicators, the tool enables more informed decisions regarding part recovery, repair timing, and lifecycle optimization.

Geometric Representations: Fourier Descriptors. Accurate geometric representation of the repaired surface is essential for evaluating the outcome of an additive remanufacturing process. In the Eco-Remanufacturing

Architect, the shape of the reconstructed profile is compactly described using Fourier Descriptors, a frequency-domain method widely used in shape analysis. Fourier descriptors (Romero-González et al., 2020) enable the transformation of a closed or open curve—represented as a sequence of 2D coordinates—into a compact set of coefficients that capture both global and local shape features. This approach provides a smooth and differentiable encoding of geometry that is invariant to translation, and, with optional normalization, can also be made invariant to scale and rotation. Considering that a curve can be represented as a sequence of *N* complex points as shown in Eq. 1:

$$\mathrm{z_n = x_n + iy_n}, \quad \mathrm{n = 0, 1, \ldots, N-1} \tag{1}$$

The Discrete Fourier Transform (DFT) of the curve can be computed as shown in Eq. 2.

$$Z_k = \sum_{n=0}^{N-1} z_n \cdot e^{-i\frac{2\pi kn}{N}}, \quad \text{for } k = 0, 1, \ldots, N-1 \tag{2}$$

The resulting complex coefficients Z_k are known as the Fourier descriptors. Lower-frequency descriptors (small k) capture coarse shape features, while higher frequencies represent fine details and noise. To ensure consistency across samples, a fixed number of descriptors $K<N$ is used, truncating higher-order terms that often correspond to noise or unimportant variations. A curve can be approximately reconstructed using the inverse DFT (Romero-González et al., 2020).

Regression Model: Random Forests (RF). To predict the reconstructed geometry of a repaired part from manufacturing parameters, the Eco-Remanufacturing Architect uses RF regression (Scornet & Hooker, 2025), a robust, non-parametric ensemble learning technique. This approach is well-suited for modelling the non-linear relationships between process variables and geometric outcomes, particularly in low-data regimes and scenarios involving noisy inputs. A RF consists of an ensemble of decision trees, where each tree is trained on a different bootstrap sample of the training data, a process known as bagging. At each split, a random subset of features is also considered. The regression output is obtained by averaging the predictions from all trees, which reduces overfitting and improves generalization. In eco-Remanufacturing Architect, a pair of RFs were developed -one for the real and one for the imaginary coefficients of the Fourier descriptors-.

Processing Pipeline. The Eco-Remanufacturing Architect predicts the geometric outcome of additive repairs by training on a dataset derived from metallographic images. In the dataset generation phase, shape contours are extracted from post-repair images using HED, denoised via a profile filter algorithm, and encoded as Fourier descriptors. These descriptors serve as the regression targets for two Random Forest models, which are trained to map process settings to geometric outcomes.

Curve Extraction from Metallographic Images. To analyze the geometry of repaired components, Eco-Remanufacturing Architect extracts shape profiles from metallographic cross-section images obtained after additive manufacturing (AM) repair trials. The **Holistically-Nested Edge Detection (HED)** method (Xie & Tu, 2017) is applied to extract the contour of the area. HED is a deep learning-based method that produces coherent contour maps by combining multi-scale features. It uses a fully convolutional neural network trained with deep supervision to perform image-to-image prediction. The ability of HED to automatically learn rich hierarchical representations is crucial in resolving challenging ambiguity in edge and object boundary detection. The resulting binary edge E isolates the outer boundary of the repair region. This E map is refined using a **profile filtering algorithm** that denoises the contour, ensuring continuity and smoothness in the final curve representation. The resulting set of 2D coordinates $\{(x_n, y_n)\}_{n=0}^{N-1}$ is stored as an ordered sequence and converted into a complex-valued vector such as $z_n = x_n + iy_n$, for $n = 0, 1, \ldots, N-1$. This vector serves as input to the subsequent Fourier descriptor generation.

Descriptor Generation and Normalization. The extracted curve is transformed into frequency space using the **DFT**, producing a set of complex coefficients (Fourier descriptors, for more information refer to section Geometric Representations: Fourier Descriptors). To ensure consistency across samples and simplify the regression task, only the first K descriptors are retained. The resulting descriptor vector becomes the ground truth for model training and the prediction target during inference.

Prediction and Reconstruction. To estimate the expected repair geometry from process parameters, the system uses two trained **RF regressors**: one for the real and one for the imaginary components of the Fourier descriptors. Given a new set of parameters (e.g., power, wire feed, speed), the RF regressors predict the real and imaginary Fourier Descriptors $\widehat{Z}_k$ of the reconstructed curve. These descriptors are then assembled and used to reconstruct the shape using the inverse DFT. The resulting curve is a visual and geometric approximation of the repaired surface expected from the selected manufacturing conditions. This enables the user to assess the outcome of different repair strategies virtually, without executing the physical process.

Data Augmentation with VAEs. To enhance model robustness and generalization, particularly in low-data scenarios, the Eco-Remanufacturing Architect integrates a VAE (Kingma & Welling 2019) for data augmentation. In this context, the generative model learns a latent distribution over the space of valid manufacturing parameters to enable the creation of synthetic input samples that remain statistically consistent with the original dataset. The VAE is composed of two main components: i) an encoder that maps each vector of real manufacturing parameters $x \epsilon \mathbb{R}^d$ into a latent representation $z \epsilon \mathbb{R}^l$, and ii) a decoder that samples from this latent space and reconstructs plausible manufacturing parameter sets $\widehat{x} \epsilon \mathbb{R}^d$. During training, the VAE minimizes a loss function composed of a reconstruction loss and the Kullback-Leibler (KL) divergence term, which regularizes the latent space towards a standard normal distribution, enabling smooth interpolation and sampling. This augmentation mechanism allows the system to explore alternative parameter configurations, balance underrepresented regions of the parameter space, and support exploration beyond the limits of the original dataset.

Evaluation. To assess the quality of the predicted shapes and their fidelity with respect to the original curves, a combination of spectral and spatial metrics that capture both geometric deviation and structural similarity were employed.

Descriptor-based metrics. Operating in the frequency domain, they were used to compare the Fourier representations of the curves. These metrics include the Root-Mean Square Error (RMSE) and the normalized RMSE (NRMSE), the cosine similarity and the L2 distance between complex Fourier descriptors, providing an invariant and compact assessment of shape similarity.

Spatial distance metrics. These metrics evaluated local and global discrepancies in physical shape directly in the 2D curvature space. These include the i) Hausdorff distance (highlighting worst-case deviations), ii) the Chamfer distance (averaging nearest-point differences), and iii) the discrete Fréchet distance (capturing sequential similarity along the curves).

Dataset. There were 200 metallographic images available for the development of the AI framework. To augment the dataset, 50 parameter configurations were generated by the VAE. From the complete dataset, 80% of the samples were used for training and 20% for testing.

Inputs. The inputs of the Eco-Remanufacturing Architect are described in Table 1.

Table 1: Inputs of the ecoRemanufacturing architect and their units.

Input	Unit
Metallographic image (optional)	-
Power	W
Process speed	mm/s
Wire feed speed	m/min
Power/speed ratio	-
Feed/speed ratio	-
Focal length	Mm
Stick-out	Mm
O_2	PPM

Outputs. The results of the Architect tool are described in Table 2.

Table 2: Outputs of the ecoRemanufacturing architect and their units.

Output	Unit
Reconstructed curve	[x,y] coordinates
Energy consumption	Wh
Process Metadata folder	-

RESULTS

After a grid search, the final hyperparameter selected for the RFRs were 100 estimators with mean squared error as loss function. Figure 2 illustrates three representative examples of curve reconstructions obtained using the Eco-Remanufacturing Architect. In each subplot, the predicted curves (blue) are generated from manufacturing parameters using the trained Random Forest models, while the real curves (red) are extracted from metallographic samples via Fourier descriptor encoding. The close alignment between predicted and ground truth curves across the three cases confirms the model's ability to capture both the global geometry and local variations of the repair profile.

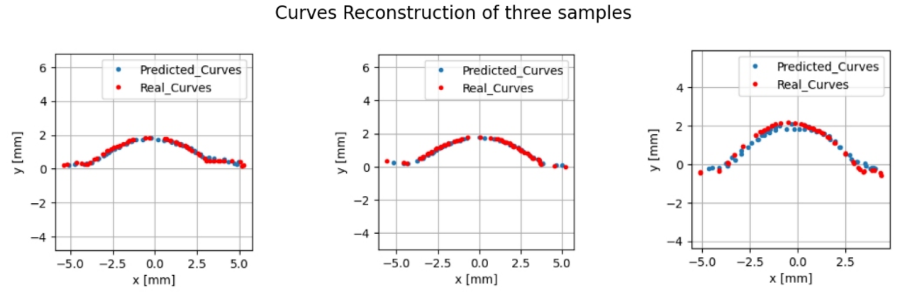

Figure 2: Visual comparison of real (red) and predicted (blue) curves.

To assess the accuracy of the predicted curve reconstructions from the analysis of the Fourier components, we evaluated the model using four descriptor-based metrics. These descriptors provide a compact and transformation-invariant representation of shapes. Table 3 summarizes the results obtained in the test dataset.

Table 3: Fourier comparative analysis between real and predicted Fourier components. Average values are shown from the test dataset.

	L2 Distance	Cosine Distance	RMSE	NMSE
Value	2.466	0.99	0.327	0.018

The average L2 distance between the predicted and ground truth curves was 2.47, indicating low absolute deviation in point-wise geometry. The cosine similarity reached 0.99, suggesting a near-perfect alignment in curve shape and orientation. Additionally, the model achieved a mean RMSE of 0.33, and a NMSE of 0.018, both reflecting a high degree of predictive accuracy relative to the variability of the target data. These results confirm that the Random Forest models are capable of reliably reconstructing complex geometric profiles from manufacturing parameters, supporting the tool's effectiveness in predictive remanufacturing applications.

In addition to the descriptor-based evaluation, we assessed the quality of the predicted curves using spatial distance metrics computed directly in 2D space. These metrics provide a geometric perspective on reconstruction accuracy by quantifying the positional differences between the predicted and ground truth curves. Unlike Fourier-based comparisons, spatial metrics are sensitive to the actual placement and alignment of points in the coordinate space. Table 4 summarize the results obtained in the test dataset considering three spatial metrics.

Table 4: Curvature deviation analysis between the real and predicted curvatures. Average values are shown from the test dataset.

	Hausdorff Distance	Chamfer Distance	Discrete Fréchet Real	Discrete Fréchet Imaginary
Value	2.237	0.058	0.722	0.328

The average Hausdorff distance was 2.24, indicating that while most regions of the contours are closely aligned, there exist localized areas with higher deviation. In contrast, the Chamfer distance, which measures the average point-to-point proximity across shapes, yielded a much lower value of 0.058, suggesting overall strong alignment between curves. Additionally, the Fréchet distances computed on the real and imaginary components of the Fourier descriptors were 0.722 and 0.328, respectively, reflecting a high degree of global similarity in both the horizontal and vertical shape profiles. Collectively, these metrics demonstrate that the reconstructed curves preserve both the general structure and fine-grained features of the original shapes, with only minor discrepancies in specific regions.

The reconstruction results validate the capability of the Eco-Remanufacturing Architect to support sustainability-oriented decision-making in additive repair contexts. By accurately predicting the repaired geometry from process parameters, the system enables quantitative estimation of critical resource indicators, including build volume, energy consumption, and associated carbon footprint. This integration of predictive geometry modeling with environmental assessment confirms the tool's potential to facilitate optimized, low-impact remanufacturing strategies aligned with circular economy objectives.

CONCLUSION

Ensuring geometric accuracy in reconstructed repair curves is essential for sustainable and cost-effective remanufacturing. The evaluation of the Eco-Remanufacturing Architect demonstrates the model's ability to accurately reconstruct repair geometries solely from manufacturing process parameters, bridging the gap between physical remanufacturing conditions and digital predictive models. Through a combination of descriptor-based and spatial evaluation metrics, the model was shown to reliably capture both the global shape and local variations of complex repair profiles. These results highlight the tool's capacity to support data-driven decision-making in sustainable manufacturing contexts, paving the way for more intelligent, efficient, and sustainable remanufacturing workflows. Moreover, the predicted repair geometries enable the estimation of key sustainability indicators—such as energy consumption, material usage, and carbon footprint—thereby reinforcing the tool's role in advancing environmentally responsible remanufacturing strategies.

Future developments will focus on embedding the Eco-Remanufacturing Architect into an interactive decision support platform tailored to industrial users. A dedicated UI will allow operators to explore and interpret model predictions with ease, while integration via Asset Administration Shells will ensure seamless communication with existing factory systems, enabling standardized data exchange and connectivity with Industry 4.0 systems.

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