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RESEARCH ARTICLE

# Assessing carbon footprint of defect repair in wind turbine blade manufacturing: a case study in an SGRE factory

[version 1; peer review: 1 approved with reservations]

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## Abstract

### Background

Wind turbine blade manufacturing by vacuum resin infusion is prone to defects that trigger repair operations, consuming additional resin, glass fibre and energy beyond the material embedded in the blade. The Horizon Europe Innovation Action TURBO (Grant Agreement No. 101058054) develops technologies to reduce these repair-related impacts. This study reports a defect-level carbon footprint assessment of three manufacturing configurations tested on a blade demonstrator.

### Methods

Three physical castings of a 16 metre section of a 108 metre blade mould were produced and inspected: a standard-process baseline, an optimised-infusion configuration, and a sensors-plus-machine-learning configuration. Repair-related resin, glass fibre and grinding-energy consumption were quantified from post-manufacturing defect inventories and converted to carbon dioxide equivalent ($CO_2$ eq) emissions using reference factors. Results were extrapolated to a full blade using a surface-area scaling factor, and to annual fleet production. Defects were grouped into four families to assess whether mitigation acted uniformly across defect types.

### Results

Optimised infusion reduced defect-repair $CO_2$ eq by 30.4% relative to baseline; the machine-learning configuration reduced it by 19.5%, a smaller benefit than its 32.1% reduction in defect count would

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1. **Evan G Sproul**, Sandia National Laboratories, Albuquerque, USA

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suggest, because the defects it fails to prevent are on average larger. Both mitigation scenarios almost completely removed root-end air pockets, delamination and miscellaneous defects (50 to 100% reduction), but left dry-spot defects, the largest baseline family, nearly unaffected (4.0% reduction). The optimised-infusion estimate, cross-checked against an independent method, agreed within 3.1%. Scaled to a realistic annual production of 490 blades, avoided impacts of optimised infusion and the machine-learning configuration represent approximately 900 and 580 tonnes $CO_2$ eq per year.

**Conclusions**

These results indicate that both TURBO technologies already deliver measurable reductions in defect-repair carbon footprint, identifying dry-spot defects as the main remaining target for further improvement, with extension to a full impact category suite identified as future work.

**Keywords**
carbon footprint; wind turbine blade manufacturing; defect repair; rework; composite materials; TURBO project

HE This article is included in the Horizon Europe gateway.

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## 1. Introduction

Wind turbine blades are large composite structures whose manufacturing process, principally vacuum-assisted resin infusion of glass-fibre and carbon-fibre laminates, is prone to defects such as porosity, dry spots, wrinkles and delamination (Murdy et al., 2022; Shevtsov et al., 2020). A significant part of the defects identified during quality inspection triggers a repair operation that consumes additional resin and glass fibre, energy and labour time, on top of the material embedded in the blade itself. At fleet scale, these repair operations represent a recurring, avoidable source of material consumption and emissions that is distinct from the structural material of the blade.

The Horizon Europe Innovation Action TURBO (Grant Agreement No. 101058054, coordinated by the Technical University of Denmark, DTU; European Commission, 2022) addresses this issue directly. Work Package 11 (WP11) is responsible for the project's life cycle assessment, life cycle costing (LCC) and social life cycle assessment (S-LCA). Under the project's Key Objectives, KO-7 requires the demonstration of "robust deltas in embedded carbon, energy and production waste" associated with defect repair, alongside a stated ambition of a 90% reduction in factory repair time and material.

From M30 onward, SGRE demonstrated successive TURBO technologies (optimised infusion, sensors and machine-learning-controlled flow) on physical castings of a 16 m section produced from a 108 m wind turbine blade mould (B108). This paper presents the resulting defect-level comparative carbon footprint assessment, built directly on measured, post-manufacturing defect inventories for three such castings, and extrapolates the results to a full 108 m blade using a surface-area scaling method confirmed by SGRE.

## 2. Materials and methods

### 2.1 System description and functional unit

This study assesses a targeted functional unit: the material, energy and time flows associated with the formation and repair of manufacturing defects on a 16 m section of the B108 wind turbine blade mould, before and after the introduction of TURBO technologies. This is not a life cycle assessment of the blade; it is a targeted inventory of the rework/repair stage, which is the stage TURBO technologies act on directly. Results are extrapolated to a full 108 m B108 blade (Section 3.5) to express the section-level findings at the scale of one manufactured blade and of SGRE's realistic forecast annual production.

### 2.2 Manufacturing scenarios: three physical demonstrator castings

Three physical castings of the 16 m B108 section were produced and inspected. Casting 1 (baseline) used the standard infusion process with no TURBO technology and was measured in March 2025. Casting 2 (optimised infusion) modified the infusion inlet and outlet positions and was reported to the consortium at month 42 (M42, March 2026). Casting 3 (sensors and machine learning) combined ML-based control of the infusion flow rate, replacing pressure-based control, with a change in the flow-enhancement material under the beam; it was measured in April 2026. Casting 3 does not simply add ML control on top of the Casting 2 configuration: the two castings use different flow-enhancement material changes, so the two scenarios cannot be used to isolate the marginal contribution of ML control alone. Table 1 summarises the three castings.

### 2.3 Impact assessment method and reference factors

Climate change impacts were computed from the physical inventory (resin mass, glass mass, grinding energy) using the emission and energy factors listed in Table 2. Grinding energy was only measured as a single total (252 kWh, baseline), covering both resin and glass removal together; it was expressed per kg of resin (k = 252/148.3 = 1.7 kWh/kg) as a calculation convenience, not because the energy is specific to resin. Electricity-related impacts used the Danish electricity mix, with a $CO_2$ eq factor of 0.1312 kg $CO_2$ eq/kWh. Because grinding energy is defined as a fixed linear function of resin mass, its relative reduction between scenarios is mathematically identical to that of resin and does not constitute an independent measurement; it is reported separately in Table 3 for completeness of the physical inventory, not as an independently observed indicator.

The glass/resin ratio of 2.5463 kg glass per kg resin was found across all 56 baseline defect lines, confirming that glass is not an independent inventory item in this system: any valid resin estimate for a defect implies its glass requirement directly, which is used in the estimation method below.

### 2.4 Estimation method for Scenario 2 (rule of three) and robustness check

The material avoided in that scenario was estimated by a rule of three: material avoided = baseline material × defect-count reduction rate. The raw SGRE defect list for this scenario recorded 45 rows, of which 9 were excluded as not relevant or not related to the TURBO process, and 39 were retained as the official, consortium-reported result. The resulting defect-

**Table 1.** **Demonstrator castings.**

| Casting | Configuration | Date | Data status |
|---|---|---|---|
| 1. Baseline | Standard infusion process, no TURBO technology | March 2025 | Measured |
| 2. Optimised infusion | Modified infusion inlet/outlet positions | September 2025 | Defect count measured; masses estimated |
| 3. Sensors + ML | ML-controlled flow rate + different flow-enhancement material | April 2026 | Defect count measured; masses estimated |

**Table 2.** **Reference emission and energy factors.**

| Parameter | Value | Unit | Source |
|---|---|---|---|
| Emission factor, epoxy resin | 4.2 | kg $CO_2$ eq/kg | ARDITEC/SGRE |
| Emission factor, glass fibre | 2.0 | kg $CO_2$ eq/kg | ARDITEC/SGRE |
| Grinding energy, baseline | 252.0 | kWh | SGRE |
| Grinding energy intensity | 1.699 | kWh/kg resin | SGRE |
| Danish electricity mix, $CO_2$ eq factor | 0.1312 | kg $CO_2$ eq/kWh | Ecoinvent |
| Glass/resin ratio (fixed) | 2.5463 | kg glass/kg resin | Verified across all 56 baseline defect lines |

**Table 3.** **Physical and environmental inventory, 16 m section, by casting.**

| Indicator | Baseline | Infusion (Sc.2) | ML (Sc.3) |
|---|---|---|---|
| Number of defects | 56 | 39 | 38 |
| Resin required (kg) | 148.35 | 103.31 | 119.41 |
| Glass required (kg) | 377.73 | 263.06 | 304.06 |
| Repair time (h) | 110.0 | 76.6 | 149.7 |
| Grinding energy (kWh) | 252.0 | 175.5 | 202.8 |
| $CO_2$ eq, materials (kg) | 1,378.5 | 960.0 | 1,109.6 |
| $CO_2$ eq, energy (kg) | 33.1 | 23.0 | 26.6 |
| $CO_2$ eq, TOTAL (kg) | 1,411.6 | 983.1 | 1,136.2 |
| $CO_2$ eq avoided vs baseline (kg) | - | 428.5 (−30.4%) | 275.3 (−19.5%) |

count reduction rate is (56-39) / 56 = 17/56 = 0.303571, i.e. 30.4%, applied uniformly to the baseline resin, glass and repair-time totals.

This approximation was cross-checked against a second, independent method, applied to the 28 (of 39 non-excluded) defects whose defect code shared a family prefix with a baseline defect (9 recognised families). For those defects, estimated resin was computed as declared length (mm) × a family-specific resin-per-millimetre ratio derived from the baseline; for the remaining defects (whose declared length proved incompatible with the baseline's physical scale, and is more likely an inspection or observation zone than a repair footprint), the baseline's average resin per defect (2.649 kg/defect) was used instead. This family-based check yielded an estimated resin mass of 100.164 kg, against 103.313 kg from the rule of three, a gap of -3.149 kg or -3.05%, confirming the rule of three within approximately 3% for this section.

## 2.5 Defect-type classification method

SGRE's defect codes are consistent across the three source lists (baseline, optimised infusion, ML), allowing defects to be grouped into families independently of the estimation issues affecting resin/glass masses in Scenario 2. All 56 baseline defect codes were grouped into four families: (i) dry spot/resin starvation defects attributable to the infusion flow front, (ii) root-end air pockets and local resin starvation, (iii) delamination, and (iv) other defects, including foreign objects and

vacuum-filter debris. The same four families were applied to the optimised-infusion and ML defect lists. This classification uses defect counts only, which are directly observed in each source list.

### 2.6 Scaling to the full blade and to fleet level

To describe the physical inventory of a complete B108 blade, defect densities per square metre measured on the 16 m section were scaled linearly to the full 108 m B108 blade, a method confirmed by SGRE (defects/$m^2$ × blade area = total defects). The resulting scaling factor is 4.293. This full-blade inventory was then multiplied by SGRE's realistic planned annual production for one plant (490 blades) to obtain fleet-scale annual figures.

## 3. Results

### 3.1 Section-level physical and environmental inventory

Table 3 presents the physical inventory and resulting $CO_2$ eq impacts for the three castings of the 16 m section. Optimised infusion reduced total repair-related $CO_2$ eq from 1,411.6 kg (baseline) to 983.1 kg, an avoided impact of 428.5 kg $CO_2$ eq (calculation: 1,411.581-983.066 = 428.516 kg, i.e. 428.516/ 1,411.581 = 30.35%). The ML scenario reduced total repair-related $CO_2$ eq to 1,136.2 kg, an avoided impact of 275.3 kg $CO_2$ eq (1,411.581-1,136.248 = 275.333 kg, i.e. 275.333/1,411.581 = 19.50%). As shown in Figure 1, the ML scenario's total impact remains between the baseline and the infusion scenario, rather than surpassing infusion's reduction.

### 3.2 Decoupling between defect count and material reduction

As shown in Figure 2, the ML scenario removed a larger share of defects than optimised infusion (32.1% vs 30.4% reduction in defect count: (56-38)/56 = 0.3214 and (56-39)/56 = 0.3036 respectively), but achieved a smaller reduction in material consumption (19.5% vs 30.4% for resin/glass). This decoupling reflects a change in the average size of the remaining defects: average repair time per defect rose from 117.9 min/defect at baseline (110 h × 60 /56 defects) to 236.3 min/defect under the ML scenario (149.667 h × 60/38 defects), an increase of 100.5%. The technologies evaluated here remove predominantly small, easily repaired defects; the defects that remain are, on average, larger and require heavier repair methods (e.g. countersunk repairs).

### 3.3 Which defect families are actually removed

Grouping defects into the four families defined in Section 2.5 shows that the two mitigation scenarios do not act uniformly across defect types. Table 4 reports the defect count per family for each scenario, using directly observed counts (not resin-based estimates).

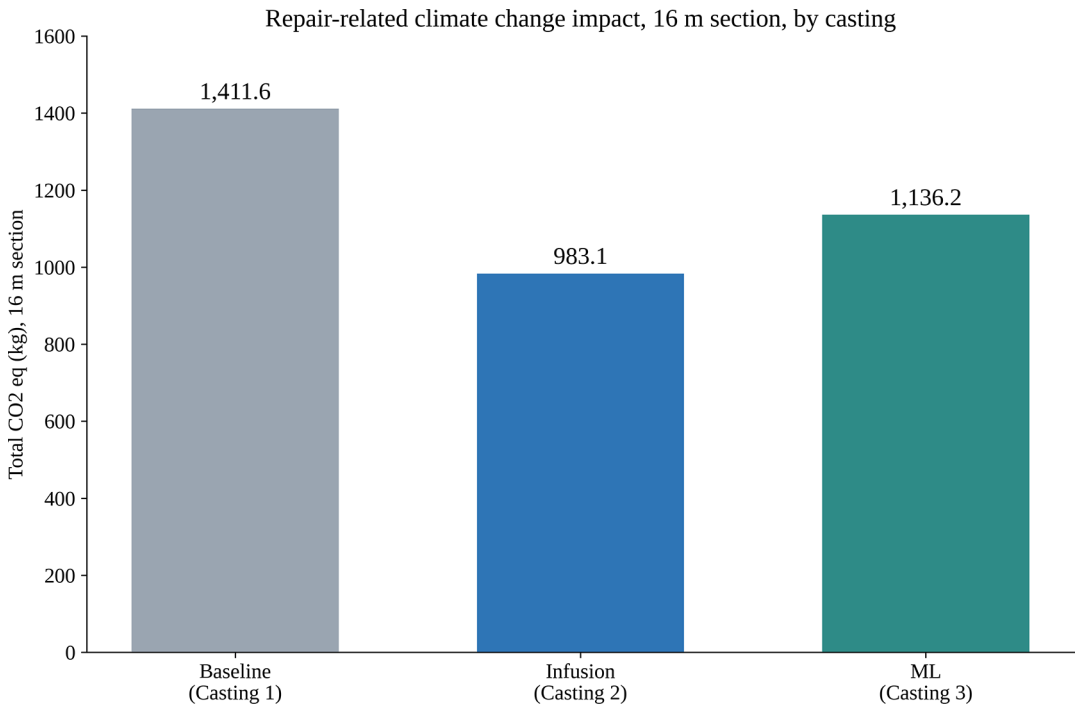


**Figure 1. Repair-related climate change impact, 16 m section, by casting.**

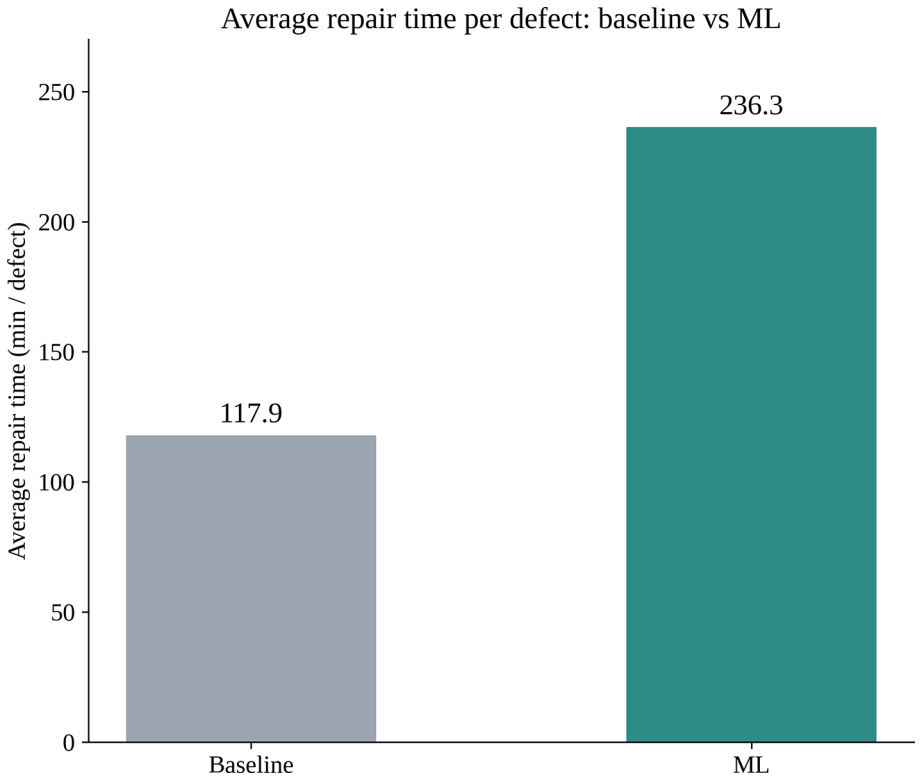


**Figure 2. Average repair time per defect: baseline vs ML.**

**Table 4. Defect count by family, baseline vs infusion vs ML.**

| Defect family | Baseline | Infusion | ML | Reduction, infusion | Reduction, ML |
|---|---|---|---|---|---|
| Dry spot (infusion-flow related) | 25 | 24 | 24 | −4.0% | −4.0% |
| Root-end air pockets | 12 | 2 | 0 | −83.3% | −100% |
| Delamination | 8 | 1 | 4 | −87.5% | −50.0% |
| Other (foreign object, filter debris, etc.) | 11 | 1 | 4 | −90.9% | −63.6% |
| Not observed in baseline (new defect types) | 0 | 11 | 6 | n/a | n/a |
| Total | 56 | 39 | 38 | - | - |

As we can see in Figure 3, the two mitigation scenarios are highly effective at eliminating three of the four defect families: root-end air pockets, delamination and miscellaneous defects are all reduced by 50-100%. The dry-spot family stands out as the exception, remaining nearly unchanged (-4.0% for both infusion and ML), which points to it as the clearest remaining opportunity for further process improvement. As this family is also the largest in the baseline (25 of 56 defects, 44.6%), it naturally becomes a larger share of the defects that remain after mitigation: 66.7% of retained defects under optimised infusion (24 of 39) and 63.2% under the ML scenario (24 of 38). This helps explain the rise in average repair time per defect documented in Section 3.2, since dry-spot defects include some of the largest individual repairs in the baseline list.

### 3.4 Robustness check for the optimised-infusion estimate

In Figure 4, the family-based robustness check (Section 2.4) confirmed the rule-of-three estimate for Scenario 2 within 3.05% on resin mass (and, by the fixed glass/resin ratio, an identical relative gap on glass mass), supporting the order of magnitude of the 30.4% $CO_2$ eq reduction reported for that scenario, while the rule of three remains the primary calculation method used in this study.

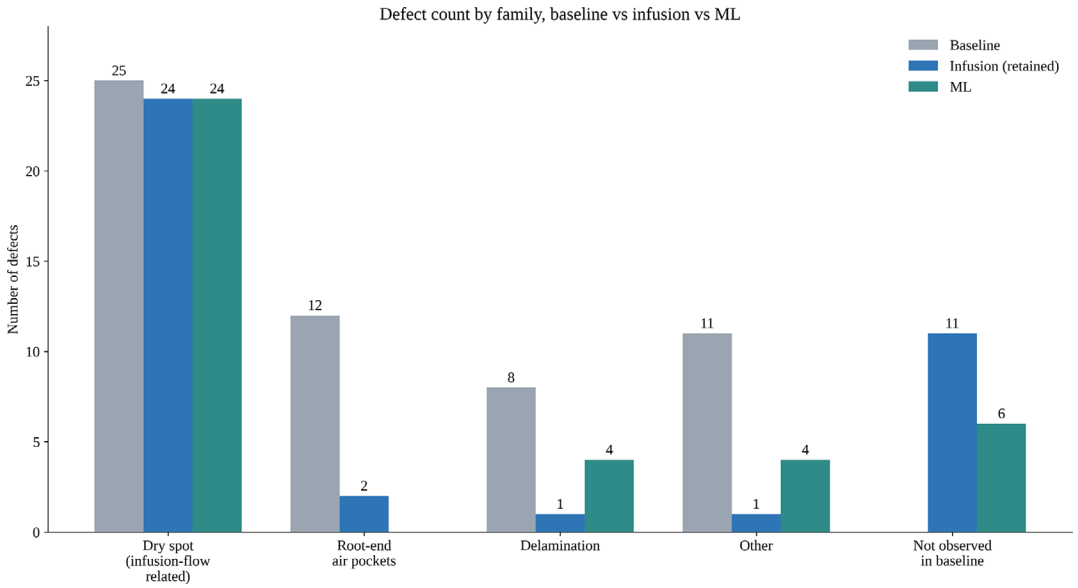


**Figure 3.** **Defect count by family, baseline vs infusion vs ML.**

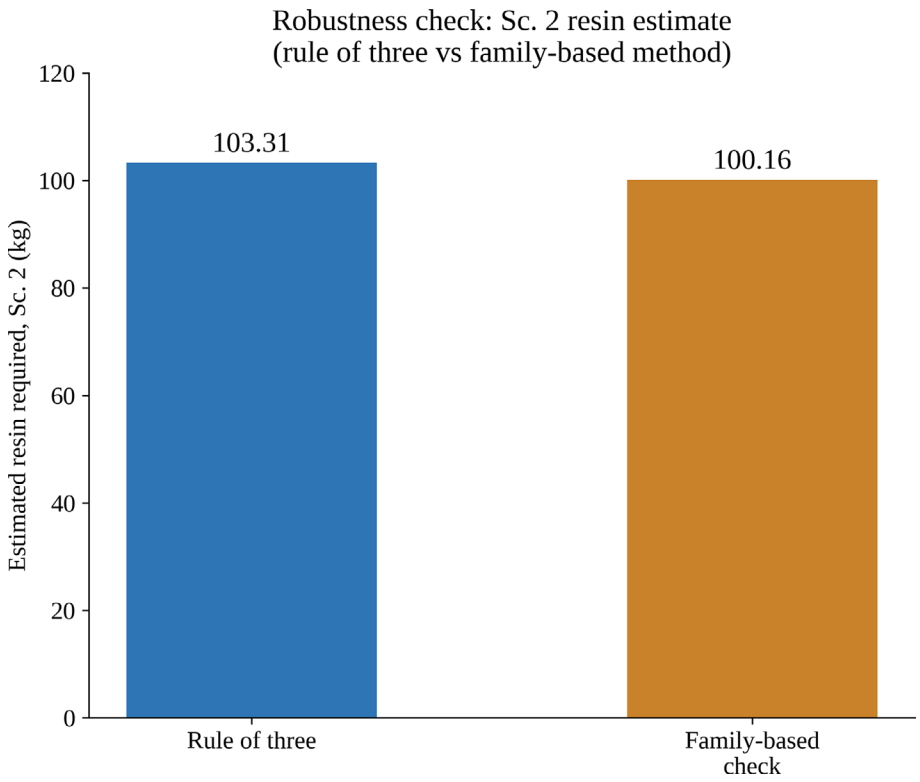


**Figure 4.** **Robustness check: optimised-infusion resin estimate, rule of three vs family-based method.**

## 3.5 Extrapolation to the full B108 blade

Table 5 and Figure 5 extrapolate the section-level inventory to a full 108 m B108 blade using the surface-area scaling factor of 4.293 confirmed by SGRE for defect density transfer within the B108 mould.

**Table 5. Physical inventory extrapolated to the full B108 blade, scaling factor 4.293.**

| Indicator | Baseline | Infusion (Sc.2) | ML (Sc.3) |
|---|---|---|---|
| Number of defects | 240.4 | 167.4 | 163.1 |
| Resin (kg) | 636.9 | 443.5 | 512.6 |
| Glass (kg) | 1,621.7 | 1,129.4 | 1,305.3 |
| Repair time (h) | 472.2 | 328.9 | 642.5 |
| Total $CO_2$ eq (kg) | 6,060.1 | 4,220.4 | 4,878.0 |

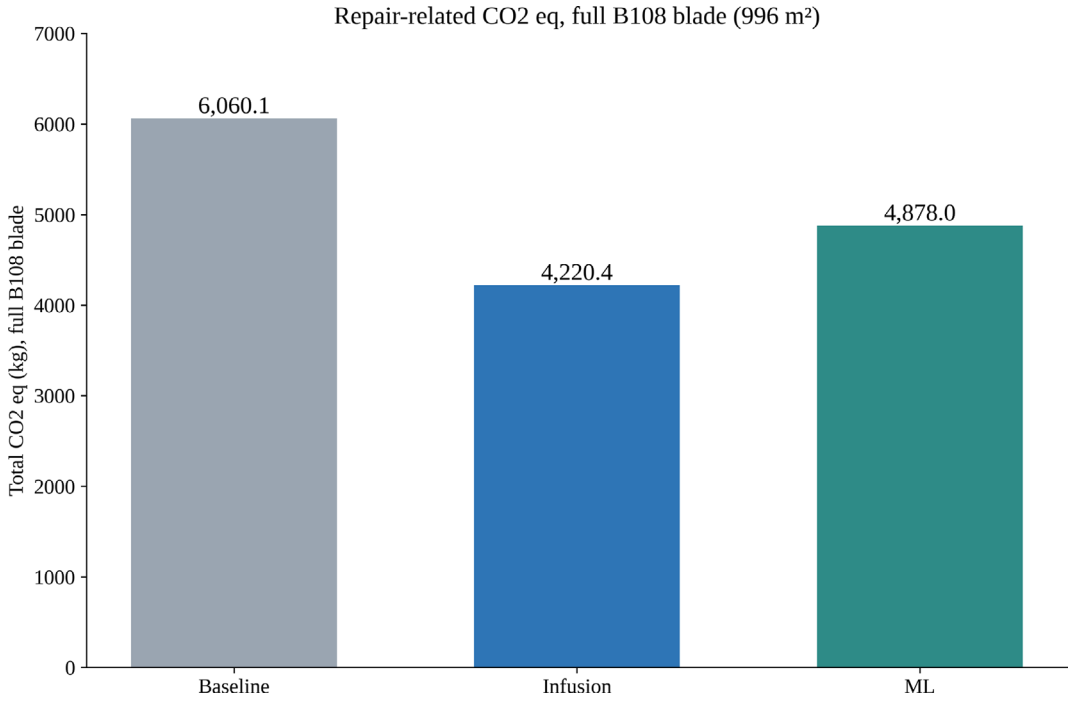


**Figure 5. Repair-related $CO_2$ eq extrapolated to the full B108 blade.**

### 3.6 Fleet-scale annual impact

Scaled to a realistic annual production rate for one plant (490 blades/year, based on Aalborg), defect-repair impacts extrapolated to the full B108 blade (Table 5) represent approximately 2,969.4 tonnes $CO_2$ eq per year at baseline. As shown in Figure 6, optimised infusion avoids 901.4 tonnes $CO_2$ eq per year, leaving 2,068.0 tonnes $CO_2$ eq per year still required; the ML scenario avoids 579.2 tonnes $CO_2$ eq per year, leaving 2,390.2 tonnes $CO_2$ eq per year still required.

## 4. Discussion

### 4.1 Progress achieved

This study confirms that TURBO technologies are already delivering measurable reductions in defect-repair carbon footprint: optimised infusion and the ML-controlled process each cut defect-repair $CO_2$ eq by roughly one-fifth to one-third relative to the standard process. Manufacturing waste, including scrap and rework material, has been identified elsewhere as a significant contributor to a wind turbine blade's overall global warming potential, on the order of 10% of cradle-to-gate impact (Pender et al., 2025), which situates the reductions reported here within a meaningful share of the blade's manufacturing footprint. Both mitigation scenarios evaluated are highly effective at eliminating three of the four defect families identified in this work (root-end air pockets, delamination and miscellaneous defects), at rates from 50% to 100%. Comparable defect-reduction magnitudes have been reported elsewhere in wind blade manufacturing: a process-modelling and Six Sigma intervention in a wind blade factory achieved a reduction in defect count of more than 30% and a 14% reduction in repair time within one month of implementation (Oliveira et al., 2024), of a similar order to the reduction observed here for optimised infusion, though achieved through a different, non-technological route (process control and quality management rather than infusion or sensor hardware changes).

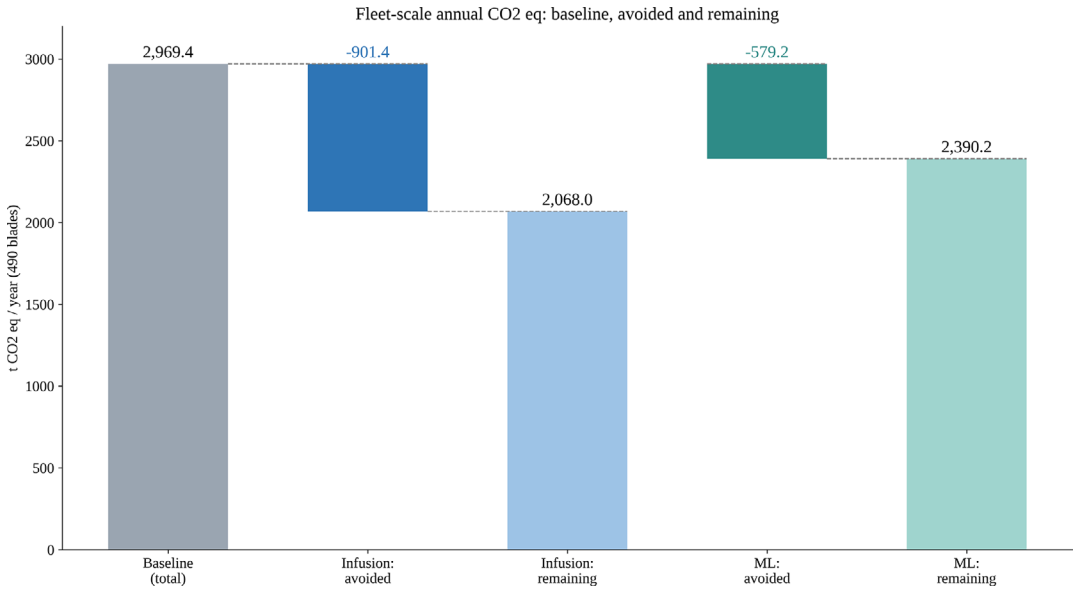


**Figure 6. Fleet-scale annual $CO_2$ eq, full B108 blade basis (490 blades/year).**

The defect-family breakdown shows that dry-spot defects, the largest single baseline family, are the type still largely untouched by either technology (-4.0%). This is consistent with the wider literature on vacuum infusion, where dry spots, caused by incomplete impregnation of the fibre reinforcement at the resin flow front, are recognised as a persistent and difficult-to-eliminate defect type even when flow-related process parameters are actively controlled, because they arise from local variations in fibre permeability and flow-front stability (Shevtsov et al., 2020). Because both mitigation scenarios evaluated here already target flow-related parameters, this points to a specific, well-characterised target for the next iteration of these technologies rather than an open-ended search.

The ML scenario's smaller net $CO_2$ eq reduction, despite removing more defects by count than optimised infusion, should be read alongside the wider literature on machine-learning-based process control in composite manufacturing, which reports adaptive flow-control and defect-reduction gains of a broadly comparable order (Malashin et al., 2025), generally demonstrated under simulated or laboratory-scale conditions. The results reported here, from a physical, factory-representative demonstrator, illustrate some of the practical gap between simulated potential and factory-floor performance, including training data quality and the confounding process change described in Section 2.2, which are less visible in simulation-based studies.

### 4.2 Limitations

Two limitations should be kept in mind when interpreting these results. First, each scenario is based on a single physical casting; with n=1 per scenario, it is not possible to distinguish genuine process-driven improvement from ordinary casting-to-casting variability, and the reported reductions should be read as point estimates rather than statistically validated effects. Second, this study covers a single impact category, climate change; a full life cycle assessment under ISO 14040/14044 ((International Organization for Standardization, 2006a, 2006b) would require extension to a full impact category suite, identified as future work.

## 5. Conclusions

This study establishes a defect-level comparative carbon footprint assessment of wind turbine blade manufacturing, built on three physical demonstrator castings and real, measured post-manufacturing defect data. Optimised infusion reduced defect-repair $CO_2$ eq by 30.4% relative to a standard-process baseline; a sensors-plus-machine-learning configuration, reduced it by 19.5%, a smaller benefit than its defect-count reduction (32.1%) alone would suggest, because it disproportionately removes small, easily repaired defects while leaving larger ones. A breakdown by defect family further shows that three of the four families are nearly eliminated by both mitigation scenarios, with dry-spot defects standing out as the clear next target: still barely reduced despite both technologies acting on the infusion process that plausibly causes them. Scaled to the full B108 blade and to SGRE's annual production, the reductions already achieved represent several hundred tonnes of avoided $CO_2$ eq per year. Future work should extend this analysis to a full impact category suite and replicate castings per scenario to validate the reductions statistically.

## Ethics and consent

Ethical approval and consent were not required.

## Data availability

The defect inventories underlying this study (post-manufacturing quality-control records for the three demonstrator castings) are restricted. These datasets were generated and are held by SGRE as part of internal manufacturing quality-control records, and contain commercially sensitive information about SGRE's production process, including process parameters and defect-level production data, that could be of competitive value if disclosed. The restriction is commercial, not ethical. No Institutional Review Board or equivalent ethics body was involved, as none was required for this type of dataset.

Readers or reviewers wishing to request access to the underlying datasets may contact the corresponding author, Léo Staccioli (leo.staccioli@arditec.net), or Grégoire Lebreton, SGRE (gregoire.lebreton@siemensgamesa.com). Access requests are considered by SGRE on a case-by-case basis and may be granted for legitimate research purposes, subject to SGRE's prior approval. Access is not automatic and is not guaranteed.

The derived, non-confidential physical and environmental inventory values reported in Table 3, Table 4, Table 5 of this article, which underlie all figures, represent the complete quantitative basis for the results, methods and conclusions reported in this article and are freely available within the manuscript itself.

## Acknowledgements

During the preparation of this manuscript, the authors used Perplexity to assist with grammar and language editing. The authors reviewed and edited the output as needed and take full responsibility for the content of this publication.

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# Open Peer Review

## Current Peer Review Status: ?

**Version 1**

Reviewer Report 30 September 2026

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**Evan G Sproul**
Sandia National Laboratories, Albuquerque, New Mexico, USA

**Summary:**

This article compares the avoided greenhouse gas emissions of two improved wind turbine blade manufacturing configurations. The results demonstrate that the improved methods could avoid 20-30% of defect repair emissions relative to a baseline manufacturing configuration. These core findings are complemented by a breakdown of different defect types and average repair times per defect for the different manufacturing configurations. Last, the findings are scaled up from a single 16m blade section to a fleet-scale estimate of 490 wind turbine blades. Overall the paper is well written, with clear data and concise findings that are relevant to the industry.

**There are four signficant issues where additional clarification is needed to increase confidence and reproducibility of the work:**

The first issue relates to the reproducibility of the scaling factor. The work clearly outlines that the results are from a 16m blade section, but there is no indication of the section's surface area. As a result, there is no way to confirm the validity of the 4.293 scaling factor. Furthermore, there is no conclusive evidence presented to demonstrate the viability of scaling the defects by surface area. Instead, there is merely a statement that SGRE has confirmed this method. To enable full transparency and reproducibility, there should be more detail or literature references that demonstrate the validity of these scaling relationships.

A second issue, also related to scaling, is the use of a single 16m blade section to predict the overall results of 490 blades. Section 4.2 states, "the reported reductions should be read as point estimates rather than statistically validated effects." Given that statement, there needs to be more justification for assuming results can be reliably translated to such a large population of blades. While this expansion to a fleet level analysis is useful in understanding the potential impact, it is currently presented in a manner that is far from conclusive.

The third issue is the lack of discussion or analysis related to uncertainty. All data and results are

presented as a single point. It is common practice within life cycle assessment to conduct some form of uncertainty analysis. For example, a simple sensitivity analysis of key input parameters would reveal which results are most sensitive to uncertainty. Alternatively, a scenario analysis could capture the importance of alternative conditions (e.g., a different electricity mix). These are key elements in a life cycle assessment and should be discussed within the article.

A fourth issue is the lack of discussion related to data inputs, specifically the energy intensity and emissions factors. For the energy intensity, it is unclear how the initial 252kWh was measured within the factory. Can a brief description be added in for clarification? For the emissions factors it is unclear why ARDITEC/SGRE inputs were used instead of readily available datasets such as Ecoinvent. What is the source of these data and why use them instead of other available references? Furthermore, in the one instance where Ecoinvent is currently used it should adhere to the guidance provided by Ecoinvent (https://support.ecoinvent.org/sources-citation), which includes citing the specific activity name used within the dataset. Without this information the existing emissions factor is challenging to reproduce.

**In addition to these issues there are some other minor issues that need to be addressed:**

Section 3.2 – Text states, “As shown in Figure 2, the ML scenario removed a larger share of defects than optimised infusion, but achieved smaller reduction in material consumption.” However, Figure 2 displays the average repair time per defect and does not contain any information regarding the share of defects. The text needs to be corrected to the appropriate figure number.

Section 3.3 – Text states, “As we can see in Figure 3, the two mitigation scenarios are highly effective at eliminating three of the four defect families: root-end air pockets, delamination and miscellaneous defects are all reduced by 50-100%.” However, terminology used in the figure (as well as Table 4) is “Other”, not miscellaneous. Please align terminology in text with figure to ensure consistency.

Figure 6 – This figure and caption should clearly identify (like top of Figure 5) that these are repair related emissions.

**Is the work clearly and accurately presented and does it cite the current literature?**
Partly

**Is the study design appropriate and does the work have academic merit?**
Yes

**Are sufficient details of methods and analysis provided to allow replication by others?**
Partly

**If applicable, is the statistical analysis and its interpretation appropriate?**
Not applicable

**Are all the source data underlying the results available to ensure full reproducibility?**
Partly

**Are the conclusions drawn adequately supported by the results?**

Partly

***Competing Interests:*** No competing interests were disclosed.

***Reviewer Expertise:*** My primary area of expertise related to this work is life cycle assessment of wind energy systems. However, I do not have detailed experience with blade manufacturing and can't confirm if the defect measurements are realistic. I have no reason to believe they are inaccurate, but my report does not include any review of the number and type of defects.

**I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.**