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Research Article

Probabilistic Feature-based Grading and Classification System for End-of-Life Building Components Toward Circular Economy Loop

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Abstract

The transition toward a circular construction economy requires robust, data-driven decision frameworks to determine whether end-of-life components can be reused. This paper proposes an adaptive probabilistic framework, the Multi-Level Grading and Classification System (MGCS), which evaluates specific component types, such as precast concrete wall panels, against the performance requirements of their intended reuse scenario. The proposed MGCS integrates Bayesian modelling with scenario-dependent performance thresholds. In the first stage, the method assigns a quality grade (A–E) based on quantitative physical condition indicators. The grade then informs a corresponding intervention class (1–5), supporting strategic reuse, upcycling, or downcycling decisions. This two-step, scenario-sensitive process enables a single component to be valued across multiple potential afterlives, maximising resource efficiency and embodied-carbon retention. The framework is demonstrated using empirical data from precast concrete panels and designed to remain transparent, auditable, and extensible to other component categories. By aligning material condition with functional demand, MGCS addresses the environmental, economic, and operational challenges of end-of-life management, reducing waste, improving value recovery, and supporting workflow optimisation within circular construction practice.

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Highlights

- A Bayesian MGCS framework grades EoL MMC components for reuse scenarios.
- Empirical data and expert input enable transparent, probabilistic classification.
- A case study shows the framework enables flexible reuse and reduces material waste.

1 Introduction

1.1 Challenges in Reusing End-of-Life Building Components

When the life span of buildings has ended, most of the building components will become construction and demolition waste (C&D) with a lower material recycling rate. Reuse is different from recycling, which generates new materials after certain processes. Reuse preserves the functions of the used components after interventions like repair (Iacovidou & Purnell, 2016). With the extensive use of building materials like concrete and the high environmental impact, the reuse of building components can ideally reduce the carbon footprint (Cai & Waldmann, 2019) and achieve carbon neutrality through reducing C&D waste and the generation of substitutes for primary materials and products. Reusing construction elements can efficiently reduce the environmental impact of building construction, especially when implemented over multiple life cycles (Fivet, 2019). Since building components with similar ages may not be in the same state (Vanier, 2001), there would be possibilities that the end-of-life (EOL) building components could be used in the same or other usage scenarios. Concrete, and exceptionally high-performance concrete, has durability qualities, which allows multiple usage cycles. Circular economy principles encourage reusing EoL products, while barriers exist in the construction sector. The biggest challenge is from the technical sector.

The transition to a circular model for construction materials is hindered by a series of deeply ingrained technical challenges. A primary obstacle is quality assurance. The varied usage histories and potential latent defects in EoL components demand robust and reliable testing methodologies to scrutinise for wear, degradation, or structural defects, often leading to augmented operational overheads (Ajayi et al., 2015; Rakhshan, Morel, Alaka, & Charef, 2020). This challenge is directly compounded by the lack of standardisation and certification. Developing universally applicable metrics to grade and validate the quality of reused components is an arduous task, yet it is fundamental for building trust and ensuring market acceptance (Gorgolewski, 2017).

Furthermore, the physical processes of recovery present significant hurdles. Deconstruction difficulties arise because, unlike demolition, reuse-focused deconstruction requires careful, labour-intensive dismantling to preserve component integrity (Akinade et al., 2017). This process feeds into subsequent logistical intricacies, where the effective management of sorting, storage, and transportation is pivotal for cost-effective and timely availability of materials (Crowther, 2005).

Once recovered, components face issues of material complexity and interoperability. The vast array of materials, shaped by different manufacturing eras and environmental exposures, requires advanced expertise to ensure they are suitably allocated. Ensuring compatibility with modern construction methods and regulatory frameworks is often intricate, necessitating adaptive strategies to align reused components with current building practices (Cheshire, 2019). This is further complicated by regulatory and compliance hurdles, as existing building codes and safety standards were often written for new materials, creating barriers for the use of reclaimed components. Finally, overcoming these barriers requires technological adaptation, including investment in advanced non-destructive testing (NDT), digital tracking systems like BIM, and other technologies that can facilitate a more reliable and efficient reuse process.

These challenges are not isolated but interconnected. For instance, the lack of 'Standardisation and Certification' directly complicates 'Quality Assurance', while 'Deconstruction Difficulties' exacerbate 'Logistical Intricacies'. This systemic bottleneck highlights that piecemeal solutions are insufficient, and the market requires a decision-support framework that can holistically evaluate multiple factors.

1.2 Research Objectives

This research aims to develop and validate a comprehensive Multi-Level Grading and Classification System (MGCS) for Modern Methods of Construction (MMC) components, facilitating their reuse, repurposing, and recycling in a circular economy context. The objectives of the research are as follows:

1. To identify and characterise the essential features influencing the performance and longevity of MMC components.
2. To formulate a grading system based on the identified features, allowing for an assessment of MMC components from 'very good' to 'bad' (grades A to E).
3. To develop a classification system that determines the most appropriate circular interventions—whether reuse, up-use, down-use, or material recycling—based on their graded condition and potential application scenarios.
4. To validate the proposed MGCS through a case study focusing on precast concrete wall panels, demonstrating its adaptive capabilities.

2 State-of-the-Art Review

2.1 EoL Component Assessment

Accurately assessing the condition of EoL components is foundational to a successful circular economy. The state-of-the-art encompasses both strategic frameworks for reuse and predictive models for component condition.

2.1.1 Circular Strategies for MMC

MMC broadly encompass techniques that involve off-site construction and later assembly on-site. The inherent modularity of MMC makes it a prime candidate for circular strategies. A pivotal concept is Design for Disassembly (DfD), a proactive strategy where components are designed from the outset for easy deconstruction, enabling multiple reuse cycles and preserving material value (Akinade et al., 2017). This design philosophy is increasingly supported by digital integration; the use of Digital Twins and Building Information Modelling (BIM) allows for comprehensive tracking of component conditions and histories, creating a data-rich environment for informed end-of-life decisions (Boje, Guerriero, Kubicki, & Rezgui, 2020). Together, these approaches facilitate advanced circular outcomes such as repurposing and refurbishment. The flexibility of modular components allows them to be adapted for new uses—for instance, converting residential units into commercial spaces (Hořínková, 2021)—which often requires targeted refurbishment to meet the new application's performance and regulatory standards (Cumo, Giustini, Pennacchia, & Romeo, 2022).

2.1.2 Condition Prediction for EoL Building Components

Predicting the residual quality and performance of EoL components is a complex task due to inherent uncertainties in their operational history and exposure conditions. Current research has explored several modelling approaches, broadly categorised into data-driven and probabilistic methods. On one hand, data-driven and machine learning (ML) models have gained traction with the increasing availability of structural health monitoring (SHM) data. Algorithms such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Random Forests are used to predict remaining service life or classify component condition (Kumar et al., 2024). However, their effectiveness often hinges on large, high-quality datasets, and they can function as 'black boxes,' lacking the transparency needed for high-stakes engineering decisions. On the other hand, probabilistic and stochastic models are widely used to explicitly handle uncertainty. Methodologies like the Markov chains model deterioration as transitions between discrete states over time (Mori & Ellingwood, 1993), while Bayesian networks offer a powerful framework for integrating diverse information sources, including expert knowledge and inspection data (Straub, 2009). Despite their power in managing uncertainty, these models often assume stationary deterioration processes and may not easily adapt to component-specific or scenario-specific performance thresholds. These existing approaches provide a strong foundation but also highlight a critical gap.

2.2 Identifying the Research Gap: The Need for a Probabilistic and Scenario-Sensitive System

The implementation of a well-defined grading and classification system is vital for upholding the quality, safety, and structural integrity of EoL building components. Such a system can effectively tackle technical challenges and foster a more sustainable and circular economy (Foster, Kreinin, & Stagl, 2020). Parallel to this, deterioration assessment methodologies grounded in structural reliability and limit-state theory (e.g., ISO 13822 and Fib Model Code frameworks) provide robust approaches for quantifying the remaining capacity of existing concrete structures. Meanwhile, rating protocols such as ISO 20245 and building condition assessment systems set qualitative thresholds to categorise the condition of second-hand goods and building assets (Faqih & Zayed, 2021; Straub, 2009).

However, these strands operate largely in isolation and do not yet converge into a unified, component-scale reuse decision system. Circular economy models focus on whole-system strategies rather than granular performance evaluation for individual MMC units. Reliability-based deterioration models assess safety and serviceability for in-use structures, but they do not support multi-scenario EoL reuse routing. Condition rating standards classify components into static categories without quantifying uncertainty or enabling re-grading under alternative application contexts. Emerging initiatives such as material passports, product data templates, and digital circularity metrics (e.g., EN 15978, Madaster, Building Passport frameworks) improve information transparency and embodied-carbon accounting, but they remain descriptive rather than decision-oriented tools.

This fragmented landscape reveals several critical gaps for EoL MMC components:

1. Lack of adaptive, scenario-dependent evaluation – existing models are tied to single intended uses and cannot adjust thresholds for multiple future applications (e.g., façade vs internal partition vs down-cycle reuse).
2. Limited probabilistic integration of uncertainty – uncertainty from material ageing, exposure history, and inspection variability is recognised in the deterioration literature but is not embedded within circular classification or reuse strategies.
3. Insufficient linkage between condition grade and intervention level – current standards describe condition, but do not translate a grade into actionable reuse, repair, upcycling, or recycling pathways.
4. Absence of a unified decision-support framework – there is no existing methodology that combines multi-feature condition assessment, scenario-specific thresholds, and circular intervention mapping at the component scale.

Therefore, there remains a clear research gap for an end-of-life MMC assessment system that is probabilistic in structure and adaptive in output, capable of evaluating a single component differently across multiple reuse contexts. The MGCS proposed in this study addresses this gap by integrating Bayesian reasoning with scenario-specific performance thresholds to produce transparent, auditable, multi-scenario reuse decisions for MMC components.

3 Development of Feature-based Probabilistic Grading System

3.1 Architecture of the Grading System

According to ISO 20245 2017, which is the first global technical specifications on second-hand goods for cross-border trade, the evaluation of the used goods is based on several acceptance criteria, namely safety, quality, production information and usage requirements (*ISO 20245:2017 Cross-Border Trade of Second-Hand Goods*, 2017). According to the criteria requirement, there are four classifications for the condition of the used goods in "A", "B", "C", "D" rankings.

- "A": "Very good" condition. Class A products should have all their primary and secondary features available (operational). In addition, operating instructions, maintenance manuals, care instructions and parts manuals should be provided, preferably in the language of the consignee.
- "B": "Good" condition. Class "B" products should have all their primary and most secondary features available (operational). Where practical, operating instructions, maintenance manuals, care instructions and parts manuals should be provided, preferably in the language of the consignee.
- "C": "Acceptable" condition. Class "C" products should have most of their primary and secondary features available (operational).
- "D": "Unfit" condition. Class "D" products have most primary and secondary features unavailable (non-operational) and should be traded only to extract parts for aftermarket needs.

There is no commonly used rating or grading system for building construction for EoL components. Some building rating systems are applied to different building types, like hospital or residential buildings, for monitoring defects (Straub, 2009) or maintenance of the existing buildings (Abbott, McDuling, Parsons, & Schoeman, 2007; Salim & Zahari, 2011). The lowest grade of the EoL building component means that the components cannot be applied at the product level and can only be recycled into material. Based on the four ranking levels of ISO 20245 2017 and commonly used rating scales for buildings (Faqih & Zayed, 2021), one additional grading level – "bad" is added, which means all the features are unavailable and the component can only be recycled.

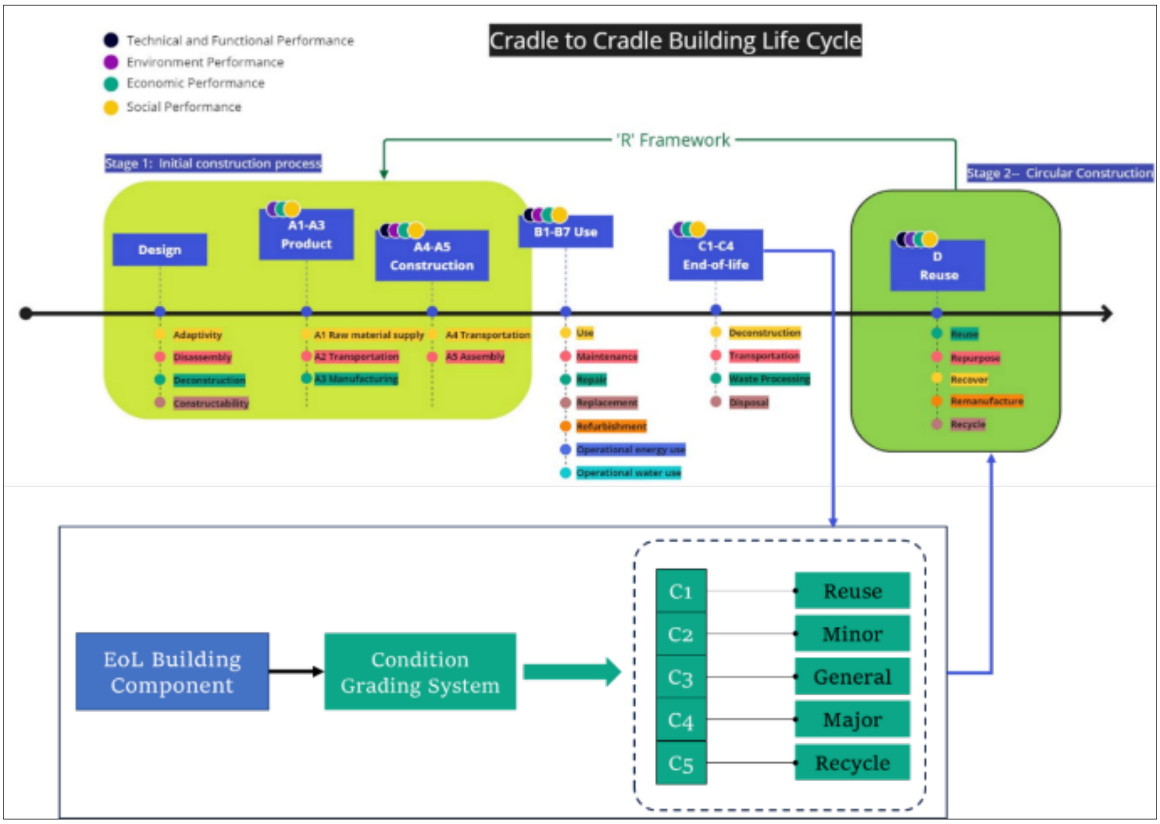
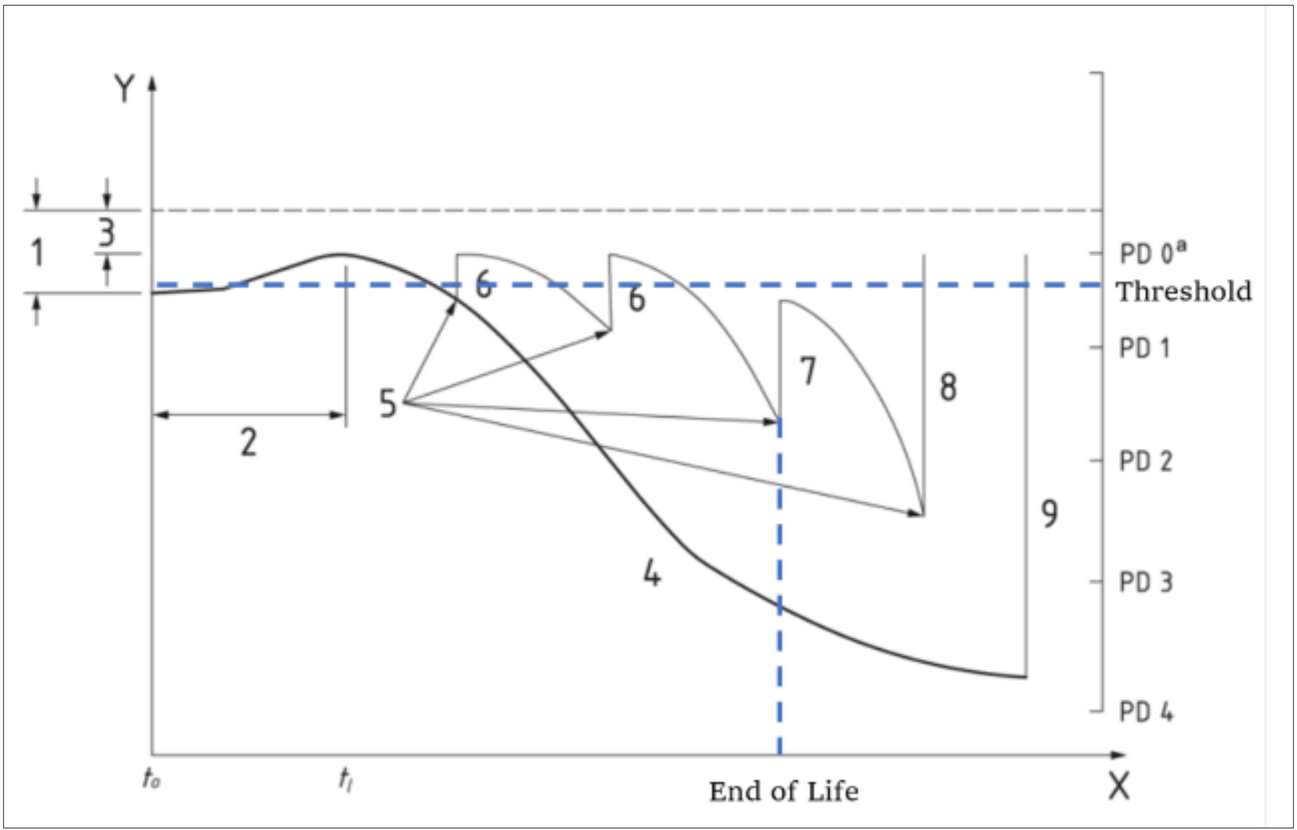


Figure 1: Grading and classification system in cradle-to-cradle life cycle.

Figure 1 displays the multi-level grading and classification (MGCS) system that encompasses the entire cradle-to-cradle life cycle. The MGCS is situated between the C1-C4 End of Life stage and the D reuse stage. It connects the grades of the EoL component conditions to various circular interventions classifications. The EoL building component undergoes a five-level grading system before being categorised under different circular interventions that dictate various "reuse" techniques like repurposing. There are five different classes that require varying levels of intervention in order to ensure reusability. The meanings of the five classes are as follows,

- Class 1 (Reusable): Components in very good condition can be reused without any or minimal refurbishment interventions.
- Class 2 (Minor Repair and Refurbishment): Components that are in good condition and can be reused with minimal refurbishment.
- Class 3 (General Maintenance): Components that require refurbishment before reuse.
- Class 4 (Major Repair and Refurbishment): Components that exhibit significant deterioration or loss of performance and require major structural repair, strengthening, or material replacement before reuse is viable.
- Class 5 (Recyclable): Components that can't be reused but can be recycled to extract material or elements

According to the performance requirements in ISO 20245 2017 and the service life of the building in 15686-7:2017 (BSI British Standards, n.d.), the performance level and the change through the whole life cycle are demonstrated. The performance degree thresholds are added to assess EoL product performances, ensuring they meet requirements for multi-cycle building components.



Y: Quality/Function
X: Time
PD: Performance Degree
t_0: Time of initial "as built"
t_i: Time at the start of "in use" stage
1: Expectation
2: Commissioning
3: Initial Performance Gap
4: Performance without preventative actions
5: Limit stats
6: Preventative and Periodic Maintenance
7: Refurbishment or Repair
8: Replacement
9: Repair

Figure 2: Revised Whole Life cycle performance of construction based on ISO 20245 2017 Part 7.

3.2 Architecture of the Grading System

The further developed workflow to operate the rating for EoL product performances to support the classification of different levels of circular interventions to ensure the performance degree and the threshold meet the expectation of the building components. The EoL component would go to the grading system composed of inspection, usage determination and regulation three parts. The inspection is conducted to assess the building's performance from quality, health, safety and stability perspectives by referencing the building components' standards and regulations. Non-Destructive Testing (NDT) instruments will support the visual inspection, which is one of the most widely used assessment methods (Faqih & Zayed, 2021), to provide more reliable evaluations. After conducting an inspection, we define the usage scenarios (e.g. internal wall for concrete panel) and essential features (fire resistance) in accordance with industry standards.

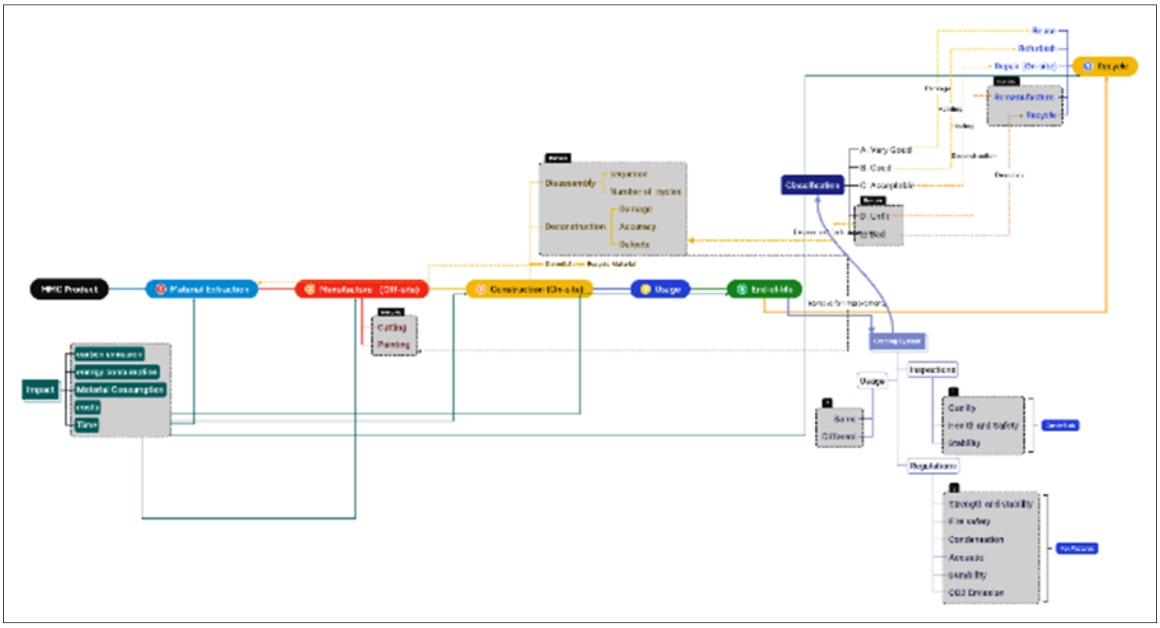


Figure 3: Grading system for EoL product based on features.

The grading system rates the EoL products for each feature i to get the collection of the grades of several features $G = \{GF_1, GF_2, \dots GF_i, \dots GF_n\}$. Based on the collections for the grades G, we can get an overall grade for different usage scenarios with certain probabilities $P_j - U_i = \{P - U_1, P - U_2, \dots P - U_i, \dots P - U_N\}$, $(i = 1,2, \dots, N, j = A, B, C, D, E)$. $P_j - U_i$ denotes the probability of grading as j under the ith usage. And $P - U_1 = (P_A - U_1, P_B - U_1, P_C - U_1\ , P_D - U_1, P_E - U_1)$ is the collection of probability of grading from A to E under the first usage. Other probability collections are the same as $P - U_1$.

$$P - U_2 = (P_A - U_2, P_B - U_2, P_C - U_2\ , P_D - U_2, P_E - U_2)$$

$$P - U_i = (P_A - U_i, P_B - U_i, P_C - U_i\ , P_D - U_i, P_E - U_i)$$

$$P - U_N = (P_A - U_N, P_B - U_N, P_C - U_N\ , P_D - U_N, P_E - U_N)$$

After the grading performances for different usage scenarios, the next step is determining whether this EoL product would be reused as the same usage, as shown in figure 4. Whether the usage is the same will affect the circular intervention levels. For example, a panel is used as a façade in the initial usage scenarios. After the life span, the inspections and the grading processes are conducted with overall grades for different usage scenarios, including the reuse as the façade, the up-cycle as the load-bearing wall and the down-cycle as the cladding. We can have the grades for the three usage scenarios according to the probabilistic grading results, supporting the following decisions: reuse as façade, upcycle as load-bearing walls, or downcycle as claddings. After the decision is made, it comes to classifying the level of circular interventions, depending on the decisions for the usage scenarios.

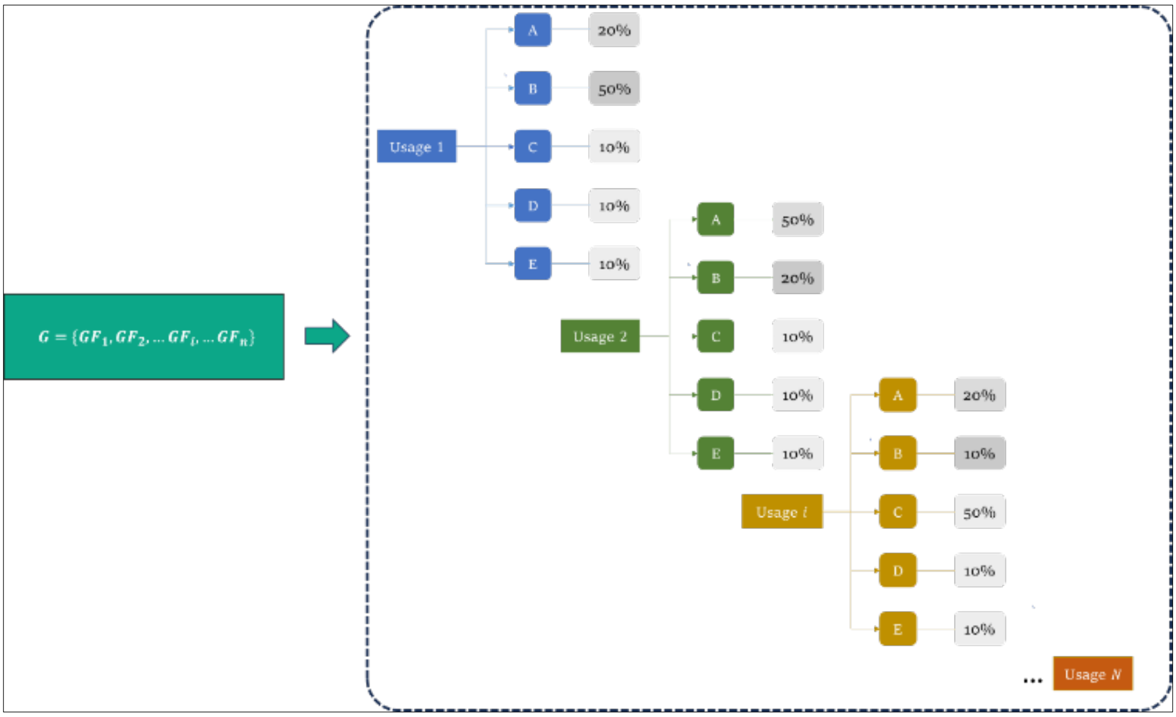


Figure 4: Probabilistic grades under different usage scenarios.

Figure 4 demonstrates an example of these probabilistic results. The grade collection G including grades for the selected features $\{GF_1, GF_2, \dots, GF_i, \dots, GF_N\}$. Based on the defined usage scenarios, which demand various performance features, for example usage 1 needs features F_1, F_2, F_3, and F_4 to meet the performance threshold. We can get the grades for the usage 1 as $\{GF_1, GF_2, GF_3, GF_4\}$ to get the overall grade from A to E with probabilistic. For example, there is a 20% probability that the grade for usage 1 will be A, which suggests that the most likely grade for this EoL product is B. Similar processes for other usage scenarios. With the usage-determined feature-based grading process, we can provide the evaluation for the performances of EoL products for different usage scenarios, which makes the results more robust.

3.3 Multi-level Reuse Route

For the classification of circular intervention levels under different usage determinations, the workflows demonstrate that, based on the assigned condition grade of each End-of-Life component, different levels of circular intervention are required to ensure that the component can meet the performance thresholds necessary for reuse. The outcome of the decision process is either reuse in a suitable application or recycling at the material level.

In detail, if a component is graded as A, it can be reused in the same application after standard procedures such as labelling and packaging. If the component is graded as B, minor refurbishment can elevate its condition to Grade A, allowing direct reuse. A similar process applies to Grades C and D, in which increasing levels of intervention are needed to achieve usable quality. In contrast, components graded as E are unsuitable for reuse because most performance features fall below acceptable thresholds; therefore, these components are directed to material-level recycling.

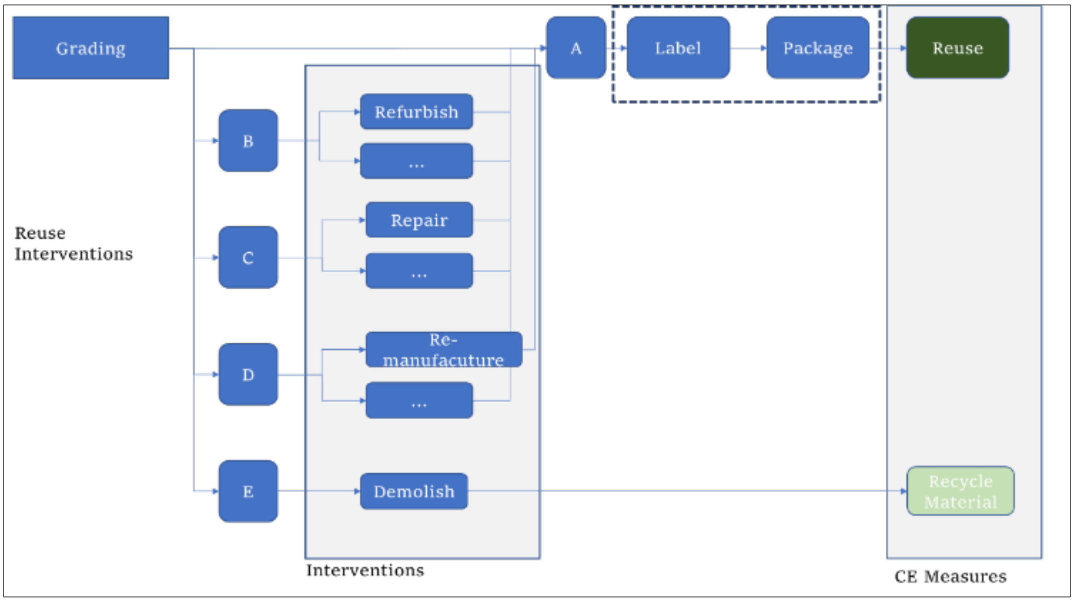


Figure 5: Circular interventions for reuse.

The process of upcycling involves creating new applications for components or reprocessing materials to recover value, and it functions in parallel with circular reuse interventions. A key assumption within this framework is that a lower performance requirement corresponds to a wider range of viable usage scenarios. Accordingly, for an End-of-Life component originally associated with a specific usage scenario i, different circular intervention levels can be applied depending on the assigned grade. These interventions have the potential to upgrade the component so that it becomes suitable for alternative or higher-value usage scenarios.

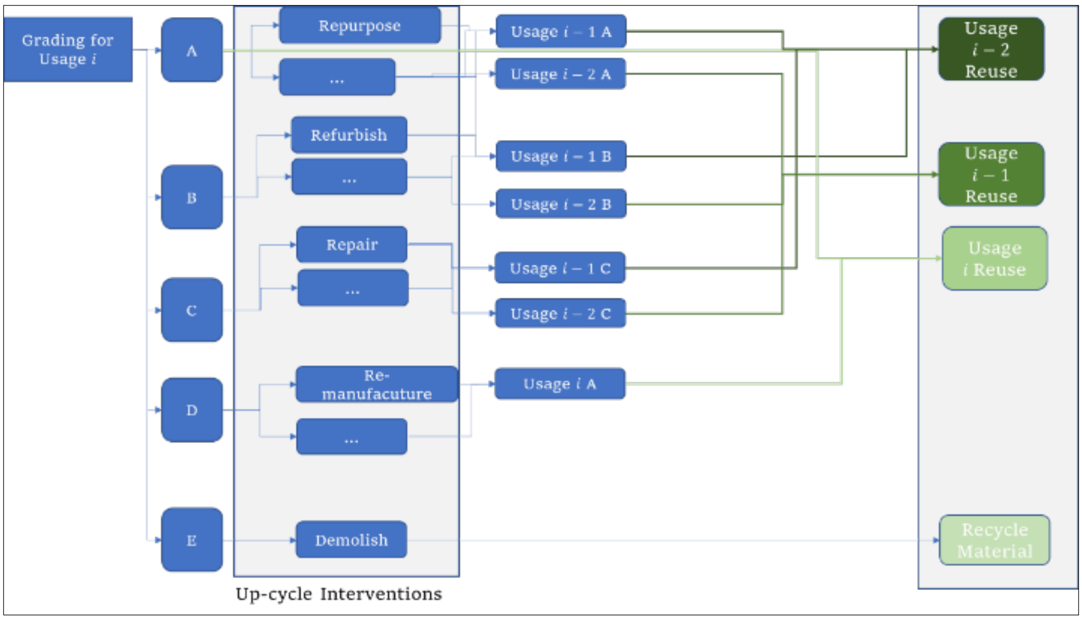


Figure 6: Circular interventions for upcycle.

If a component receives a Grade A classification under usage scenario i, it may, following additional processes such as cutting or repurposing, also satisfy the performance thresholds required for higher-value scenarios (e.g., usage $i-1$or usage $i-2$). This represents an upward reuse pathway in which the component is redirected to a more demanding application. If the End-of-Life component is graded as B or C under usage i, minor or general circular interventions can upgrade its condition sufficiently for reuse under higher or equal usage scenarios, enabling the component to achieve Grade B or C performance in usage $i-1$or $i-2$. For components graded as D within scenario i, more substantial intervention enables improvement to Grade A within the same scenario, maintaining functional viability. In contrast, when a component is graded as E in scenario i, most essential performance features fall below acceptable thresholds, and the only feasible option is material-level recycling

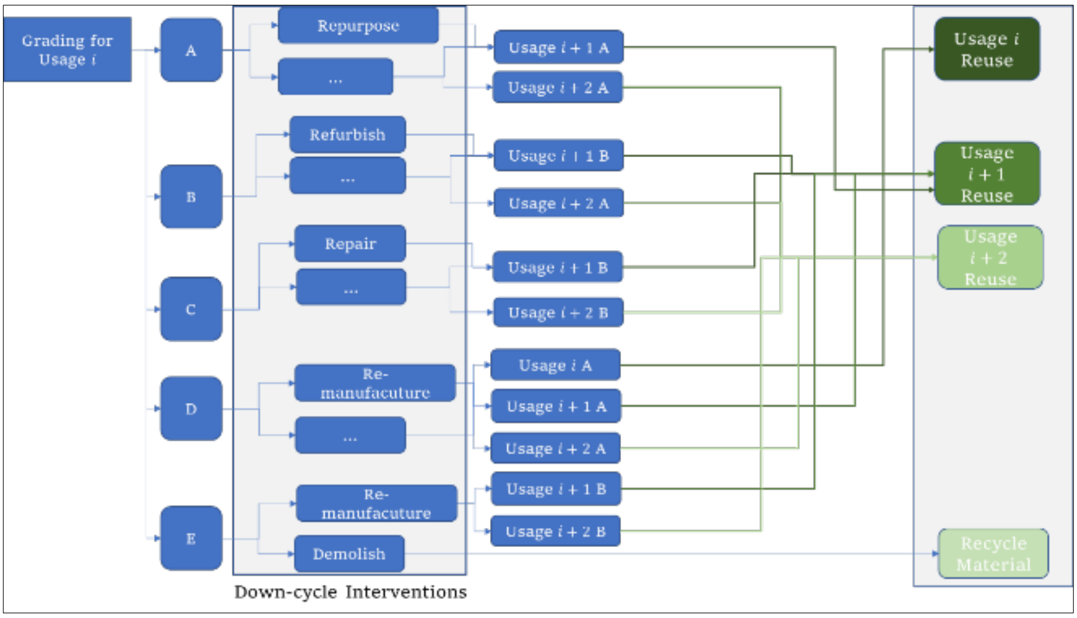


Figure 7: Circular interventions for downcycle.

The workflow for downcycling interventions follows a similar logic to the upcycling process. As performance requirements decrease, the number of suitable usage scenarios increases. For a component originally associated with usage scenario i, if it is classified as Grade A under that scenario, minor repurposing interventions (e.g., repainting) may allow it to meet the performance thresholds for Grade A under lower-level scenarios, such as usage $i+1$or $i+2$. A comparable pattern applies to components graded B, C, or D under usage i: following minor, general, or major interventions respectively, their performance can be improved sufficiently to achieve Grade A or B outcomes within lower-demand scenarios. In some cases, components graded as E under usage $i$may still be upgraded to Grade B or C for usage $i+1$or $i+2$where performance requirements are less demanding. However, if essential features are severely degraded such that upgrading is not feasible, the component will be directed to material-level recycling.

3.4 Design Logic for MGCS Grades and Criteria

The selection of attributes, grading thresholds and aggregation rules within the MGCS was developed by combining three sources of evidence: (i) requirements formalised in existing standards for precast/MMC performance, (ii) expert judgement from structural engineering practitioners, and (iii) inspection data obtained from precast concrete panel case studies.

3.4.1 Attribute and Feature Selection

The attributes used for component grading align with existing technical and warranty standards for prefabricated assemblies (ISO 20245; ISO 15686-7; NHBC; premier guarantee technical standards). These specify structural safety, fire resistance, material durability, thermal properties, and environmental exposure as core indicators of functional performance. The attributes selected in MGCS—load bearing capacity, carbonation depth, insulation performance, fire resistance duration, and surface degradation—were chosen because each appears as a measurable requirement across these standards and each provides quantifiable, non-overlapping information about the deterioration state of precast components.

3.4.2 Threshold Definition and Scaling

Performance thresholds for each attribute were generated by mapping standard requirements to continuous scales. For instance, the boundary between Grade B and Grade C for residual capacity follows typical limit-state guidance, where values below 70–75% of design resistance are associated with increased brittleness or reinforcement yield risk. Carbonation thresholds are informed by BS EN 206 durability exposure limits and testing guidance. Fire resistance thresholds reflect the REI duration classes commonly used for precast façade and partition systems. These boundaries were subsequently reviewed through a structured expert elicitation exercise involving three chartered engineers with direct MMC and concrete inspection experience. For each feature, experts validated whether threshold bands reflected realistic deterioration patterns observed in practice. This combination of standard anchoring and expert review provides traceability and transparency for the feature rating scales.

3.4.3 Aggregation and Grade Construction

Scores for individual attributes are aggregated probabilistically rather than through deterministic weighting. This avoids arbitrary weighting coefficients and allows the Bayesian classifier to infer the importance of each feature through likelihood strength. For example, attributes that display strong separation between grades naturally generate clearer posterior probability differences, whereas weaker indicators produce flatter responses. This approach reflects ISO 20245 logic—components must satisfy multiple performance dimensions—and avoids dominance of any single parameter. To demonstrate traceability, links each MGCS feature to its normative reference basis and the associated threshold source are established as shown in Table 1.

Table 1: Design logic of MGCS.

Attribute	Threshold Basis	Source Type	Explanation
Residual load capacity	75%, 60% limits	Limit-state & expert review	Aligns with concrete reliability thresholds for reuse
Fire resistance	90 min / 30 min	EN/ISO guidance	Distinguishes high vs low reuse scenarios
Carbonation depth	deterioration scaling	EN 206 exposure classes	Reflects durability loss progression
Thermal conductivity	U-value ranges	UK MM housing guidelines	Defines suitability for envelope reuse
Surface damage	visual + NDT scoring	Field inspection practice	Controls finishing/refurbishment demand

4 Classification of Circular Intervention Categories

Another essential part of MGCS for the EoL MMC components is the circular interventions, which aims to improve the performance degree of the components after EoL to a certain level to achieve reusability. These interventions are based on the component's types or functions and dictate what measures to take. According to the MMC definition framework, seven categories of MMC processes and products happen off-site, near-site and on-site. MMC can produce products for different types of buildings like houses, low-rise (<5 story), mid-rise (6-9 story), and high-rise (10 stories and above) using different building materials ('Modern Methods of Construction Working Group', n.d.). The MMC products includes structural and non-structural assemblies in panelised and volumetric forms. According to Construction Playbook of UK (GOV UK, 2022), the Department for Business, Energy and Industrial Strategy (BEIS) and Infrastructure and Projects Authority (IPA) are developing metrics that can be commonly used to assess the performances of MMC components and buildings. There are different standards and requirements for component performance based on the various forms of MMC product categories, resulting in different types of interventions to achieve the reuse of EoL MMC components. For the performance degree assessment of MMC components, the standards specifically test or accredit for MMC products are limited. There are some accreditation schemes for MMC[1], which are not universal schemes. The existing quality assurance standards and legislations are applicable to MMC ('Modern Methods of Construction', n.d.), like ISO, British Standards, and product certification schemes. The circular interventions aim to enhance the reusability of end-of-life (EoL) mobile manufacturing cell (MMC) products. For the inspection of the performance degree, the warranty requirements for new MMC products are selected as a reference. Generally, the technical assessment includes the detailed performance information ('Technical_manual_v11', n.d.):

- Structural integrity
- Performance in fire situations
- Resistance to water penetration
- Safety in use
- Acoustic characteristics
- Thermal and movement characteristics
- Compatibility of materials (interaction between components, structural or otherwise)
- Durability and longevity of materials
- Maintenance Issues

According to NHBC technical document for prefabricated building units (NHBC, n.d.), the performance requirements for the prefabricated components include the strength and stability, energy efficiency, fire resistance, durability and safety in use. Therefore, the inspection for the EoL MMC components should follow these performance requirements according to the specific usage scenarios.

When it comes to preserving and improving the performance of EoL MMC components through circular interventions, the main variation lies in the level of intervention. This indicates that components with different grades may have the same measures, such as refurbishment, but the material consumption or duration may differ. The classification of the level of interventions depends on these factors, and we use the sustainability impact as the benchmark to set the boundaries of different levels: minor, general, and major.

4.1 Design Logic for MGCS Grades and Criteria

As the EoL product is graded based on different features, to obtain the overall grade for the product, the Bayesian classifier is applied to use a probability method to get the results.

Bayesian Classification is a statistical method for predicting an object's class based on one or more features. In the context of grading and classifying EoL MMC components, Bayesian Classification can be employed to systematically and predictively classify units into various grades (A-E) based on multiple features or characteristics.

1. Defining Classes: Define the classes clearly, for example, Grade A to Grade E, based on the predetermined criteria and descriptions for various features like structural integrity, material health, safety compliance, aesthetics, and more.
2. Defining Features: Define the features that impact the classification, such as structural integrity, aesthetics, material health, etc. Feature values quantify component condition and may be represented as binary (damaged/not damaged), categorical (e.g., minor/major), or continuous measures (e.g., percentage of original load-bearing capacity).
3. Data Collection: Gather information/data about EoL components, considering all defined features. Historical data from previous assessments and interventions, where available, should also be collected and utilised.
4. Training the Classifier: Use the collected data to train the Bayesian classifier, providing it with examples of EoL components and their assigned grades based on assessments. Feature

[1] The most widely used accreditation for MMC is Build Offsite Property Assurance Scheme (BOPAS) and NHBC in UK.

probability refers to estimating the likelihood of particular feature conditions given a specific grade or class

5. Probabilistic Classification: Use Bayes' theorem to calculate the probability of a component belonging to a particular grade, given its feature conditions. Classification involves assigning each component to the grade associated with the highest posterior probability.
6. Testing and Validation: Use a separate set of data (not used in training) to test the classifier's accuracy and reliability. Validation involves comparing the classification results with actual assessments to evaluate the efficacy of the classifier.

The In this study, prior probabilities for Grades A–E are established using a hybrid data–expert approach. Empirical defect frequency statistics from the case study panel dataset (n ≈ ...) provide the primary basis for these priors, supplemented by expert judgement where data are sparse, particularly for Grades A and E. Conditional likelihoods, $P(\text{features} \mid \text{Grade } G, \text{Usage } U)$, are developed in two forms. For continuous variables (e.g., residual strength and fire resistance duration), Gaussian likelihood functions are fitted to observed inspection data. Where sample sizes are insufficient, mean and variance parameters are estimated from published deterioration studies (e.g., carbonation penetration and compressive strength ageing models) and cross-checked through expert interviews. For bounded or categorical indicators (e.g., surface damage extent), likelihood values are constructed using frequency tables derived from the inspection dataset to reflect typical deterioration clustering within each grade category.

A conditional independence assumption is applied between features, given the grade and usage scenario. Although deterioration mechanisms may be correlated, this assumption is commonly used in Bayesian structural classification models and enables tractable inference across multiple features. It is explicitly acknowledged here as a modelling simplification that can be relaxed in future developments. Posterior probabilities are then computed directly using Bayes' theorem and normalised across all grades to generate transparent, probabilistic classification outcomes rather than deterministic threshold judgements. To support model traceability and reproducibility, an illustrative dataset, full prior and likelihood matrices, and the computational script are provided as supplementary material, enabling verification and recalibration for alternative datasets or regional applications.

4.2 Applying Bayesian Classifier for Overall Grade and Multiple Usage Scenarios

Bayesian Classification is used to determine the overall grade of EoL MMC components based on multiple feature observations. The approach derives the probability of a component belonging to a specific grade by combining prior knowledge with evidence from inspection data through Bayes' theorem.

4.2.1 Prior Probabilities

Prior probabilities $P(G)$are assigned for each overall grade $G = \{A, B, C, D, E\}$using historical defect distributions and expert judgement. An illustrative example is shown as:

$$P(G = A) = 0.2,\ P(G = B) = 0.3,\ P(G = C) = 0.3,\ P(G = D) = 0.15,\ P(G = E) = 0.05$$

These priors represent the initial belief about grade distribution before feature observations are considered.

4.2.2 Likelihood Formulation

The likelihood term $P(F_1, F_2, \dots, F_7 \mid G)$represents the probability of observing the feature grades given grade G. Likelihood values may be derived from inspection datasets when available and supplemented by expert estimation where data are limited.

Posterior probabilities are calculated using Bayes' theorem as:

$$P(G \mid F_1, F_2, \ldots, F_7) = \frac{P(F_1, F_2, \ldots, F_7 \mid G)\, P(G)}{P(F_1, F_2, \ldots, F_7)}$$

Where:

$$P(F_1, F_2, \ldots, F_7) = \sum_G [P(F_1, F_2, \ldots, F_7 \mid G)\, P(G)]$$

This evidence term normalises the posterior distribution across all grades.

4.2.3 Final Grade Selection

The overall grade assigned to a component corresponds to the class with the highest posterior probability:

$$G_{\text{final}} = \arg\max_G P(G \mid F_1, F_2, \ldots, F_7)$$

This ensures a transparent, probability-based categorisation rather than deterministic threshold assignment.

4.2.4 Bayesian Classification for Multiple Usage Scenarios

The MGCS framework incorporates the influence of usage scenarios on grading outcomes. Different afterlife applications require different subsets of features (e.g., seven features for U_1, five for U_2, and three for U_3). Accordingly, both priors and likelihoods become conditional on usage U, ensuring that results reflect scenario-specific performance requirements.

The adjusted Bayesian classifier considers the conditional dependence of feature behaviour on usage context:

$$P(G \mid F, U) = \frac{P(F \mid G, U)\, P(G \mid U)}{P(F \mid U)}$$

Where:

• $P(G \mid U)$is the prior probability of grade Gunder usage U,
• $P(F \mid G, U)$is the likelihood of observing feature set $F$for grade Gunder usage U,
• $P(F \mid U)$is the probability of observing feature set Funder usage U, computed as:

$$P(F \mid U) = \sum_G [P(F \mid G, U)\, P(G \mid U)]$$

Let $F_i = (F_{i,1}, F_{i,2}, \ldots, F_{i,N})$denote the feature subset used for usage scenario $U_j (j = 1,2, \ldots, M)$.

The computational steps for multi-scenario classification follow the same Bayesian sequence:

1. Define Usage-Dependent Priors: Specify $P(G \mid U_j)$for each grade based on structural relevance and safety requirements associated with usage U_j.
2. Define Usage-Dependent Likelihoods: Construct $P(F_i \mid G, U_j)$using observed data or expert elicitation for the relevant feature subset.
3. Calculate Evidence: Compute $P(F_i \mid U_j) = \sum_G [P(F_i \mid G, U_j)\, P(G \mid U_j)]$to normalise posterior probabilities for usage scenario U_j.
4. Derive Posterior Probabilities: Obtain $P(G \mid F_i, U_j)$for each scenario and feature subset, producing usage-specific classification outcomes such as: $P(G \mid F_1, U_1), P(G \mid F_2, U_2), \ldots, P(G \mid F_N, U_M)$.

This scenario-sensitive formulation allows a single component to receive different posterior grades depending on its potential reuse application, aligning the classification outcome with required performance demand.

5 Case Study

The objective of this classification task is to predict the quality grade $G \in \{A, B, C, D, E\}$ of prefabricated concrete wall panels based on five input features $F = (F_1, F_2, F_3, F_4, F_5)$ and contextual usage scenario U. According to the sample data listed in Table 2 for a precast concrete wall, the two usage scenarios are defined as:

- $\boldsymbol{U_1}$: External walls of commercial buildings (high-performance requirements: load ≥ 75%, fire resistance ≥ 90 min)
- $\boldsymbol{U_2}$: Internal walls of warehouses (low-performance requirements: load ≥ 60%, fire resistance ≥ 30 min)

Table 2: Sample data.

Feature	Value	Physical Interpretation
F_1	82%	Residual load-bearing capacity
F_2	7mm	Carbonation depth
F_3	0.32W/m2k	Thermal insulation performance
F_4	110min	Fire resistance duration
F_5	12%	Surface damage rate

The probabilistic parameters used within the likelihood functions are derived through a combined empirical and expert-driven process. Where continuous features are available in the inspection dataset (e.g., residual load capacity, carbonation depth, surface condition metrics), the mean and variance values are calculated directly from observed sample distributions. In cases where dataset size is insufficient to produce stable estimates, parameter values are supplemented using published deterioration statistics for concrete structures (e.g., carbonation growth curves, fire resistance retention factors) and then validated through expert elicitation. This hybrid approach ensures that the likelihood functions reflect realistic deterioration behaviour rather than arbitrary numerical assignment. The prior probabilities $P(G|U)$ is summarised in Table 3.

Table 3: Prior probability for scenario U_1.

Grade	$P(G\|U_1)$	Justification
A	0.15	U_1emphasizes high performance
B	0.25	
C	0.30	U_2 accepts moderate performance
D	0.20	
E	0.10	E-grade rarely accepted in U_1

To ensure rigorous and consistent probabilistic reasoning, each feature's contribution to the likelihood $P(F \mid G, U)$ is explicitly modelled. Two types of features are considered:

- Continuous Features (e.g., load-bearing capacity, fire resistance): Modelled using Gaussian distributions $\boldsymbol{N(\mu_{G,U}, \sigma_{G,U})}$, where parameters are scenario- and grade-specific.
- Categorical/Bounded Features (e.g., surface damage rate): Modelled using empirically defined probability tables based on proximity to accepted grade thresholds.

To illustrate the approach, we consider a scenario U_1 and calculate the likelihood for each feature value under each possible grade. Table 4 summarizes the outcome of these computations, where continuous values have been converted into probabilities using the appropriate normal distribution function.

Table 4: Likelihood table for scenario U_1.

Feature F_k	G=A	G=B	G=C	G=D	G=E
$F_1 = 82\%$	0.004 ($\mu = 90, \sigma = 5$)	0.11 ($\mu = 80, \sigma = 5$)	0.07 ($\mu = 70, \sigma = 10$)	0.01 ($\mu = 60, \sigma = 10$)	0.00 ($\mu = 50, \sigma = 15$)
$F_2 = 7mm$	0.8	0.6	0.4	0.2	0.1

$F_3 = 0.32$	0.7	0.9	0.5	0.3	0.1
$F_4 = 110min$	0.9	0.8	0.6	0.3	0.0
$F_5 = 12\%$	0.6	0.8	0.7	0.5	0.3

Based on the value in Table 3 and Table 4, the following is to compute the joint likelihood for each grade by multiplying the likelihoods of the five features, assuming conditional independence given the grade and scenario.

Grade A:

$$P(F \mid A, U_1) = 0.004 \times 0.8 \times 0.7 \times 0.9 \times 0.6 = 0.0012$$

Grade B:

$$P(F \mid B, U_1) = 0.11 \times 0.6 \times 0.9 \times 0.8 \times 0.8 = 0.0304$$

Grade C:

$$P(F \mid C, U_1)0.07 \times 0.4 \times 0.5 \times 0.6 \times 0.7 = 0.0059$$

For the likelihood of Grades D and E, the likelihoods are approximately zero, primarily due to violations of critical thresholds in F_1 and F_4.

The evidence term $P(F \mid U_1)$, serving as the denominator in Bayes' theorem, is obtained by summing the weighted joint likelihoods across all grades:

$$P(F \mid U_1) = 0.0012 \cdot 0.15 + 0.0304 \cdot 0.25 + 0.0059 \cdot 0.30 + (\text{negligible terms}) \approx 0.0089$$

With all necessary components derived, the posterior probabilities $P(G|F, U_1)$ is computed following:

$$P(G|F, U_1) = \frac{P(F|G, U_1) \cdot P(G|U_1)}{P(F|U_1)}$$

Grade A:

$$P(A \mid F, U_1) = \frac{0.0012 \cdot 0.15}{0.0089} = 2\%$$

Grade B:

$$P(B \mid F, U_1) = \frac{0.0304 \cdot 0.25}{0.0089} = 85.4\%$$

Grade C:

$$P(B \mid F, U_1) = \frac{0.0059 \cdot 0.30}{0.0089} = 12.6\%$$

The analysis concludes that, under scenario U_1, the sample wall panel is most likely to be classified as Grade B, with a posterior probability of 85.4%. This outcome reflects a high-performance profile across most criteria, albeit marginally below the strict thresholds of Grade A.

Similarly, for scenario $, U_2$ the likelihood is calculated following the same steps. In contrast to commercial facades, warehouses exhibit more relaxed performance requirements, particularly in terms of structural load and fire resistance. Given the lower performance thresholds of U_2 the prior distribution of grades is adjusted accordingly, reflecting the higher acceptability of moderate- to low-performance components in warehouse settings. Table 5 presents the revised prior probabilities. This distribution serves as a reflection of industry tolerance under scenario-specific performance constraints.

Table 5: Prior probability for scenario U_2.

Grade	$P(G\|U_2)$	Justification
A	0.05	High-performance components rarely required
B	0.20	Moderate performance generally sufficient
C	0.50	Most common acceptance grade
D	0.20	Occasionally accepted with minor repairs
E	0.05	Poor-performance components rarely used

To reflect the reduced structural and fire-performance demands associated with usage scenario U_2, the likelihood function $P(F \mid G, U_2)$is modified accordingly. Under this scenario, load-bearing capacity and fire resistance exert a weaker influence on grade assignment than in U_1. For example, lower values of load-bearing capacity remain acceptable within U_2, shifting probability mass towards mid-range grades (such as B and C). Similarly, the minimum fire-performance requirement for $U_2$is 30 minutes; therefore, a measured resistance of 110 minutes substantially exceeds the scenario threshold. Rather than forcing a high-grade classification, this result increases the likelihood of assigning the component to intermediate grades, reflecting scenario-appropriate valuation rather than universal structural benchmarking.

Table 6: Likelihood table for scenario U_2.

Feature F_k	G=A	G=B	G=C	G=D	G=E
$F_1 = 82\%$	0.004	0.9	0.8	0.4	0.1
$F_2 = 7mm$	0.6	0.9	0.6	0.3	0.1
$F_3 = 0.32$	0.5	0.7	0.6	0.4	0.2
$F_4 = 110min$	0.6	0.5	0.7	0.5	0.1
$F_5 = 12\%$	0.5	0.6	0.7	0.6	0.4

These adjusted likelihoods in Table 6 reflect the relaxed performance requirements of $U_2$and feed directly into the scenario-specific posterior inference. The joint likelihood for each grade is obtained by multiplying the individual feature likelihoods, under the conditional independence assumption. For example, the likelihood under Grade C in scenario $U_2$is calculated as:

$$P(F \mid C, U_2) = 0.8 \times 0.6 \times 0.6 \times 0.7 \times 0.7 = 0.141$$

A complete summary of likelihood values for all grade categories under scenario $U_2$is presented in Table 7.

Table 7. Joint likelihoods for all grades under scenario U_2.

Grade	$P(F\|G, U_2)$
A	0.7×0.6×0.5×0.6×0.5 = 0.063
B	0.9×0.7×0.7×0.5×0.6 = 0.132
C	0.8×0.6×0.6×0.7×0.7 = 0.141
D	0.4×0.3×0.4×0.5×0.6 = 0.014
E	0.1×0.1×0.2×0.1×0.4 = 0.000

To normalise the posterior distribution, the evidence term $P(F \mid U_2)$is computed as the weighted sum of the joint likelihoods, using the scenario-specific prior probabilities:

$$P(F \mid U_2) = (0.063 \times 0.05) + (0.132 \times 0.20) + (0.141 \times 0.50) + (0.014 \times 0.20) + (0.000 \times 0.05) = 0.092$$

Posterior probabilities for each grade, in Table 8 are then obtained by applying Bayes' rule. Under the warehouse interior wall scenario U_2, the sample panel is most likely to be classified as Grade C, with a posterior probability of 76.6%. This result indicates that the component can be reused directly without repair or reinforcement, reflecting the more relaxed performance criteria associated with warehouse applications.

Table 8: Posterior probabilities for each grade under scenario U_2.

Grade	$P(G\|F, U_2)$
A	0.063×0.05 / 0.092 = 0.034
B	0.132×0.20 / 0.092 = 0.287
C	0.141×0.50 / 0.092 = 0.766
D	0.014×0.20 / 0.092 = 0.030
E	0.000×0.05 / 0.092 = 0.000

To demonstrate the adaptability of the Bayesian classifier, results, shown in Table 9 from scenario U_2 are compared with outcomes from scenario U_1, highlighting how usage-specific requirements influence grade allocation.

Table 9. Scenario comparison summary.

Aspect	U_1: Commercial Exterior Wall	U_2: Warehouse Interior Wall
Most Probable Grade	B (85.4%)	C (76.6%)
Repair Requirement	Moderate (minor repair may be needed)	Low (suitable as-is)
Dominant Features	Load-bearing, fire resistance	Load-bearing, surface quality

This comparison in Figure 2 clearly showing how the same panel is more likely to be Grade B under commercial conditions (U_1) and Grade C under warehouse conditions (U_2).

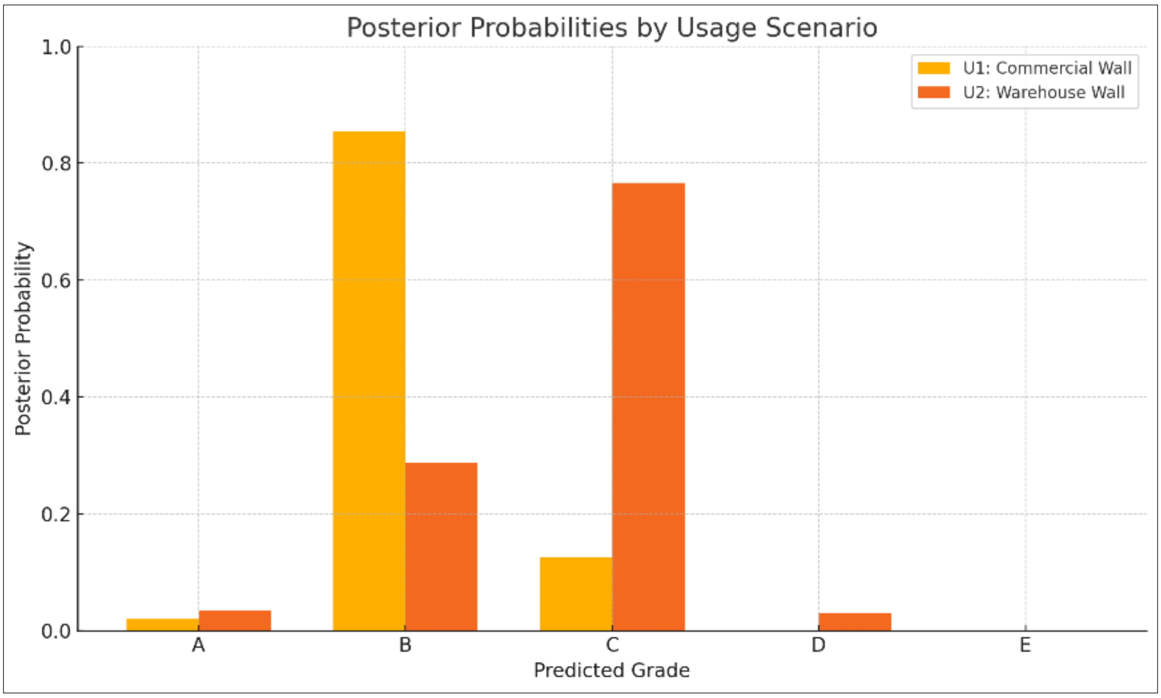


Figure 2: Posterior probabilities by usage scenario.

6 Discussion

6.1 Discussion of Results

The results for the U_1 and U_2 illustrates the model's capacity to respond to diverse functional contexts, ensuring performance-based classification aligned with practical engineering requirements. The hypothetical confusion matrix in Figure 9, assuming the true grade is C in both cases. It demonstrates that the model might over-predict one level higher (Grade B) under stricter criteria, reflecting a cautious classification stance under scenario U_1. This indicates the feature-based model is sensitive to contextual expectations and tends to err on the side of caution when requirements are strict which beneficial in high-risk settings.

The Sankey diagram in Figure 9 illustrates the flow of probabilities and scenario influence. This diagram illustrates the flow of classification probability from a synthetic precast concrete panel through two distinct usage scenarios U_1 (Commercial Exterior Wall) and U_2 (Warehouse Interior Wall). Each scenario leads to a distribution of reuse grades (A–E), reflecting how contextual performance requirements influence probabilistic classification outcomes.

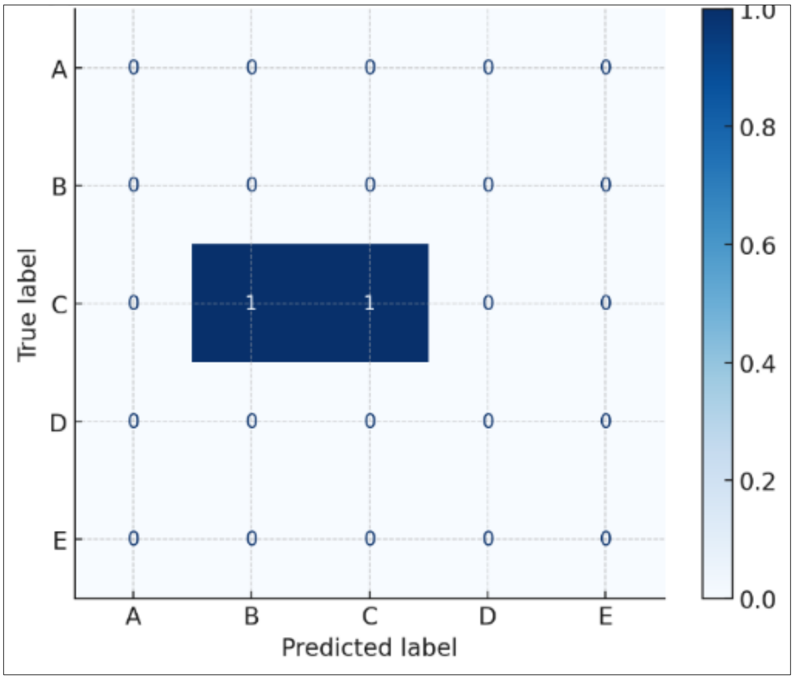


Figure 9: Hypothetical confusion matrix for U_1 and U_2.

Under U_1, stricter demands on load capacity and fire resistance result in a higher likelihood of classification as Grade B, while U_2's more lenient criteria increase the probability of assignment to Grade C. This visualisation enhances explainability by making the relationship between the usage scenario and grade prediction transparent.

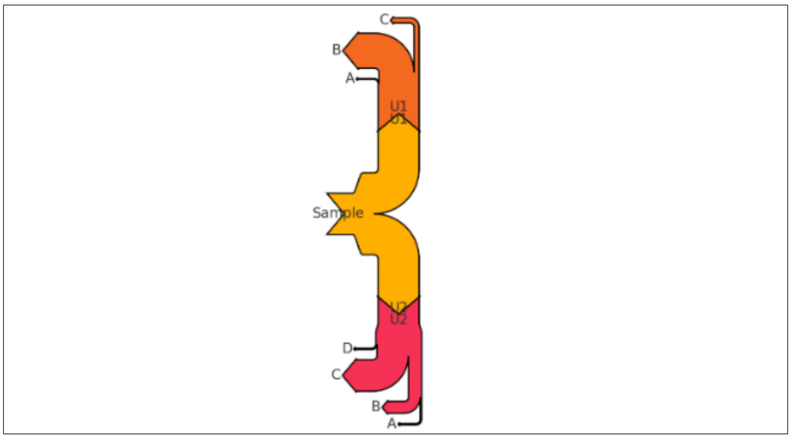


Figure 10: Scenario-based Grade Classification.

The decision tree in Figure 11 maps logical decision paths used for classification. This decision tree represents a rule-based model trained on key features, such as load capacity, carbonation depth, fire resistance, and surface damage, to predict the reuse grade of precast concrete panels.

Each split corresponds to a learned threshold value, supporting engineering interpretability by revealing how different attributes influence classification decisions. The structure allows practitioners to trace the path leading to a specific grade and understand which physical performance measures triggered each decision, thus reinforcing alignment with engineering design logic.

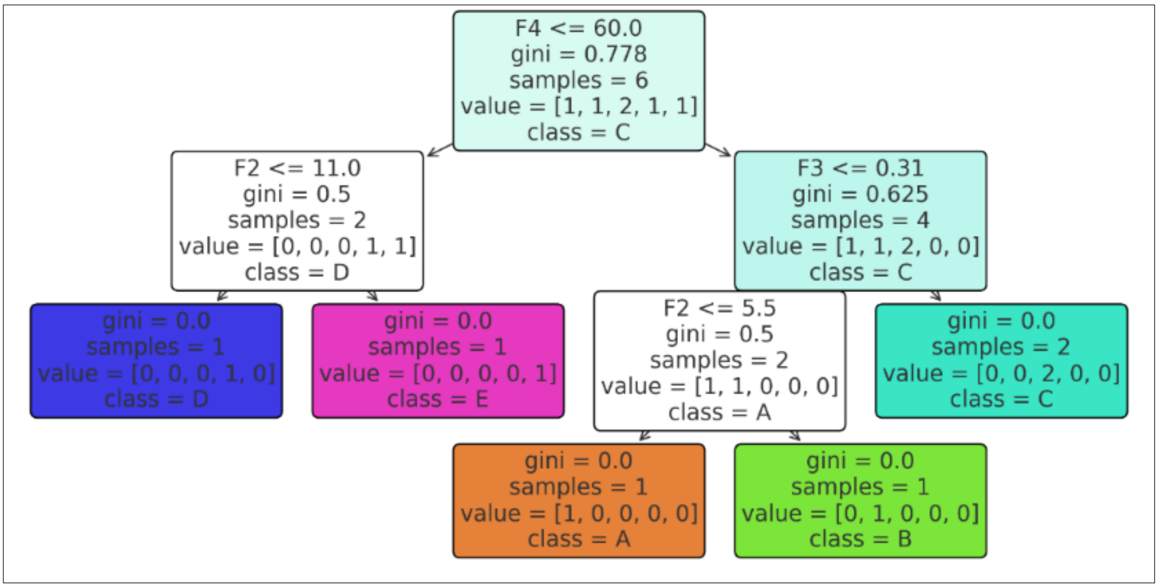


Figure 11: Feature-based Grade Classification.

6.2 Limitations and Future Work

While the MGCS framework demonstrates strong potential, several limitations should be acknowledged. First, the approach is data-dependent; Bayesian posterior probabilities are influenced by the availability and quality of inspection data, as well as expert judgement where datasets are sparse. Second, the Bayesian classifier assumes conditional independence among features given the grade and usage scenario. This assumption simplifies computation and aligns with common structural reliability practice, but correlations may exist between deterioration indicators (e.g., carbonation and strength loss) that could influence posterior results. Third, thresholds and likelihood forms were developed for precast concrete wall panels, and further validation is required when adapting MGCS to other MMC component types or inspection modalities. Future work will include expanded datasets, correlation modelling between features, and sensitivity analysis to quantify the impact of these assumptions.

7 Discussion

This study presents an interpretable and adaptive framework for classifying the reuse potential of end-of-life building components. The Multi-Level Grading and Classification System (MGCS) advances the circular economy agenda by integrating Bayesian inference with engineering-specific decision rules to produce scenario-sensitive reuse grades. Its probabilistic reasoning and rule-based logic are designed to predict outcomes and support transparent, auditable decision-making aligned with real-world performance expectations.

Notably, the framework addresses three critical domains of impact: (1) it enhances sustainability by diverting reusable materials from landfill and reducing environmental burden; (2) it improves economic outcomes by preserving material value and supporting cost-effective repair strategies; and (3) it streamlines operational efficacy in EoL handling, enabling more intelligent sorting, planning, and material logistics.

Sankey diagrams depict scenario-driven grade flows, and decision trees clarify feature-based reasoning, strengthening the model's explainability. With future extensions, such as dynamic feature weighting, integration with digital twin systems, and lifecycle impact coupling, the MGCS framework holds promise as a core decision-support tool for scalable, intelligent material reuse in the built environment.

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Ethical Approval Declaration

The study was conducted in accordance with established standards for research integrity and ethics.

Informed Consent Statement

All participants provided informed consent before participating in the study.

Data Availability Statement

The data supporting the findings of this study are not publicly available due to usage agreements and confidentiality restrictions associated with the industrial case study. Access to the dataset may be granted upon reasonable request. Interested parties should contact the corresponding author to discuss potential data-sharing arrangements and conditions of use.

Conflicts of Interest

The authors declare no conflict of interest.

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