Assessment of Estimation Methods for Demolition Waste Volume and Cost

Mohammad Movahedi, S.M.ASCE[1]; Juyeong Choi, Ph.D., A.M.ASCE[2]; Seungwon Seo[3]; and Choongwan Koo[4]

[1]Research Assistant, Dept. of Civil and Environmental Engineering, FAMU-FSU College of Engineering. Email: mmovahedi@fsu.edu
[2]Assistant Professor, Dept. of Civil and Environmental Engineering, FAMU-FSU College of Engineering. Email: jchoi@eng.famu.fsu.edu
[3]Research Assistant, Division of Architecture and Urban Design, Incheon National Univ., Incheon, Republic of Korea. Email: ssw9541@inu.ac.kr
[4]Associate Professor, Division of Architecture and Urban Design, Incheon National Univ., Incheon, Republic of Korea. Email: cwkoo@inu.ac.kr

ABSTRACT

For the past few decades, researchers have tried to make a sustainable built environment by maximizing recycling and reuse of construction and demolition (C&D) waste. In particular, demolition waste accounts for more than 90% of the total C&D waste generated in the US, thus signifying substantial potential for recycling and reuse. While there have been several models to estimate construction waste available for supporting its waste reduction planning, however, there has been a lack of estimation models for demolition waste. This research seeks to evaluate and compare the feasibility and accuracy of four common estimation approaches for demolition waste (i.e., demolition waste volume and cost): a linear regression, an artificial neural network, and two advanced case-based reasoning approaches, which utilize several regression models on selected instances to improve the overall accuracy of predicted cost and volume of demolition waste. A database of 52 demolition projects, containing information on architectural characteristics, permit history, value, and contract requirements, is used to train models and facilitate evaluation. Different estimation methods are compared in terms of estimation accuracies while discussing the potential improvement of each method. This study will serve as the cornerstone to develop a more reliable demolition estimation model in the future.

INTRODUCTION

The construction and demolition waste (CDW) sector constitutes a significant portion of the solid waste stream in the United States, accounting for approximately 67% of the total. Notably, about 90% of CDW originates from demolition sites, underscoring the importance of effective demolition waste management in achieving a sustainable built environment (U.S. Environmental Protection Agency 2020). As the demand for urban development and infrastructure projects rises, so does the production of demolition waste (D.W.), resulting in substantial implications for resource consumption and environmental sustainability. Thus, the implementation of recycling and reusing strategies for CDW, specifically D.W., is of paramount importance, given its direct impact on the construction industry characterized by high raw material utilization and waste generation rates.

Recycling and reusing DW entail considerable resource allocation. For instance, on-site material separation, which is crucial for maximizing material recovery, requires more time compared to sending materials to landfills in a mix, thereby necessitating allocating additional resources during the planning stage to compensate for the reduced productivity resulting from on-site separation (Jalloul et al. 2022). In addition, selling materials to recycling markets is a major source of revenue to demolition contractors. As such, knowing how much materials are recyclable is important for the contractors to assess project feasibility during the bidding stage(Shaurette 2006). In light of these considerations, accurate waste estimation tools are indispensable for anticipating the potential volume and type of waste to be generated from upcoming demolition projects. Such tools enable more effective, sustainable demolition planning and resource allocation, thus contributing to a circular economy model that promotes sustainable practices by accurately quantifying waste for reuse, recycling, and recovery (Hill et al. 2023).

Numerous studies have attempted to develop estimation models for DW, utilizing various regression models (Llatas and Osmani 2016; Mah et al. 2016; Paz and Lafayette 2016), artificial neural networks (Coskuner et al. 2021; Ihsanullah et al. 2022; Lu et al. 2016) and model-based methods (Akinade et al. 2018). However, these studies primarily focus on overall DW rather than specifically addressing the recoverable portion, limiting their applicability in promoting a more sustainable built environment.

The effective management of D.W. requires a comprehensive understanding of its generation process. By recovering and reutilizing D.W., communities can alleviate the strain on finite natural resources, facilitating the transition towards a circular economy and fostering economic resilience and ecological stewardship. Quantifying the recoverable materials from demolition sites represents the first step toward achieving this goal. As such, this study aims to compare the four most common estimation approaches (i.e., regression, artificial neural networks, and two model-based methods (i.e., two different versions of Case-based Reasoning [CBR])) and recommend the best method for estimating the amount of recoverable D.W. The recoverability of materials depends on various factors that are not only available within demolition contractors (e.g., demolition methods and resources) but also from external data sources, such as city authorities and building appraisers (e.g., for maintenance records). This study will first briefly review the aforesaid estimation techniques within the context of construction project planning, followed by a comparison of the aforesaid estimation models and discussions.

LITERATURE REVIEW

During the last few decades, numerous models have been developed to estimate the volume of waste generated during demolition activities. Traditionally, regression models serve as valuable tools for estimating D.W. by leveraging building characteristics as predictors. The waste generation rate approach falls in this category (Mah et al. 2016; Paz and Lafayette 2016). These models are highly specified for certain conditions and applications. By correlating specific attributes, such as building age, materials used, structural design, and construction techniques, with the volume of D.W. generated, these models facilitate the development of predictive equations. Latlas and Osmani (2016) considered multinominal regression can consider multiple attributes to estimate the D.W.

While regression models could be a valuable tool to predict the volume of D.W., it faces a few limitations. Firstly, it assumes a linear relationship between predictor variables and the output, which may not always hold true in complex real-world cases. Secondly, it requires that predictor variables be independent, an assumption often violated due to multicollinearity in practice. Finally, it is sensitive to outliers, which can unduly influence the model’s performance.

In demolition processes, these outliers could correspond to unusual projects with unique characteristics, such as those with extraordinary demolition costs or volumes of D.W. (Lu et al. 2016). Since each building has its unique characteristics, and there are limited number of buildings available in the database, the high sensitivity to outliers will pose additional challenges.

Prevailing research has often employed regression models that fail to address the intricate and often non-linear interconnections among variables. However, artificial neural networks, due to their inherent flexibility, can effectively map these multifaceted relationships. This has led to a paradigm shift in recent years, with researchers increasingly employing these networks to accurately estimate the quantity of DW (Coskuner et al. 2021; Ihsanullah et al. 2022; Lu et al. 2016). The ability of these networks to encapsulate non-linear relationships among variables provides a nuanced approach to waste estimation, marking a significant advancement in the field.

ANN comes with its own set of limitations. Firstly, ANNs require a large amount of data to learn effectively, and acquiring such data in the context of demolition activities can be challenging due to the project-specific nature of these operations. Secondly, ANNs are often considered as 'black box' models, due to their lack of interpretability. This means that while they can make accurate predictions, understanding the rationale behind these predictions can be difficult. Lastly, ANNs are sensitive to the choice of hyperparameters and the initialization of weights, requiring careful tuning and potentially multiple runs to ensure model stability and optimal performance (Ihsanullah et al. 2022).

More recently, Case-Based Reasoning (CBR), a problem-solving paradigm that uses past knowledge, was used to develop the D.W. volume and cost estimation models (Kim and Shim 2014; Tatiya et al. 2018). The CBR models combine the estimation accuracy of black box models, such as ANN, with the interpretability of the regression models by providing similar cases as references to support its inference. The support cases create more opportunities for further applications beyond project planning and can instigate fundamental changes in the construction. Despite its utility, CBR also has notable limitations. The performance hinges upon the quality and relevance of its case library. In the context of D.W. estimation, these databases developing such databases have not been the priority for many stakeholders and planners (Tatiya et al. 2018).

While prior research primarily focuses on estimating the amount of D.W., it is important to quantify the recoverable portion - a critically understudied area. Such an estimation approach, beyond merely calculating the total amount of D.W., is essential as it directly contributes to a sustainable built environment (Hill et al. 2023). In addition, previous studies have not considered the building life cycle in estimating the generated D.W. at the end-of-life stage, such as the maintenance history of a building. The renovation, repairs, and rehabilitation of building subsystems and components can greatly impact the recoverability of materials during demolition activities.

DEVELOPING THE RECOVERABLE DEMOLITION WASTE ESTIMATION MODELS

In this study, the conventional waste estimation methodologies—multiple regression analysis and artificial neural network—are compared to the more sophisticated case-based reasoning technique. To develop these models, it is necessary to develop a comprehensive database, encapsulating details of demolished projects with explicit emphasis on building characteristics and maintenance history.

The objective of the estimation tool is to leverage building characteristics at the end-of-life stage to predict demolition outcomes. In addition to various building characteristics (i.e., building age (Poon 1997), geometric characteristics (Shi and Xu 2006), gross floor area (Lu et al. 2011), number of floors (Parisi Kern et al. 2015), land use (Banias et al. 2011), and historical maintenance records (Bergsdal et al. 2007)); factors like demolition project specifics (i.e., nature of the project (Chen and Lu 2017) and location (Poon et al. 2004)) available from the collaborating demolition contractor, will be used as independent variables to predict the volume of recyclable DW and the cost of demolition.

Linear Regression Analysis. Linear regression Analysis is a statistical technique that enables the prediction of a dependent variable based on several independent variables. This technique not only reveals the relationship between these variables but also provides a quantifiable measure of the impact each independent variable has on the dependent variable (Bakshan et al. 2015). By accounting for multiple factors simultaneously, it offers a nuanced understanding of complex phenomena (Goodfellow et al. 2016). Equation 1 describes how linear regression is trying to predict Y, by finding the appropriate coefficients b_n and a for n attributes x.

$$Y = a + b_1x_1 + b_2x_2 + \cdots + b_nx_n \tag{1}$$

Estimation model 1: Artificial Neural Network. Artificial Neural Network (ANN) can be employed as a potent regressor for estimating the volume of recoverable D.W. and the cost of demolition operations (Coskuner et al. 2021; Ihsanullah et al. 2022; Lu et al. 2016). Through learning the intricate nonlinear relationships between various building attributes and the target outcomes, ANNs can predict these continuous variables with substantial accuracy. The process involves adjusting internal weights according to the input data, thereby learning the underlying function that maps the inputs, in this case building attributes and maintenance history, to the outputs, the demolitions outputs (Goodfellow et al. 2016). Figure 1 illustrates the structure of a hypothetical ANN. The goal of the ANN is to determine the weight of each relationship in this network, and through that, it can estimate the outcome of the demolition project.

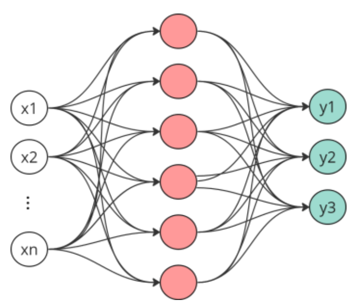

Figure 1. The architecture of Artificial neural network

Estimation model 2: Advanced Case-based Reasoning models. CBR harnesses the power of historical data and analogical reasoning to adapt and improve its estimations as more cases are added to the knowledge base. As a result, CBR can often provide more accurate and robust estimations, especially when encountering novel scenarios or when the underlying relationships between variables cannot easily be captured by conventional modeling techniques. Advanced Case-based Reasoning (ACBR) is a variation of CBR models that uses Analysis of Prediction

Accuracy (APA) on two regression algorithms, Multiple Regression Analysis (MRA) and Artificial Neural Network (ANN), to estimate the outcome of these studies. Multiple studies have demonstrated the feasibility and accuracy of ACBR (Koo et al. 2011, 2014) when it comes to identifying the underlying relationships between several independent variables and dependent variables, like this case.

The CBR model embodies an evolving process that continuously refines its reasoning based on an expanding historical knowledge base. This dynamic model, in essence, learns from past instances, optimizes its logic, and concurrently enriches its knowledge repository, thereby ensuring an adaptable and progressive reasoning mechanism. This process can be summarized into four steps: retrieve, during which one retrieves similar cases from the knowledgebase, reuse, during which a reasoning method derive information from those historically similar cases, revise, where the reasoning results from the last step being evaluated, and finally, retain, where the knowledge learned from this process can be added to the knowledge base for future uses. The core idea behind the ACBR method improves the reasoning process by constantly improving the case selection criteria (Koo et al. 2011).

Figure 2 illustrates the structure of the ACBR. The cornerstone of the case retrieval stage lies in utilizing cases most similar to the input case, whose outcome is yet to be determined. One can use absolute percentage error (APE) to calculate similarity between the input case and each preceding demolition case, grounded on project attributes. By introducing a Minimum Criterion for Scoring Attribute Similarity (MCAS) functions as a filtering threshold, it is possible to exclude attribute values that bear insignificant similarity and ultimately, enhances the relevance and accuracy of the case retrieval process, ensuring only the most similar historical cases are considered. The similarity between the cases can be quantified by a similarity score, which can be calculated using the weighted average method.

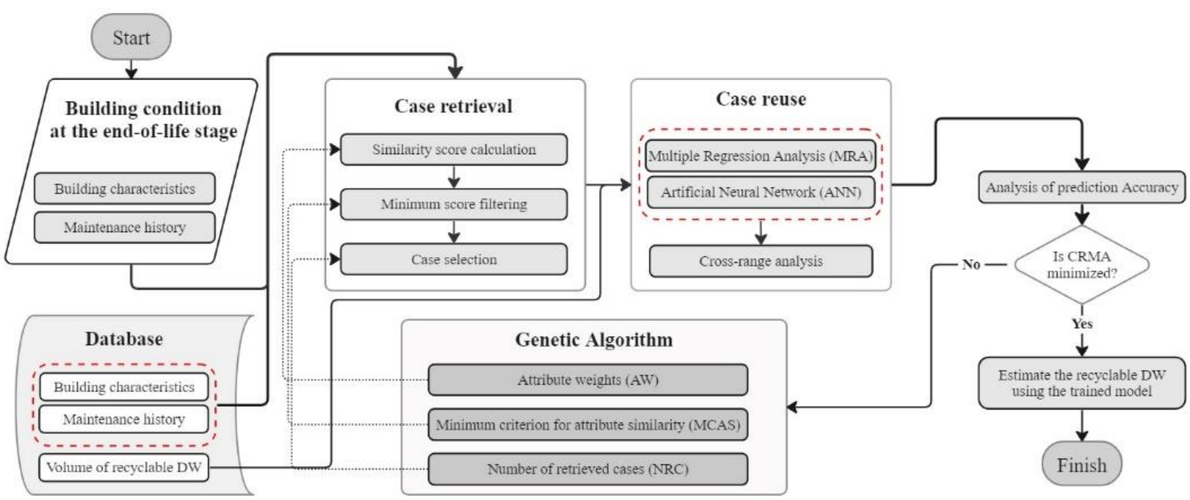

Figure 2. The flowchart describing the Advanced Case-based Reasoning (ACBR) for estimating the cost and volume of recyclable demolition waste.

By analysis of prediction accuracy, the ACBR model can combine the knowledge gained from each approach to make better predictions. For each model one can calculate the absolute percentage error ($APE_{\ model}$). Using the APE and the predicted value, the predicted range PR_{MRA} and PR_{ANN} can be calculated for MRA and ANN outputs using Equation 2.

$$PV_{model} \times (1 - \frac{APE_{model}}{100}) \leq PR_{model} \leq PV_{model} \times (1 + \frac{APE_{model}}{100}) \quad (2)$$

By minimizing the union of these ranges across different regressors, the genetic algorithm will find the best set of hyperparameters that can result in a more robust and accurate estimation, thereby enhancing the overall predictability of the model. By minimizing the cross-range, the ACBR can reduce the variance in the predictions made by the MRA and ANN models, thereby increasing the accuracy of the final predicted value for DW volume. This innovative approach allows to leverage the strengths of both statistical and machine learning methods, delivering a more accurate, robust, and reliable estimation model.

The next step in the case-based reasoning is to derive the outcome and estimate the demolition cost and the volume of the recoverable material. This estimation can be carried out by employing one of the following approaches:

Estimation model 3: ACBR (Averaging) Koo (2011) proposed an averaging mechanism where the response variables are predicted by averaging the outcomes of selected cases (ACBR-Averaging), meaning that the estimation of demolition cost and the volume of recoverable materials will be the average of these variables in previous cases.

Estimation model 4: ACBR (Trained model) Using a similar approach, an alternative methodology employs trained models for estimation post case selection (ACBR-Trained Model). Hence, after case selection, the algorithm utilizes the trained model to predict the response variables. The ACBR-Trained model can depict the nonlinear relationships between the historical cases and new demolition projects.

RESULT AND DISCUSSION

In this study, project data and buidling attributes collected from 52 demolition projects located near Tallahassee, Florida, was used for analyses. The attributes of each project, which play a crucial role in generating reliable estimations, were meticulously gathered from various online sources, including local property appraisal and city permit records. Additionally, for each project, the researchers obtained data on the volume of recyclable DW generated and the associated cost of the demolition operation from a collaborating local demolition contractor. This diverse range of data sources provided a comprehensive view of each project and laid the groundwork for the development of the estimation models.

The dataset is employed to train, test, and compare the developed models. Sensitivity analysis is also performed to investigate the impact of different models on the performance of the estimation tool (i.e., prediction accuracy). A model that consistently maintains its performance across a wide range of input values is typically considered more robust and reliable.

Table 1 presents the sensitivity of the models' accuracy using each of the developed models to predict the cost of demolition and the volume of recovered materials. Key performance metrics include average accuracy, standard deviation of accuracies, and the coefficient of variation (CV). The CV, a statistical measure quantifying data dispersion relative to the mean, serves as a pivotal criterion for assessing and comparing model performance. A lower CV score signifies a lower variability around the mean, which indicates enhanced model consistency and reliability, thereby implying a more dependable predictive model.

For the Demolition Cost, the MRA model has the highest mean accuracy at 76.12%, but it also has a relatively high standard deviation (30.31%), indicating relatively lower reliability. The ACBR (Trained model) performs with the lowest standard deviation (26.11%), suggesting that its predictions are more consistently accurate. When it comes to estimating the volume of recoverable concrete, the ACBR (Trained model) outperforms others with the highest mean accuracy of 80.92% and the lowest standard deviation (16.42%), implying a high level of consistent accuracy. This model would be a good choice to predict the volume of other recoverable materials, as the ACBR (Trained model) model achieved the highest mean accuracy (66.09%) with relatively low standard deviation among other models. Figure 3 illustrates the distribution of estimation accuracies for the cost of operation and the volume of recoverable concrete and other materials, as predicted by the ACBR model.

Table 1. The sensitivity of models' accuracies in percentage

	Demolition Cost				Recoverable Concrete				Other recoverable materials			
	MRA	ANN	ACBR (Avg)	ACBR (Trained)	MRA	ANN	ACBR (Avg)	ACBR (Trained)	MRA	ANN	ACBR (Avg)	ACBR (Trained)
mean	**76.12**	31.37	71.58	56.36	73.09	67.84	65.62	**80.92**	65.65	42.43	57.81	**66.09**
std	30.31	32.37	33.77	26.11	31.99	30.87	37.90	16.42	36.01	32.33	40.10	25.26
CV	0.40	1.03	0.47	0.46	0.44	0.46	0.58	0.20	0.55	0.76	0.69	0.38

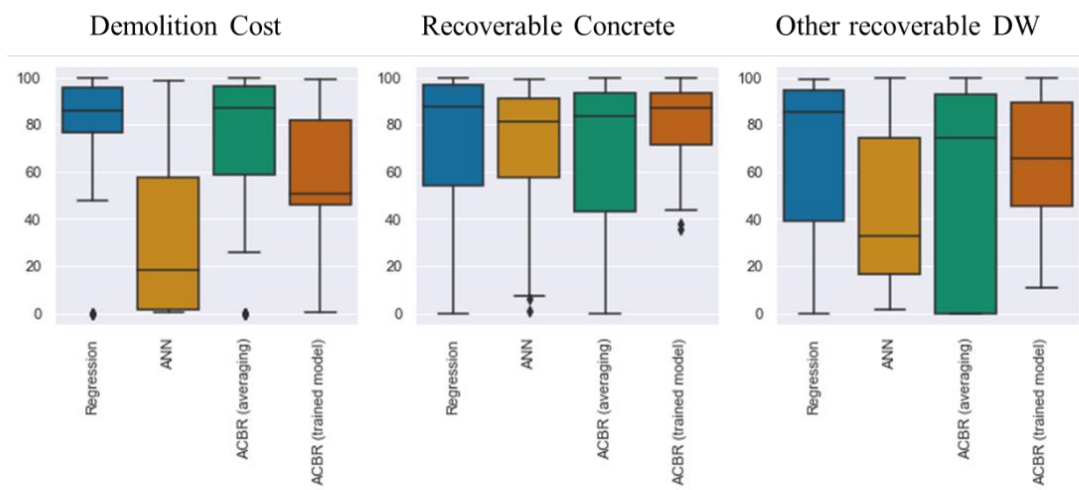

Figure 3. Models' estimation accuracies for demolition process outcomes.

These findings highlight the potential of the ACBR-based models as a valuable tool for practitioners in the field of DW management, enabling more accurate planning and forecasting for sustainable waste management strategies. Still, there is still room for improvement. For instance, by using more sophisticated regressors, such as auto-tuned artificial neural networks, can mitigate the adverse impact of model architecture.

Cross-correlation is a sophisticated approach to identify the external factors that significantly influence the outcome of a demolition project. By calculating the cross-correlation for each pair of independent and dependent variables, it is possible to discern which project attributes exert the most substantial influence on the project's outcome. This method thereby establishes a foundational understanding of the role played by building characteristics formed at different stages of the project's life cycle in determining the project's outcome (Sun et al. 2021). Figure 4 reveals the cross-correlation analysis results between the project attribute and demolition cost and volume of recoverable D.W. The duration of the last renovation, external walls maintenance, and value and duration of the lase mechanical maintenance exert substantial impact on the estimated demolition costs.

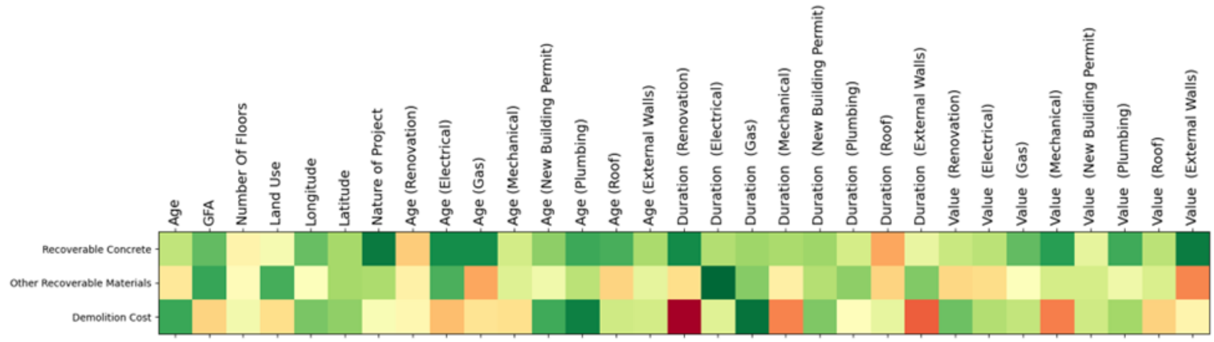

Figure 4. Cross Correlation analysis output

In contrast, the volume of recyclable concrete waste generated during demolition is most affected by the nature of the project, the value of the last external walls maintenance, the duration of the last renovation, and the duration of the last roof maintenance activities. For the volume of other recoverable materials, factors such as the duration of the last electrical maintenance activity, the value of the last external walls maintenance activity, the time elapsed from the last roofing maintenance, and GFA play crucial roles.

CONCLUSION

The study conducted herein has demonstrated the promising potential of different estimation models, and particularly ACBR as a robust tool for estimating demolition costs and recyclable waste volumes. The developed models were trained and tested using a comprehensive database of 52 diverse demolition projects, whose attributes were meticulously gathered from local property appraisal, city permit records, and demolition contractor reports.

The developed models demonstrated impressive accuracy rates in its predictions, achieving 76.12% for estimating demolition costs, 80.92% for recoverable concrete volumes, and 66.09% for other recyclable materials. These results underscore the model's value to stakeholders in DW management, enabling enhanced planning and forecasting for sustainable waste management strategies, while highlighting the promising potential of using ACBR models in DW estimation.

The cross-correlation analysis highlighted the pivotal role of maintenance history in material recoverability during the end-of-life stage of buildings. It elucidated that variables such as cost, duration, and elapsed time since maintenance activities can significantly modulate the volume of materials that can be reclaimed. This analysis brings to light the profound influence that decisions during the usage and operational phase on the outcomes of the end-of-life stage. In essence, this finding illuminates the interconnectedness of building life cycle stages and signifies the potential of informed decision-making to foster sustainable outcomes.

Database development challenges are the most important limitations of this study. The development of a database was not deemed a high-priority task by stakeholders during the end-of-life phase of the building life cycle, which may affect the accuracy of the model's predictions.

Additionally, while the ACBR approach has demonstrated substantial promise, there remains potential for improvement. The dynamic nature of the problem at hand may necessitate the development of a more robust algorithm, one that can adapt to the changing contours of DW management. This presents an opportunity for future research to modify and refine the ACBR methodology, with the ultimate aim of yielding even more precise predictions.

The study's findings contribute to the growing body of knowledge in the field of DW management, while highlighting the importance of the decisions made through the use and operation stage on the outcome of the end-of-life stage. Future research could focus on refining the model further and exploring the role of the decision-makers in different stages of the life cycle on the recoverability of different materials at the end-of-life stage of the building.

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