# Robotic Binder Deposition for the Reuse of Construction Demolition Waste

## A novel pathfinding algorithm with optimization for adaptive binder application in irregular material assemblies

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*Automation techniques, specifically in robotic setups have been an emerging field in the context of computer aided design and construction. Although a great number of construction related manufacturing have been transferred to this field, there is still use of manual binder deposition, which essentially disrupts the robotic sequence, and causes loss of time as it is a repetitive task that can be eased with use of robotic systems. Besides, there is a lack of precise and efficient robotic systems for automating the bonding process in the construction reuse industry, specifically with irregular waste. To address these challenges, this paper presents a method for the process of reusing construction demolition waste to produce new cladding elements by using computational design, optimization, and robotic assembly techniques. The main contribution is an automated and customized pathfinding algorithm that generates motion paths relying on grids utilizing closest point logic and the paths are calculated to determine the binder amount needed based on the bonding requirements of the elements to be joined. This ensures that the application process aligns with engineering and structural standards, enhancing the strength and durability of the final products. The path finding algorithm is specifically designed to enable a waste-free, fully automated process that eliminates errors commonly associated with manual labor. This novel method facilitates the reuse of demolition waste materials and establishes a framework for scalable, automated binder applications in sustainable construction practices.*

**Keywords:** *Robotic Integration*, *Construction Waste*, *Demolition*, *Pathfinding Algorithm*, *Computational Design*, *Optimization*, *Binder Deposition*

## INTRODUCTION

As the construction industry migrates toward a more automated and sustainable way of practice, robotics implement a critical potential in improving precision of application, reducing labor dependency and enabling material-aware workflows. Within these implementations, robotic binder deposition has emerged as an alternative and promising strategy – which includes automating the applications of binders or adhesives for cleaner, more efficient and faster processes (You et al., 2023). Meanwhile, the reuse of construction and demolition waste (CDW), has become more critical, as their waste stream is a representation of up to 40% of the global material consumption, and at the same time, is a

significant contributor to environmental degradation (Wu et al., 2019). Although a significant amount of progress has been made in automated fabrication and assembly, most of the existing systems are designed for controlled environment with standard component, which leaves a gap when irregular and unpredictable waste materials are in question.

In retrospect, there is a lack of robotic binder deposition systems that can adapt to the irregularity of the material spatial variability connected to CDW. Binder application workflows are generally relying on fixed paths and uniform geometries, which usually requires human intervention or operation under idealized conditions. Similarly, robotic pathfinding algorithms are rarely adapted to the complexities and challenges of binder deposition across irregular assemblies.

In response, this study proposes a novel method of combining custom pathfinding algorithms and robotic binder deposition to enable the reuse of CDW in assembly processes of cladding elements. Unlike traditional processes, this system is designed specifically to handle material irregularity by adapting paths for the binder to the geometry and control stop points. The approach builds on existing research in robotic motion planning but diverges in its emphasis on adaptivity, material heterogeneity, and in-situ reuse.

## BACKGROUND

A significant number of recent innovations have supported this convergence of robotics and CDW reuse. One of these projects is VOXELJET and Parastruct's binder jetting process, in this, mineral adhesives are used to transform recycled construction powders into brand new components to be molded with up to 90% material reuse, which supports the circular economy goals with use of robotic additive manufacturing (VOXELJET, 2024). A similar research is the Stone Spray project, which demonstrates multi-directional robotic deposition of sand based structures using a binder spraying nozzle. This process illustrates how robots can fabricate architectural elements from either local or waste-based material solutions (Kulik et al., 2012). While both of the aforementioned projects showcase how robotics are an ally of circular material flows, they are operated within a specific type of material or form.

A fundamental component of robotic binder deposition is pathfinding and motion planning, which indicates the generation of optimized, collision-free trajectories for robots, to achieve precise binder application. In adhesive specific applications, specifically some researchers, such as Svensson et al. (2016), have applied automated path planning to tasks involving adhesives, these depend on idealized CAD inputs that is not relevant for material variation. Adaptive approaches emerge daily, from a force-controlled glue dispensing system in the footwear industry by Castelli et al. (2021) and mobile sealing robots for repairs of pavements by SealMaster (2023). These have introduced sensing and feedback mechanism that potentially improve precision; however, they remain domain-specific, and haven't been applied to architectural scale tasks. Algorithms such as RRT*, A* and D* are known for their usage in robotic motion planning, specifically for navigating through constrained environments (Dai et al., 2022). All of these approaches, in the end, assume clean geometry, static joints and high accuracy, which is usually not a feasible approach in demolition waste reuse contexts.

## METHODOLOGY

### Initial workflow

The reuse of CDW presents a significant opportunity to reduce material loss and embodied carbon in the built environment. A promising strategy is the robotic reassembly of

this salvaged waste into non-load-bearing cladding panels, which would require precise classification of the waste elements according to size and material type, and arranging them within predefined frames.

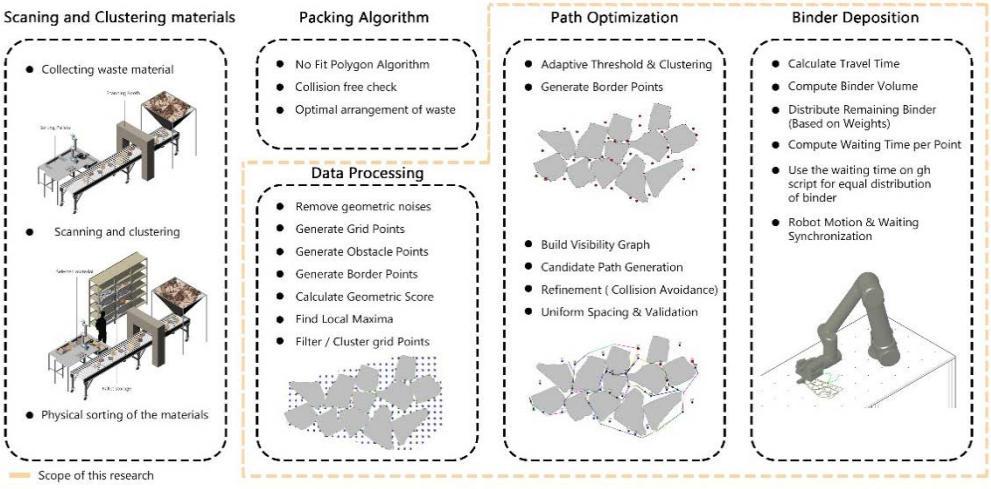



Figure 1
Overview of the workflow

In the initial workflow of this research, a system for automated classification and clustering was introduced. The top-view of the debris was taken as 2D scans, which in turn was compared against a material database compiled from open-source image APIs. A pre-trained ResNet-50 convolutional neural network was used to extract feature vectors from the scanned and the reference images in order to enable the identification of the materials by using vector similarity.

Following this classification, a 2D No-Fit Polygon (NFP) algorithm was implemented to optimize the spatial arrangement of irregular elements within an introduced frame. This parametric strategy showcases the potential of utilizing robotic arms for systematic, geometry-drivcen reuse of CDW in cladding assembly. Although the algorithm was set and ready, there was a critical limitation, which was the absence of an automated binder application process. Addressing the gap that has formed in the initial flow of the method has become the central objective of the research, which is developing a robotic system capable of continuous, geometry aware binder deposition in order to integrate CDW into cohesive and reusable cladding assemblies.

## Data processing

The workflow of the robotic deposition is initiated by loading spatial data, consisting of polygonal representations of the cladding frame and the reused brick construction demolition waste elements. Each of these objects are classified as either a “frame” or a “piece” and are parsed using a Python script. These geometries are then converted into binary spatial representations using the Shapely geometry library, where the frame defines the boundary of the working space and the pieces act as internals obstacles. The resulting geometry is then binarized and made smooth to enable grid generation and help define valid movement regions for the robot.

A structured 2D grid is generated within the frame area that has been appointed, excluding any of the cells that end up intersecting with the obstacle geometries. The resolution of the grid is defined by the user to balance spatial accuracy with computational efficiency. All the valid grid points are then stores ads potential adhesive deposition candidates.

The zones for the obstacles are sampled utilizing a denser sub-grid which captures finer geometric details and assigning penalty scores to points that are nearing or within collision. This is to ensure that the robot avoids these areas during path planning while still acknowledging their influence of the layout within the space. It is especially important to acknowledge irregular boundaries that come with the construction demolition waste.

Each valid grid point is then assigned with a scalar score reflecting on the suitability for adhesive deposition, which is essentially based on their geometric centrality. The scoring function essentially favors points that have a maximized distance from both the frame boundary and the obstacles that take place nearby. The normalized scoring metric is given by:

$$Score(p) = min\left(\frac{d_{piece}}{d_{max}}, \frac{d_{frame}}{d_{max}}\right)^2 \qquad (1)$$

Where:

- $d_{piece}$ : Distance to nearest piece
- $d_{frame}$ : Distance to frame boundary
- $d_{max}$ : Maximum distance for normalization

The algorithm then proceeds to identify a local maxima in the scoring field, which are the grid points with the highest scores defined within a configurable neighboring radius. A threshold point of 0.05 is applied to eliminate any noise from low-value elements, which ensures the consideration of mechanically relevant points. This process yields a discrete set of optimal deposition zones, that are stored with their corresponding score. These points serve as anchors for the path planning algorithm, helping guide the robotic system's adhesive trajectory with spatial precision and mechanical favoring logic.

## Path optimization

In the approach used in this research, the optimization of the path is achieved by a multi-phase algorithm designed to connect all high-score regions without going beyond spatial restrictions. The procedure starts by establishing navigation points around the geometries, also called obstacles, generating border points for these geometries, and creating "negative" points to discourage collision within the path. These elements are then integrated to a visibility graph which concludes in the derivation of multiple potential paths. At last, an initial path is constructed by the use of nearest-neighbor logic, and has been refined through local improvements, which are then verified piece by piece to ensure fitness with constraints.

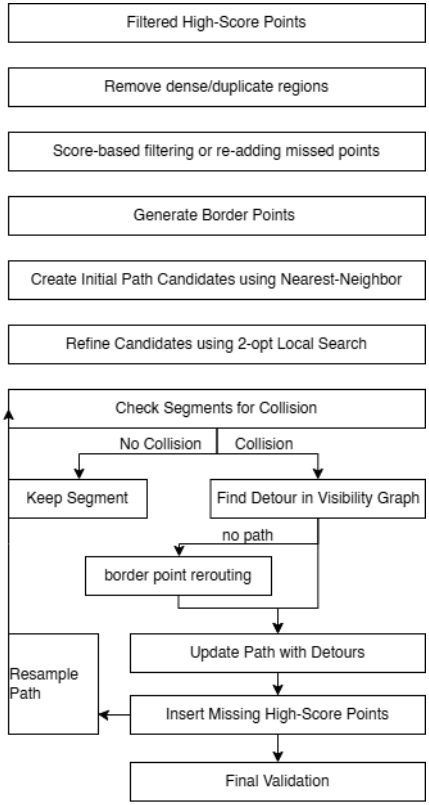
The algorithm first initiates an adaptive thresholding strategy to identify high-score points, which dynamically balances point density hat ensures sufficient workspace coverage without gaps. When the density of the points gets too excessive, a clustering technique implemented into the algorithm only keeps the highest-scoring point per cluster. If the opposite were to happen, and too few points remain instead, the previously filtered points are reincorporated into the cluster based on their score rankings.

In order to navigate around the obstacles (geometries), a perimeter-based sampling strategy generated a dense set of border points. Each of these have been placed along the geometry's boundary and offset using normal vectors that have been derived from the local tangents. This system called multi-distance offsetting, provides a flexible set of navigation

opportunities for both tight and wide maneuvers, depending on the area.

Once the high-score and border points have been implemented, they are integrated into a visibility graph that discretizes the area of navigation. Each node point stores spatial coordinates, classification of type and scores, while the edges of the geometries are looked into by a combination of Euclidean distance and score bias. Intricate geometric operations are implemented to test all of the edges for intersection or crash possibility to ensure only collision-free connections are utilized. If there is any component of the graph that seem to be disconnected, forced connections are encouraged to restore path continuity, preferably between high score nodes.

Figure 2
Path optimization flowchart

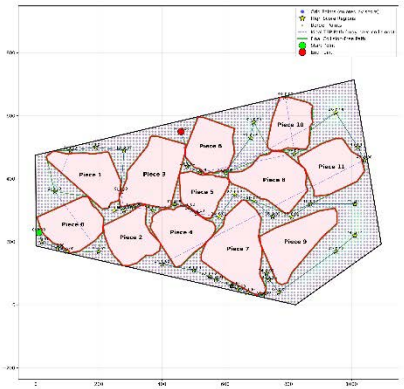



As you can see in figure 3 section A, potential solutions are generated using a nearest-neighbor heuristic, which starts from a number of high-score nodes and paths by selecting the closest point that remain unvisited. Even though obstacles are initially disregarded, this stage produces diverse starting paths. The best potential solutions are then refined using a 2-opt local optimization process, which helps reverse path segments to reduce total length systematically.

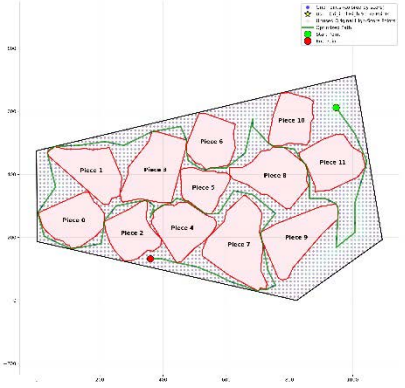
This is followed by a collision avoidance phase, which helps convert path segments to LineStrings and test them for intersections. In case of any collision, detours are generated using A* searches on the visibility graph. In the case that graph-based detours are insufficient, nearby border points of the obstacles work as waypoints to maintain efficiency in highly constrained regions.

In the final stage, there's a path enhancement phase included to address any omissions. If a high-score has been missed, the algorithm cross checks the insertion points based on minimal addition of the path length, and detours are applied as needed. This path is resampled at uniform intervals after this, which ensures a smooth trajectory and consistent distribution of points for robotic execution. A final validation makes sure the path remains collision free and frame compliant, while including all necessary spaces and maintains continuity.

The finalized path is exported as a JSON file to be used in the Grasshopper file that includes the rest of the algorithm responsible for the coordination of robotic movement and binder deposition timing. The combination of the adaptive point selection, strategic handling of the objects and graph-based routing and iterative optimization results in a practical, efficient and implementable path to be used for the robotic adhesive application in the context of reuse of construction demolition waste.




(A)




(B)

Figure 3
Path generation before and after obstacle-aware optimization of frame and pieces (obstacle).
(A) Initial nearest-neighbor path with collisions.
(B) Refined, collision-free path after 2-opt and detour correction using the visibility graph (final path)

## Robotic binder deposition

Precise synchronization between the robotic motion and the deposition of the binder is significant for the efficiency and mechanical sensitivity of the cladding elements. Given the fact that the robot has a constant pouring rate, the algorithmic system is required to compute additional waiting times at spatially critical regions that are identified by the scoring mechanism, to ensure sufficient adhesive application.

The allocation process of the binder begins with the calculation of the continuous deposition volume based on the speed of the robot and the total path length. The difference between these and the total available binder volume designates the amount that has been reserved for the targeted deposition that will take place at the high-score points.

To distribute the remaining volume in an efficient way, each of the aforementioned high-score point is assigned to a normalized weight inversely proportional to its score, which suggests that lower scores (which make up the more critical areas) receive more binder. The corresponding waiting time at each of these points is computed by using:

$$T_i = \frac{(1 - S_i)}{\sum(1 - S_i)} \cdot \frac{V_{total} - V_{travel}}{R} \qquad (2)$$

Where:

- $S_i$ : Normalized score at point i
- $V_{total}$ : Total binder volume
- $V_{travel}$ : Volume deposited during continuous motion
- R: Constant binder flow rate

This method ensures a data-driven, spatially adaptive distribution of the binder, which reduces excess material usage.

## EXPERIMENT AND RESULTS

In order to verify the robustness of the algorithm and the setup, a series of digital simulations were conducted by using diverse frame geometries and internal arrangements of materials. These configurations represent various degrees of complexity, within the scope of irregular obstacle placement and differentiating spatial densities. In all of the tested scenarios, the algorithm has successfully generated continuous, collision-free binder paths with waiting times at high-score regions that have been dynamically assigned. System was able to consistently dap to each and every single one of the setups, confirming that the

workflow is generalizable and parametric. As illustrated in the top row of Figure X, the pathfinding algorithm has performed across multiple constraints reliably.

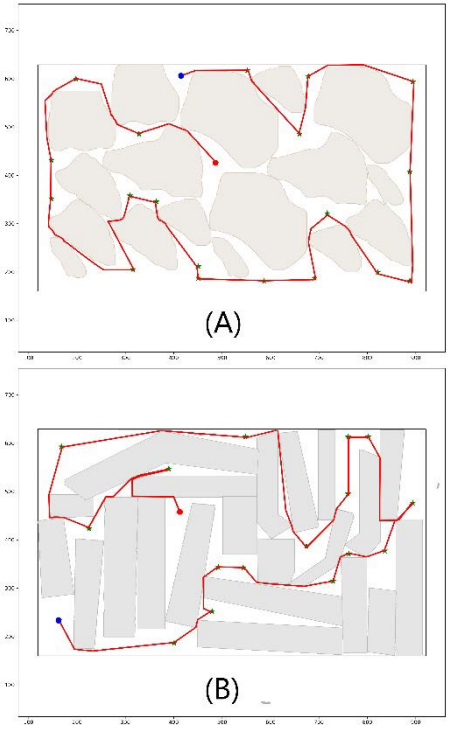



Figure 4
Example of the validation of path generation with different material arrangements. **(A)** Rounded, irregular stone geometries. **(B)** Semi-regular aluminum waste.

Figure 5
Robotic binder deposition test using irregular demolition bricks and wooden frame

After the digital validation, a set of experiments have been performed using construction demolition clay bricks arranged inside of frames built from demolition wood as physical proofs of concept. The brick elements were robotically placed based on the optimized layouts that the algorithm has concluded in. A UR5 co-bot was used to execute the deposition path of the binder. Due to irregular geometries and the porous surfaces of the CDW bricks, a low viscosity biobased epoxy was used to ensure sufficient penetration and bonding. The dispensing rate of the epoxy was controlled at a rate of 0.5 mL/s, proving efficiency for achieving uniform distribution without overaccumulation.

The UR5 arm has successfully and accurately followed the generated paths and paused at the correct high-score points to apply binder volumes proportional to the required binder. Multiple physical configurations have also been tested throughout this process, all with successful outcomes.

## DISCUSSION

The scientific method incorporates a binder allocation strategy that takes into consideration volumetric constraints, and calculates binder distribution and required robotic stop times based on movement speed, and deposition continuity of each area. This control level showcases precise synchronization between robotic movement and binder flow, which in turn enhances the mechanical reliability of the outcome while maximizing binder efficiency.

Focusing primarily on geometric and spatial parameters, this research closes a significant

scientific gap in existing robotic binder implementations, which most often lack adaptability and overlook material irregularity, especially in the context of CDW. Benchmarked in an Intel i7 laptop, the path planning algorithm was executed within 20 minutes in relation to the input complexity, using close to 500 MB RAM, which support real-time feasibility in the given context. It is still important to note that the performance of the algorithm is inherently tied to the context of use. Variations in the material behavior, structural requirements (when applicable), and binder types introduce new challenges and constraints that are beyond the scope of this study. The current research and implementation have been validated using clay bricks as a proof of concept, however further research is required to evaluate the system through a broader spectrum of materials and binders. Future work should explore context-specific performance metrics, structural validation and real-time sensory feedback implementation, as well as varied adhesives and large-scale material validation to have a more extended variety of the system's applicability to diverse and real-life construction scenarios.

## CONCLUSION

This research demonstrates a refined method for robotic binder deposition in the context of CDW, addressing a gap in automated binder application for irregular geometries. The proposed solution incorporates on applying a custom multi-phase pathfinding algorithm that optimizes binder deposition by adapting dynamically to geometry and space constraints. Through a sequence of high score point selection, perimeter-based obstacle handling, visibility path generation and iterative path refinement, the algorithm comes up with collision-free, efficient binder paths.

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