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# An Investigation into Machine Learning Matchmaking for Reused Rubble Concrete Masonry Units (RR-CMU)

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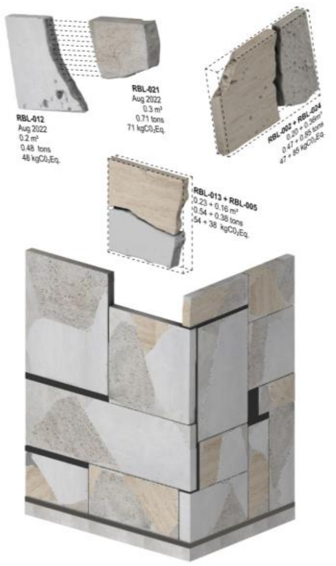


## Abstract

This paper attempts to situate concrete recycling within the contemporary economically convenient waste streams. In the case of concrete, the economically convenient waste stream is to demolish it into rubble and take it to landfill or grind it into aggregates. This research introduces a novel method using machine learning algorithms to analyze and match concrete irregular rubble surfaces, transforming them into a new assembly called “Reused Rubble Concrete Masonry Units” (RR-CMU). The process involves digitally scanning rubble, fixed length vector candidate extraction and a machine learning assisted matching process capable of searching for and aligning data-rich digital meshes. The output of this matching process is a modular structural unit produced within a factory quality control setting. Case studies demonstrate the performance of the matching process for both simulated data sets and a digitally scanned set of real-world rubble. We present results to demonstrate the quality of the matching with one-to-one matched rubble examples. This paper shows the viability of this new upcycling workflow for the construction of RR-CMU directly from a waste stream and demonstrates a ninety percent reduction in embodied carbon (kg$CO_2$eq) when compared to conventional concrete construction.

**Keywords**: Rubble, Demolition, Recycling, Circular Economy, Concrete, Embodied Carbon, Machine Learning, Computational Matching, Computational Design

## 1. Introduction

The volume of concrete manufactured globally has and does continue to increase exponentially.[1] It follows that the demolition of concrete buildings is likely to increase exponentially in the future. This paper presents tools to help the construction industry in the future usefully recover more of the material that previous generations amassed. Concrete is typically taken to landfill or ground to aggregate; however, examples of end-of-building-life concrete reuse do exist.[2] Past examples typically involve careful extraction of complete concrete units from the demolition site. This paper differs in that it attempts to situate the recycling process within the contemporary economically convenient waste streams. In the case of concrete, the economically convenient waste streams happen to be rubble.[3]

This paper explores the use of machine learning to help automate and navigate the complexity of matching complex irregular rubble surfaces. Automation of this process is necessary if rubble is to be cost competitive to other highly industrialized/standardized concrete products. This paper positions complex scanning and matching technologies as a process which could happen in a factory setting, and the output as a factory produced competitive block.

The applications anticipated include the use of RR-CMU for compression only walls or vaults. Recycling concrete into RR-CMU offers a significant reduction in the embodied carbon relative to concrete structure; particularly by reducing the need for virgin cement, as demonstrated in 4.1.1.

### 1.1. Related Work

Strategies for re-configuring rubble have received recent attention from Gramazio Kohler Research at ETH [4], The Structural Exploration Lab at EPFL [5], and the Matter Design group at MIT [6][7]. The broad idea of using machine learning strategies to assist in material reuse has been posited by Certain Measures in Cambridge MA,[8] and the Circular Engineering Lab at ETH [9]. Companies like Zenrobotics also contribute to the use of spectrometry & computer vision in the waste stream. [10]

### 1.2. Research gaps and new contributions.

Firstly, most research into concrete rubble reuse focuses on field assembly; this paper suggests that sophisticated matching and assembly could in the future occur in a factory, where an irregular rubble element can be tamed into an easy-to-use block with appropriate quality control. Secondly, this paper also introduces machine learning methods for matching one irregular rubble edge to another irregular rubble edge and evaluates this systems viability as a low carbon construction alternative.

## 2. Processing Rubble for Matching

This multistep process involves scanning rubble, computationally orienting it, simplifying it, and extracting candidate sub-surfaces for matching comparisons, then serializing those numbers into fixed length vectors which machine learning networks and matching algorithms can process and pair.

### 2.1 Scanning

Figure 1 – Scanning in process at Tinguely Recyclage SA, located in in Écublens, Vaud, Switzerland

The rubble was scanned with a Faro freestyle handheld 3d Structured Light Scanner. Circular Positional Tag Markers were used to assist in the scan registration. Concrete rubble was on timber 2”x4” studs, which allows the bottom edge of the concrete to be captured by the scanner more easily. Scanning always misses one face, which is acceptable if using flat rubble (like floor slabs), but would not work for more complex pieces of concrete rubble. This scanning set-up is sufficient to scan the exposed edges.

## 2.2 Mesh Processing

The point cloud scans are processed in Rhino using a shrink-wrap feature. A minimal bounding box is found for each mesh, and it is orientated to sit on the edge closest to the center of gravity.

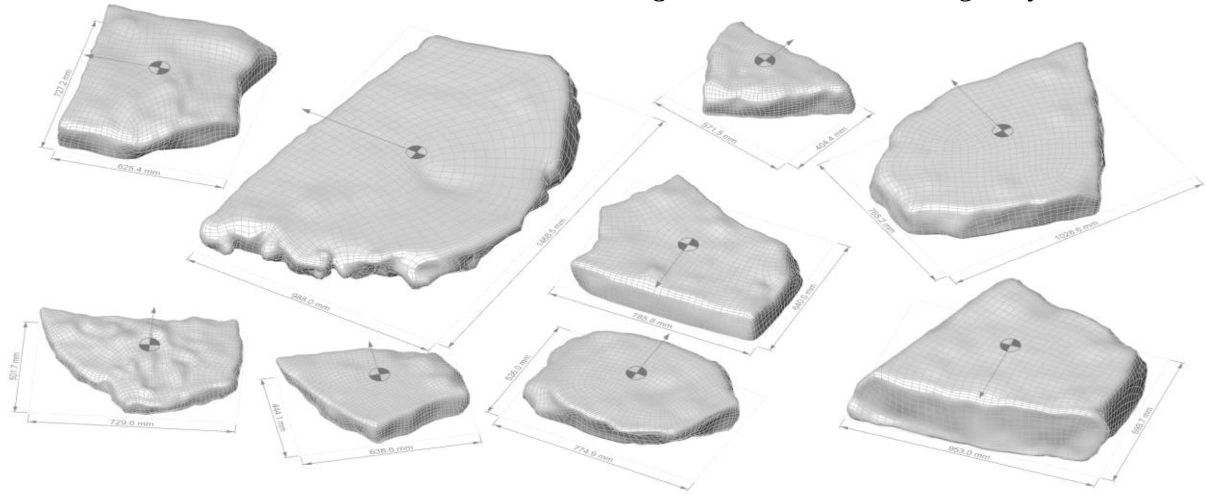

Figure 2 - Scanned Rubble meshes with minimal bounding dimensions, center of mass, and an arrow pointing to the “base”.

### *2.2.1 Sub-mesh extraction*

A complete batch of all possible rectangular sub-surface grids and are procedurally generated for each shape. These subsurface are extracted in three directions, with the “flat base” not considered for matching as these forms will form one side of the RR-CMU rectangle. The minimum size of the subsurface can be varied, such that matching only occurs on a reasonably substantial proportion of the shape and we will yield a match with at least twenty percent or more of the shape in each projection.

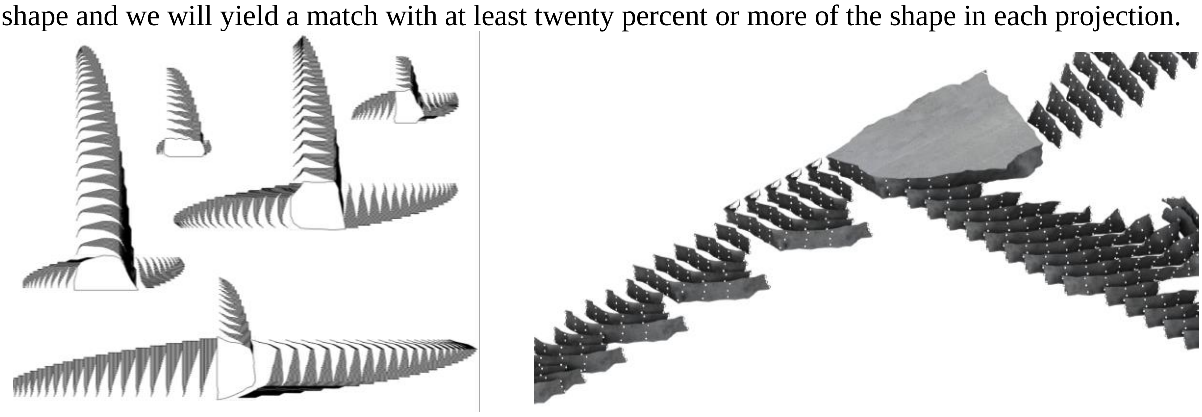

Figure 3 – Diagrams to express the sub-surface Extraction for multiple rubble elements

### *2.2.1 Fixed Length Vector Creation*

An analysis grid is created with a fixed number of points. In the case of this study the analysis grid is 255 floating point numbers. The creation of fixed length vectors allows for matching algorithms to compare the values [11]. This same analysis grid is used for the three different directions of analysis.

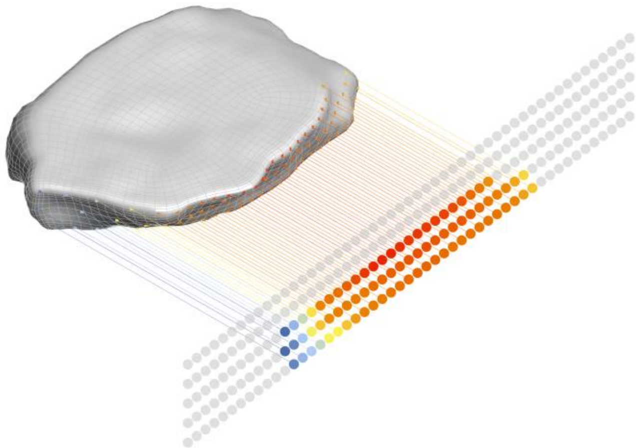

Figure 4 - Example 255 data point Extraction.

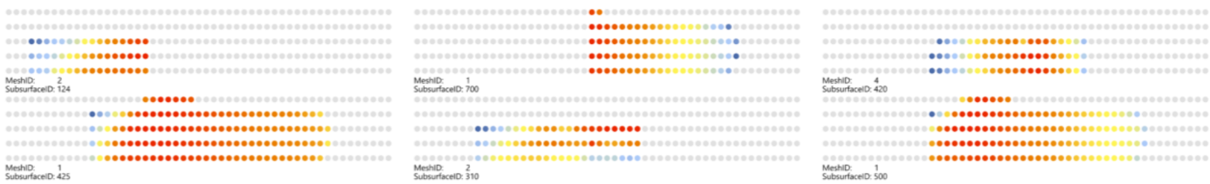


Figure 5 – Examples of the rock sub-surface extraction

*2.2.1 Orient slices around origin*

Each subsurface analysis grid is centered to make matching more comparable; all edges normalized relative to their own bounds such that the location on the mesh does not matter, only the bounds of the specific extracted sub-mesh. The analysis grid is stretched to the size of the maximum bounding box for the input geometries.

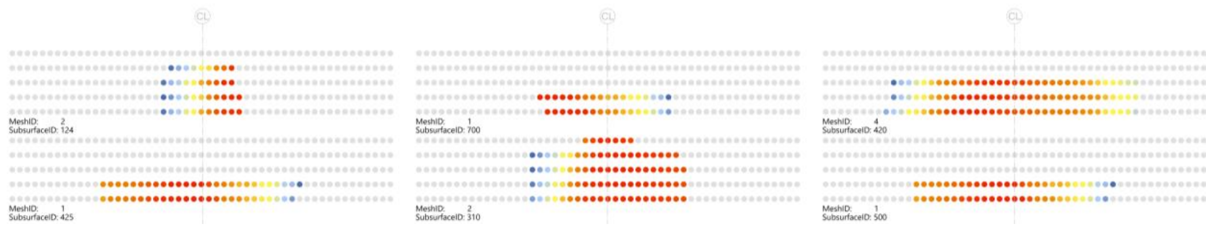


Figure 6 – Examples of the rock sub-surface data centered on the analysis grid.

## 3. Matching Rubble

### 3.1. Machine Learning Mapping for Different Rubble Edge Types

These meshes are dense and require a lot of computer time to compare against one another. Machine learning can be used to speed up this process. In this case, a classifier is trained to differentiate different types of edges. This is essentially a dimensionality reduction problem, from a very dense set of mesh into a low dimension embedding of data. This requires many pieces of training data to show the kinds of edges that could be processed. In our case we supplemented the 8 one-to-one scanned pieces of rubble with a library of 100 pieces of rubble scanned by the authors, and also downloaded from a dataset in literature (see figure 7).[12]

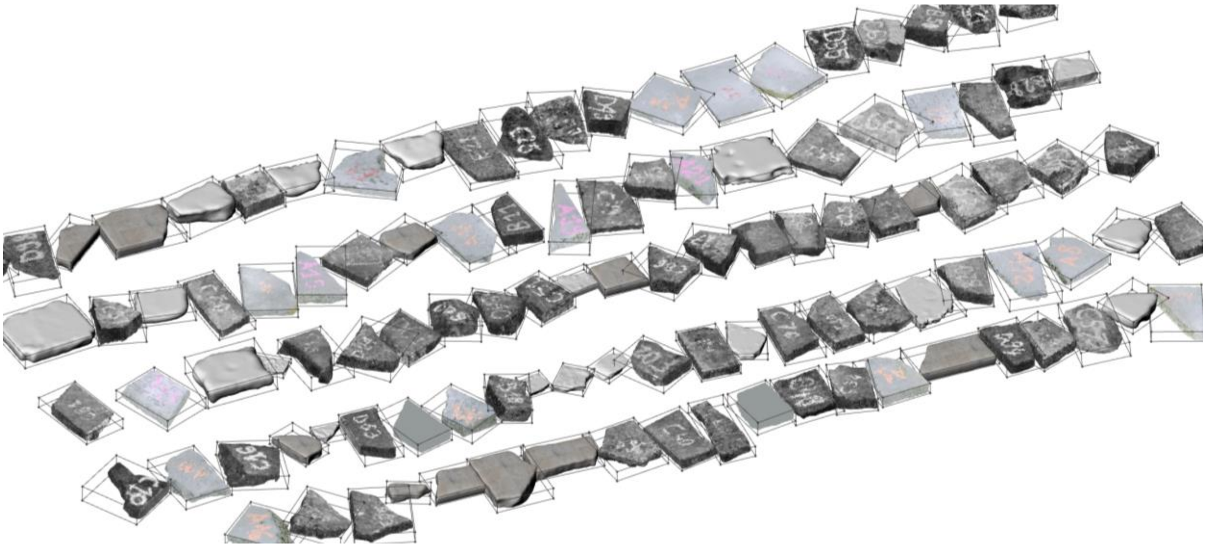

Figure 7: Training Data

### *3.1.2 Dimensionality Reduction Embedding*

The fixed length vectors described in 2.2.1 are taken for all meshes within the training data. These arrays are mapped together using either t-SNE or via a TensorFlow autoencoder.[13] Three points is a useful dimensionality reduction, as the results can be presented in a 3d-mapping (see fig. 8).

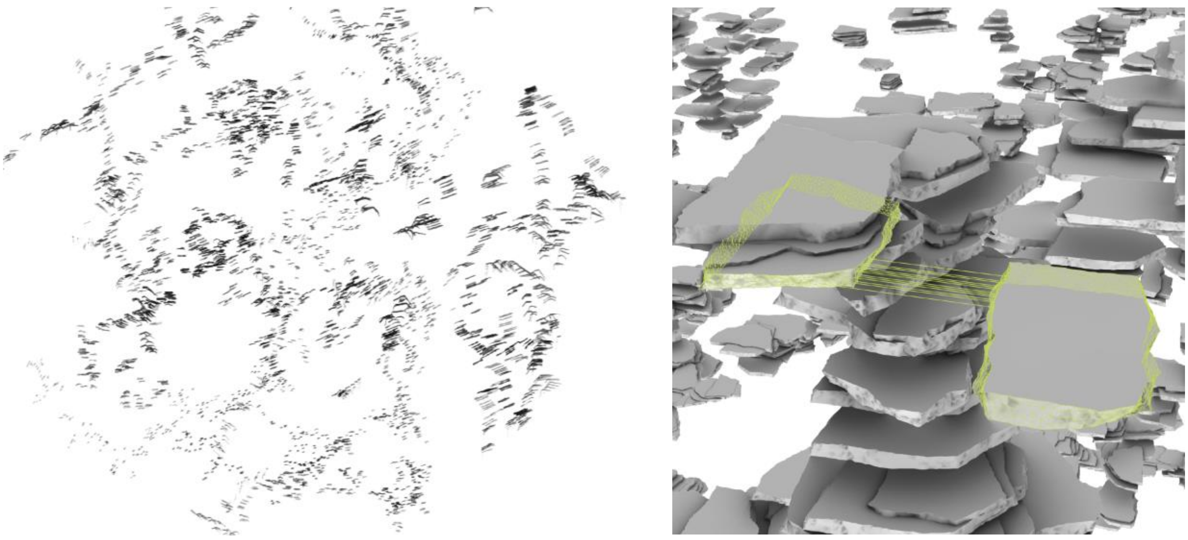

**Figure 8.** Rubble Edge Embedding Map After Training

### *3.1.3 Training a ML network to speak a "Rubble" Language*

Once the network is trained, we can then query the neural network and locate rubble elements within the embedding map. Fixed length vectors from Rhino are compiled and dispatched to TensorFlow using a remote procedure call (RPC). This RPC call is made using the COMPAS framework [14].

### *3.1.3 Finding Pairs – Surface Matches*

Input surfaces can be oriented by the neural network into the 3d embedding space. We can then survey the surfaces which are in a similar place on the map and assess which of those shapes to consider for matching. These candidate pairs receive a more onerous and direct matching, whereby direct evaluation to find the best matching 255 fixed length vectors is undertaken.

### *3.1.3 Finding Pairs – Other Optimization Parameters*

In addition to creating good edge matches, it is also important to consider other features which will allow for the creation of optimal RR-CMU units. These include the notion that we want to reduce the amount of new concrete necessary to add into the unit. We also want to consider the stability of the unit, and its capacity to resist force, however that is currently beyond the scope of this study. For this study we consider multiple options for each rubble element and compare the entity with performance features including how good the surface match is, and how little new concrete (black) is needed to be added to complete the RR-CMU.

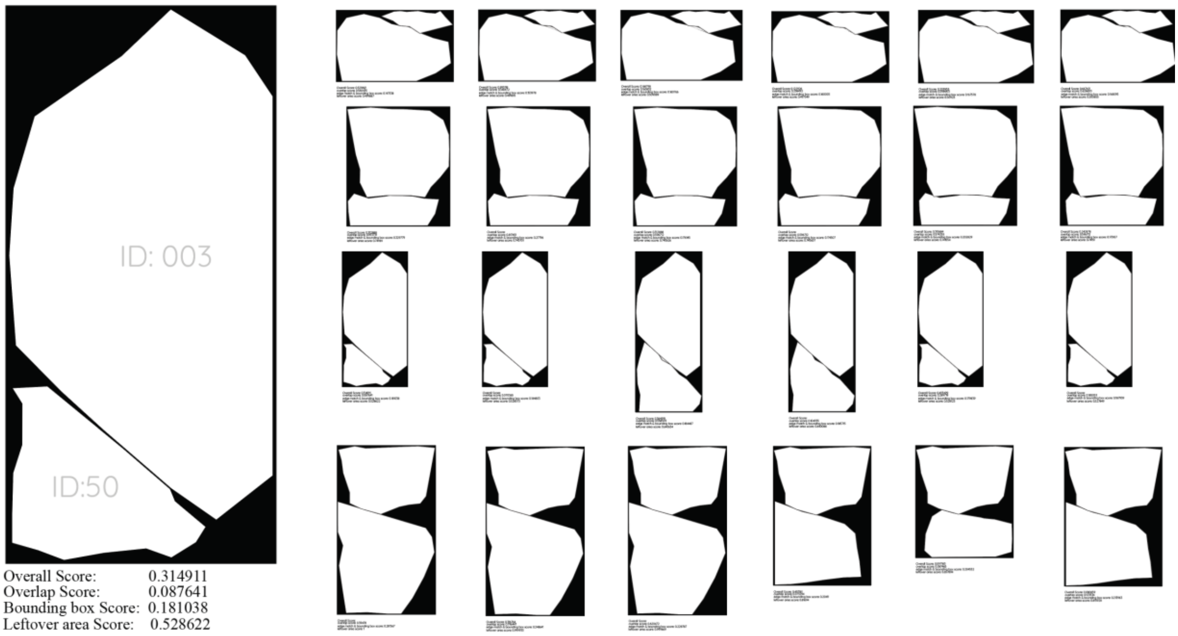


Figure 9: Example of the interface for selecting the best match between two rubble elements.

## 3.2 One-to-One Matched Rubble Example

The One-to-One matched rubble example was assembled in the field at the re-cycling facility for ease of handling. The scans shown in figure 3 were taken on a cloudy day for better scanning results, the scans were then processed in the field, before moving the matched pairs in the field the next day. Creating tools which streamline the review of possible matching options would be beneficial for reviewing options in the field. Two matched pairs were made and recorded.

Figure 10: Photos of One-to-One Matched Rubble Example. ID:07 & ID:10

Figure 11 – Photos of One-to-One Matched Rubble Example. ID:07 & ID:08)

### *3.2.1 Matching 1:1 Example - Results Evaluation*

Once the matched pairs were positioned, the two rubble units were scanned to record the quality of the match and analyze the results digitally. The same scanning process as described previously, with the Faro Freestyle 2 handheld 3D scanner with onboard registration was implemented.

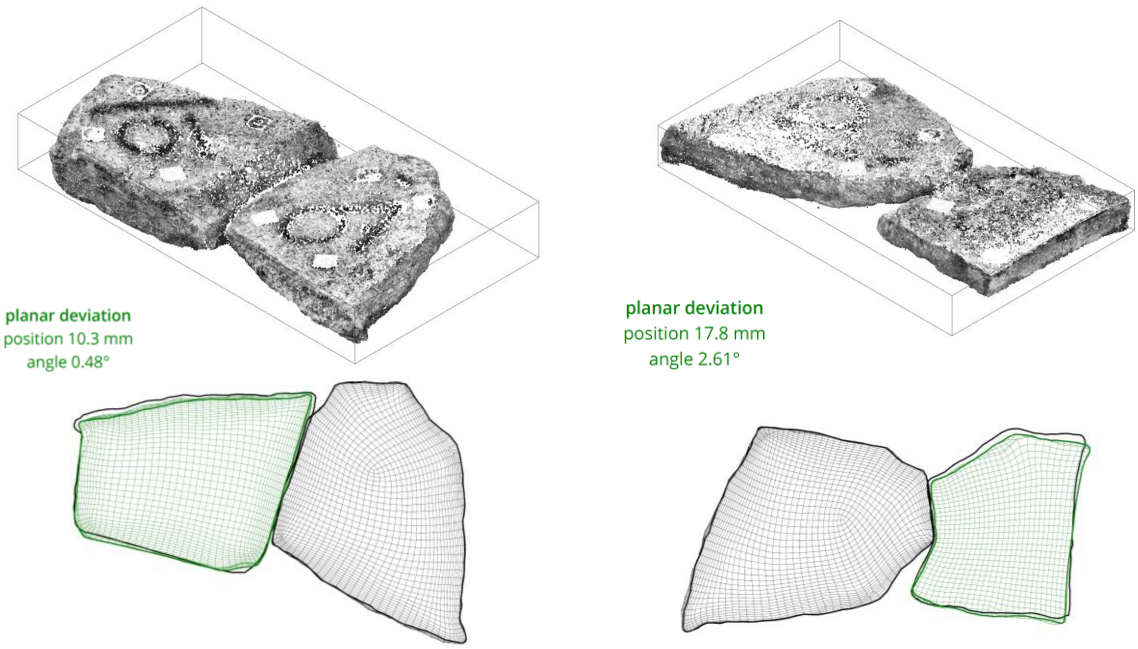


Figure 12 – Digital scans of the One-to-One matched example, set against the matching algorithm output.

The results reveal that the real world positioned units were relatively close to the location anticipated by the matching algorithm script, within 10-20mm from the intended location. Using the various scans of the rubble, it is possible to evaluate the proximity between the two units, for the two One-to-One matched examples see figure 12. This analysis shows red hotspots where the two pieces of rubble are in contact. It is encouraging that the match between 10 and 07 maintain multiple points of red proximity.

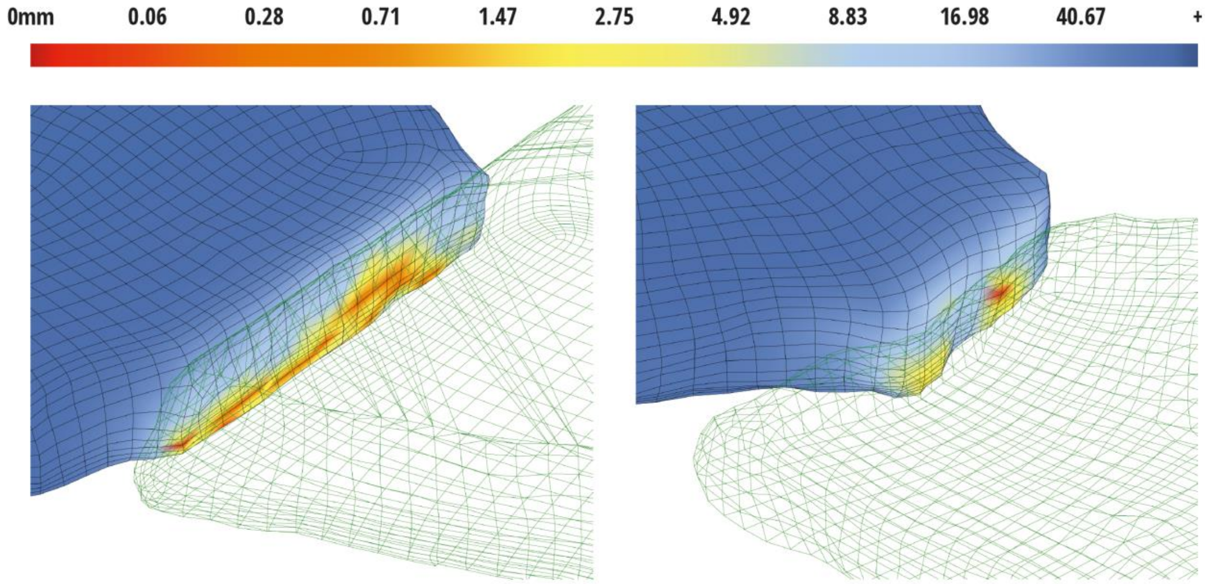


Figure 13: Proximity between the matched pairs for the two One-to-One Examples

### *3.2.2 Performance Evaluation of the One-to-One Matched Example Mockup:*

While matching the objects in a computer, it is easier to assess absolute distance from one fixed length vector set to another fixed length vector set with both overlaps, and space between the meshes. However, when matching objects in three dimensional overlaps are not possible. Part of the reason for the 20mm positional deviation is understood to have been caused by surface geometry not captured in the scan causing an early bump which then inhibited a closer match to be created. Higher resolutions and algorithms which take specific precautions in relation to overlaps will improve the quality of matches available.

Additionally, through the One-to-One mockup. It was found that breakage during the handling is a risk which could compromise the matching, and care must be taken when handling and moving these heavy objects. Digital sensing machines are based on millimeter precision, but the fine scale movements of such heavy units' do not necessarily correlate; anticipate ~20mm tolerance matching due to construction processes.

The process can take time; to arrange concrete on 2"x4" timbers in a way that allows the scanner to read the edges, to scan the concrete and process those scans into a usable mesh, to run the matching algorithm, assign, to log and track rubble in the field, to move blocks in the field. It would take further time to cast units together and to run further structural checks or vetting on the units to ensure that they are safe for use. A production line designed specifically for this rubble with heavy lift equipment would be recommended rather than the field approach as described here.

## 4. RR-CMU Wall applications

The use of reclaimed rubble as a concrete masonry unit in a wall application will subject the wall to a variety of compression and tension forces. Concrete rubble may have steel reinforcement within it allowing the unit themselves to have some tensile capacity, however locating and documenting the steel reinforcements bars within rubble concrete poses difficulties. The focus of this study is on the edge matching analysis and design. Further study should explore the possibilities of using RR-CMU for compression only vault structures.

### 4.1 Wall Application

#### *4.1.1 Wall Application Embodied Carbon*

Tables 1 and 2 compare a mock-up shingle curtainwall against an industry baseline. Note that in table one, the reclaimed concrete is assessed as having an emissions factor of zero. An RR-CMU is calculated to be 15% of the kgC02eq for an equivalent concrete wall.

**Table 1.** Reused Rubble CMU – 30m$^2$ of wall

| | A1 - Raw Materials for Façade Contractor | | | | | A2 - Transport of Raw Materials | | | A1 + A2 |
|---|---|---|---|---|---|---|---|---|---|
| MATERIAL | Volume (m3) | Density (kg/m3) | Weight (kg) | Emissions factor (kgC0$_2$eq/kg) | A1-A3 GWP (kgCO$_2$eq) | Distance to Site (km) | Truck (kgC0$_{2eq}$ /ton km) | A2 -Transit (kgC0$_2$eq) | A1-A2 GWP (kgCO$_2$eq) |
| Concrete (Reclaimed) | 1.7 | 2300 | 3910 | 0 | 0 | 100 | 0.07 | 27.4 | 27.4 |
| New Concrete | 0.15 | 2300 | 356 | 0.1 | 36.6 | 300 | 0.07 | 7.47 | 44.1 |
| Grout Infill | 0.24 | 2300 | 557 | 0.1 | 57.3 | 300 | 0.07 | 11.69 | 69.0 |
| | | | | | | | | | **140.4** |

**Table 2.** Concrete Wall – 30m$^2$ of wall

| | A1 - Raw Materials for Façade Contractor | | | | | A2 - Transport of Raw Materials | | | A1 + A2 |
|---|---|---|---|---|---|---|---|---|---|
| MATERIAL | Volume (m3) | Density (kg/m3) | Weight (kg) | Emissions factor (kgC0$_2$eq/kg) | A1-A3 GWP (kgCO$_2$eq) | Distance to Site (km) | Truck (kgC0$_{2eq}$ /ton km) | A2 -Transit (kgC0$_2$eq) | A1-A2 GWP (kgCO$_2$eq) |
| 15cm thick Concrete | 4.28 | 2300 | 9833 | 0.1 | 1,012 | 300 | 0.07 | 206.5 | 1,219 |
| OSB Formwork | 0.6 | 650 | 390 | 0.1 | 39 | 300 | 0.07 | 8.2 | 47.2 |
| Steel Rebar | 0.04 | 7750 | 299 | 2.3 | 688 | 300 | 0.07 | 6.3 | 694.6 |
| | | | | | | | | | **1,961** |

## 5. Conclusion

This paper presents a new avenue for the upcycling of concrete rubble. By scanning rubble edges, sub-selecting candidate surfaces, and matching them together into optimized rectangles. These matched assemblies can be used to create Reused Rubble Concrete Masonry Units (RR-CMU). Our findings demonstrate early feasibility and efficiency of this method, showing a process which is aligned with the material available in contemporary concrete recycling plants. If RR-CMUs were proved to have a similar compressive strength bearing capacity, they could present a significant alternative option for many different concrete applications. Future research should explore structural performance, full size mockups and delve deeper into quality assurance and quality control. By reimagining concrete rubble, this research contributes meaningfully to the circular economy within the construction industry, paving the way for low-carbon construction practices.

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