

Estimating construction waste generation in residential buildings: A fuzzy set theory approach in the Brazilian Amazon

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Abstract

The estimate of construction waste generation is the key decision-making information for policy-makers, construction managers, and the like to devise informed waste management strategies. However, estimating construction waste generated from projects is particularly onerous, as numerous factors related to design, site, and construction are largely in a fuzzy nature when the estimating job is conducted. Built upon previous studies, this paper seeks to develop a model that can be used to estimate construction waste generation based on fuzzy set theory. It follows a trilogy of methodology, including model development, sensitivity analysis, and model validation. A set of IF-THEN rules are developed based on two independent variables, built area and number of floors. A sensitive analysis was conducted to evaluate the influence of the independent variables on waste generation. The model is further calibrated and verified through a case study of 23 residential buildings constructed in the Brazilian Amazon. The model obtained an accuracy of 64.29% in the development phase and 66.67% in the validation phase, showing that the results are largely acceptable. By using this model, it is possible for a waste manager to draw up a baseline graph to indicate the volume of construction waste generation as his/her building project as it progresses. The research is also of novelty by using fuzzy set theory to deal with the fuzzy nature of waste generation in construction projects. Further studies are recommended to enhance the accuracy level of the model by engaging more factors and more quality data.

Keywords: Construction waste; Building; Waste quantification; Fuzzy set theory; Brazil.

1. Introduction

The exponential growth of construction activities and their associated waste have given rise to construction waste management (CWM) around the world. Construction and demolition (C&D) waste, using interchangeably with the term construction waste, refers to the solid waste that arises from construction activities, such as new building, site formation, renovation, or demolition (HKEPD, 2019; Roche and Hegarty, 2006). It normally forms a signification portion

34 of total solid waste. Approximately 35% of the solid waste generated in the world comes from
35 construction. It is usually disposed of in landfills or uncontrolled/inadequately maintained
36 locations. Without proper management, C&D waste will cause severe damage to the natural
37 environment and quality of life.

38
39 Estimating construction waste generation lies at the kernel of any effort to properly manage
40 construction waste (Lu et al., 2016a). Such management strategies may include developing a
41 waste management plan comprising of onsite and offsite storage, transportation, reduction, reuse,
42 and recycling, which is also known as the “3R”. Numerous studies have been previously
43 conducted to estimate and forecast construction waste generation; these studies are normally put
44 under the nomenclature name of “quantifying waste generation”. Wu et al. (2014) conducted one
45 of the most comprehensive reviews on C&D waste quantification studies. They classified the
46 studies of this stream into six types: site visit, waste generation rate (WGR), lifecycle analysis,
47 classification accumulation, variables modeling, and others. The methods could be used
48 standalone or combined in the real-life estimate. Yu et al. (2019) provided a detailed elaboration
49 of WGR and its related data collection methods such as on-site investigation, analyzing waste
50 disposal records (Kleemann et al., 2016), or material flow onsite or offsite (Cochran and
51 Townsend, 2010). Researchers (e.g., Li et al., 2013; Lu et al. 2016b; Lu et al., 2015b) have
52 reported that unit of analysis of estimating C&D waste generation could be a project, a region,
53 or a nation. The unit of analysis of this research is a project, as it has a clear system boundary
54 and its result can be used to estimate the waste generation at a regional or national level, e.g., by
55 summing up the project level estimations.

56
57 Estimating construction waste generation is particularly onerous, as projects are different from
58 each other in terms of design (e.g., modular design, or parametric design), site and surrounding
59 (e.g., excavation, land terrace), and construction (e.g., technologies, material handling, and
60 craftsmanship). All these factors, particularly after combinations, will impact construction waste
61 generation to a varying extent. There exists vagueness between the factor descriptions and their
62 causal waste generation. For example, modular design is adopted as one of the curtailing
63 strategies to reduce construction waste. However, how to measure the level of modular design is
64 quite controversial. It is even far from clear what level of modular design will lead to what level
65 of construction waste generation. Dealing with the fuzziness is particularly important in
66 developing countries where exponentially growing construction activities generate massive
67 waste while statistics about it are largely in absence. Notably, fuzzy set logic derived from fuzzy
68 set theory is particularly useful to deal with some practical issues with uncertainties and
69 vagueness. Previous studies have seen its application across fields, including the estimate of
70 waste generation. However, rather limited research has applied fuzzy set theory to estimate
71 specifically construction waste generation, which is the research gap this study intends to fill.

72
73 This paper aims at developing a model to quantify the potential construction waste generation
74 from a project by taking the fuzziness of the project and its waste generation nature into

75 consideration. It does so by mainly following a trilogy of methodology, including model
76 development, sensitivity analysis, and model validation. The model is developed from a case
77 study of a series of high-rise residential buildings in the Amazon region, Brazil, where
78 construction activities are thriving, but the estimation of waste generation is still lacking. The
79 remainder of the paper is structured as follows. Following this introductory section is a literature
80 review of two issues: waste estimation studies, and fuzzy set theory. Section 3 is a detailed
81 description of the fuzzy logic-based model. Section 4 is to elaborate on the background of the
82 case study and data sample. Section 5 is data analyses and findings, followed by a discussion in
83 Section 6, and conclusions in Section 7. This research provides useful references to estimating
84 construction waste generation by considering the fuzziness of the subject under investigation. It
85 can be used in other projects, particularly when data is sparse, to estimate waste generation and
86 devise proper construction waste management plans.

87 88 **2. Quantification of construction waste generation**

89 Wu et al. (2014) highlight the importance of quantifying construction waste generation, seeing
90 it “a prerequisite for the implementation of successful waste management”. They conducted one
91 of the most comprehensive literature reviews by focusing on 57 journal papers with a niche of
92 quantifying construction waste generation. There is no need for this paper to “reinvent the wheel”
93 to repeat such review. Rather, here it is to highlight some relevant findings and update the latest
94 references since then, with a view to providing a solid literature foundation for this study.

95
96 Wu et al. (2014) identified three primary waste generation activities: (i) new construction, (ii)
97 demolition of old facilities, and (iii) civil and infrastructure works. This echoes with the
98 definition of construction waste as the solid waste that arises from the construction activities as
99 rehearsed above. The 57 papers reviewed by them did not allow the renovation surface as a major
100 construction activity leading to waste generation. This reflects the fact that renovation waste has
101 not been well documented (Lu et al., 2016). Renovation actually generates a considerable amount
102 of waste, but such activities are often small-scale and dispersed around, making it difficult to be
103 traced and documented. As will be elaborated later, this study focuses on new buildings.

104
105 Their review also identified two “estimation levels” (i.e., units of analysis): project level and
106 regional level. The focus of this paper is at a project level. What is most relevant to the review
107 is the quantification methodology. The methods adopted in previous studies were categorized
108 into six major categories, which consist of site visit (e.g., direct or indirect measurement), WGR
109 calculation (e.g., per-capita, per-floor area), classification accumulation, lifetime analysis (e.g.,
110 lifecycle analysis, and material lifetime analysis), modelling based on multiple parameters, and
111 other particular methods. Particularly, WGR has been broadly adopted to measure the waste
112 generation, and also the effectiveness of waste management. Table 1 is a non-exhaustive list of
113 the WGR indicators adopted in previous studies. There is little uniformity in the literature in
114 relation to the indicators of either the volume or the mass of construction waste generated. For
115 example, in Table 1, the largest indicator of the volume of construction waste generated is 0.4193

m³/m², more than three times as the smallest volume of 0.118 m³/m². Lu et al. (2011) provided a comprehensive review of WGRs before using them in their empirical studies. The bright side is that construction waste is tangible and able to be measured. The indicators can be converted from one another based on some experiential formula. Whether to use one indicator or another is also dependent on the availability of data or construction quantity convention in a region (Lu et al., 2011).

Table 1 Waste generation indicators

| Author | Year | Country | Indicator |
|-------------------------|--------|----------|---|
| Dias | (2013) | Brazil | 0.128 m ³ /m ² |
| Villoria Sáez et al. | (2012) | Spain | 0.2 m ³ /m ² |
| Llatas | (2011) | Spain | 0.1388 m ³ /m ² without soil 0.4193 m ³ /m ² with soil |
| Katz and Baum | (2011) | Israel | 0.200 m ³ /m ² |
| Ortiz et al. | (2010) | Spain | 205.9 kg/m ² |
| Kofoworola and Gheewala | (2009) | Thailand | 21.38 kg/m ² |
| Kharrufa | (2007) | Iraq | 215 kg/m ² |
| Maña I Reixach et al. | (2000) | Spain | 0.118 m ³ /m ² |
| Pinto | (1999) | Brazil | 150 kg/m ² |

Previous studies have also well explored the factors that can lead to different waste generation level. From a project perspective, Wimalasena et al. (2010) established a quantification framework, which identified five generic factors to estimate construction waste generation: “(1) activity specific factors; (2) labour and equipment-related factors; (3) material and storage-related factors; (4) site condition and weather-related factors; (5) company policies”. Using big data analytics, Chen and Lu (2017) found that location, building types, and the clients of a building project have an impact on demolition waste generation to a varying extent in the Hong Kong context. Although construction waste is generated during the construction stage, it is also determined by design stage (Baldwin et al., 2009; Lu et al., 2017); With these factors, researchers have developed different models to quantify construction waste generation (See Table 2). Generally, as shown in Table 2, the most commonly adopted model to estimate construction waste generation in projects is statistical quantification factors, while statistical multiple regression and web-based construction waste estimation system are less frequently adopted.

Table 2 Models to estimate construction waste generation in projects

| Author | Country | Model |
|---------------------------|-----------|--|
| Mah et al. (2016) | Malaysia | Statistical quantification factors |
| Parise Kern et al. (2015) | Brazil | Statistical multiple regression |
| Li and Zhang (2013) | Hong Kong | Web-based construction waste estimation system |

| | | |
|--------------------------------|----------|------------------------------------|
| Villoria Sáez et al. (2012) | Spain | Statistical quantification factors |
| Katz and Baum (2011) | Israel | Statistical multiple regression |
| Llatas (2011) | Spain | Statistical quantification factors |
| Kofoworola and Gheewala (2009) | Thailand | Statistical quantification factors |
| Cochran et al. (2007) | USA | Statistical quantification factors |

A major shortcoming of previous models is that they are yet to consider the complexity of the factors, their interactions, and in particular their fuzziness. The majority of the factors mentioned above cannot be clear-cut defined and measured in construction projects. For example, in addition to the modular design as a strategy to curtail construction waste, there are many 3R factors, which cannot be simply put in classical bivalent sets. Rather, they can be straddling in different grades, i.e., they presenting fuzziness. Foundation design and construction is different from one project to another, which will lead to different waste generation. Demolition methods, such as blaster, deconstruction, or their mixture will be different and in turn, determine waste generation levels. It is not surprising that previous models yield quite divergent estimates (e.g., Lu et al., 2011).

3. Research methodology

3.1 Fuzzy set theory

Unlike the classic set theory wherein membership of an element in a set is in dichotomous terms (i.e., either 0 or 1), the fuzzy set theory allows partial membership, which means it is containing elements that have varying degrees of membership in the set; it follows a membership function valued interval $[0,1]$. The theory was introduced by Zadeh (1965) to reflect the fact that most modes of human reasoning in uncertain and imprecise environments are approximate in nature. Fuzzy set theory is a paradigm shift from traditional set theory. The theory can be applied in a wide range of domains, particularly useful under the condition where information is incomplete or imprecise. For example, in the domain of bioinformatics, Liang et al. (2006) identified disease-associated genes from microarray gene expression profiles based on the fuzzy set theory. Fuzzy logic is derived from fuzzy set theory. It is capable of handling inherently imprecise (i.e., vague, inexact, rough, or inaccurate) concepts. Both fuzzy set theory and fuzzy logic thus received widespread applications. In the scientific literature, for example, fuzzy models are used to make diffuse predictions in several areas of knowledge (Carvalho and Costa, 2017; Ghadi et al., 2016; Islam et al., 2017). Some of these possible applications in the area of geotechnics include the hybrid model using fuzzy logic and Bayesian networks to evaluate the risk, as to the quality and safety in the execution of deep tubular foundations of buildings in urban areas (Zhou et al., 2011). Fuzzy logic was also used in the evaluation of the experiments where ceramic material residues were added as material to be added to asphalt composition (Kara and Karacasu, 2017).

In construction management, fuzzy logic empowered by other tools was used to perform modeling for risk analysis, e.g., Khazaeni et al. (2012) supporting decision making in the

177 allocation of resources in contract management; Lam et al. (2007) in relation to the risk between
178 the contracting parties of construction projects. Other applications can be found in Afshar et al.
179 (2017), (Mirahadi and Zayed, 2016). In the environmental field, Huang and Hsu (2011) created
180 a model using fuzzy to evaluate the performance of environmental indicators of sustainable
181 construction. Ighravwe and Oke (2019) developed a multi-criteria method with the use of the
182 diffuse technique to evaluate the adaptation of sustainable requirements in public buildings.
183 Zarghami et al. (2018) elaborated a method to prioritize the aspects that should be used in Iranian
184 buildings with respect to sustainability requirements. Particularly, Li and Chen (2011) developed
185 a stochastic linear hybrid model to aid the estimate of municipal waste generation under
186 uncertainties. Cai et al. (2007) also used fuzzy logic to create a hybrid model to assist Municipal
187 Solid Waste (MSW) management under uncertainty. It can be summarized from the literature
188 review that fuzzy set logic, properly developed, can handle the uncertainties and vagueness of
189 waste generation from construction projects.

190
191 A classification model of the potential of waste generation was created based on diffuse logic,
192 the choice of the fuzzy methodology occurred in function of the same one to provide the creation
193 of models for the decision making in uncertain and imprecise environments, using two
194 independent variables (built area and number of floors of buildings), and the triangular and
195 trapezoidal pertinence functions were used in the modeling. Basically, the research methodology
196 can be known as trilogy, from fuzzy model development stage where some simple fuzzy logic
197 can be derived from experienced practitioners, then the sensitivity analysis stage to identify the
198 two independent variables, the built area and number of floors, whichever is more sensitive to
199 the waste generation, to the final model validation stage where the percentage of assertiveness
200 of the model can be verified with another batch of data independent from the data used in the
201 model development stage. The detailed description for each stage of the methodology is
202 elaborated separately as follows.

203 204 **3.2 Fuzzy modelling**

205 With the elaboration of this method in the modeling, the number of rules used was 25. Therefore,
206 the IF-THEN rules that were developed in this study were generated from the combination of
207 the two functions of relevance for each of the variables. IF-THEN rules are normally used to
208 formulate the conditional statements comprising fuzzy logic. For this, 18 construction engineers
209 were interviewed by means of a questionnaire, aiming to know the opinions of specialists to
210 elaborate the fuzzy rules, the mode values of the interviews were used to define the functions of
211 pertinence, as shown in the following Table 3. Here, in Table 3, two conditional statements,
212 which are number of floors and built area are required to elicit the result, construction waste
213 generation. For example, if number of floors is high while built area is low, then the estimate of
214 construction waste generation is medium.

215
216 **Table 3** List of “IF-THEN” rules for estimating waste (m^3) based on area and number of floors

| Area | Number of floors | | | | |
|-----------|------------------|-----|--------|------|-----------|
| | Very low | Low | Medium | High | Very high |
| Very low | VL | VL | L | M | H |
| Low | VL | VL | L | M | H |
| Medium | L | L | M | H | VH |
| High | L | L | M | H | VH |
| Very high | L | M | H | VH | VH |

Note: VL= very low, L= low, M= medium, H= high, and VH= very high

In order to perform the modeling, the following fuzzy characteristics were used: Let X be the universe of discourse of the linguistic variable Z_i : $i = 1;2;\dots; n$ ($n \leq T$) and $\phi(Z_i)$ a fuzzy number represented by using a triangular and trapezoidal fuzzy set A_j ($j = 1;2;\dots;m$) associated with Z_i . Then, $\phi(Z_i): X \rightarrow [0;1]$ and A_j will be considered a triangular and trapezoidal fuzzy set if it is defined on an interval $x_j \subset X$ ($j = 1;2;\dots;m$) according to the function with respect to the following:

-Triangular fuzzy set

$$\mu A(x) \begin{cases} 0, \text{ if } Z_i \leq a_j \\ (Z_i - a_j) / (b_j - a_j), \text{ if } Z_i \in] a_j, b_j [\\ (c_j - Z_i) / (c_j - b_j), \text{ if } Z_i \in [b_j, c_j [\\ 0, \text{ se } Z_i \geq c_j \end{cases}$$

and

- Trapezoidal fuzzy set

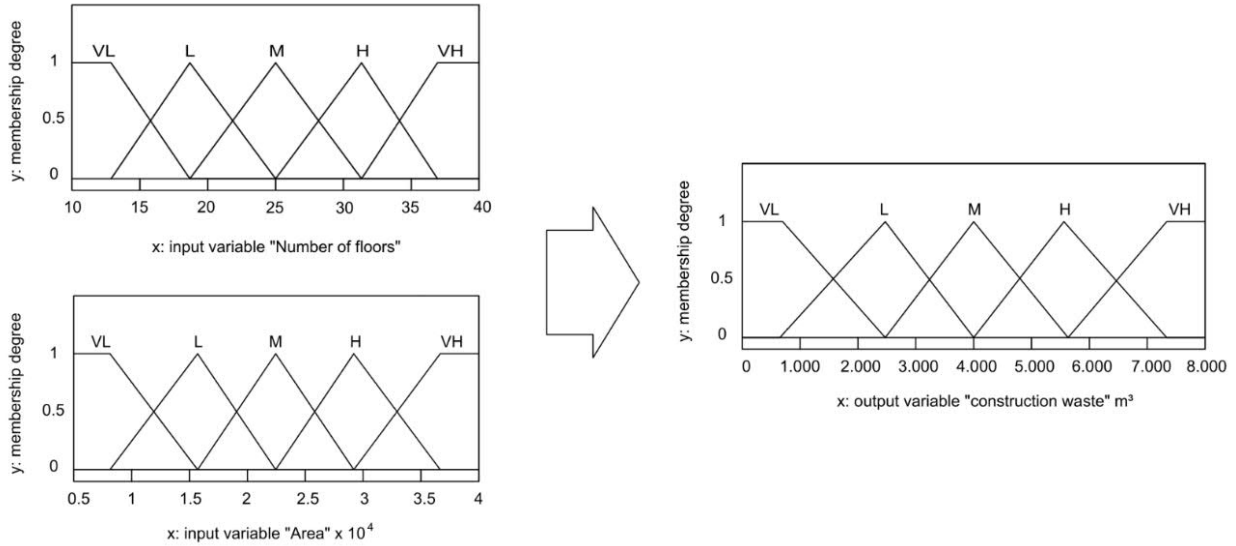
$$\mu A(x) \begin{cases} 0, \text{ if } Z_i \leq d_j \\ (Z_i - d_j) / (e_j - d_j), \text{ if } Z_i \in] d_j, e_j [\\ 1, \text{ if } Z_i \in [e_j, f_j] \\ (g_j - Z_i) / (g_j - f_j), \text{ if } Z_i \in [f_j, g_j [\\ 0, \text{ if } Z_i \geq g_j \end{cases}$$

where a_j , c_j , and b_j are scalar parameters that show the position of the vertices and the midpoint of an isosceles triangle, respectively; d_j and g_j are the scalar parameters that indicate the position of the vertices of the bottom end of a trapezoid; e_j and f_j are the vertices of the upper base of the ends of a trapezoid; and u_j is the support of the triangular fuzzy sets m associated with Z_i .

The application of the mathematical concepts of fuzzy logic to the construction of the model was, therefore, used from the two functions described above because the combination of the two types of pertinence function allowed the model to have good precision, as opposed to the use of only one type of function, which resulted in low assertiveness. The applied model is represented in Fig. 1. For example, when a building has a fuzzy number of floors at 80% “Low” and 20%

251 “Medium” and a fuzzy area at 40% “Low” and 60% “Medium,” the chance of “Very Low” waste
 252 in the model will be 32% according to Table 3; while the chances of “Low” and “Medium”
 253 wastes will be 56% and 12%, respectively. The task of the fuzzy model calibration in this paper
 254 is thus to find the optimal parameters to maximize the predictions made by the model shown in
 255 Table 3 and Fig. 1.

256



257

258 **Fig. 1.** Input and output of the fuzzy subset

259 Note: VL= very low, L= low, M= medium, H= high, and VH= very high

260

261 **3.3 Developing a fuzzy classifier:** A classification of the constructions was carried out from the
 262 perspective of the potential volume of residues to be generated during the works. A fuzzy
 263 classifier was created based on the volume of waste generated. As shown in Table 4, this
 264 classification occurs through the results of the inference from the model described in the previous
 265 step.

266

267 **Table 4** The fuzzy set classifier in relation to waste generation potentials

| Classification regarding the potential to produce waste | Very low (class 1) | Low (class 2) | Medium (class 3) | High (class 4) | Very high (class 5) |
|--|--------------------|---------------|------------------|----------------|---------------------|
| Classification intervals regarding the volume of waste to be generated | [0, 1800] | (1800, 3800] | (3800, 5800] | (5800, 7300] | (7300, +∞) |

268

269 This classification becomes an important indicator in the phase of identification of the
 270 construction waste volume. Therefore, a classification with five classes was created (see Table
 271 4). Each class created has an interval regarding the volume of waste to be generated from the
 272 lowest [0, 1800] to the highest (7300, +∞) and also a descriptive classification regarding the

273 potential to produce waste from the lowest ‘Very low (class 1)’ to the highest ‘Very high (class
274 5)’.

275
276 **3.4 Sensitivity analysis:** In this stage, a sensitivity study of the results generated through the
277 proposed model was conducted to evaluate the influence of the independent variables (built area
278 and number of floors of the building) in the generation of waste. For this, the values of built-up
279 areas were stated in the fuzzy model, starting at 8,000 m² on a growing scale every 2,000 m², up
280 to the limit of 40,000 m², leaving another fixed independent variable (number of floors) constant.
281 For each value released, the value inferred by the fuzzy system regarding the volume of waste
282 generated was recorded. Afterward, the same procedure was performed by inverting the
283 independent variables, varying the number of floors (starting with 14 going up to 36 type
284 pavements) and leaving the variable built area fixed. In this way, a graph can be constructed to
285 obtain the potential volume of waste to be generated as a function of the two independent
286 variables.

287
288 **3.5 Model verification:** After performing fuzzy inference using the proposed model, a
289 comparison of the obtained results was performed, through the classifier of the potential of waste
290 generation of the work, aiming at verifying the percentage of assertiveness of the model in
291 relation to the data collected in the works. This assertiveness was performed by means of the
292 percentage of correct classifications found among the five classes defined in item “d”. After the
293 validation of the model, the classification (among the five classes, see item “d”) in terms of the
294 number of works that fit each classification in relation to the potential of waste generation
295 volume was performed.

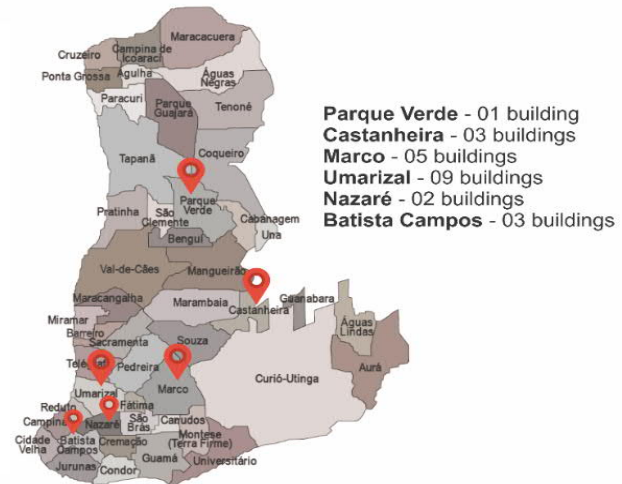
296 297 **4. Case description**

298 The case area in this study is located in the city of Belém, the Brazilian Amazon (see Fig. 2).
299 Data were collected from 23 residential buildings that have completed their works between the
300 years 2016 and 2018 (see Fig. 3). All these projects located in the center of the city. It is important
301 to note that construction companies in Brazil do not have a tradition of collecting and
302 disseminating indices, whether they are performance, consumption, productivity and mainly
303 about the generation of waste in their works. This makes it difficult to access information and
304 conduct research. The information used in this work was obtained after a large number of
305 dialogue with the companies, so that they would allow access to their construction sites and
306 allowing to collect the data used in this research; a fact that highlights the importance of this
307 information.

Brazil



Districts of Belém



312

313

Fig. 2. Location of the research targeted buildings

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Fig. 3. A glance of some of the construction projects participated in this research

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The construction projects in this samples have the following characteristics: deeply excavated substructures, reinforced-concrete superstructures using cast in-situ technology, and ceramic blocks with interior and exterior vertical envelopment systems. The exterior walls and floors are made of concrete, and with sand mortar and ceramic tiles as the finishing. The interior floors are fitted with ceramic or porcelain tiles. Kitchens and bathrooms are fitted with wall ceramic tiles. This construction system is widespread in the region for vertical constructions (Maués et al., 2017). In this way, knowing that all the research works have the same characteristics and constructive methods, it was possible to make a comparison according to the homogeneity of the samples.

Data collection was carried out by a master's degree student in civil engineering under the supervision of a professor at Universidade Federal do Pará. Monthly visits were conducted at all working sites where information on the volume of waste generated in the month was collected. This information came from the records of the number of containers that were used by the company responsible for transport and disposal, as this service was performed by outsourced

333 companies. The quantification of the residues was conducted based on the construction waste
 334 routinely removed from the construction site in special containers by a specialized company. The
 335 brief information of the 23 sample buildings is listed in Table 5 where each labelled building has
 336 three characteristics, including total construction area, number of floors and respective generated
 337 construction waste by volume. Of the 23 construction sites in the sample, 14 projects (B1-B14)
 338 were randomly selected to train the fuzzy logic model, and the other 9 projects (B15-B23) were
 339 used to validate the model.

340

341 **Table 5** Brief information of the 23 sample projects

| | Buildings | Total constructed area | Number of floors | Construction Wast (m³) |
|--------------------|------------------|-------------------------------|-------------------------|--|
| Model Construction | B1 | 20.542,02 | 35 | 1.588,22 |
| | B2 | 8.375,49 | 25 | 4.092,00 |
| | B3 | 12.347,91 | 26 | 1.925,00 |
| | B4 | 18.877,59 | 14 | 5.320,00 |
| | B5 | 40.691,34 | 35 | 12.375,00 |
| | B6 | 30.718,78 | 35 | 11.450,00 |
| | B7 | 18.079,21 | 30 | 6.020,00 |
| | B8 | 15.303,61 | 32 | 4.145,00 |
| | B9 | 15.023,38 | 28 | 3.305,00 |
| | B10 | 22.667,32 | 26 | 3.520,00 |
| | B11 | 8.605,74 | 33 | 2.880,00 |
| | B12 | 10.919,69 | 35 | 2.635,00 |
| | B13 | 14.790,55 | 28 | 3.279,00 |
| | B14 | 16.732,00 | 26 | 2.045,00 |
| Model Validation | B15 | 14.831,00 | 29 | 5.360,00 |
| | B16 | 42.000,00 | 12 | 4.660,00 |
| | B17 | 25.320,00 | 14 | 4.510,00 |
| | B18 | 9.870,39 | 21 | 2.130,00 |
| | B19 | 10.919,69 | 34 | 3.140,00 |
| | B20 | 9.858,00 | 28 | 3.355,00 |
| | B21 | 12.840,50 | 25 | 3.435,00 |
| | B22 | 28.297,96 | 29 | 4.780,00 |
| | B23 | 41.559,52 | 17 | 5.030,00 |

342

| | Buildings | Total constructed area | Number of floors | Construction Wast (m³) |
|--------------------|------------------|-------------------------------|-------------------------|--|
| Model Construction | B1 | 20.542,02 | 35 | 1.588,22 |
| | B2 | 8.375,49 | 25 | 4.092,00 |
| | B3 | 12.347,91 | 26 | 1.925,00 |
| | B4 | 18.877,59 | 14 | 5.320,00 |
| | B5 | 40.691,34 | 35 | 12.375,00 |

| | | | | |
|------------------|-----|-----------|----|-----------|
| | B6 | 30.718,78 | 35 | 11.450,00 |
| | B7 | 18.079,21 | 30 | 6.020,00 |
| | B8 | 15.303,61 | 32 | 4.145,00 |
| | B9 | 15.023,38 | 28 | 3.305,00 |
| | B10 | 22.667,32 | 26 | 3.520,00 |
| | B11 | 8.605,74 | 33 | 2.880,00 |
| | B12 | 10.919,69 | 35 | 2.635,00 |
| | B13 | 14.790,55 | 28 | 3.279,00 |
| | B14 | 16.732,00 | 26 | 2.045,00 |
| Model Validation | B15 | 14.831,00 | 29 | 5.360,00 |
| | B16 | 42.000,00 | 12 | 4.660,00 |
| | B17 | 25.320,00 | 14 | 4.510,00 |
| | B18 | 9.870,39 | 21 | 2.130,00 |
| | B19 | 10.919,69 | 34 | 3.140,00 |
| | B20 | 9.858,00 | 28 | 3.355,00 |
| | B21 | 12.840,50 | 25 | 3.435,00 |
| | B22 | 28.297,96 | 29 | 4.780,00 |
| | B23 | 41.559,52 | 17 | 5.030,00 |

5. Results and findings

The general structure of the model developed is a fuzzy logic-based decision-making model with Mamdani inference (see Table 6). The accuracy of the model developed is dependent on whether the actual volume of waste generated (left half of Table 6) and the predicted volume of waste with the model (right half of Table 6) fall within the same classification interval. During the construction of the fuzzy model, 9 of the 14 sample values were correctly classified in relation to the volumes of waste generated during the construction of the projects. This represents an accuracy of 64.29%, and a 27.20% MAPE (mean abs percentage error) for waste volume (m3) prediction. Of these, four works are small waste generators (28.57%), three (21.42%) are medium waste generators, and two (14.28%) are very high waste generators.

After analyzing the result generated by the model, the margin of accuracy was considered acceptable and therefore met its expectations. A validation phase was then performed with the purpose of validating the model, this time with the other nine works of the initial sample that were not used in the construction of the model (being chosen randomly among the 23 works of the sample) (See Table 7). As shown in Table 7, there are totally 6 buildings (B16, B19, B20, B21, B22, and B23) of which their actual waste generated and predicted waste fall in the same classification interval, which indicates a 66.67% accuracy in the second modelling. Among these, two works (60.86%) were classified with a small risk and seven (30.43%) with a medium risk in the generation of residues. In terms of construction waste volume (m3) prediction, the MAPE was 33.62%; in comparison, the linear regression ($\text{Waste} = -1,595.309 + 0.312 * \text{area} + 19.086 * \text{No. of floors}$) returned an MAPE at 86.25%. The performance of positive classifications in the modelling (among the 23 works of the sample in the target region of the research) shows that there is a tendency of the works to present a potential in the generation of residues such as

367 small (34.78%), medium (21.74%) and very large (08.69%); the other 34.78% of the samples
368 were not correctly classified by the model.

Table 6 The fuzzy classifier of construction waste generation – Model development

| Fuzzy Classifier Risk - Construction waste | | | | | | | | | | | | | | |
|--|--------------------------------------|-----------|--------------|--------------|--------------|------------|------------|--------------------------------------|-----------|--------------|--------------|--------------|------------|----------------|
| Buildings | Construction Waste (m ³) | very low | low | medium | high | very high | Wast Class | Fuzzy Modeling | very low | low | medium | high | very high | Fuzzy Modeling |
| | | [0, 1800] | (1800, 3800] | (3800, 5800] | (5800, 7300] | (7300, +∞) | | Construction Waste (m ³) | [0, 1800] | (1800, 3800] | (3800, 5800] | (5800, 7300] | (7300, +∞) | Wast Class |
| B1 | 1588 | 1 | | | | | 1 | 2080 | | 1 | | | | 2 |
| B2 | 4092 | | | 1 | | | 3 | 2400 | | 1 | | | | 2 |
| B3 | 1925 | | 1 | | | | 2 | 3260 | | 1 | | | | 2 |
| B4 | 5320 | | | 1 | | | 3 | 4780 | | | 1 | | | 3 |
| B5 | 12375 | | | | | 1 | 5 | 7010 | | | | | 1 | 5 |
| B6 | 11450 | | | | | 1 | 5 | 7110 | | | | | 1 | 5 |
| B7 | 6020 | | | | 1 | | 4 | 2260 | | 1 | | | | 2 |
| B8 | 4145 | | | 1 | | | 3 | 3940 | | | 1 | | | 3 |
| B9 | 3305 | | 1 | | | | 2 | 3850 | | | 1 | | | 3 |
| B10 | 3520 | | 1 | | | | 2 | 4370 | | | 1 | | | 3 |
| B11 | 2880 | | 1 | | | | 2 | 2430 | | 1 | | | | 2 |
| B12 | 2635 | | 1 | | | | 2 | 3000 | | 1 | | | | 2 |
| B13 | 3279 | | 1 | | | | 2 | 3780 | | 1 | | | | 2 |
| B14 | 2045 | | 1 | | | | 2 | 3780 | | 1 | | | | 2 |

| Fuzzy Classifier Risk - Construction waste | | | | | | | | | | | | | | |
|--|--------------------------------------|-----------|--------------|--------------|--------------|------------|------------|--------------------------------------|-----------|--------------|--------------|--------------|------------|----------------|
| Buildings | Construction Waste (m ³) | very low | low | medium | high | very high | Wast Class | Fuzzy Modeling | very low | low | medium | high | very high | Fuzzy Modeling |
| | | [0, 1800] | (1800, 3800] | (3800, 5800] | (5800, 7300] | (7300, +∞) | | Construction Waste (m ³) | [0, 1800] | (1800, 3800] | (3800, 5800] | (5800, 7300] | (7300, +∞) | Wast Class |
| B1 | 1588 | 1 | | | | | 1 | 2080 | | 1 | | | | 2 |
| B2 | 4092 | | | 1 | | | 3 | 2400 | | 1 | | | | 2 |
| B3 | 1925 | | 1 | | | | 2 | 3260 | | 1 | | | | 2 |
| B4 | 5320 | | | 1 | | | 3 | 4780 | | | 1 | | | 3 |
| B5 | 12375 | | | | | 1 | 5 | 7010 | | | | | 1 | 5 |

| | | | | | | | | | | | | |
|-----|-------|---|---|--|---|---|------|--|---|---|---|---|
| B6 | 11450 | | | | 1 | 5 | 7110 | | | | 1 | 5 |
| B7 | 6020 | | | | 1 | 4 | 2260 | | 1 | | | 2 |
| B8 | 4145 | | 1 | | | 3 | 3940 | | | 1 | | 3 |
| B9 | 3305 | 1 | | | | 2 | 3850 | | | 1 | | 3 |
| B10 | 3520 | 1 | | | | 2 | 4370 | | | 1 | | 3 |
| B11 | 2880 | 1 | | | | 2 | 2430 | | 1 | | | 2 |
| B12 | 2635 | 1 | | | | 2 | 3000 | | 1 | | | 2 |
| B13 | 3279 | 1 | | | | 2 | 3780 | | 1 | | | 2 |
| B14 | 2045 | 1 | | | | 2 | 3780 | | 1 | | | 2 |

Table 7 The fuzzy classifier of construction waste generation - Model validation

| Fuzzy Classifier Risk - Construction waste -Model Validation | | | | | | | | | | | | | | |
|--|-------------------------------------|-----------|--------------|--------------|--------------|------------|------------|---|--------------|--------------|--------------|------------|-----------|---------------------------|
| Buildings | Construction Wast (m ³) | very low | low | medium | high | very high | Wast Class | Fuzzy Modeling Construction Waste (m ³) | very low | low | medium | high | very high | Fuzzy Modeling Wast Class |
| | | [0, 1800] | (1800, 3800] | (3800, 5800] | (5800, 7300] | (7300, +∞) | | [0, 1800] | (1800, 3800] | (3800, 5800] | (5800, 7300] | (7300, +∞) | | |
| B15 | 5360 | | | 1 | | | 3 | 2400 | | 1 | | | | 2 |
| B16 | 4660 | | | 1 | | | 3 | 5600 | | | 1 | | | 3 |
| B17 | 4510 | | | 1 | | | 3 | 3070 | | 1 | | | | 2 |
| B18 | 2130 | | 1 | | | | 2 | 1530 | 1 | | | | | 1 |
| B19 | 3140 | | 1 | | | | 2 | 2200 | | 1 | | | | 2 |

| | | | | | | | | | |
|-----|------|---|---|--|---|------|---|---|---|
| B20 | 3355 | 1 | | | 2 | 2400 | 1 | | 2 |
| B21 | 3435 | 1 | | | 2 | 2400 | 1 | | 2 |
| B22 | 4780 | | 1 | | 3 | 5230 | | 1 | 3 |
| B23 | 5030 | | 1 | | 3 | 5600 | | 1 | 3 |

| Fuzzy Classifier Risk - Construction waste -Model Validation | | | | | | | | | | | | | | |
|--|--|-----------|-----------------|-----------------|-----------------|------------|---------------|--|-----------------|-----------------|-----------------|---------------|-----------|------------------------------------|
| Buildings | Construction Wast (m ³) | very low | low | medium | high | very high | Wast Class | Fuzzy Modeling Construction Waste (m ³) | very low | low | medium | high | very high | Fuzzy Modeling Wast Class |
| | | [0, 1800] | (1800, 3800] | (3800, 5800] | (5800, 7300] | (7300, +∞) | | [0, 1800] | (1800, 3800] | (3800, 5800] | (5800, 7300] | (7300, +∞) | | |
| B15 | 5360 | | | 1 | | | 3 | 2400 | | 1 | | | | 2 |
| B16 | 4660 | | | 1 | | | 3 | 5600 | | | 1 | | | 3 |
| B17 | 4510 | | | 1 | | | 3 | 3070 | | 1 | | | | 2 |
| B18 | 2130 | | 1 | | | | 2 | 1530 | 1 | | | | | 1 |
| B19 | 3140 | | 1 | | | | 2 | 2200 | | 1 | | | | 2 |
| B20 | 3355 | | 1 | | | | 2 | 2400 | | 1 | | | | 2 |
| B21 | 3435 | | 1 | | | | 2 | 2400 | | 1 | | | | 2 |
| B22 | 4780 | | | 1 | | | 3 | 5230 | | | 1 | | | 3 |
| B23 | 5030 | | | 1 | | | 3 | 5600 | | | 1 | | | 3 |

Based on the results obtained, a sensitivity analysis was performed to test the reliability of the model. This analysis was carried out based on the variation of the independent variables (area and floors), by generating a graph that easily allows the prediction of the possible volume of construction waste to be generated in future construction projects in the target city. Results in Fig. 4 show that the volume of construction waste is strongly related to the construction area of the building, representing the growth of waste generation in a more significant way, as there was a 248% increase in waste between the range of 8,000 m² and 40,000 m². The increase in relation to the higher number of floors, for the interval between 14 and 36 floors, was 66.67%.

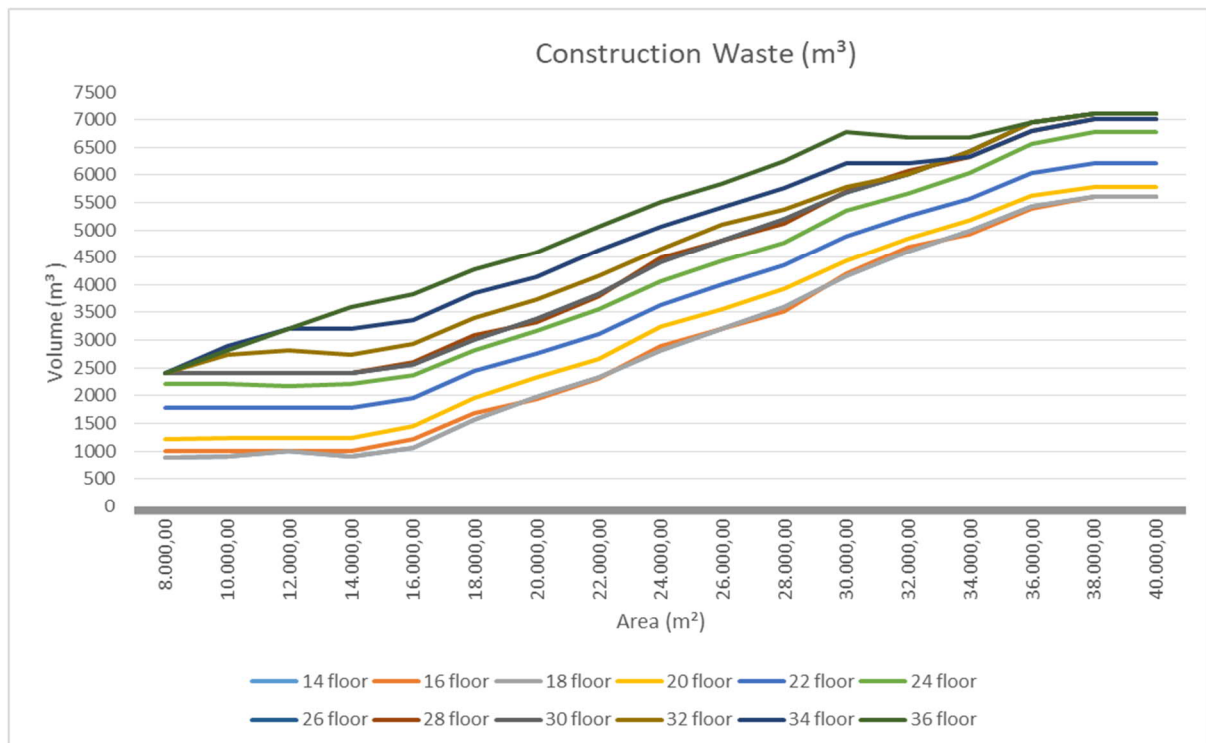


Fig. 4. A sensitivity analysis of potential waste generation volume in new construction

This result also shows no variation in the increase of construction waste between buildings that have between 14 and 18 floors, as compared to those between 26 and 30 floors. This analysis and the plotting of the graph allow managers to easily estimate the construction waste generated in new construction simply by defining the area and number of floors of the residential building. Thus, the information will be available without the need to use the model created through fuzzy logic. This could restrict its applicability.

With this study, it was still possible to identify the average construction waste volume generated by the 23 works surveyed, being 0.21 m³/m² of construction floor area, which serves as the initial indicator for works in the region, given that there is no reference value in it. This value is very close to that found by Villoria Sáez et al. of 0.20 m³/m² (2012) in Spain and much higher than those found by Kern et al. (2015) in a city in the southern region of Brazil, which was 0.128 m³/m², and by Maña I Reixach et al. (2000), 0.118 m³/m², also in Spain, thus demonstrating that

there is still considerable potential for action to be taken to reduce the impact of waste from building construction.

6. Discussion

Estimating construction waste generation can provide critical decision-making information for the many efforts to manage waste in construction projects. Researchers have developed a popular measurement of WGR, e.g., volume (m³) or quantity (tons) of waste generated per m² of Gross Floor Area (GFA) (Lu and Yuan, 2011), assuming that by timing the WGR and the GFA an overall volume of construction waste generation can be derived. However, there are two primary hurdles preventing this WGR-based approach from practical applications. First, the WGRs are too disparate to be accepted as the estimate. Therefore, researchers have used big data to refine the resulted WGR, as suggested by the Law of Large Numbers, the mean of the results obtained from numerous tries should tend to become convergent as more data is available (Sen and Singer, 1993). Lu et al. (2015a; 2015b) proved this law, but in many developing economies such as the Brazilian Amazon, big data is not available. Second, construction waste generation from a project is rarely linear. For example, Lu et al. (2016b) modeled it as an S-curve in high-rise concrete buildings. Wu et al. (2019) used an off-site snapshot methodology to estimate building waste. Construction waste generation is impacted by a large number of factors which are largely in a fuzzy nature.

The fuzzy logic-based approach developed in this study overcame the above hurdles to a large extent. It uses some simple fuzzy logic derived from experienced practitioners. It captures the tacit knowledge residing in these practitioners' mind about the fuzzy nature of waste generation. It requires no heavy data, but the estimated result of 66.67% is still acceptable for developing a waste management plan or the like, particularly when the project is at a very early stage. Future studies can be conducted to refine the estimate result further. Actually, in real-life construction time and cost management, no one will naively stick to an initial estimate without any change as the project progresses. Rather, experienced managers will rely on emerging information to fine-tune their baseline estimate and devise interventions accordingly. To this end, other factors can be incorporated into the fuzzy logic model to refine the estimate for practical use continuously.

7. Conclusions and future works

Construction waste generation is the key information for devising reduce, reuse, and recycle (i.e., 3R) measures. However, estimating waste generation from a new project is rather difficult as it is essentially an attempt to extrapolate current understanding to a future situation that is often full of uncertainties and fuzziness. This research tried to capture the fuzzy nature of construction waste generation estimate by developing a fuzzy logic model from a case study in the Brazilian Amazon. We used the sample data from 14 construction projects and further validated the model using the sample data from nine other projects. The construction projects were classified on a five-class scale for the potential of waste generation, and a graph that allows us to estimate the volume of waste to be generated by new building projects was plotted. An accuracy level of

64.29% in the classification of waste generation was achieved by the model. In the validation stage, the level of accuracy was improved and reached to 66.67%. It is discovered that the floor area is much more significant than the number of floors in predicting the volume of waste generation. It also enabled the creation of a graph that allows the agents involved in the construction to estimate the volume of waste to be generated by new enterprises quickly and with an adequate degree of reliability.

One of the limitations of the model is its generalizability. It cannot be applied to other localities or other types of construction projects, given the fact that in each region, the volume of waste residues is well-differentiated according to the cultural characteristics and the construction techniques used. However, the research provides a good reference for comparative studies in the future. The overall methodology is also inspiring for quantifying waste generation from construction projects, particularly by incorporating in their fuzziness. Future studies are recommended to refine further the fuzzy logic model, e.g., by introducing bigger data, to enhance its level of accuracy in estimating. [It may also be possible to seek to use other methods such as Artificial Neural Network \(ANN\) or Long Short-Term Memory \(LSTM\) when data is allowed.](#) Studies are recommended to redevelop the model for other sectors of the construction industry, with respect to their project typologies and regional particularities. It is expected to extend the validation to other locations and other project sets or small urban areas to calibrate the method.

Glossary table

| Symbol | Meaning |
|--------|-------------------------------|
| CWM | Construction waste management |
| C&D | Construction and demolition |
| GFA | Gross floor area |
| MAPE | Mean abs percentage error |
| MSW | Municipal solid waste |
| WGR | Waste generation rate |

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