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Parametric Stock Flow Modelling of Historical Building Typologies

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Abstract: While the construction sector is a major consumer of new raw materials, it also contributes largely to waste generation. Therefore, improved estimates of demolition waste and the identification of components and materials for reuse or recycling are an important prerequisite for better waste management in the construction sector. The aim of this study is to investigate the differences and possibilities between static bottom-up models and parametric BIM-integrated bottom-up models for material flow analyses to predict the building material composition of historical building typologies. Findings are, when comparing the predictive capabilities of the pre-audit model with a novel implementation of a generative parametric model, that we see a drastic improvement in the error-reduction. The test models and test cases are based on limited data but given the significance of the magnitude of variance between the two models, there is a strong indication that the most precise modelling approach is obtained when utilizing a parametric model based on historical building traditions. In contrast, the use of normal static prediction-based modelling is hard to justify since data on demolition waste is of poor quality. Combining the two modelling approaches might present a new alternative to reduce factor errors in predictions of demolition waste and create a foundation for better pre-demolition audits and BIM models for material passports.

Keywords: material flow analysis (MFA); building stock; parametric modelling; construction and demolition waste; building information modelling (BIM)

Citation: Negendahl, K.; Barholm-Hansen, A.; Andersen, R. Parametric Stock Flow Modelling of Historical Building Typologies. *Buildings* **2022**, *12*, 1423. https://doi.org/10.3390/buildings12091423

Academic Editor: Hong Zhang

Received: 18 August 2022
Accepted: 6 September 2022
Published: 10 September 2022

1. Introduction

The construction sector is one of the largest consumers of new raw materials, with a yearly depletion rate of 40% [1], but it is also responsible of a large share of the generation of waste, producing 34% of all waste in OECD countries [2]. In addition to its large-scale consumption of materials, the production of new building components also generates large CO_2 emissions during production, which means that 11% of all anthropogenically created CO_2 emissions can be related to the production of building components [3]. Construction is therefore an important focus area for the circular economy, where high rates of reuse and the recycling of building components and materials from the demolition of existing buildings can help reduce the need for new materials in the construction of new buildings [4]. The current reuse and recycling rates for construction waste vary widely from country to country. Some European countries have high recycling rates, but many of the heavy waste fractions such as concrete are still recycled to a low value, often being crushed as a base for roads or backfilling [5]. There are already many annual inventories of the historical production of waste from the demolition of buildings in the European Union, which are mainly driven by major international initiatives such as the 70% recycling target in European waste legislation [6], but there is still a lack of knowledge about the materials stored in the existing building stock and that will become waste at some point in the future. At the same time, embedded materials have the potential to be included in circular material flows when buildings are demolished in the future. Being able to calculate better estimates of future waste generation from the existing building stock is therefore an important prerequisite for improving waste management [7].

Material flow analysis (MFA) has been used for many years to determine the flows of materials in anthropogenic systems. If an MFA only covers a certain point in time, it is called a static MFA, whereas an MFA that considers a system over time is called a dynamic MFA. The materials embedded in a stock can be calculated using top-down or bottom-up approaches [8]. The bottom-up method considers the embedded materials in a limited part of the system and subsequently scales them up. The top-down method assesses the embedded materials by examining the difference between inflow and outflow in a system. In addition, MFA can be either retrospective by examining stocks and flows in the past based on historical data, or prospective by trying to predict developments in flows and stocks through historical data and extrapolation [9]. In terms of modelling resource flows, the retrospective top-down method is the most used [9,10], whereas the retrospective bottom-up approach is the most widely used to calculate stock flows, such as in buildings [8]. These bottom-up studies of the material composition of buildings often use a calculated material intensity, composition or mass flow for a particular typology of buildings, after which a retrospective assessment of the historical stock for that typology can be calculated, as demonstrated by [11–18]. Alternatively a prospective analysis can be added to predict future changes or outputs from that typology, as demonstrated by [19–25]. However, several studies also use a top-down model to estimate materials in the building stock by examining either in- or out-flows of materials [13,26,27]. A better coupling of bottom-up and top-down approaches with better data on material intensities and component life times is needed to increase the reliability of stock and flow estimates [28].

Although more reliable data on material intensities for buildings are needed to make accurate material stock studies, these data are not available in most countries [29]. In addition, the integration of building information modelling (BIM) into MFA can contribute to a better handling and storage of material-specific data on buildings and thereby contribute to accurate estimates in terms of the volumes of building components and materials in existing buildings [30] and the recoverability of materials [31]. One of the advantages of applying BIM may be its ability to quantify material estimates based on volumes in early design [32], whereas traditional stock estimates are mainly based on m^2 floor area [33]. Given the innumerable parameters that can define a parametric model [34], it is relevant to describe links to the typology of the building to acquire a deeper understanding of building traditions for that given typology in a parametrical sense [35]. BIM models with material data also create a better foundation for making integrated BIM-LCA calculations for assessing environmental impact of renovation of existing buildings [36,37]. Attempts to model historic buildings with BIM and parametric tools have been made in recent studies e.g., [38]. However, previous work in integrated material estimations in BIM has focus on salvaging possibilities [31], design for disassembly [39] or storing material data in BIM models [40] and has not shown in-depth typological modelling at scale with parametric tools for MFA in stock flows. This is in contrast to many recent attempts to provide high-quality quantitative take outs from BIM in planning [41–43] and arguably model-based quantity take-offs are the most valuable use of BIM in cost management of new buildings [44]. Unfortunately, (high-quality) BIM models of existing and historical buildings are rare and inaccessible.

The aim of this study is to investigate the differences and possibilities between static bottom-up models and parametric BIM-integrated bottom-up models for MFA to predict the building material composition (BMC) of existing building typologies. The objective is to identify the framework, scope and boundary conditions for (i) BMC-relevant data (ii) BMC-relevant typology and (iii) BMC-relevant predictive models. In the present study, two types of predictive MFA models for material composition are tested and analyzed. The first model is static and based on material data from pre-demolition audits in Copenhagen. The second is a generative parametric model based on data from public building registers and literature on building practices specific to historical typologies. The models are tested and compared based on four case studies.

2. Materials and Methods

The reliability of the models is analyzed for the accuracy of the prediction of BMC within the model by using statistical techniques (k-fold cross-validation and Monte Carlo simulations). Factorial dependencies outside the model are analyzed empirically and use references from the literature. High-level mathematical notification of factorial dependencies within and outside static and parametric modelling approaches are used to describe and compare the models.

2.1. Static Material-Flow Analysis

The static model uses information on individual buildings as the fundamental source of data in predicting the material composition of buildings. Similar models based on demolition data have been used in previous studies [45] to predict material flows. Static MFA is limited to describing systems at a specific time in a current state [46], feedback loops and other similar system dynamics cannot be captured from such models. Nonetheless, from this simplistic approach, we define the precision of each data point as the ability to (i) identify a building material and (ii) measure the quantity of the material.

One impractical yet straightforward way of determining the material composition of any building is to map the building waste composition (BWC) of demolitions. Buildings can theoretically be dismantled, sorted and weighed for each material composition and thus efficiently serve as the fundamental data source for BMC. It is safe to assume that two identical buildings, one having been demolished, the other still standing, have the same BMC. Based on this assumption, we can describe the translation of post-audit building waste composition from BWC to BMC for equivalent existing buildings as:

$$BMC_{eqv} \approx BWC_{post} \tag{1}$$

In the ideal world, with any model for predicting BMC for any building, the following terms are given if:

BWC data are abundant and accurate.

Equivalence derives from building typology.

Unfortunately, neither term can be assumed to be met safely with current data and current building typologies, which is why the model needs to take this into account. To generalize, the model is introduced with discrepancy factors, f, per material category/waste category:

$$BMC_{eqv} = f_{CD} \cdot f_{sCD} \cdot BWC_{post} \tag{2}$$

where f_{CD} and f_{sCD} are tied to the auditor and systemic components of a construction and demolition waste system, which handles the identification and measurements of the BWC (see Table 1 for a detailed description of these factors). Many different approaches have been developed to measure demolition waste system data both directly and indirectly [7] to account for such factors. We assume that a model based on the direct weights of materials at a waste sorting and handling facility will have the highest accuracy potential.

To accurately translate all the categories of materials present in a building in terms of an equivalent waste composition from demolitions, the few mandatory categories being registered in the dataset, such as the pre-demolition audit, do not explain all the materials in a building, since it is based on a professional assessment performed by an auditor. It is therefore necessary to accommodate non-registered, not-yet-registered and future-registered building (waste) material categories, BWC_d, in contrast to all the materials that are registered BWC_r:

$$BMC_{post} = BWC_r + BWC_d \tag{3}$$

Table 1. Factors/flow origins identified for BMC models.

Audit System Factors, *fsa*	**Auditor Factors, *fa***
• Approximation method for measurement of physical quantities	• Practical experience of various building typologies
• Approximation method for destructive and non-destructive tests on materials	• Skills and equipment in identifying materials and amounts
• Training, education, certification and support of auditors	• Quality assurance of audits
• Systemic political, financial and cultural influence	• Educational & certification level of auditor
Demolition waste system factors, f_{sCD}	**Demolition waste factors, f_{CD}**
• Method for measurement of physical quantities	• Skills and equipment for identification of materials
• Method for destructive and non-destructive tests on materials	• Physical capacity for sorting and storage of materials
• Method for sorting and storing materials	• Quality assurance of C&D facility, its assessors and processes
• Systemic political, financial and cultural influence (e.g., accessibility of data)	
Typological factors f_{type}	**Model-centric factors, f_{fit}**
• Method and requirements on typological categorization of buildings and materials.	• Method for fitting the data to the model
• Available documentation and details on structure and building envelope per typological category.	• Method of fitting the generative parametric model to measured data
• Available overlapping data to determine a building typology category, if selected category is not given in the source data set.	• Identification of most influential parameters that describes a typology
• Typological links to historic building codes, local planning requirements, etc.	• Implementation factors, such as possible states per parameter, choice of tools, coding language, speed, flexibility and accuracy of the implementation.
• Systemic political, financial and cultural influence (e.g., non-compliance of building codes)	• Quality assurance of waste facility, its assessors and processes.

We may rewrite the model to consider demolition waste factors for all identified categories, BWC_{eqv} as follows:

$$BMC_{eqv} = f_{fit} \cdot f_{sCD} \cdot \left(\sum_{BWC_r=1} (W_{BWC_r} \cdot f_{CD}) + \sum_{BWC_d=1} (W_{BWC_d} \cdot f_{CD}) \right) \quad (4)$$

where $BWC_r = 1$ is the building waste categories included in the waste system, and BWC_d is the materials not identified as building waste categories within this system. W_{BWC} is the measured weight of a building waste category, while W_{BWCd} is the measured weight of materials outside the identified building waste categories. f_{sCD} is the systemic errors generated due to higher-level waste conditions and management, and finally f_{cd} is the errors associated with the measurements and identification of the specific materials at the specific waste-sorting facility.

At this point, we have yet to account for the factors that apply when equivalence derives from typology, instead of assuming full equivalence between BMC_{eqv} and BWC_{post}. In other words, the results of the MFA depend on the way the typologies are grouped. If we assume some type of audit/assessment of buildings are used to determine its typology, we can adopt these errors under the two factors f_a and f_{sa} (see Table 1 for a detailed description of these factors), which account for faulty typological inspections at a varying level of detail:

$$BMC_{typo} = BMC_{eqv} \cdot f_a \cdot f_{sa} \quad (5)$$

This gives a generalized MFA baseline for BMC based on typology and BWC data:

$$BMC_{typo}\frac{1}{f_a \cdot f_{sa}} = f_{fit} \cdot f_{sCD} \cdot \left(\sum_{BWC_r=1} (W_{BWC_r} \cdot f_{CD}) + \sum_{BWC_d=1} (W_{BWC_d} \cdot f_{CD}) \right) \tag{6}$$

The typology BMC_{typo} calculated through the static MFA is based on pre-demolition audit data reported to Copenhagen Municipality, which are not publicly available. The reported pre-demolition data is based on the requirements in Waste Law BEK no. 224 from 08/03/2019 [47] and the previous version of the Waste Law BEK no. 1759 from 27/12/2018 [48]. The data contain information on demolition waste from both total and partial demolition, as well as renovations. The municipality's construction waste in the notification is reported on the address level. The notification contains quantities of waste in whole tonnes is divided into material fractions and the expected handling of the waste (preparation for reuse, recycling, other recovery or disposal). The reported data are based on a pre-demolition audit, and which material fractions and quantities were actually generated during the demolition or renovation are not subsequently checked. The data input to the static MFA model is based on data from 474 cases of demolition cases and 946 cases of renovation carried out over a two-year period from 2018 to 2019. A linear regression model for W_{bwc} using k-fold cross-validation covers 16 building waste categories ($BWC_{i,n=1}$. $BWC_{i,n=16}$) where its assumed that every W_{BWC} is independently described as:

$$W_{BWC,i} = \beta_0 + \beta_{1XBMC,i=1} + \cdots + \beta_{nXBMC,i=n} + \varepsilon_i \tag{7}$$

where β and ε are model response variables, and χ is the id of a building in the data set.

Thus, the linear predictive building material composition for each typology category, t as presented in Table 2, is described as:

$$BMC_{typo,t} = f_{fit} \cdot \left(f_{sCD} \cdot \sum_{BMC_r=1}^{i} (W_{BWC_r,i} \cdot f_{CD,i}) + \sum_{other=1}^{i} (W_{other,i} \cdot f_{CD,i}) \right) \tag{8}$$

where t is one of the first five typology categories (See Table 2) that filters the selected span of years, BWC,i represent the material categories except the category "other", which is assumed to represent the $BWCd$ fraction of the building material composition. f_{fit} represents the model-centric parameters that describe how well the model fits the data. f_{sCD} and $f_{CD,i}$ are ignored in this case and equal 1.

The static MFA is tested on two different buildings with two different typologies. Case study 1 is an office building in typology category 8, which was constructed in 1999, then demolished in 2020. The floor area of the office was 1497 m^2 excluding the basement and roof area. The office building had a single floor, excluding basement and roof. The height of the building was assumed to be 4 m, resulting in a gross volume of 5868 m^3. Case study 2 is a daycare center, constructed in 1976 and demolished in 2020. The floor area of the daycare center was 578 m^2, excluding basement and roof area. Similarly to the office building, the building had a single floor. Its height was assumed to be 4 m, resulting in a gross volume of 2312 m^3.

The registrations of waste in the pre-demolition audit for the two case-study buildings can be found in Supplementary Material Table S1.

2.2. Parametric Material Flow Analysis

The principle behind this parametric approach is the generation of a high level of detail from low-level data by utilizing rule-based modelling techniques by encoding geometric Boolean operations. While it is unfeasible to describe every set of parametric encoding in detail with mathematical notations for comparative reasons, the parametric model is summarized in Equation (9) with a description of the flow origin parameters in Table 1 and the parametric Grasshopper model can be accessed in raw encoded form (see Supplementary Material Table S2). To assess the results comparatively for our test models, a set of procedurally connected requirements is defined to validate the model's implementation. These requirements, which are meant to systematically reduce errors from model-centric factors represented by the factor f_{fit} are associated with the choice of typology (in this case, limited to buildings from the period 1851–1930, typology category two; see also Table 2).

Table 2. Danish typology based on construction periods in TABULA [49] focusing on energy requirements. BR is the Danish Building Regulations.

Construction Period	Changes in Typology	Typical Materials	Typology Categories
Before 1850	Shift in building tradition	Masonry, Thatched, Wood beams	1
1851–1930	Shift in building tradition	Masonry, Tiles, Wood beams	2 Case study 3 & 4 (parametric MFA)
1931–1950	Cavity walls introduced	Masonry, Tiles, Wood beams	3
1951–1960	Insulated cavity walls introduced	Masonry, Eternit, Wood beams	4
1961–1972	First energy requirements in BR1961	Masonry, Concrete bricks, Tiles, Eternit, Wood beams	5
1973–1978	Tightened energy requirements in BR1972	Masonry, Concrete backwall, Eternit, Tiles, Wood beams	6 Case study 2 (static MFA)
1979–1998	Tightened energy requirements in BR1978	Masonry, Tiles, Concrete backwall, Eternit, Wood and Concrete beams	7
1999–2007	Tightened energy requirements in BR1998	Masonry, Tiles, Concrete backwall, roof, Wood, Steel and Concrete beams	8 Case study 1 (static MFA)
2007–2011	Tightened energy requirements in BR2006/2008	Masonry, Tiles, Concrete backwall and roof, Wood, Steel and Concrete beams	9

The parametric model, based on an extensive collection of articles on typologies in Denmark, is mapped and curated by BYG-ERFA [50], combined with detailed descriptions of multi-story residential buildings categorized by typology 2 (see Table 2) [51,52]. Input from the Danish national building register (BBR) [53] includes area, number of floors, building age, outer wall materials, roof materials, building footprint and free parameters identified. This leads to the following approach to selecting influential parameters for the parametric model:

1. Generate a complete 3D model of essential building elements through the 11 steps shown in Figure 1; foundations, load-bearing walls, load-bearing decks and roof structures for a given typology based on definitions and rules defined by Engelmark and input from BBR implemented with the least amount of free parameters.
2. Calculate volume of generated building elements. Each element is assigned with material id based on [49] and amounts are calculated based on generic densities. For known parameters, each parameter is chosen by the state given the dataset BBR for that particular building in question. For unknown parameters (not present in BBR), each parameter includes variance and boundaries for the Monte Carlo simulation approach. The variances in our test case are derived from a small test/training set of carefully measured building material compositions.
3. The results of the building material composition generated from a building is recorded in two formats, one for human inspection (for visual inspection, 3D models, and 2D renders), for comparison with photos; the output, in this case, shows the most likely (summarized median) of all possible parameter states. The second forma is a machine-

readable file format for further processing and boundary checks with pre-modeled sets of buildings with a given typology.

4. While the algorithm used to generate the 3D model is implemented to present the most probable constructions and materials (based on its available data set), it is possible to adjust the settings for the algorithms. Based on human inspection for comparison with land sat photo material (Google maps), changes to the fixed and free parameters are modified (see Figure 2), thus generating a new model through step 13 in Figure 1. This process can be repeated until the user's visual inspection has been satisfied.

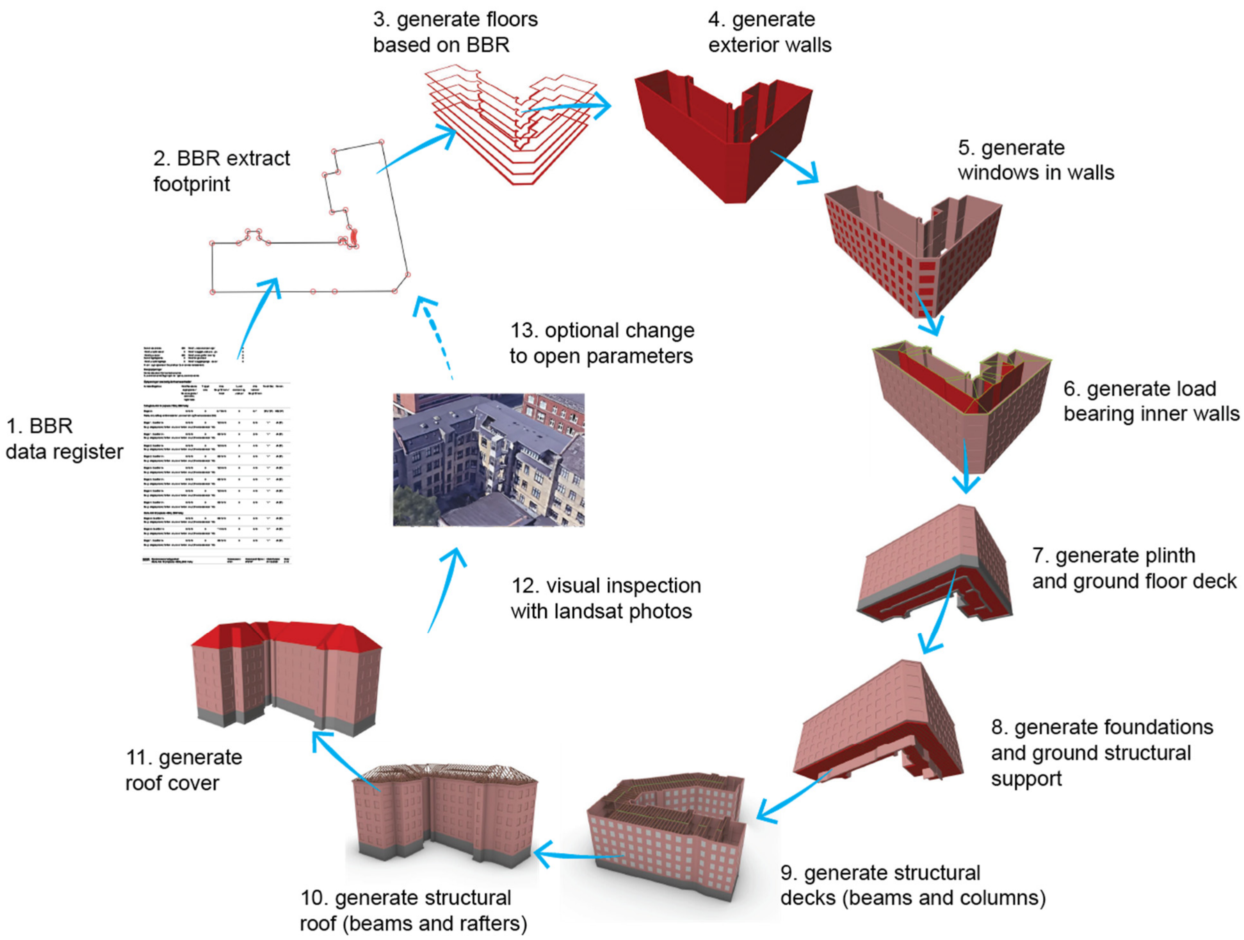


Figure 1. Step by step guide to the auto generation of the parametric BIM model with assignment of specific building components based on typical historical building practice.

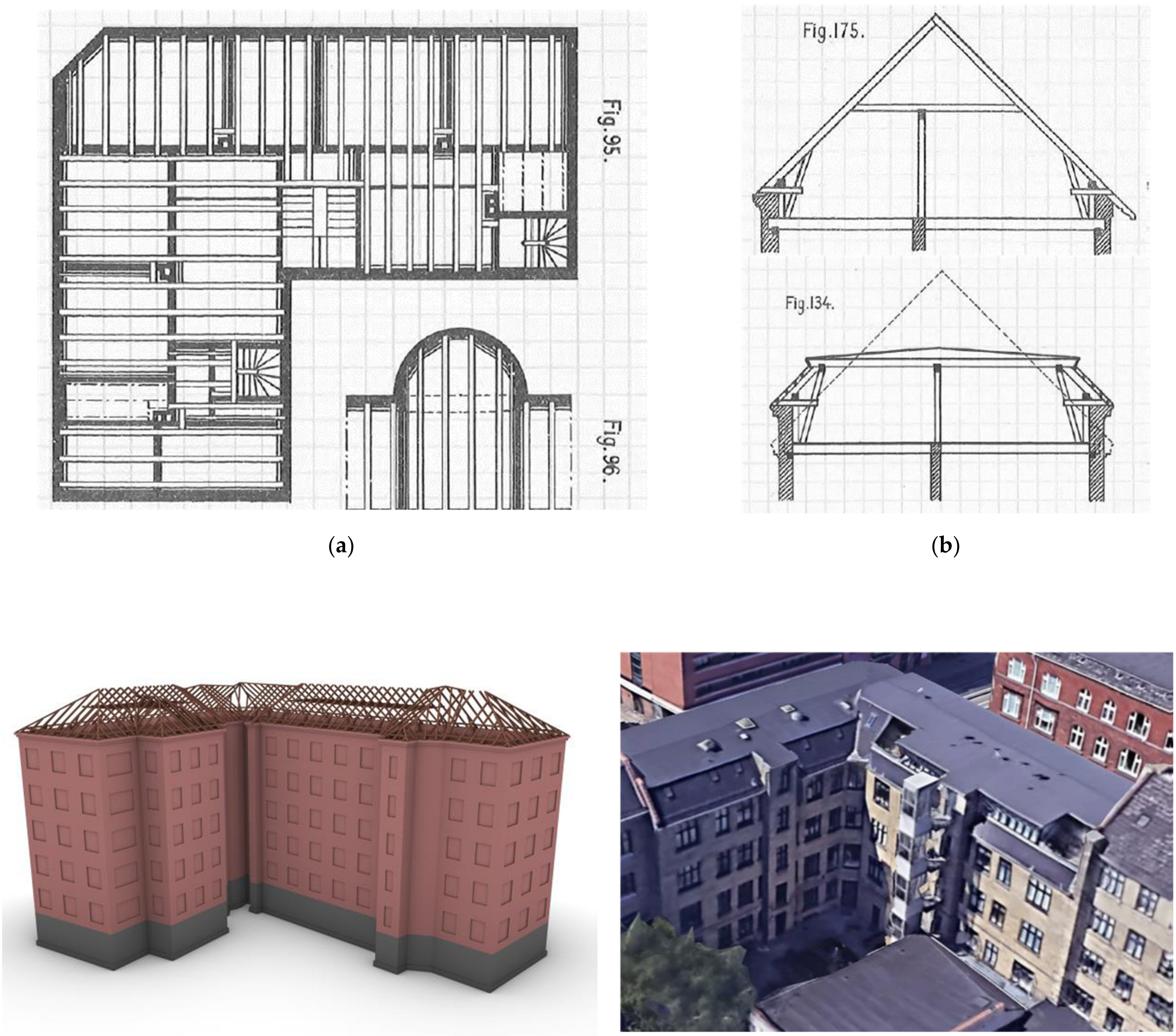
Each parameter is either modelled with a standard uniform normal distribution (P (X > 1.96)) or through a cumulative function given by the distinct value for the parameter assigned by the probability between 0–1, depending on how many times it occurs. The BMC for typology 2 is described as:

$$BMC_{typo,t} = (Fh, WH, WW, BH, FH, FDT, MCH, RH) \cdot f_a \cdot f_{sa} \quad (9)$$

where each of the variables FH to RH described in Table 6 depend and are modelled parametrically using Grasshopper3d. f_{fit} represents the model-centric parameters that describe how well the model fits the data. f_a and f_{sa} are modelled by introducing variance determined by using the one-at-a-time (OAT) simulation principle, as each parameter is simulated 300 times based on the Monte Carlo selection. Inner alignment of the model sensitivity index is calculated for each parameter. The sensitivity index is calculated using the all-at-a-time (AAT) simulation principle, where all parameters are varied simultaneously based on a set of 500 as defined by [54]:

$$S(P_i) = \frac{\frac{1}{n}\sum_j^n |y_{ij} - \beta|}{\sum_j^n \left(\frac{1}{n}|y_{ij} - \beta|\right)} \tag{10}$$

where i is the index of the parameter, n is the state of the parameter P. x_i, y_{ij} are the outputs of the system for the jth measure of x_i, k corresponds to the number of parameters and β is the base solution.



(**a**) (**b**)

(**c**) (**d**)

Figure 2. Based on typological rules and drawings, typical floor for typology (**a**), and typical roof build-up several alternatives for the typology (**b**), it is possible to generate a full 3D representation of a building (**c**). The visual inspection shows that the BIM generated roof (**d**) is of the wrong type of the two typical roof construction alternatives, meaning changes of specific fixed or free parameters need modification.

Case study 3 is a residential building in typology category 2, it was constructed in 1895 and is still in use. The floor area of the building is 2003 m^2, excluding basement and roof area. The residential building has four floors, excluding basement and roof. Detailed historic drawings are used to assess the accuracy of the model, but they are not used as input in modelling the case study.

Case study 4 is a residential building in typology category 2, constructed in 1903 and still in use. The floor area of the building is 1467 m^2, excluding basement and roof area. The residential building has five floors, excluding basement and roof. Detailed historic drawings are used to assess the accuracy of the model, but they were not used as input in modeling the case study.

3. Results and Discussions

3.1. Accuracy of the Static Stock Flow Model

In general, we see how the model overshoots minerals (stone, concrete and ceramics), iron and metal. On average, for the two cases, the model overshoots by a factor of 2 and a factor of 100, respectively (see Table 3). The static stock flow model based on typology and age is unfit to describe the nuances of materials in buildings, at least based on currently available data. Depending on the building typology, the waste composition on wood can cause inaccurate predictions with a factor of 2–3. The static MFA model poorly depicts concrete, iron and metal, natural stone and unglazed bricks in general. All building waste categories typically found in large amounts (weight-wise) come with significant variance when predicted across all typologies. Even with a relatively large data set, the quality of this particular data set differs critically in serving as accurate predictors. Two mechanisms explain the high variance: (1) poor data quality (with a high noise ratio serving as prior for the model) and (2) the spread of typologies vary significantly within the data, meaning that the typologies show low internal correlations and/or are falsely identified by the filter (address, building age, type, size). Both mechanisms result in offshoots of actual BMC with an unknown but assumingly high margin.

Table 3. Two cases comparing predicted building material compositions vs. actual measured building material compositions.

	Case 1: Office Building		**Case 2: Daycare Center**	
	Actual BWC_r [kg/m³]	**Predicted BMC_r [kg/m³]**	**Actual BWC_r [kg/m³]**	**Predicted BMC_r [kg/m³]**
Minerals	281.1	335.8	49.0	182.1
Iron and metal	0	15.5	4.8	116.2
Wood	3.6	1.2	3.6	6.7
Total (BWC, BMC)	291.8	403.6	161.4	384.4

These variances are very high, and one should be cautious in relying on such data and models. Given the quality of the data set, we expect high variance outputs, making the approach is imprecise and challenging to apply in practice. However, since 2020 regulatory changes in the ways data are collected and verified are likely to improve data quality in the future. Thus, the method of predicting BMC from BWC using static MFA cannot entirely be ruled out. However, until much more accurate data become available, the presented type of predictive model will deliver significant forecast errors of building material stock.

3.2. Factorial Dependencies of the Static Stock-Flow Model

The variance across all buildings in the test set related to f_{fit} in the model is expressed by the mean absolute error (MAE) per material composition (see Table 4). While we do not have supporting data to derive the real f_{sCD} and f_{CD} in detail for all the data points in question, we tested the model against two waste audit cases. These present the measured building material waste composition measured by a demolition company versus the predicted waste BMC, i.e., the BWC, assuming all materials are accounted for. This gives an idea of the prediction variance (associated with the factors f_{sCD}, f_{CD} and f_{fit}).

Table 4. Post demolition BMC model and its MAE.

$BMC_{typo,1–5}$	$MAE_{Typo,1–5}$ [ton]	$MAE_{Typo,2\ Only}$ [ton]
Natural stone, e.g., granite and flint	4.0	1.1
Asphalt	95.0	10.3
Concrete	545.0	495.3
Asphalt and concrete mix	4.0	0.5
Natural stone, unglazed tiles and concrete mix	148.0	343.0
Gypsum	10.0	1.1
Iron and metal	233.0	45.4
Glass	9.0	0.4
Unglazed brick and tiles	147.0	52.6
Roofing felt	2.0	0.7
Stone wool	9.0	0.9
Wood	11.0	38.5
PVC	0.2	0.0
Plastic	0.1	0.0
Cardboard	0.03	0.0
Others	24.0	4.7

To quantify the margin of error due to audit practice and the practitioners in an audit system that may serve as much better predictions in a future data set, we conjecture that other audit systems within the demolition sector may give insights into the approximate factors of f_{sCD} and f_{CD}. As an example, we use the experience of the Danish energy-labeling scheme. Its purpose is to rank buildings on their energy use and to help the authorities regulate the energy consumption of buildings according to EU 2018/844 [55]. The system is composed of a certification standard maintained by a nationally regulated organ (Danish Ministry of Environment), which places a high authority level on the system itself but is handled through certified companies and their auditors. Data on inspection of these certifications are available in a public energy label database, which makes it possible to inspect and compare audits and take out random inspections of audits to incentivize measurements that are more accurate. Audits are based on version-controlled guidelines for auditors, which challenge the comparability of audits over time. This has contributed to criticism of the system because 23% of audits in 2018 contained errors that would affect the result so much that the energy label had to be changed [56]. Because the system does not explicitly include materials, the materials' volumes can only be extrapolated from the building envelope and not from the rest of the building composition.

This same kind of error rate of 23% can be associated with the errors that are chargeable to audit-system factors and auditor factors. Given this assumption, the material composition is based on audits using a similar approach, and the given audits can take into account equivalent measurements of interior building surfaces (floors, inner walls, etc.) and BMC for the entire building.

To generalize further, we surmise that BMC from audits will contain around 20% inaccurate information caused by systemic errors and errors due to the specific auditor, equivalent to those reported by [56]. We can further speculate if auditors who are trained systematically on differences in typologies will reduce f_a-inaccuracies. While these errors are likely to be minimized, with a higher frequency of quality assurance and better training of auditors, the model suggests that divergences between audited material compositions and "true" material compositions cannot be minimized, since no term for feedback is introduced. This sets up a BMC model approach for high-precision measurements of material waste compositions based on post-demolition data, as introduced in the regulatory change to how to manage BWC, mentioned earlier.

3.3. Accuracy of the Parametric Stock-Flow Model

Compared to the static MFA, we obtain more accurate predictions for all materials with the parametric MFA (see Table 5). The highest recorded errors are for concrete, again consistent with the static MFA model, but in this case the variance is much smaller, and the predictions are more consistent compared to the pre-audit model using BBR data as its prior. This suggests that rule-based parametric models generate reliable quantities and/or identify materials significantly better than a somewhat unregulated pre-audit system as that represented by the demolition waste measured data set.

Table 5. Building material composition for two cases, actual vs. predicted.

	Case 1: Mølle Alle		**Case 2: Brysselgade**	
	Actual BMC [kg/m^3]	**Predicted BMC [kg/m^3]**	**Actual BMC [kg/m^3]**	**Predicted BMC [kg/m^3]**
Masonry	179.1	179.3 +/− 12.5	192.6	193.9 +/− 33.3
Concrete	102.2	104.1 +/− 7.0	110.3	111.5 +/− 19.3
Wood	39.0	39.6 +/− 2.7	41.9	42.2 +/− 7.2
Iron/Steel	13.5	13.5 +/− 1.0	13.1	13.3 +/− 2.2
Total (~BMC)	333.7	336.5 +/− 23.1	357.9	361.0 +/− 62.0

The parametric model also generates a deeper typological breakdown than what is possible to generate from the BBR set alone. The "typologysation" is equivalent to the number of open parameters in the model. This allows for a selective tweaking of the generated building components and their material compositions adjusted for all other parameters. The primary benefit with the parametric MFA ties in with the qualified opportunities for component types linked with the option to visually inspect the building in the model. This is currently not possible in the static MFA approach.

3.4. Factorial Dependencies in the Parametric Stock-Flow Model

To explain the model's insights, we show the simulated variance along with the sensitivity index of each relevant parameter in the model. Three distinct experiments were performed with 100 simulations each. The analysis took place individually on the parts of the building that had significant variance during the uncertainty analysis. For masonry, the floor height, the height and cantilever of the wall, and the window area were selected as open parameters. Specifically relevant for concrete, there were variations in basement height, foundation height and width, and deck thickness. In the roof construction, the height and cantilever height of the wall, the roof slope with a uniform slope, slopes with a two-part roof slope and the roof height varied.

Inaccuracies due to floor heights were mainly caused by the differences in the BBR data for declared areas vs. generated areas based on a polyline-footprint multiplied by the number of floors (see Table 6 column 2). We see the majority of errors as linked as expected to the BMC of the façade and not the internal structure or the foundation. The generative model itself had a mean absolute error ranging from 0.03 to 102.15 tonnes, where heavy materials such as masonry and concrete have larger mean absolute errors, which is consistent with the pre-audit results. Of the two cases (tested against the model; see Table 6 column 4) we saw a lower mean error than in the model (see Table 6 column 3). This was expected, as the buildings in the test set are likely to be closer to mean values than the outliers, due to the limited test set used.

What remains relevant to conclude is that, when the model generates buildings that resemble the "correct typology", its expected variance is reduced significantly, and highly accurate predictions can be made. At the same time, this also means that if the model attempts to predict BMC outside its actual typology, the predictions will almost certainly be less accurate. The case studies in the test set summarize the BMC for primary structural materials (material compositions), as shown in Table 7.

Table 6. Essential free parameters identified for housing constructed between 1931 and 1950.

Parameter	Parameter Type	Mean State [m]	Variance, OAT [m]	Sensitivity Index, AAt [-]
Floor height, Fh	Cumulative function	3.20	0.117	0.39
Window height, Wh	Uniform distribution	1.80	0.274	-
Window width, WW	Uniform distribution	1.40	0.016	-
Window area (derived)	Uniform distribution	-	-	0.45
Basement height, BH	Cumulative function	2.80	0.018	0.26
Foundation height, FH	Uniform distribution	0.50	0.008	0.27
Foundation deck thickness, FDT	Uniform distribution	0.30	0.528	0.41
Mural crown height, MCH	Cumulative function	0.65	0.0135	0.12
Roof height, RH	Cumulative function	2.70	0.0837	0.20

Table 7. Errors due to generative parametric modelling factors.

$BMC_{typo\ 2}$	MAE (f_{type}) [ton]	MAE (f_{fit}), in Model [ton]	MAE (f_{fit}), Test Set [ton]
Masonry	20.8	102.15	2.30
Secondary masonry	0.0	11.65	2.00
Concrete	4.0	55.65	10.75
Wood beams t1	0.0	1.00	−0.03
Wood beams t2	0.0	9.61	0.04
Wood rafters t3	0.3	2.04	0.23
Wood roof t4	0.0	0.39	−0.01
Wood laths t5	0.0	0.03	−0.02
Steel profiles	0.0	1.53	0.05

3.5. Predictive Capabilities of the Pre-Audit Model and the Generative Parametric Model

To begin with, we see that the methods determining the relevant factors that affect the accuracy of harvesting BMC vary significantly between the approaches we present in this paper. The models are based on different data sets, but they also refer to different domains of modelling that are rarely seen in the same research projects. Since the models range from direct data transfer based on low-level multiclass linear regression to high-level generative parametric models, we chose to focus on the most critical aspects of our experiments' model results and indications.

Several test implementations of the parametric algorithms have been performed including different ways of generating the structural beams at every floor as shown in Figure 3. During these tests cases studies were used to calculate the errors on BMC for the beams.

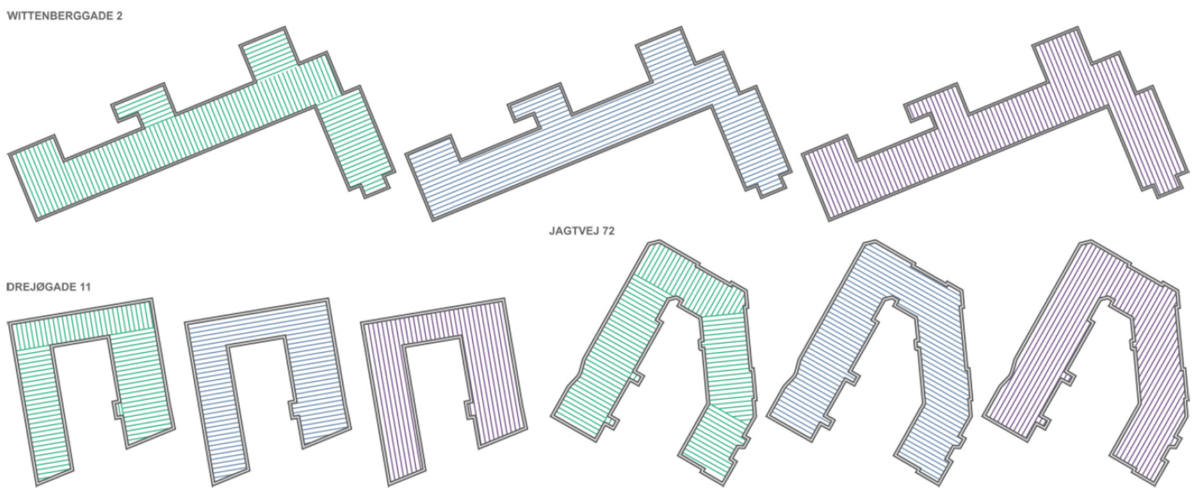


Figure 3. Beam span algorithm test, here showing three buildings actual span (green) and two different implementations tested (blue and purple).

Summing up, we suggest that factors can be classified similarly, regardless of the modelling approach. The models all share the same distinction between two types of factor:

The quality of direct measurements of building material compositions from material waste composition is a result of the following factors:

- Demolition waste system factors associated with the method of measuring construction demolition waste made by the waste-handling facility.
- Demolition waste factors associated with the specific waste-handling facility.

The quality of building material compositions by indirect measurements performed through audits is a result of two types of factor:

- Audit system factors associated with an established building audit system.
- Auditor factors associated with the specific auditor.

The quality of generated building material compositions from a parametric model of BMC is a result of the following factors:

- Typological factors associated with historical and cultural factors.
- Model-centric factors associated with the method of modelling.

We have shown that, when predictive modelling is used, the model-centric factors (f_{fit}) are easier to quantify compared to the systemic factors e.g., f_{sa} and f_{sCD} and the "human in the loop factors", such as f_a and f_{CD}. Nonetheless, it is possible to quantify such factors. When this can be done, interventions can be introduced to reduce their inaccuracies.

When comparing the predictive capabilities of the pre-audit model with the generative parametric model, we see a drastic improvement in the error-reduction of f_{fit}. Our test models and test cases are based on limited data, and the model's data priors are not directly comparable. However, given the significance of the magnitude of variance between the two models, we see an indication of a more precise modelling approach when utilizing a parametric model. The consequence of a pre-audit model that relies purely on the statistical significance of its raw data is the acquisition of good-quality data. We see that the pre-audit model is highly susceptible to errors in the waste pre-demolition audit even after heavy pre-processing of the data. In addition, the material intensities for existing buildings have increased due to the growing amount of material that is used for replacements [57], which will not be reflected in the results when the data is historical. We also see that the number of individual building data points in every typology category matters for the precision of the model. The generative parametric model can be based on testing the implementation of typology 2, defined on the basis of a relatively small prior data set, as long as the parametric rules are realistically accounted for in the model. This, however, does not mean that every typological category is equally well defined or that it can be described with few and efficient parameters derived from other datasets (i.e., BBR). It is unlikely that, e.g., typology category 4 can be modelled with as few parameters as we present for typology 2, simply because typology 4 ranges much further in material choices and building traditions.

Without speculating whether the models are likely to be transferred to other cities and countries, we do suggest that if other countries were to rely on similar ways of collecting waste data through pre-demolition audits, they would find that currently available data on demolition waste is of such bad quality that static prediction-based modelling is hard to justify. It would therefore be better to use the parametric approach, that, given (a) well-defined sets of rules and (b) an accurately assessed typology, BMC can be predicted with high levels of precision. This assumes that the BMC calculated from technical drawings and rules actually does account for the built BMC.

3.6. Implications for Future Predictions of Material Composition and Registration of Waste Data

It seems a natural step to develop better techniques and methods to fit existing buildings into distinct typologies and possibly rethink the typological systems used internationally. We found that TABULA lacks detailed information on BMC but supports derivatives of expected materials used in the mapped typologies. A systematic use of existing typologies in TABULA, combined with other sources of BMC-relevant data is possible, as shown in this paper, but our results indicate that a more "fine-grained" version of TABULA would further improve the model's predictions.

This situation has since changed through the revision of waste legislation BEK no. 2159 from 09/12/2020 [58]. From 2021, upon notification of a pre-audit, each case is given a serial number, which must be reported to the waste management center to which the demolition waste is being delivered according to the new added paragraph § 76 [58]. Data on this regulatory change are sparse and have not been used in the following analyses.

There is a need to further develop the model's predictive capabilities by reducing the model-centric factors of f_{fit} using more advanced machine-learning models (for the pre-audit approach) or more complex parametric models that can combine ever more data from several sources. However, we stress that we simply cannot wait until data on demolition waste is "good enough" to make useful BMC predictions. If society is to transition into a circular economy within a few decades, and if data collected through current waste handling facilities does not improve, we shall be unlikely to acquire the necessary knowledge of BMC at the level of future reuse and recycling at scale for a circular economy. Thus, new ways of efficiently and accurately measuring BMC are needed to establish a better "ground truth" for any bottom-up approaches to predictive modelling. That said, we find that, over time, data from demolition waste, combined with established systems such as waste pre-audits, will be an important source of BWC data that can be used to extrapolate from similar typologies to existing building stock.

One interesting aspect of the different models is the synergy between them. If deployed widely in practice they can be used to reduce factor errors. Future BWC data are expected to give much more precise BMC data, thus creating an opportunity to confirm/challenge pre-audit data when buildings are torn down or renovated. It is possible that in time auditors will benefit from the more precise waste data to form predictions that are more precise for the BMC of buildings that are still standing. Ideally, some such system will be created without direct rebukes from auditors and will be set in place to help and justify specific methods of measurement and ways of identifying materials. Such a system will work if it creates indirect feedback made through the baseline from the generative parametric BMC, rather than purely based on infrequent feedback from the waste-handling facilities of demolished buildings, as shown in Figure 4.

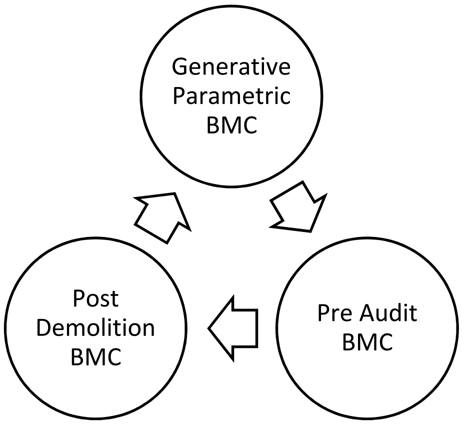


Figure 4. BMC synergies to improve reliability in material prediction between the post demolition BMC and future predictions of BMC.

The advantage of such set-up is that BMC can be generated for all buildings nationwide, while knowing that some buildings have been falsely categorized (by typology) and that input data are poorly depicted in the relevant databases. Auditors can step in and correct the typology, further enhancing the BMC by means of qualitative identifications and measurements. This helps to improve and calibrate the parametric model from two directions, from the auditors' assessment side and the actual BWC = BMC test when the building is demolished. Given continuous recalibration and improvement of generative parametric models, $f_{fit} \rightarrow 0$ across the models, which states that we can assume more precise BMC, thus making the potentials for urban mining and recovery more reliable.

4. Conclusions

The aim of this study was to investigate the differences and possibilities between static bottom-up models and parametric BIM-integrated bottom-up models for material flow analyses to predict the building material composition of historical building typologies. Hereby we also investigated the inner factorial dependencies of material flow analysis on predictions of building material composition by a static and a parametric model. Among the factors identified are the mechanisms related to the systemic impacts of auditors and waste-handling facilities, the factors associated with specific methods of measuring material composition and the particular model's ability to represent the available data. The results show the key differences between a static bottom-up modelling approach and a parametric BIM-integrated bottom-up modelling approach for material flow analyses of historical building typologies. When comparing the predictive capabilities of the static model with a parametric model we see a drastic improvement in the error-reduction of material flow predictions. While the parametric model is more reliable in quantifying building material compositions, it is also has the potential to improve over time with new and better implementations. The study concludes that a more precise modelling approach is obtained when utilizing implementations of heuristic and statistic historical building tradition documentation specifically addressing a narrow building typology and when elementary data of key parameters (such as number of floors) are consistent when delivered by a public data set. Furthermore, the results shows that demolition waste data is of poor quality and in itself is prohibiting useful quantity predictions of building material compositions on existing building stock. While it is expected that future waste data are more reliable, the article argues for a combined static and parametric modelling approach to reduce factor errors in predictions of demolition waste. This can be used as a proxy for creating more precise pre-demolition audits and BIM models for material passports to support a circular construction transition.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/buildings12091423/s1, Supplementary Material Table S1, Supplementary Material Table S2, Supplementary Material_2_Parametric_Model.

Author Contributions: Conceptualization, K.N., R.A. and A.B.-H.; data curation, R.A.; formal analysis, K.N. and R.A.; funding acquisition, R.A.; investigation, K.N. and R.A.; methodology, K.N. and R.A.; project administration, R.A.; software, A.B.-H.; validation, K.N. and R.A.; visualization, K.N. and A.B.-H.; writing—original draft, K.N. and R.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partly funded by European Union's Horizon 2020 research and innovation programme, grant number 821201.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: We would like to thank the European Union's Horizon 2020 research and innovation programme for its support though the Circular Construction In Regenerative Cities (CIRCuIT) project (grant agreement no. 821201), which has helped fund part of this research. In addition, we would like to thank Copenhagen's municipal government and the Danish demolition company Tscherning for providing data on demolitions.

Conflicts of Interest: The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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