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Data driven quantification of the temporal scope of building LCAs

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Abstract

In the construction sector, LCAs typically apply an approach based on fixed or partially fixed building lifespans/service lives/reference study period. The temporal scopes applied in building LCAs are hence typically not reflecting that the timeframes buildings can provide the service they are intended to provide, are (highly) dependent on numerous factors e.g.: building location, materials used to construct the building, energy supply and the use of the building. Inaccurate estimation of the temporal scope of a building LCA will lead to incorrect quantification of the environmental impacts of buildings. Incorrect quantification of the environmental performance of buildings may, in the worst case, derange/decelerate the development within the building sector towards more sustainable buildings. In this paper, a data set consisting of 20999 Danish buildings, demolished between 2009 and 2015, is analyzed. A multiple linear regression model is derived and used to quantify the temporal scope (often referred to as the reference study period) of building LCAs in an attempt to improve the accuracy of sustainability assessment of buildings, taking several influencing factors into account. The results obtained from the derived model are subsequently compared with several fixed/partially fixed building lifespan/service life/reference study period quantification approaches The regression model proved to estimate the lifespan with lower errors (compared to observed values) than the prevailing approach relying on a single fixed value for all building locations, uses and building materials. The application of model based site, use, and/or material specific etc. temporal scope quantification in LCA is new and provides a mean to reduce the uncertainty of LCA results; however, the approach needs to be formalized.

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Keywords: temporal scope, building service life; building lifespan, building LCA

1. Introduction

The construction sector is a key contributor to the global anthropogenic environmental burden, accounting for 20–40% of the energy consumption in developed countries [1], and contributes significantly to most environmental impact categories, e.g. toxicological impacts, water and land use, waste generation, resources consumption, etc. (see [2,3]).

Numerous attempts have been made to conduct sustainability assessments of buildings and building materials [4]. Sustainability assessments of buildings typically report results relative to a functional unit [5]. The functional unit defines the time window a service is being delivered by a product, for buildings typically quantified by the Reference Study Period (RSP), for commodities the Life Span (LS) or in more generic LCA terms the Service Life (SL) or of a product [6,7,8,10,11]. The product RSP/SL/LS plays a critical role in quantification of the overall impacts of the assessed product.

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The focus of our paper is to assess and improve the TS approximated through the LS (i.e. the parameter generally compiled in Danish building registers/statistics) quantification of buildings in relation to environmental performance assessment (EPA) of buildings. Our approach relies on a data set consisting of 20999 records on buildings demolished in Denmark between 2009 and 2015. A multiple linear regression (MLR) model is used to derive a quantitative LS model, where five building characteristics are included as categorical variables.

1.1. SL and LS of buildings

From the considerable variation observed in building LSs, it is evidently important to derive realistic estimation routines for the expected LS of new buildings when these are to undergo economic and EPA. Formally, [8] defines the SL of buildings as the period after installation during which a building or its parts meet/exceed the performance requirements. The temporal scope (TS) of a building LCA is larger than the RSP, most often different from the SL of the building (see Fig. 1) and is defined as the timespan in which a building is capable to provide its intended service (i.e. providing accommodation space, office space, storage space etc.). In addition to the overall SL, various types of sub-service lives have been proposed and studied in the literature, e.g. technical, economic, physical, etc. (see [9,10]). The LS quantified in our paper is assumed to match the TS/RSP of building LCAs as close as possible by relying on generally compiled building data.

Fig. 1. Illustration of the perceived most frequent relation between building LS, SL, RSP and the TS of a building LCA. As is evident is the TS of a building LCA suggested to be (considerable) longer than the building SL and closer to the LS.

The availability and quality of data on building SLs, RSPs and LSs is a considerable obstacle, particularly in EPAs [12]. LS, contrary to RSP and SL, is being compiled on a large scale and variations between different countries are known to exist. The observed variation is related to spatial variability caused by local characteristics, policies and regulations. Estimates of the mean building LS can be found in recent publications for some countries; e.g. 180 yrs. for Switzerland [13], 80 yrs. for Spain [14], 34 yrs. for China [15] and 50 yrs. for Finland [16]. An LS of 75–80 yrs. is typically applied for building components [17].

The expected LS of a building is a factor known to affect the real estate price. Hedonic models are widely used as a real estate pricing tool (see e.g. [18]). Various factors such as internal characteristics of the structure and location descriptors are used to estimate real estate prices [19]. The most common statistical method applied to assess how various factors affect pricing is regression analysis. An example of this approach is presented by [20] where real estate prices in Turkey were predicted relying on a hedonic model. Hedonic regression models have also been promoted as an ecosystem (service) valuation approach [21], capable of relating to a multitude of factors potentially affecting the real estate prices e.g. environmental quality and amenities [22]. Hedonic models have more recently been used to estimate the SL of buildings [15]. In [14], the authors applied a multiple semi-logarithmic (level-log) regression model on demolished buildings in China to predict a building's SL taking into account five factors as continuous independent variables.

1.2. LS and environmental impact quantification

Recent publications demonstrate that including the LS in sustainability assessments has a significant impact on the assessment results and hencen the environmental performance (EP) of the building. In the building sector, one of the most developed and applied methodologies for assessment of sustainability performance is life cycle assessment (LCA) [3,23,24,25,26]. In relation to building LCAs, it is important to note that an environmental impact of a building is typically quantified as the impact per unit area per RSP year.

As presented by [27], the applied TS for residential building LCAs is often set within the range of 50–100 yrs, although in many studies the TS is explicitly stated as having been set arbitrarily. The summarized literature presented by [25] addresses the combination of various life cycle based assessment approaches and the TSs of these assessments. By prolonging the LS from 50 to 100 yrs., the annual environmental impacts quantified in a typical building LCA are as presented by [28] as reduced by app. 38%. The application of a common TS for LCAs across all types of buildings is not reflecting the observed conditions and may lead to overestimation of the environmental impacts per service year, and hence to a misrepresentation of the sustainability performance of e.g. more durable buildings and further obscure e.g. absolute sustainability assessment of buildings in general. The quantification of the LS of buildings and building components needs to be as accurate as possible in order to improve validity and realism of the EP of the services provided by real estate and building components.

For Danish buildings, the Green Building Council Denmark (GBC-DK) provides certifications of buildings partially based on LCA (see [28]). In LCAs performed in relation to building certification in accordance with Deutsche Gesellschaft für Nachhaltiges Bauen (DGNB), a default building RSP of 50 yrs. is used, as the TS for most primary building LCAs. A secondary evaluation within the DGNB framework allows for use of functional dependent LSs (as presented by the Danish Building Research Institute, SBi), within the range of 60–120 yrs. [29]. The results of the primary and secondary LCA are weighted 70% and 30% respectively in the final assessment.

2. Method

2.1. Data description

The raw data set, which our building LS quantification model relies on, consists of 26320 observations of buildings in Denmark demolished between 2009 and 2015, collected by the Danish Building and Residence Register (BBR). The raw data set was initially filtered; observations with missing values and redundant records were removed from the data set. Moreover, buildings with a LS lower than 5 yrs. or those constructed before 1800 were excluded since these were not considered representative for modern buildings undergoing EPA/certification. The final sample thus consists of 20999 observations.

Table 1. Classification of building characteristics included in the LS model. Sub-characteristics covered equals the data available from BBR.

Characteristics	Sub-characteristics
Region	RH
	OR
Refurbishment	Refurbished
	Not Refurbished
Use type	Residential
	Commercial
	Agricultural
	Recreational
	Institutional
	Other use
Wall material	Brick
	Wooden panelling
	Light Concrete
	Concrete
	Sheet metal
	Cementitious fiber board
	Timber
	Undefined/Other material
Roof material	Fibre cement (excl. asbestos)
	Sheet metal
	Asphalt roofing
	Clay/brick tiles
	Concrete tiles
	Build up
	Thatched roof

Table 1 summarizes the variation options for the five building characteristics along with their sub-characteristic names. Examples for each use type are given in Table 2.

The most useful characteristics of the demolished buildings, along with the construction and demolition yrs., are selected based on the availability of the data and the expert judgement on the potential influencing factors. First of all, the building location may contain information on the regional characteristics (economics, politics etc.), while the building function is determined by the intended classification of use. Additionally, information relating to whether the building was refurbished or not may reflect the building condition. Finally, the materials applied for the building envelops are considered as fundamental factors influencing the LS of buildings. Five characteristics are included in our model as variables; namely region (i.e. building location), refurbishment, use type, wall material/cladding and roof material.

Depending on its location, each building is assigned to one of the five regions of Denmark; Hovedstaden (i.e. the capital region of Denmark), Midtjylland, Nordjylland, Sjælland and Syddanmark.

An initial analysis on the regional characteristic revealed overlaps of the confidence intervals (significance level = 0.05), for the mean LSs of buildings located in Midtjylland, Nordjylland and Syddanmark, indicating that these three regions are not significantly different. Furthermore, the mean LSs for the Midtjylland, Nordjylland, Syddanmark and Sjælland regions varies between 71 and 74 yrs., compared to a 60 yrs. LS mean value for Region Hovedstaden (RH). It is therefore reasonable to pool all data into two regions; RH and the rest of Denmark/Other Regions (OR).

2.2. Multiple linear regression model

A multiple linear regression (MLR) model [30] is used to describe the mathematical relation between the LS (dependent variable) and the characteristics of Danish buildings listed in Table 1 (independent variables). Note that all independent variables are categorical; hence 22 indicator variables are used totally in the model, i.e. the total number of sub-characteristics (27) minus the number of characteristics (5). The form of the MLR model applied in this paper follows equation (1),

$$y_i = \beta_0 + \beta_{1x1,i} + \cdot \cdot \cdot + \beta_{pxp,i} + E_i, \qquad (1)$$

where y_i is the dependent variable, $x1,i..x_{p,i}$ are the independent variables, p is the number of indicator variables (i.e. p = 22), E_i are normally distributed residuals and β_0, $\beta_1..\beta_p$ are the model estimates. The indicator variables $x_{1,i}$ and $x_{2,i}$ stand for region and refurbishment, respectively, $x_{3,i} - x_{7,i}$ are the indicators for the use type, $x_{8,i} - x_{14,i}$ for the wall material/cladding and $x_{15,i} - x_{22,i}$ for the roof material. The model is cross-validated using 80 % of the data for calibration and the remaining 20 % of the data for the validation of the model.

Table 2. Examples of buildings by function.

Use type	Buildings type examples
Residential	Permanent habitation buildings, residential institutions
Commercial	Offices, warehouse, public administration
Agricultural	Farmhouses, buildings for agriculture
Recreational,	Sport/amusement facilities, religious buildings
Institutional	Hospitals, nursing homes, day-care, schools, prisons
Other use	Transport, energy plants, hotels, restaurants

3. Results

An initial analysis of the data set revealed that a considerable proportion (app. 10%) of the buildings, were demolished when their LSs reached approximatively 50 yrs.

3.1. Building LS influencing factor

Table 3 provides a summary of the descriptive statistics for the LSs of buildings in accordance with the classification presented in Table 1. Generally, low availability of data within certain subcategories will result in less reliable statistics, model and eventual LS predictions.

Table 3. Summary of descriptive statistics for the LS by characteristic. Std.= standard deviation.

Variables	Percent [%]	Mean [yrs.]	Median [yrs.]	Std. [yrs.]
Overall				
Entire data set	100	70	59	38
Region				
RH	13	60	55	27
OR	87	72	60	39
Refurbishment				
Refurbished	19	74	61	36
Not refurbished	81	69	58	38
Use type				
Residential	32	67	55	34
Commercial	55	72	63	38
Agricultural	5	103	110	46
Recreational	2	51	43	34
Institutional	1	44	41	29
Other Use	5	48	44	27
Wall material/cladding				
Brick	52	83	79	37
Wooden panelling	19	49	47	22
Light concrete	9	54	51	22
Concrete	1	44	42	21
Sheet metal	3	31	24	23
Cementitious fiber board	3	51	47	24
Timber	2	138	137	35
Undefined/Other material	10	61	49	38
Roof material				
Fiber cement (incl. asbestos)	43	71	59	38
Fiber cement (excl. asbestos)	1	68	58	36
Sheet metal	13	70	58	37
Asphalt roofing	8	71	60	39
Clay/brick tiles	6	71	60	38
Cement stone	5	69	58	38
Build up	3	69	59	37
Thatched roof	2	70	59	39
Undefined/Other Material	20	69	57	38

The statistical analysis of the buildings grouped by region revealed that RH was different from OR with a mean LS of 60 and 72 yrs. respectively. For the refurbished buildings, the average LSs before and after refurbishment were calculated to 39 and 35 yrs., respectively (see Table 3). The LS of buildings grouped by use type also reveals noticeable differences, with variations from 44 to 103 yrs. Agricultural buildings appear to stand out with the highest mean LS, while the lowest mean is found in the institutional building group. Regarding the results grouped by building materials/wall claddings in Table 3, the mean LS in the wall material/cladding group varies significantly, from 31 yrs. (sheet metal) to 138 yrs. (timber). It is observed that all roof materials have almost the same median and mean LS, highlighting that the building LS does not depend on the roof material. The fact that less variation is observed among different roof materials compared to wall materials/claddings aligns well with the observations made by [31].

3.2. Regression analysis

Initial results of the MLR analysis revealed that roof materials are not statistically significant and indicator variables relating to the roof material (i.e. $x_{15,i} - x_{22,i}$) were hence excluded using backward elimination. A new trimmed MLR model excluding roof materials was derived. The regression model results are presented in Table 4.

Table 4. Results of multiple regression analysis for LS.

Variables	Estimate [yrs.]	Std. [yrs.]
Intercept	156.5	1.86
Region		
RH	-5.8	0.75
Refurbishment		
Refurbished	5.4	0.64
Use type		
Residential	-22.9	1.18
Commercial	-22.3	1.11
Recreational	-35.1	2.30
Institutional	-43.5	2.66
Other Use	-38.4	1.55
Wall material/cladding		
Brick	-52.0	1.63
Wooden paneling	-82.5	1.69
Light concrete	-79.9	1.80
Concrete	-86.9	2.69
Sheet metal	-102.5	2.18
Cementitious fiber board	81.0	2.19
Undefined/Other material	-72.3	1.78
Number of observations		16800
Root mean squared error		31.8
R-squared		0.296
Adjusted R-squared		0.295

Correlation analysis among the included parameters revealed low dependency. The weak interrelationship among the variables reveals that these are not linearly dependent, meaning the variables can be combined in MLR regression model types. It is also observed that wall material/cladding is the only independent variable related moderately to LS, followed by the fairly weak correlation with use type. The fact that the adjusted R-squared value does not decrease when the roof material is excluded, indicates that the inclusion of this characteristic did not improve the model. The intercept estimate presents a default value, or rather the estimated LS of an arbitrarily chosen reference building in the dataset, here a non-refurbished, agricultural building with timber walls, located in OR. Concerning the interpretation of the estimates in Table 4, the estimate for RH means e.g. that the LS is reduced by 5.8 yrs. (negative sign), if the building is located in RH, while the estimate for refurbishment implies that the LS is increased by 5.4 yrs. The same approach can be applied for the remaining estimates of use types and wall materials/claddings, as well as combinations hereof.

4. Discussion

4.1. SL vs. LS

The data used to derive a MLR model capable of quantifying the TS of a building LCA, compile almost all larger buildings in Denmark and are representative for the time in between a building is reported complete and being demolished – here referred to as the building LS. This timeframe is different from the timeframe delimiting the RSP, SL (see section 1.1) and the TS of a building LCA (see Fig.1). We estimate that the timeframe a building can provide the service it is intended for, most frequently is (noticeable) longer than the SL, (slightly) longer than the RSP and shorter than the LS as previously defined (see also Fig. 1). We also approximate, that the timeframe a building can provide the service it is intended for (i.e. TS), most often is much closer to the RSP and LS than the SL. This is because buildings being demolished only rarely meet or exceed the building performance requirements, and since buildings rarely are allowed to remain unused for longer times due to high price of land in Denmark – meaning that buildings being demolished most often only recently have stopped providing the service they were intended to provide. The reason why buildings are demolished are numerous and rarely recorded. The exact reason why the buildings compiled in our data set have been demolished is not covered by the BBR data compilation procedure, which clearly affects the overall validity and applicability of our model.

A critical issue with the LS quantification approach presented here, is that the data used for quantifying the LS are representative only for buildings that have been demolished in a rather narrow time window and not for buildings still standing. Application of data on demolished buildings for quantification of buildings' service lives is however acknowledged in the scientific literature [14]. Demolished buildings have, contrary to standing buildings, a discrete (i.e. the life cycle is completed) LS and thus suited for a calibration model. Applying the LSs of standing buildings will yield a dynamic TS modelling approach, which will need frequent updates (i.e. app. every 5-10 yrs.). Application of dynamically evolving models for LCA has however proven difficult within the building sector due to the potential of non-static assessment and certification results, i.e. results of an LCA may change and certified buildings may lose their certification due to updates of models used in the certification. The ideal TS model should integrate data on demolished as well as buildings still standing. Data on buildings still standing, are in DK due to legal constraints, only available with a rather coarse resolution (see [28]) lacking information on building location and materials.

4.2. Fixed TS vs. model based quantification of TSs

The average SL/RSP/LS of Danish buildings can be estimated, relying on three simple approaches not taking building location, use and building materials into consideration; a 70 yrs. LS obtained in the present study, the DGNB primary 50-year SL setting [27] and the 100-year functional SL calculated by SBi [28]. It is obvious that these estimated average TSs varies significantly. The main reasons for this variation may arise from the different estimation methods and data sets used to obtain these values. Furthermore, the three TS estimates reflect different purposes for which the values are intended to be used, e.g. for certification purposes the DGNB SL is proposed [27] while for general building design optimization the SBi SL [28] is proposed.

Statistical analysis of our data set yielded a mean building LS in Denmark of 70 yrs. (see Table 3), which means that the average SL in our data set is app. 40% higher than the 50-year SL approach recommended by [27]. Table 5 presents the average errors of the different estimation approaches relative to the total sampled buildings' LSs

Table 5. Average errors (in yrs.) of SL/LS estimation for calibration and validation data sets. Calibration set = 80 % of data set and the Validation set = 20 % of the data set. * - values obtained from analysis of our data set.

TS quantification method	Calibration set (80% of data)	Validation set (20% of data)
Const. SL of 50 yrs. [27]	30.9	28.2
Avg. LS of 70 yrs.*	30.9	30.0
LS - MLR model estimate*	24.7	23.3

4.3. Influencing factors

Region: The regression analysis revealed that the building location has significant influence on the LS. Being able to quantify this influence in sustainability assessments is a new concept. TS models facilitate precise quantification of the spatial scope of an LCA. In literature, sustainability assessments relying on modelling approaches for defining the TS of building LCAs and LCAs in general are rarely reported.

Refurbishment: The LS of refurbished buildings on average increases by (only) app. 7% compared to non-refurbished buildings (see Table 3). The BBR mainly includes refurbishments increasing the build-up area, although details of the refurbishments are not part of a single building's record, yielding it impossible to asses which types of refurbishments extend the building LSs the most.

Use type: In addition to the estimations of the functional service lives provided by SBi, the National Statistical Institute of Denmark (Danmarks Statistik) in 2012 released a database (StatBank Denmark) containing the existing building stock by their function/use type (see [29]). It is relevant to notice that the mean values calculated for our data set of demolished buildings match the StatBank means better than the SBi means (see Table 6) thereby supporting the validation of our MLR model.

Wall material/cladding: The last significant building characteristic is the wall material/cladding. Table 4 indicates (surprisingly) that buildings with wood and concrete walls have close to similar LSs within the same use groups and for similar locations. This is most likely caused by different factors: wooden houses degrade while concrete buildings often have a rather unappealing architecture, both factors taking their toll on the LS. It is also obvious from the data presented, that buildings with cementitious fiber board walls are the longest lasting buildings. This observation is most likely caused by uncertainties introduced to the model due to few data records on buildings with cementitious fiber board walls.

Table 6. Mean LSs (in yrs.) by *Use type* according to three different approaches. Calculated mean are representative for our data set. StatBank and SBi data from [29].

Buidling use type	Calculated mean	StatBank means	SBi means
Residential	67	63	120
Commercial	72	39	80
Agricultural	103	52	120
Recreational	51	39	60–120
Institutional	44	55	100

4.4. Limitations and future prospects

A limitation of the model proposed here, is that no information on the reason for demolishment is provided by BBR. The reasons for building demolishment are nevertheless numerous. In addition, the fact that refurbishments of a building is covered by the data set, the extent hereof remains unknown. In addition, the data set only contains limited information on building energy consumption.

5. Conclusion

In order to assess the EP of buildings, an accurate estimation of buildings' LS is essential. In this paper, different approaches used for assessing buildings' LSs and for quantification hereof are evaluated and derived. The considerable variation of the LS of buildings indicate that the hypothesis of a single default LS for all building types is ill suited for LCA. The use of the average 70-year LS derived from our data set does not necessarily improve the accuracy of the LS estimation in comparison to a default 50-year LS. Including various determining factors, more advanced statistical models (i.e. more advanced than MLR applied in this study) to estimate more accurate LSs, can help reducing uncertainty of sustainability assessments of buildings.

The statistical analysis presented in this paper demonstrated that factors such as location (i.e. region), refurbishment, use type and building materials (i.e. wall materials) potentially could (i.e. considering the (very) low R-squared presented in Table 4) be significant variables in relation to quantification of the TS of building LCAs.

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