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# How important are realistic building lifespan assumptions for material stock and demolition waste accounts?

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ABSTRACT

Accurate assessments of construction materials stocked in the built environment have received increased attention in the Industrial Ecology literature over the past few years. Many recent models that estimate building material inflows, stock accumulation and end-of-life waste, however, rely on simplistic assumptions about the lifespan of built infrastructure. While several probability distributions have been proposed (normal, Weibull, log-normal, and so on) there is no agreement on which model is best suited for modelling the accumulation of building material stock at urban and national levels. In this study we introduce an analysis of the hazard rate of buildings and discuss alternative distribution functions to model lifespan, testing the fit of five commonly used distributions to real data from the cities of Nagoya (Japan), Wakayama (Japan), and Salford (UK). The results highlight how cities with fast replacement rates are overall best modelled by right-skewed distributions, but single cohort levels express independent behaviours based on their characteristics. We investigate the sensitivity of a top-down stock accumulation model to the choice of different distributions and input parameters uncertainties. The results show that different lifespan distribution functions result in very similar overall stock accumulation at the national level, but have large impacts on calculated demolition waste flows. Differences are more pronounced for cities and the choice of a certain distribution will significantly affect the calculation of the average lifetime. Our results suggest that top-down national material stock accounts have high reliability, and are only weakly affected by the choice of one distribution over another. For cities, it is beneficial to use a distribution based on the characteristics of the buildings analysed, with regard to density and building characteristics. Stock accumulation research would profit from future bottom-up research into building lifespans to validate top-down estimation procedures.



## 1. Introduction

Studies of material throughput have become a common feature of the Industrial Ecology literature over the past two decades (Adriaanse et al., 1997; Matthews et al., 2000; Fischer-Kowalski et al., 2011). Some materials, such as biomass or fossil fuels, are usually quickly consumed, and rapidly leave the economic sphere in the form of waste and emissions, while others stay within the economy for much longer periods. Of those, construction minerals are probably the materials which have the longest use phase and lifespan. A recent study by Haas and colleagues showed that over 99% of the 24 Gt of construction materials that entered the economy in 2005 ended as material stock (Haas et al., 2015). In recent years an increasing number of studies have attempted to calculate stocks of several key materials at different levels adopting different methodologies (for an extensive review see Müller et al., 2014; Tanikawa et al., 2015). Accounting for accumulated material stock through this approach is apparently trivial: inflows + domestic extraction − outflows + a number of correction factors[1] = net addition to stock. It is then sufficient to repeat this “simple” equation for a sufficiently long time series to calculate total (in-use) material stock. Nevertheless, despite its apparent simplicity, solving this formula is far from trivial. Robust and reliable data for outflows from the con-

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[1] With “a number of correction factors” we intend all those operations needed to ensure a material mass balance, since often statistical yearbooks are affected by inconsistencies and imprecisions.

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struction sector, i.e. construction demolition waste data, is hard to come by (Thomsen and van der Flier, 2009). In rare cases, demolition data is collected at the national level, allowing for analysis of trends and the spatial distribution of demolitions for the whole country (Huuhka and Lahdensivu, 2016). In other cases, researchers have managed to extrapolate detailed data of construction and demolition activities at the city level (Aksözen et al., 2016b). A possible strategy to overcome data limitation is creating models which simulate waste outflows, but this obviously poses new challenges in terms of data requirements, and modelling assumptions and limitations. It is generally agreed that a better understanding of the dynamics that characterise the construction and demolition of buildings is a necessary step towards a more sustainable built environment (e.g. Aksözen et al., 2016a; Allen and Hinks, 1996; Thomsen and van der Flier, 2009; Thuvander et al., 2015)

Tanikawa and colleagues identified four different approaches to material stock accounting, including bottom-up accounts, top-down accounts, demand-driven accounts, and accounts based on remote sensing technologies (Tanikawa et al., 2015). Each of these methodologies has its own strengths and weaknesses. Bottom-up accounting relies on item inventories and materials intensities (e.g. Wiedenhofer et al., 2015). At times this information is supported by spatial maps, making the stock geographically explicit, but involves a very time-consuming compilation process (e.g. Lichtensteiger and Baccini, 2008; Tanikawa et al., 2015; Tanikawa and Hashimoto, 2009). The top-down method looks at the stocks using inflow statistical data and imposing a lifetime distribution on the depreciation of stock. While this method is relatively quick to compile it loses information on the spatial distribution of the stock and relies on the goodness of the chosen lifetime distribution and parameters (e.g. Fishman et al., 2014; Hashimoto et al., 2007; Hatayama et al., 2010). Demand-driven accounts use a series of parameters such as population, average household size and material intensity to derive inflows, stock, and outflows of materials (e.g. Müller, 2006; Pauliuk et al., 2013; Vásquez et al., 2016). Remote sensing accounting uses satellite images to investigate stock levels and, despite not reaching the popularity of other methods – mainly due to the lack of validation of the accounts against independent data, could be the only viable option for countries where material flow statistics and detailed maps are not available (e.g. Liang et al., 2014; Rauch, 2009; Yoshida et al., 2016). Among these four methodologies, two depend on lifespan assumptions: the top-down approach, and the demand-driven approach.

Most stock accounts available in the scholarly literature have used top-down and demand driven approaches, and relied on assumptions regarding lifespan distribution to model demolition outflows in some way. Müller and colleagues identified that dynamic material flow analysis used to account for metal flows and stocks mainly relied on the Dirac delta distribution and the Weibull distribution (Müller et al., 2014). Accounts of construction material stocks relied mainly on the normal distribution (e.g. Fishman et al., 2014; Müller, 2006) and Weibull distribution (e.g. Cai et al., 2015; Sandberg et al., 2014).

The main issue, common to all the approaches which rely on lifespan data, is that, up to today, a proper cohort-based dataset is yet to be available, especially for non-residential buildings and infrastructure. A comprehensive comparison of the effect of different distribution functions on stock accounts is yet to be done and is the main aim of this research. We ask:

- How does the choice of a specific lifespan distribution affect the stock account?
- How does this choice influence the forecast of demolition waste?
- Can we identify a demolition probability distribution function that better fits the lifetime of buildings in the real world?

To answer these questions, we first present a theoretical discussion on modelling lifespan distribution, starting from the concept of hazard rate and how this applies to buildings. We then discuss the limitations of some popular probability distribution functions that have commonly been used in lifespan modelling. We demonstrate how the choice of different lifespan distributions and parameters affects the material stock account and waste flow account in a case study of building stock in Japan and the United States. Finally, we test the sensitivity of our results by changing the lifespan distribution parameters to identify those parameters that most affect the results.

## 2. Calculating building lifespan of real world data

A widespread interest in lifespan analysis arose during the 1970s, when several fields, including engineering, electronic component manufacturing, medicine, and insurance, gained interest in the systematic and scientific analysis of the mortality of particular artefacts, products and people. From the 1980s specific software, such as SAS (SAS Institute) and S-Plus (Statistical Sciences Inc., now TIBCO Software Inc.), became available to study lifetime data. The research field of survival analysis emerged quickly after that.

With lifespan, or lifetime, in its broadest sense, we indicate the period that elapses between two events: from birth to death of a living being, from the production of an engine till its failure, from the construction of a building till its demolition, or even from university graduation till first employment. While common sense suggests that lifespan is something that measures cradle-to-grave intervals, its meaning in the context of survival analysis is much broader.

The lifespan of a single building can be calculated as the difference between the year of its construction and the year of its demolition, whether deliberate or caused by a natural disaster. For objects such as buildings and infrastructure the number of years has been chosen as a convenient unit of time, on the one hand because it is often impossible to retrieve more detailed information (month and day of completion and demolition are usually non-reported, or not disclosed), and on the other because these types of objects have lifespans in the order of decades – sometime centuries – and accounts in months or days would be redundant.

This section will not explain in detail all the methods available to model lifespan. Readers interested in survival analysis will find plenty of literature available (e.g. Lawless, 2011), but we will limit it to the explanation of the concept of hazard rate. This will be followed by the analysis of lifespan distribution models and relative hazard rate, as widely used and suggested in the literature.

### 2.1. Hazard rate

The hazard rate, or hazard function, is a mathematical expression that indicates the instantaneous rate of death of a unit of interest at a given time $t$; formally it is defined as:

$$h(t) = \lambda = \lim_{\Delta t \to 0} \frac{Pr(t \leq T \leq t + \Delta t | T \geq t)}{\Delta t} \tag{1}$$

Reminding that $\Pr(A|B)$ is the probability of A under the condition B, the previous equation indicates the probability of the event $T$ happening in the interval between $t$ and $t+\Delta t$, given that $T$ did not happen before $t$, divided by $\Delta t$. The normalisation by $\Delta t$ is important since it makes two hazard rates comparable even if they have been calculated using two different time intervals. It is important to point out that the hazard rate function is not a probability distribution, and that its unit of measure is time$^{-1}$.

An alternative way of expressing the hazard rate is:

$$h(t) = \lambda = \frac{f(t)}{S(t)} = \frac{f(t)}{1 - F(t)} \tag{2}$$