Developing a generic System Dynamics model for building stock transformation towards energy efficiency and low-carbon development

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Keywords building stock; System Dynamics; disaggregation; aging chain; energy retrofit

JEL Classification C6, O18, Q4

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1 Introduction

The construction, operation and maintenance of buildings collectively are responsible for 36% of global final energy consumption and 39% of total direct and indirect energy-related CO_2 emissions in 2017 (Global Alliance for Buildings and Construction, 2018). Energy demand from buildings is expected to continue to rise. The main driving factors include a growing population, improved access to energy in emerging economies and developing countries, greater ownership and usage of energy-consuming equipment and devices, and rapid growth in the floor area of buildings. Operational emissions from buildings in 2018 reached a record high of 9.6 gigatonnes of CO_2 as a result of the demand for building energy services growing at a faster pace than the decarbonisation of power generation for consumption of electricity and commercial heat (IEA, 2019b).

There exist enormous opportunities for energy savings and emission reductions from the operation of buildings, many of which are immediately available, highly cost-effective and often associated with significant co-benefits (IPCC, 2014; World Bank, 2014; IEA and IPEEC, 2015). Globally, widespread deployment of the best available technologies and effective implementation of energy efficiency policies have the potential to yield annual savings of approximately 53 EJ by 2050 in the final energy consumption of buildings (IEA and IPEEC, 2015). This equates to a 29% reduction in projected building energy consumption relative to the business-as-usual scenario in 2050, a level equivalent to the sum of building energy consumption in China, France, Germany, Russia, UK and US in 2012 (IEA, 2015), or nearly three-quarters of global electricity demand in 2014 (IEA, 2015, 2016, 2017; IEA and IPEEC, 2015).

However, the progress towards energy savings and emission reductions in buildings achieved by the international community so far has been limited and inadequate (Global Alliance for Buildings and Construction, 2019). This has resulted in the building sector being listed as well "off-track" of the pathway required to achieve the IEA's Sustainable Development Scenario (SDS) and the goal of the Paris Agreement (IEA, 2019a). While energy use per unit floor area in buildings has been falling, the annual rate of reduction has actually been slowing over the last few years, from around 2% in 2015 to around 0.6% in 2018. Such rates of improvement are far from being sufficient to offset the annual increase in global building floor area, which between 2017 and 2018 was 2.5% (IEA, 2019b). To bring buildings "on track" with the SDS, the annual rate of building energy intensity reduction globally would therefore need to increase to at least 2.5%. Achieving this high-level target suggests a pressing need for expansion, strengthening and enforcement of mandatory building energy codes and standards, accelerated and scaled-up adoption of advanced technologies and best practices in new construction and retrofits, and enhanced access to finance to leverage more investments in sustainable buildings in the market. All these actions call for strong commitments from governments and specific policy measures that are well designed and effectively implemented.

Ex-ante evaluation is an integral part of designing policies relating to energy savings and emission reductions in major energy end-use sectors such as buildings and construction sector. Modelling plays a key role in the evaluation process by allowing for the investigation of the trajectories of energy and emissions and enabling experimentation with potential policy interventions, therefore exploring possible pathways towards transformation to a highly energy efficient and low-carbon buildings and construction sector. There are a range of modelling paradigms applicable to model building stock performance and analyse energy saving and carbon emission reduction potential, either from a top-down perspective or a bottom-up perspective. This paper focuses specifically on one particular methodology, System Dynamics, which has been used in multiple settings. System Dynamics is a powerful modelling approach to policy design and analysis, featuring a capacity to model and investigate dynamic complexities arising from the model structures, causal relationships, feedback loops, non-linearities and time lags of the system in question (Sterman, 2000; Richardson, 2001; Shepherd and Emberger, 2010; Kelly *et al.*, 2013). Its emphasis on stock-and-flow dynamic relationships makes System Dynamics particularly well placed for use as a tool to model building stock energy and carbon performance. In turn, this performance is determined by stock turnover dynamics, increased energy demand due to incoming new buildings that are energy efficient, decreased energy demand due to removal of inefficient old buildings, and gains in energy savings through energy retrofits involving building envelopes and systems. The use of System Dynamics in buildings-related studies has been gradually increasing in recent years. Up until 2010, just two studies have been identified, which focused on qualitative causal loop diagrams and decision-making relating to buildings and construction (Groesser, Ulli-Beer and Mojtahedzadeh, 2006; Groesser and Bruppacher, 2007). Since 2010, there have been a number of models developed to carry out national-level building stock energy analysis (Müller and Ulli-Beer, 2010, 2012; Schmidt, Jäger and Karl, 2012; Yücel, 2013; Onat, Egilmez and Tatari, 2014; Fazeli and Davidsdottir, 2015, 2017; Kleemann, 2016; Nachtrieb *et al.*, 2017). There are also a few studies applying System Dynamics to model building physics at a detailed level (Xing, Lannon and Eames, 2013; Motawa and Oladokun, 2015). This paper aims to present a detailed critique of the fundamental structural and behavioural characteristics of existing System Dynamics models focusing specifically on building stock dynamics and energy performance. It then develops an improved model with high transparency enabling reproducibility and improvements, great flexibility for structural and functional extensions, and high generality and adaptability for applications in a wide variety of built environment contexts.

The rest of this paper is organised as follows. Section 2 reviews existing System Dynamics based models for building stock and energy use and identifies and analyses some common structural and behavioural features that lead to unrealistic results. Section 3 then describes the proposed new model in detail and explains how it contributes to addressing the methodological limitations of previous models, while Section 4 summarises and concludes the paper.

2 A review of System Dynamics models for the building sector

Energy models can be broadly grouped into two categories, "top-down" and "bottom-up" (van Vuuren *et al.*, 2009; Herbst *et al.*, 2012; Scrieciu, Rezai and Mechler, 2013; Hall and Buckley, 2016). Energy models for buildings, a major energy end use sector, can be similarly categorised (Swan and Ugursal, 2009; Kavgic *et al.*, 2010; Fazeli and Davidsdottir, 2017). Top-down building energy models treat the target building stock (such as the residential sector of a country or city) as an energy sink, without differentiating between individual end-uses. Using historical aggregated data on building energy consumption, top-down building energy models regress the energy consumption of building stock as a function of high-level demographic, macroeconomic, and climate related variables. Energy consumption can therefore be attributed to the characteristics of the entire building stock. This makes top-down models generally well positioned to conduct long-term energy demand and supply analysis, but not in the presence of discontinuities, such as paradigm shifts of the target building stock, energy-related technological advances or breakthroughs, etc (Swan and Ugursal, 2009; Hall and Buckley, 2016). Bottom-up building energy models, by contrast, are based on detailed samples of individual buildings instead of the entire building stock. Estimated energy consumption of samples of buildings is then extrapolated to represent the building stock, based on weights that reflect the representativeness of the samples. Bottom-up building energy models can be broadly divided into two subcategories, namely, statistical methods and engineering methods. Statistical methods utilise data from energy bills and surveys of a sample of buildings to establish statistical relationships between energy consumption and a range of potential explanatory variables through regression. A notable advantage of statistical methods is the ability to discern the effect of occupant behaviour, which can vary significantly. Engineering methods, on the other hand, explicitly calculate energy consumption of end-uses based on detailed descriptions of the sampled buildings' properties, such as geometry and envelope, and the energy end uses' characteristics such as capacity ratings and use patterns of equipment and appliances, indoor temperatures, etc. Such a high level of detail, as well as a high degree of flexibility, enable engineering methods to model technological options and the impacts of new technologies which have no historical consumption data (Swan and Ugursal, 2009; Kavgic *et al.*, 2010; Lopes, Antunes and Martins, 2012; Wilson *et al.*, 2016).

A more detailed discussion of top-down and bottom-up building energy models is beyond the scope of this paper. It is, however, useful to highlight that, according to the IPCC AR5 (Lucon *et al.*, 2014), top-down/integrated models and bottom-up/sectoral models do not fully agree with regard to the extent of the mitigation potential of buildings and the key mitigation strategies. Top-down models place a greater focus on energy supply-side measures for decarbonisation (e.g. fuel switching) than on final energy use reduction opportunities in buildings. By contrast, bottom-up models emphasise the reduction of energy demand for both primary fuels and electricity through technologies for energy efficiency improvement, which is supplemented by further measures such as the shift towards low or zero carbon electricity.

This paper focuses specifically on building energy models developed using System Dynamics. While usually addressing regional or national building stocks, due to the common approach of extrapolating the energy use of a representative set of buildings to the total energy use of regional or national building stock and not quantitatively involving the interrelations between building sector energy use and economic variables such as economic growth, income, fuel prices and so on, these existing System Dynamics based models for building sector energy use may be classified as bottom-up models (Swan and Ugursal, 2009; Kavgic *et al.*, 2010; Fazeli and Davidsdottir, 2017).

Previous such System Dynamics based building energy models have been applied in various national or regional contexts. One such model was developed by Müller and Ulli-Beer (2010) to analyse the transformation of Switzerland's stock of residential buildings towards high energy efficiency. The same model was also used by the authors as part of a larger model to explore how the market, technology, civil society and the state govern the diffusion dynamics of energy efficiency retrofits and the carbon emissions of building stock in Switzerland (Müller and Ulli-Beer, 2012). With a high level of aggregation, the model defines buildings in the stock as being in one of three conditions, new, good or bad. Over time, buildings move from being in a new condition to a good condition and later from a good condition to a bad condition. The shifts are modelled as first-order delays, with the assumptions that new buildings remain ‘new’ for 10 years on average, buildings in a good condition remain ‘good’ for 30 years on average, and buildings in a bad condition remain ‘bad’ and are not retrofitted, for 15 years on average. They used first-order delay in order to take account of variations in building-specific situations. However, mathematically this results in unrealistic extremities where some buildings move from new to bad condition in just a few years, while some other buildings remain in new or good condition for very long periods. Meanwhile, the model does not consider the removal of buildings, despite the high share of buildings in a bad condition in the total stock. This implies a very long building lifetime which is not further discussed in the study. The model further assumes that buildings in a bad condition are either retrofitted to reach the energy efficiency level of buildings in a good condition, or are reconstructed to become buildings in a new condition. The use of first-order delays for retrofit or reconstruction, together with the first-order delays used for the building aging process create a closed loop, which results in unrealistic scenarios where a new building can become old, get retrofitted and return again to a bad condition, within a very short timeframe, and unrealistically keep going through such cycles.

A similar but expanded model structure was developed by Schmidt, Jäger and Karl (2012) to study the German residential heat market in. Compared to Müller and Ulli-Beer (2010), this model applied a demolition quota to model demolition of buildings in poor condition, which reflects reality more closely. However, the same three-vintage first-order structure is used to represent the aging process of buildings. As for retrofit, buildings in a poor condition, according to a defined retrofit quota, will undergo either non-energy-related retrofit or energy-related retrofit, and subsequently be converted to buildings in good condition. Again, this retrofit dynamic is modelled using first-order delay resulting in the same problem of a potential rapid cycle of condition deterioration and retrofit as observed in the previous model. Inevitably, this has implications for the modelled heat demand of buildings and the evolution of heating systems on the supply-side, which are interlinked in their model through heating demand reduction. The three-vintage first-order structure was also used by Yücel (2013) to investigate the extent of inertia caused by the existing building stock in the Netherlands. The first stock is for newly constructed buildings for 20 years on average, the second stock for medium-stage buildings for the next 20 years of life on average, and eventually the third stock for older buildings for the rest of their lifetimes. Demolition occurs to buildings in the third stock only. As in previous cases, this three-vintage first-order setup inevitably allows unrealistically short lifetimes of some buildings in the stock – some buildings will go through the three vintages in several years and subsequently get demolished. The retrofit structure of this model is different from previous models in that there is no movement of retrofitted buildings from old to medium-aged or new buildings. Instead, each of the three vintages (new, medium and old) undergoes a quota-based energy retrofit. However, as an implicit result, some buildings may undergo a very fast aging process, be retrofitted three times, and get demolished shortly after the last retrofit. Fazeli and Davidsdottir (2015) used largely the same three-vintage first-order delay structure to model the housing stock in Denmark, and to study the impact of various policies on the energy performance of residential stock in Iceland (Fazeli and Davidsdottir, 2017). Despite their claim that their study improved the model of Yücel (2013), the energy demand of each vintage of buildings is modelled to reduce as a result of retrofit, thereby resulting inevitably in the same methodological issues as found in (Yücel, 2013), with newly constructed buildings potentially experiencing multiple rounds of retrofits over very short lifetimes.

Onat, Egilmez and Tatari (2014) studied the mid- and long-term impacts of green building related policies on the possible 2050 trajectories of GHG emissions from the residential buildings in the US. They claimed that their study was the first attempt to quantify and outline the relative importance of retrofitting compared with constructing new green buildings or net zero buildings in the US, modelling a total of 19 policy strategies. Structurally, their model has a lower degree of granularity compared with the 3-vintage models discussed above, with just two stocks: existing traditional buildings are represented by a single stock, as is the stock representing green buildings. The transformation of traditional buildings to green buildings through retrofitting is modelled through a first-order delay. Likewise, the demolition of traditional buildings is modelled as a first-order delay. This structure unavoidably makes their model subject to the same methodological problems as those discussed above. In addition, the model assumes that green buildings are never demolished, despite the fact that the model is designed to study long-term impacts.

Kleemann (2016) examined the potential self-attenuation of a residential building energy retrofit quota under various energy policy scenarios. The author developed and compared five models, including a non-dynamic model of retrofit, a simple dynamic retrofit model, a retrofit cycle model, a renovation-retrofit cycle model, and a retrofit chain model. The development from the first to the fifth model involved an increasing level of granularity of structural details, greater sophistication of logical and mathematical representations, and more plausible and less ad-hoc assumptions, which collectively lead to enhanced methodological robustness. However, similar to the other models mentioned above, there is a fundamental issue inherent in even the fifth and most elaborate version of Kleemann's models. The first-order delay mechanism used to link a stock of buildings retrofitted n times with a stock of building retrofitted n+1 times implies that there always exist buildings that can be retrofitted on a continuous basis with very short intervals between two consecutive retrofits. Clearly this is not reasonable in reality, either technically or economically.

A related issue is the way in which Kleemann's model handles the demolition of buildings. Compared to previous models, demolition is tracked on an age-specific basis, with the 'age' of a building being relative to the time elapsed since its last retrofit; this is therefore a methodological advance compared to previous models. However, it sets the annual demolition fraction of buildings, which are either unretrofitted or have been retrofitted for multiple times, as a proportion of the annual retrofit fraction, applied to the same buildings. Kleemann's justification for taking this approach is that demolition is an alternative option to retrofit that reacts to the fact that a building has an accumulated ‘retrofit potential’ (which may also therefore be a ‘demolition potential’). However, this treatment tends to correlate demolition with retrofit and consequently downplays the impact of demolition, which may play a much more significant role in situations where building turnover rate is high. In addition, Kleemann's model does not include structures or components relating directly to energy, e.g. energy demand or energy consumption of buildings, energy savings due to retrofit, etc. What is modelled is indeed simply the "status" of buildings being retrofitted.

Nachtrieb et al. (2017) presented a modelling framework for building energy consumption at national level, known as the CERC-BEE (Clean Energy Research Center – Building Energy Efficiency) Impact Model. Compared to Kleemann's model, the CERC-BEE model is a fuller framework where not only building construction and retrofit but also energy end use technology adoption are included. However, the way in which building retrofit is modelled by the CERC-BEE model is essentially the same as Kleemann's model, namely, periodic retrofit is assumed. The flow of retrofitted buildings, from the stock of buildings retrofitted x times to the stock of buildings retrofitted x+1 times, is modelled through dividing the stock of buildings retrofitted x times by a fixed time between retrofits. Since this again is a first-order delay, it does not rule out the possibility that a building retrofitted in a given year is retrofitted again in the immediately following year. Also, similar to Kleemann's model, this model assumes that buildings that remain in use for over 50 years will undergo energy retrofit five times. As the model's structure contains five cycles of retrofit, the five cascading first-order delays technically form a fifth-order delay. Hence, if t_0 is the initial year when a cohort of new buildings are constructed, the stock representing buildings having been retrofitted x times starts to build up from year t_0+x+1, implying a certain non-negligible amount of buildings will undergo energy retrofit once every year, from year t_0+1 to year t_0+x+1. For example, a portion of the new buildings that are constructed and put into use in 2019 will therefore have been retrofitted five times by 2025. Moreover, while the model uses a hazard function to model demolition, an approach more reasonable than Kleemann's method, its setup results in the same problem – some buildings will still be demolished immediately after their retrofits.

In summary, previous System Dynamics based models for stock-level building energy performance share some common structural setups and behavioural characteristics with respect to building aging dynamics and energy-related retrofits. From a methodological perspective, these are, either explicitly or implicitly, based on assumptions that appear to be questionable or implausible in the real world. The 3-vintage structure pre-defines a fixed profile of building lifetime distribution which may be significantly different from the reality. A related issue is that buildings within a vintage (a stock) are implicitly assumed to be subject to the same risk of being demolished regardless of their actual age and physical conditions. Regarding retrofit as a key measure to improve building energy efficiency, it is also unrealistic to see a building undergo multiple rounds of retrofits within a short timeframe. Similarly, retrofitting a building soon after it is built, or demolishing a building soon after it is retrofitted, makes little economic or technological sense in the real world. Although these studies have begun to address some of the stock-flow dynamics in the building sector, the identified shortcomings call into question the robustness and fidelity of the models, the resultant emergent behaviours in terms of stock dynamics and energy performance, and the subsequent analysis of policies based on these models.

From this detailed review, we conclude that although there has been substantial progress in developing a first wave of System Dynamics models of building stock energy, important research gaps remain. An improved model is needed which will better capture and model building stock and energy dynamics, which will, in turn, generate more reasonable and meaningful modelling outputs that can inform policy design and evaluation. In Section 3, we further elaborate these methodological issues and their implications and explain how they are addressed in our model.

3 Model description and discussion

This section presents an enhanced System Dynamics model for building stock turnover and the associated energy performance of buildings. It describes in detail how the model has been conceptualised and developed to address the methodological limitations of previous models as discussed above.

3.1 Level of stock disaggregation

The collective salient features of the previous building stock models can be represented using the model in Figure 1. Essentially the building stock is composed of 3 vintages (sub-stocks) representing buildings that are newly constructed and in their early stage, buildings that are relatively aged and in their medium stage, and buildings that are old and in their late stage leading to final demolition. Outflows from each sub-stock are modelled using first-order delays.

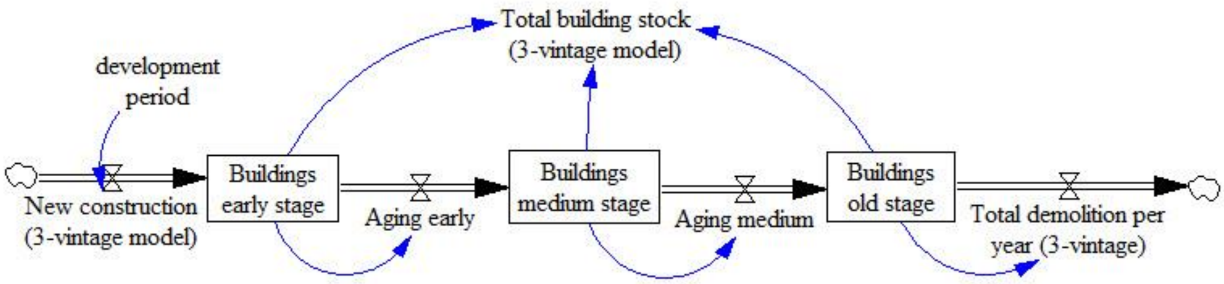

Figure 1: Commonly used 3-vintage structure in previous models

Assuming the delay time for each stage is equal, e.g. 10 years, the setup of cascading the 3 first-order delays in series creates a third-order delay. Mathematically, the final outflow representing building demolition is the convolution of the sequence of first-order delays (Fadali and Visioli, 2013). Statistically, the distribution of the final outflow is equivalent to the Erlang distribution specified by a shape parameter equal to 3 and a scale parameter equal to 10 (Forbes *et al.*, 2011). These two parameters suggest that the average lifetime of buildings in the stock is 30 years and the standard deviation is 17.3. Such a model setup implicitly pre-defines a fixed lifetime distribution of a cohort of new buildings, without considering that it is highly likely to be different from the situation in reality. Even if the delay time for each stage is not set to be identical, as with some models, the cascaded third-order delay leads to a unique pre-defined and fixed lifetime distribution. Therefore, the problem that the assumed lifetime distribution substantially differs from reality remains.

More fundamentally and critically, the first-order delay mechanism for outflow from a stock, as commonly seen in the above-mentioned models, implies perfect mixing of the individual elements in the stock (Eberlein, Thompson and Matchar, 2012). Once an individual item flows into the stock, it immediately gets mixed up with (and becomes indistinguishable from) all other items that flow into the stock at the same time and also those existing items that have already been in the stock for some time. All items in the stock have the same average residence time in the stock and therefore are subject to the same probability of exiting the stock, which is equal to the reciprocal of the average residence time, regardless of their age. The same feature is also described by statisticians as an exponential distribution having a “lack of memory” or being “memoryless”, suggesting that the hazard rate is constant and independent of time and past survival experience (Forbes *et al.*, 2011; Liu, 2012). This feature results in an undesired consequence that is referred to as “cohort blending” in some contexts. Cohort blending leads to, for example, large distortions in simulated mortality and morbidity in chronological aging processes in demographic dynamics (Eberlein and Thompson, 2013).

Analogously, in the context of building stock, perfect mixing implies that all buildings have the same chance of leaving the stock. This means, for example, as in previous three-vintage models, all buildings in the early-stage sub-stock have the same chance of moving to the medium-stage sub-stock, regardless of their actual age and physical condition. Similarly, all buildings in the late-stage sub-stock have the same chance of leaving due to physical demolition or functional disuse, regardless of their age and physical condition. In practice, it is considered highly unlikely that a newly constructed building would be equally likely to be demolished or disused as an old building that already has been in use for 50 years. Intuitively, for a given stock consisting of buildings built at different times, the probability of buildings leaving the stock would be expected to be higher for older buildings than for younger buildings, suggesting a general trend of increasing risk for buildings in the stock over time. As an equivalent way of interpreting this logic, it is unrealistic to assume that a cohort of new buildings entering a stock would be in service for exactly the same time period, say, 50 or 100 years, and then leave the stock due to demolition or disuse simultaneously. Uncertainties associated with their lifetimes within the stock shall be taken into account appropriately.

Taking account of these concerns, our model disaggregates the aging process of buildings into a chain of a series of cascading sub-stocks, each of which represents a particular age group of buildings. The fundamental mechanism is that, on the aging chain, the sub-stock *j* receives the outflow of sub-stock *j-1* as its inflow, undergoes an aging process, and subsequently sends its outflow to sub-stock *j+1*. It is necessary to explicitly model the removal of demolished/disused buildings from each sub-stock to reflect the consideration that each sub-stock of buildings is subject to its own specific hazard rate. In addition, it is also necessary to include the residence time length of buildings in each sub-stock, which is used to calculate the aging flow rate that connects two neighbouring sub-stocks. The residence time length is termed the age group duration in the model (Figure 2). Whilst it is also likely that there might be additional inflows to the sub-stocks, e.g. reinjection of retrofitted buildings, they are not illustrated here for visual succinctness, but will be discussed in detail in later sections.

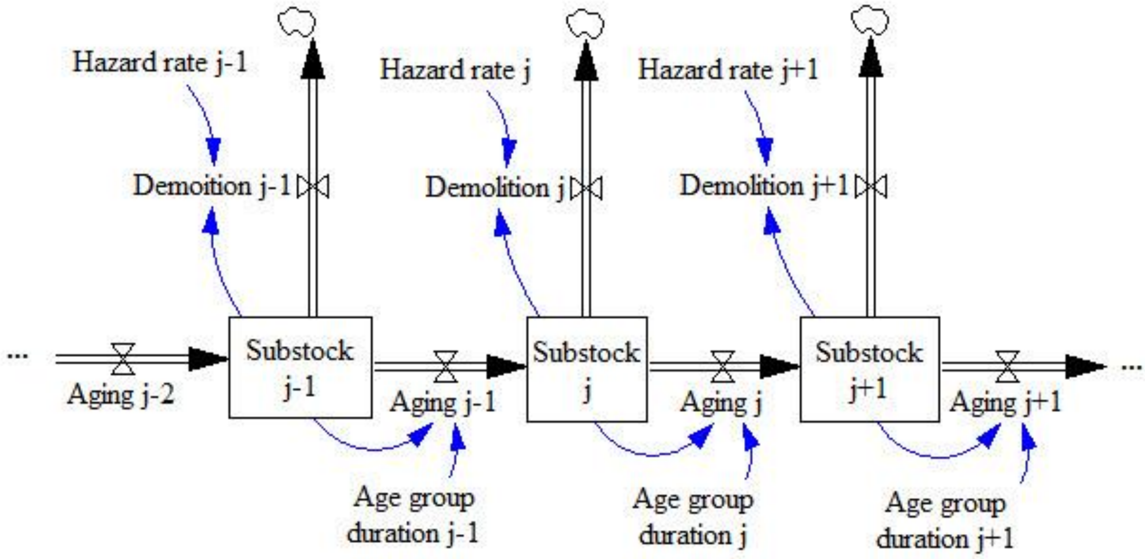

Figure 2: Aging chain with explicit modelling of sub-stock specific demolition

Key to the above aging chain structure is the extent of disaggregation. The question therefore is what the appropriate duration of each age group would be. As a sub-stock is used to group buildings in an age range, buildings within a sub-stock are considered homogenous. Therefore, the aging from this sub-stock to the next one is modelled as a first-order exponential delay process. To avoid having the undesirable perfect mixing effect, which is precisely the original purpose of applying an aging chain, the duration of each age group is set to be no longer than 1 year. Setting each age group to 1 year means that buildings do not reside in a sub-stock for longer than 1 year before shifting to the next sub-stock. Meanwhile, it would make little sense in practice to look at building age at a resolution level finer than 1 year, e.g. 1 month. Therefore, the duration of each age group is set to be 1 year. More critically, for this level of disaggregation to fully make sense, it is necessary to set the computational interval (dt), namely, the time step of the model, to be the same as the age group duration, i.e. 1 year. Technically, the computational interval could be finer than 1 year, however this would cause mixing within a sub-stock as long as the age group duration is larger than it, such as 1 year. Although the same solution can be applied to overcome the mixing issue, namely, by further disaggregating each sub-stock into 1/(computational interval) sub-stocks, this is not considered practically useful because: (a) building age and probability of being demolished/disused estimated at a resolution level finer than 1 year would not make much sense in reality; and (b) a significantly larger number of sub-stocks will be created, inevitably adding excessive details with little extra value and unnecessarily increasing model complexity and computational cost.

This setup discretises the chronological aging process. The high level of granularity offers a detailed representation of sub-stocks characterised by heterogeneity with respect to factors affecting building lifetime (and associated energy properties, once additional layers are added to the model). It therefore enables the functionality of separately tracking the discretely aging process of buildings and experimenting policy interventions targeting buildings of specific age groups. For example, given a large stock consisting of residential buildings constructed over the past 40 years, a policy-maker may want to know how buildings constructed in 2010 have been performing in terms of energy consumption from 2011 to 2019, what the building stock in 2019 looks like in terms of its composition of buildings of different ages and the corresponding energy performance, what would be the possible trajectories of stock-wide average energy intensity from 2020 to 2030 if an energy efficiency retrofit programme targeting buildings older than 20 years is implemented in 2020, and so on.

Using subscripting techniques, the model structure is then re-formulated to improve representation and analytical convenience, while keeping the same underlying concept and capacity. As shown in Figure 3, the building stock can be viewed as a stack of multiple sub-stocks that are not explicitly represented but rather implicitly included. The number of the sub-stocks can be flexibly set, depending upon the possible maximum lifetime of buildings in the context being investigated. For any given year, the total stock of buildings in use is the sum of the age-specific sub-stocks.

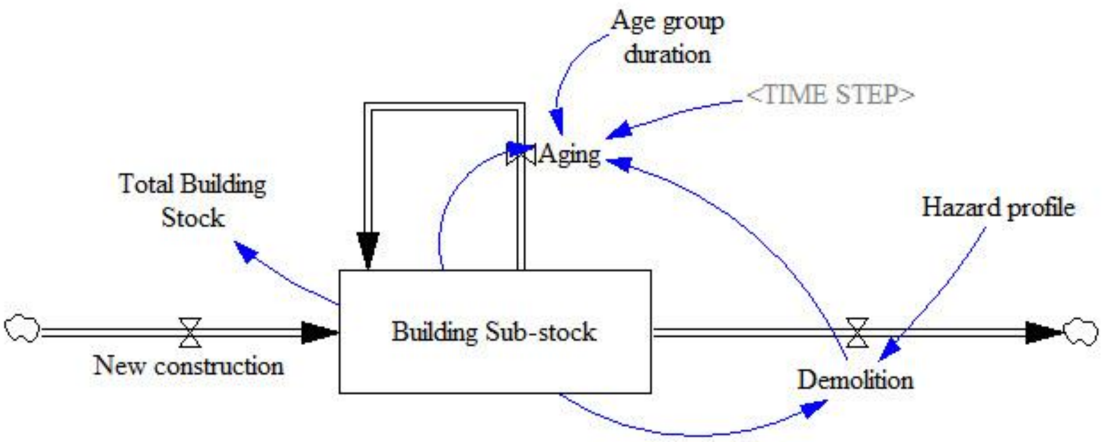

Figure 3: Reformulated aging chain structure

This model structure enables setting the age-specific risk (hazard rate) of building demolition based on available information and data, as opposed to previous models where the lifetime distribution of buildings is arbitrarily pre-defined and fixed. Introducing such flexibility in the model's functionality is significant because it allows context-specific variations to be taken into consideration. As demonstrated by Figure 4, for a given pulse input representing a cohort of new buildings put into use in 2019, the Erlang-distributed outflow of the 3-vintage model (mean 30 and standard deviation 17.3) can be moderately different from that of the disaggregated aging chain model. In the latter, the age-specific risk (hazard rate) may be derived from a certain form of building lifetime distribution with the same mean (30) and standard deviation (17.3), such as Lognormal, Weibull, etc. However, it should be noted that this is an extreme and rare scenario most in favour of the Erlang distribution derived from the 3-vintage model. The actual building lifetime distribution, which may be approximated by a Weibull, Lognormal or some other form of parametric distribution, can be significantly different from this pre-defined Erlang distribution, which consequently is a seriously distorted representation of reality. To illustrate this point, consider a much less extreme and more general scenario where the standard deviation of a Weibull or Lognormal distribution is different from that of the pre-defined distribution; in these cases, the difference in the shape of the demolition distribution as the outflow from the building stock is much more pronounced (Figure 5(a)). To further loosen the constrain by allowing a mean value different from the per-defined distribution, we obtain the most general and common scenario where the actual building lifetime distribution (approximated by a Weibull or Lognormal distribution) is significantly different from the pre-defined Erlang distribution, as shown by the difference in the shape of annual demolition in Figure 5(b). Inevitably such difference in stock aging dynamics, which can be very significant, will be propagated to stock energy performance, which in turn will have direct implications for policy analysis. As the stock size and composition are fundamental determinants of stock-level energy performance, an overly simplified model representation of lifetime distribution and aging process that deviates significantly from what is close to the reality is highly unlikely to generate reasonable modelling results and deliver insightful policy recommendations.

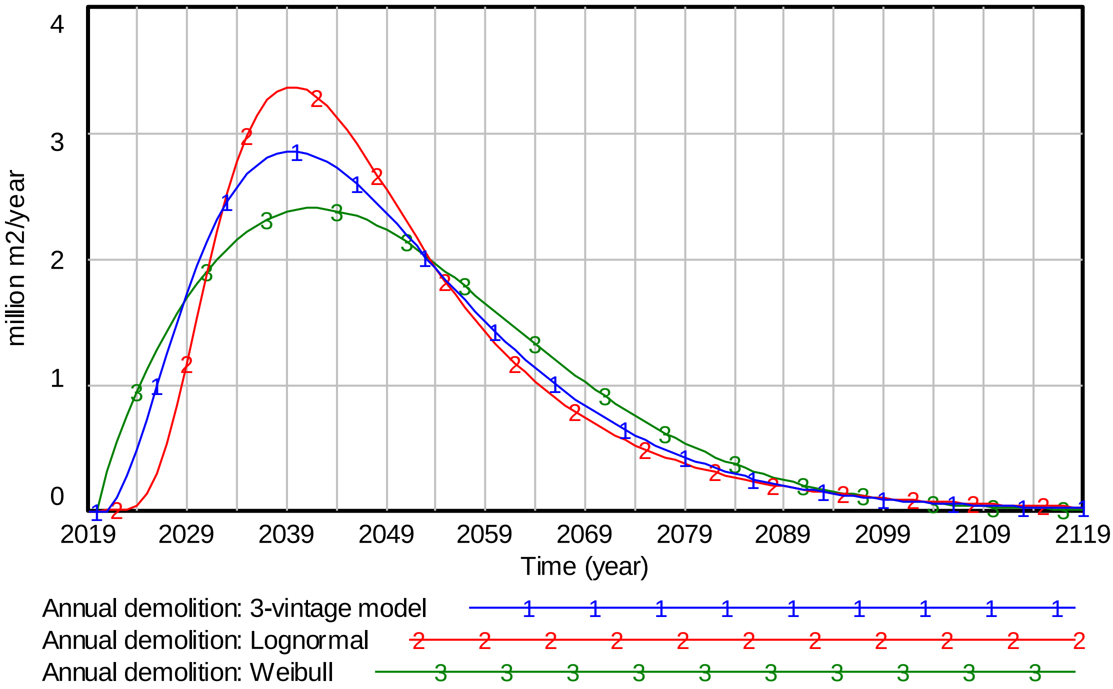

Figure 4: Comparison of outflow profile between the 3-vintage model based on an Erlang distribution and the disaggregated aging chain model based on a Lognormal or Weibull distribution of building lifetime. Same mean (30) and same standard deviation (17.3) are assumed.

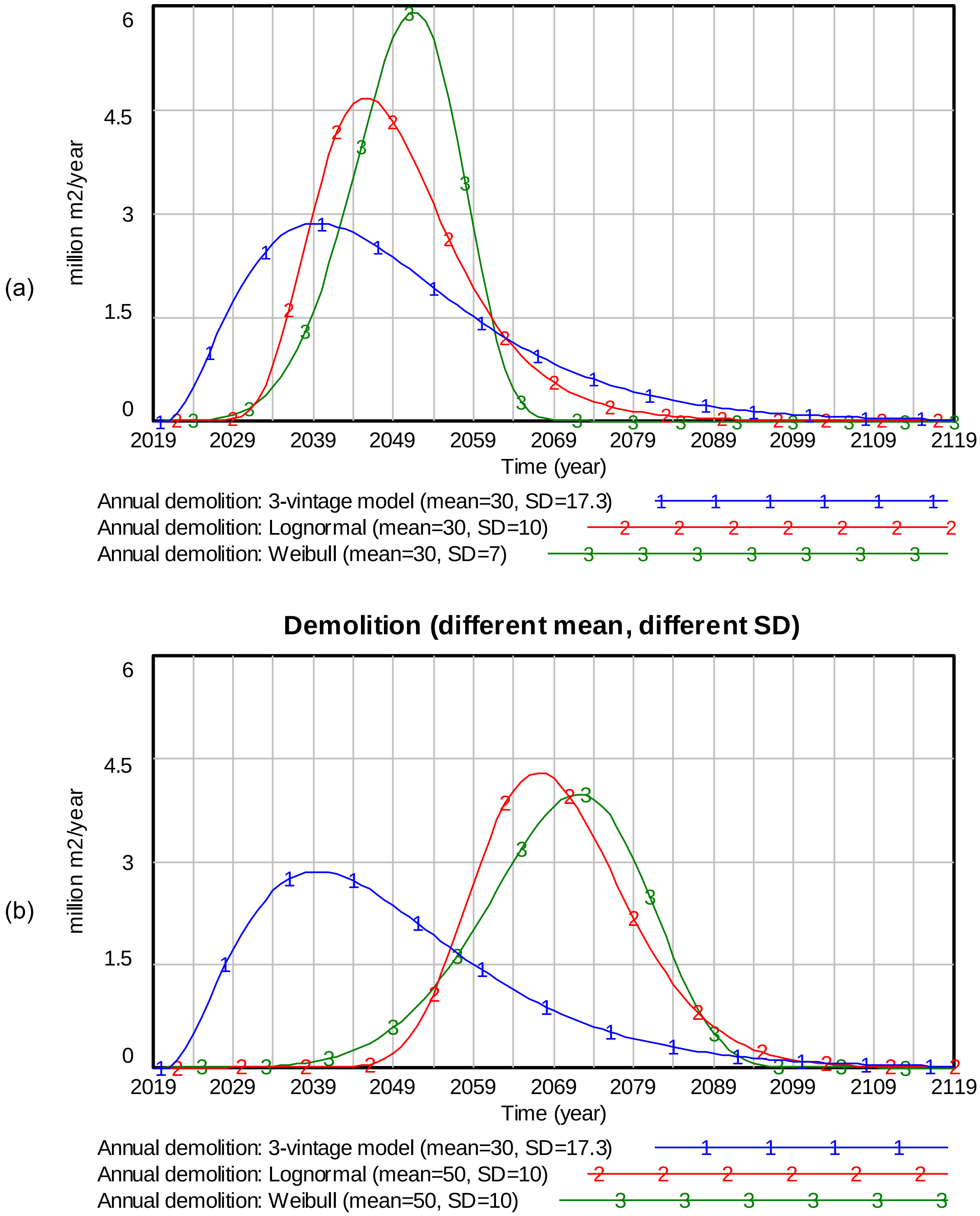

Figure 5: Comparison of outflow profile between the 3-vintage model based on an Erlang distribution and the disaggregated aging chain model based on a Lognormal or Weibull distribution of building lifetime. (a) Same mean (30) but different standard deviations; (b) different means and different standard deviations.

The outflow is determined by the age-specific hazard rate. Its shape reflects the lifetime distribution of the same cohort of buildings. Therefore, provided that sufficient empirical data on building lifetime can be obtained, such as through on-site survey targeting demolished buildings, the approximate lifetime distribution can be derived for use in the disaggregated aging chain model. Alternatively, when lifetime data is limited or unavailable, but data on annual total stock size and annual new construction is available, it is possible to calibrate the parameters specifying the lifetime distribution function, e.g. the shape and scale parameters of a Weibull distribution.

Thus, going from Figure 4 to Figure 5(a) and further to Figure 5(b), we have taken a progressive approach to illustrate the fundamental methodological limitation of those 3-vintage models and contrast it with our model, which can overcome this limitation. The highly disaggregated structure of our model enables the representation of building lifetime distribution in a significantly more realistic manner than the previous 3-vintage models. It offers the functionality of calibrating the lifetime distribution (the shape of the curve) based on empirical data, whereas the previous models do not, because they pre-defined and fixed the lifetime distribution, such as an Erlang distribution.

In summary, in comparison with the 3-vintage first-order delay structure which pre-defines and fixes building lifetime distribution, our proposed model setup provides both the high granularity and the flexibility necessary for calibrating the building lifetime distribution profile using empirical data.

3.2 Dynamics of retrofits for energy efficiency

The effect of adding new energy-efficient buildings will be limited when there is a very large stock of existing less efficient buildings, which creates inertia against stock-wide energy transition. This situation calls for energy-related retrofit of existing buildings. Depending upon the strategies taken, retrofit has the potential to significantly accelerate the process of transforming a building stock to attain a desired level of energy efficiency[5].

[5] This assumes that building operational characteristics and occupant behaviours do not vary significantly.

Energy retrofit can be explicitly modelled by adding an additional sub-stock “retrofitted building sub-stock”, auxiliary variables and related feedback loops to the original aging chain (Figure 6). The inflow to this sub-stock is the amount of buildings at various ages that undergo retrofit, which is taken out from the original building sub-stock. In the retrofitted sub-stock, buildings continue their aging process while being subject to age-specific hazard rates. They differ from buildings in the original sub-stock in terms of their energy intensity levels as the result of retrofit. The age-specific retrofit rate per year is controlled by a default retrofit profile and a retrofit accelerator functioning as a multiplier to model various policy scenarios.

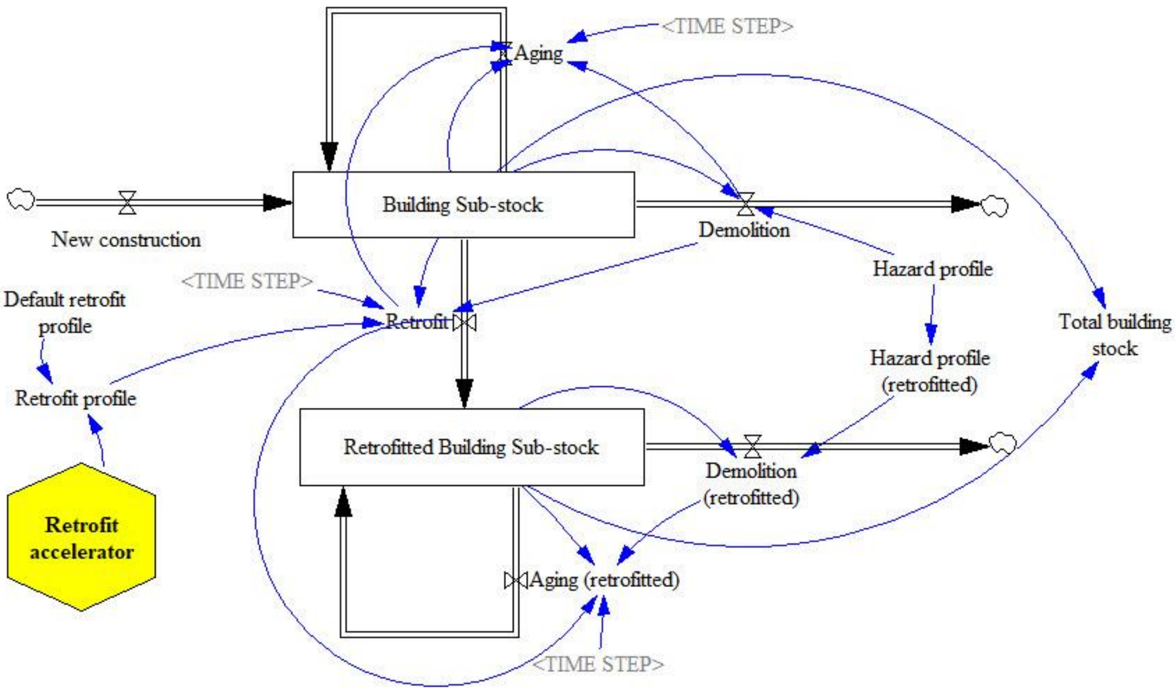

Figure 6: Interaction between main and dedicated sub-stocks of retrofit model

The energy demand reduction due to retrofit is represented by an additional outflow applied to the energy demand sub-stock of the original co-flow structure (Figure 7). This outflow is determined by the amount of retrofitted buildings and the energy intensity reduction achieved by retrofit. The latter is modelled as a percentage of the age-specific average energy intensity of existing buildings (including both retrofitted and unretrofitted buildings). The percentage is controlled by the variable “retrofit depth”, representing the extent to which the energy intensity of existing buildings will be improved through a number of possible energy-related retrofit options in this context. It is fully recognised that in reality there exist a range of energy-related retrofit activities, with considerable variability and uncertainty over the achieved energy intensity reduction. As the purpose of this study is to develop a high-level generic model, the granularity at the level of specific retrofit activities is beyond the boundary. However, the model has the capability of taking account of the retrofit depth's variability. This can be done through converting the retrofit depth from a single value (e.g. 10%) to a distributional profile, which represents the share of a certain level of retrofit depth in all practically feasible levels of retrofit depth. For example, retrofit activities realising a depth of 5% to 10% accounts for 30%, retrofit activities realising a depth of 11% to 15% accounts for 40%, and so on. Such a profile will need to be established using empirical data collected from the specific context to which this generic model will be applied. In this paper, the generic model uses a single value for retrofit depth just as an indicative value.

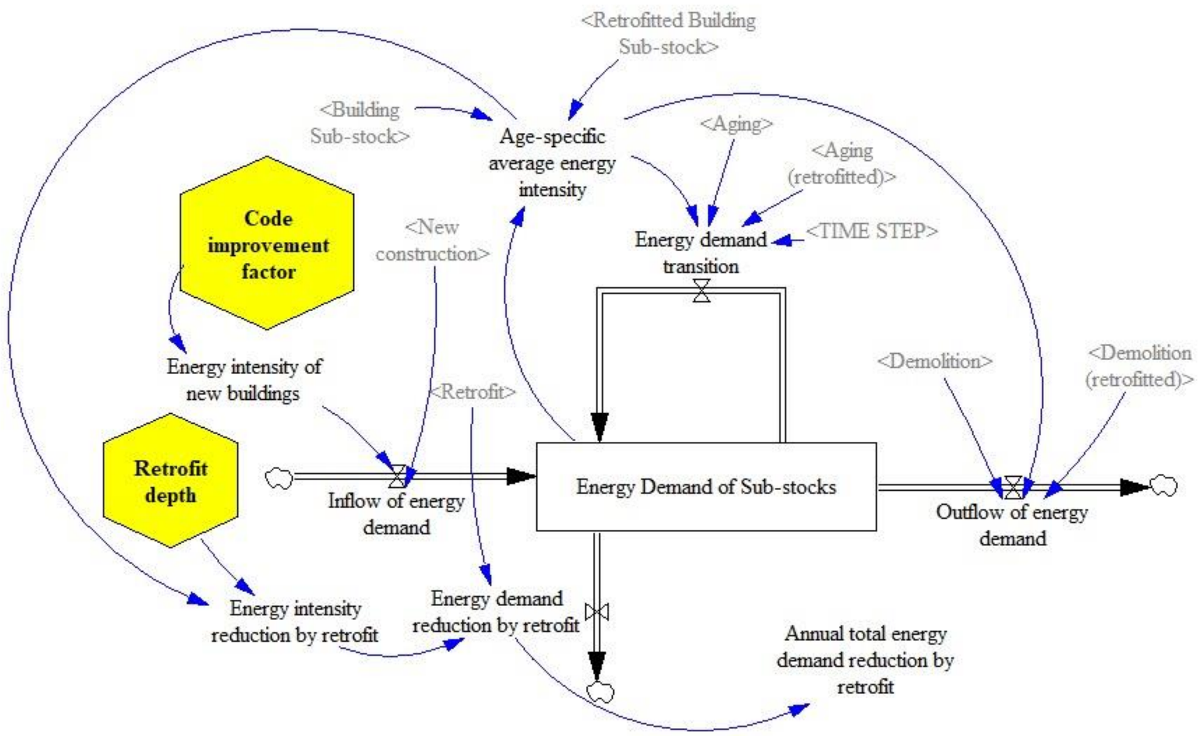

Figure 7: Dynamics of energy demand of retrofit model

So far, the model setup has assumed that a building will undergo at most one energy retrofit throughout its lifetime. The possibility that a building may be retrofitted two or more times is currently ruled out. This, however, is not necessarily consistent with real world behaviour, particularly in contexts where buildings are relatively long-lived. Sometimes for a large stock with a significant share of old buildings, strong policies may be designed and implemented to accelerate stock transformation by stimulating multiple rounds of retrofit that would not necessarily have been carried out otherwise. To accommodate the possibility of multiple retrofits, the model is now therefore extended by adding additional variables and functionalities.

Key to the multiple-retrofits model is the reinjection of retrofitted buildings back into the building sub-stock. Unlike the previous single-retrofit model, where retrofitted buildings stay in the retrofitted building sub-stock and undergo aging and demolition process, the retrofitted buildings in the multiple-retrofits model only stay in the retrofitted building sub-stock only for a certain period of time before being reinjected into the main building sub-stock, which is then a mix of non-retrofitted and retrofitted buildings. During the period in the dedicated retrofitted building sub-stock, the retrofitted buildings undergo an aging process as usual, and also continue to be subject to age-specific probabilities of being demolished/disused (Figure 8).

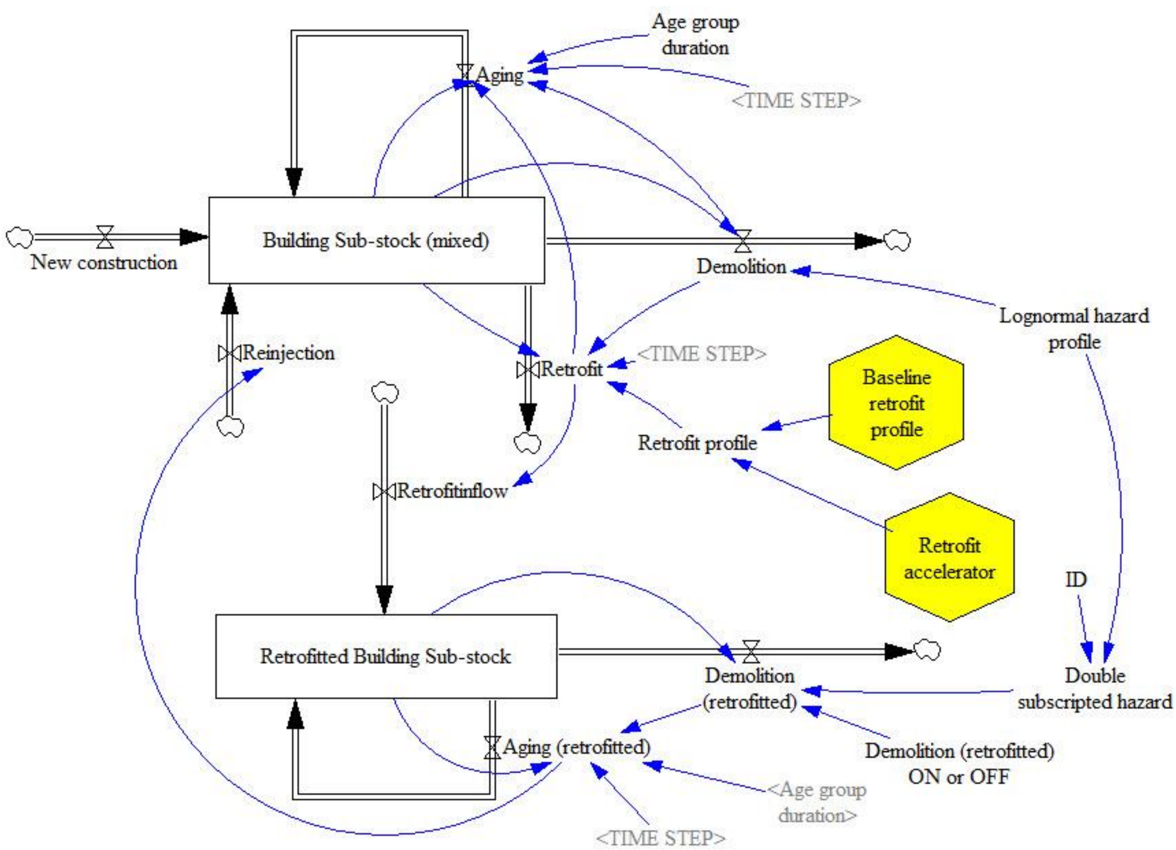

Figure 8: Interaction between main and dedicated sub-stocks of multiple-retrofits model

Here, the major purpose of having the dedicated sub-stock for retrofitted buildings is to take into account the fact that a newly retrofitted building is highly unlikely to be retrofitted for the same purpose again in the short term. This overcomes the issue of too-early retrofits found in previous models. Holding these retrofitted buildings in this sub-stock for a certain period prevents this situation from happening in our model. The retrofitted buildings in this dedicated sub-stock will continue to age and may possibly be removed due to demolition, depending upon age-specific hazard rates, but will not be retrofitted. The secondary purpose is to take into account the fact that a newly retrofitted building is much less likely to be demolished or become disused in the short term. Whilst in reality the possibility of being demolished or disused cannot be completely ruled out due to various factors, it would be reasonable to assume that newly retrofitted buildings are likely to be subject to lower hazard rates than other buildings of the same age which have not been recently retrofitted. This is intuitive because building retrofit involves not only technological analysis, but also economic evaluation which is more important in practice. The decision to retrofit or not has to be informed by cost and benefit analysis. A decision to retrofit would not have been made if the decision-maker had known there would not be a sufficiently long remaining lifetime of a building to cover the payback period. An equivalent way of interpreting this logic is that, given a large sample size, newly retrofitted buildings are expected to have on average longer remaining lifetimes than non-retrofitted buildings with the same ages. In addition, sometimes an energy-related retrofit activity is carried out as part of a more general renovation activity such as structure and facade, which can result in building lifetime extension (Crawford *et al.*, 2014) and a reduced hazard rate over the expected remaining lifetime of a building. The difference in hazard rate (demolition probabilities) between retrofitted and non-retrofitted buildings is accounted for in the model, as discussed below.

As a default setting, the "holding" period of the dedicated sub-stock, i.e. the interval between two retrofits, is set at 10 years. This means the dedicated sub-stock is a stack of 11 sub-stocks representing 1 year for completing the retrofit and the subsequent 10 years of having the benefits of improved energy efficiency while undergoing the aging process. The choice of a 10-year-period is indicative. The model allows the length of this period to be changed recognising the variation in different contexts and thus the need for adaptation. Under the default setting of a 10-year holding period, a retrofitted building enters into the dedicated sub-stock and starts to age for 10 years with respect to its original lifetime, provided that it will survive to the expiry of the holding period. Meanwhile, it also becomes "older" with respect to its post-retrofit age, e.g. 5 years after its retrofit. In a sense, this can be viewed as a double-aging process in the dedicated sub-stock. For example, by 2025, a 20-year-old building retrofitted in year 2020 will be both 25 years old and in the 5th year post retrofit. Provided that this particular building remains in use, when it leaves the dedicated sub-stock in 2030 it will be 30 years old and also 10 years post retrofit. To model this double-aging process, the model uses a double-subscripting method to denote a building in the dedicated sub-stock, i.e. year-after-construction and year-after-retrofit. This process can be illustrated using Figure 9.

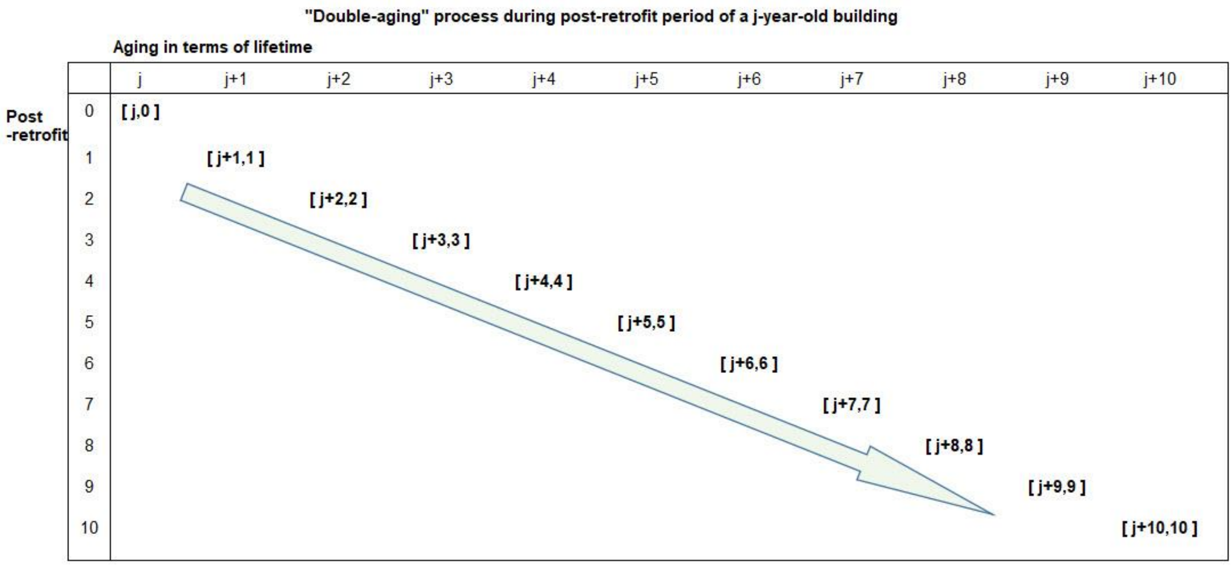

Figure 9: Illustration of “double-aging” process during post-retrofit period

As for the demolition, the default hazard profile is set to be the same as the one applied to the main sub-stock, e.g. a hazard profile derived from a parametric survival model estimated from empirical data. The variable "double-subscripted hazard" is numerically treated in such a way that it ensures, in the default scenario, that a t-year-old building that is retrofitted and thus enters into the dedicated sub-stock will have age-specific hazard rates for the next 10 years (holding period) as if it did not undergo retrofit and remained in the main sub-stock. In other words, the default setting assumes that a building's aging process and demolition profile are not changed, before and after its retrofit. What have changed are its property (energy performance) and its temporary status of not undergoing retrofit over the next 10 years while staying in the dedicated sub-stock. As discussed above, it would be reasonably expected that a newly retrofitted building will be subject to much lower risk of demolition or disuse, at least during the initial few years after its retrofit. The double-subscripted hazard variable can be adjusted to reflect this consideration, either arbitrarily or based on empirical evidence. The variable "Demolition (retrofitted) On/Off" serves as a switch, with “On” enabling the application of any profile of double-subscripted hazard, and “Off” representing an extreme scenario where no demolition/disuse will happen to a retrofitted building within the 10-year post-retrofit period. The default hazard profile of retrofitted buildings in the dedicated sub-stock is set to be the same as the one for the main sub-stock. In real applications, this profile can be flexibly set, for example, to a higher mean value as the result of retrofitted buildings' lifetimes being prolonged. The “Off” setting is therefore a special case of the flexible hazard profile of retrofitted buildings. In short, various settings can be made to the dedicated sub-stock to experiment with different policy scenarios and the resultant dynamics of retrofitted buildings and implications for energy performance.

Retrofitted buildings surviving to the expiry of the holding period are released and reinjected back into the main building sub-stock, where they get mixed with other buildings, including newly constructed buildings, old buildings which have never been retrofitted, and those which have already been retrofitted once or more. In the main sub-stock, buildings of the same age have the same chance of being retrofitted, regardless of whether or not they have already been retrofitted. A retrofit profile is applied to different age groups. The default setting takes a simple approach: the profile is arbitrarily exogenously defined to be time-invariant. The time-invariance means the retrofit rate applied to a specific age group of buildings is not a function of time, e.g. 10-year-old buildings in 2019 have the same retrofit rate as 10-year-old buildings in 2029. Depending upon modelling assumptions, the profile can be time-variant to reflect policy strengths in response to the trend of building stock energy performance. It may also be converted to an endogenously defined variable to enable the dynamic interplay between stock energy performance and policy interventions.

As afore-mentioned, the default setting of the holding period is fixed as 10 years. This is indicative, assuming a constant interval between two retrofits. In reality, retrofit intervals of buildings may vary due to a range of technological, economic and social factors. To recognise the uncertainty with respect to this parameter, a solution is to create multiple dedicated sub-stocks for retrofitted buildings and place them in parallel with the existing one. Each dedicated sub-stock is used to keep retrofitted buildings for a different holding period, e.g. a dedicated sub-stock with 12 vintages is for 11-year holding period, a dedicated sub-stock with 13 vintages is for 12-year holding period, and so on. Then the to-be-retrofitted buildings flowing into the original dedicated sub-stock can be distributed across these parallel dedicated sub-stocks, based on some distribution profile. For example, a total of 11 dedicated sub-stocks may be used to represent the range of 10-year to 20-year holding periods, with the first one having 11 vintages and the last one having 21 vintages. As an initial setting, the inflow into these sub-stocks may be distributed uniformly. When empirical data is available and sufficient, a distribution better describing the probability densities of various length of the holding period may be informed. Such a more sophisticated setup can be easily reduced back to the original default version by adjusting the distribution so that all to-be-retrofitted buildings will flow into the first dedicated sub-stock, namely the original one with 11 vintages (10-year holding period).

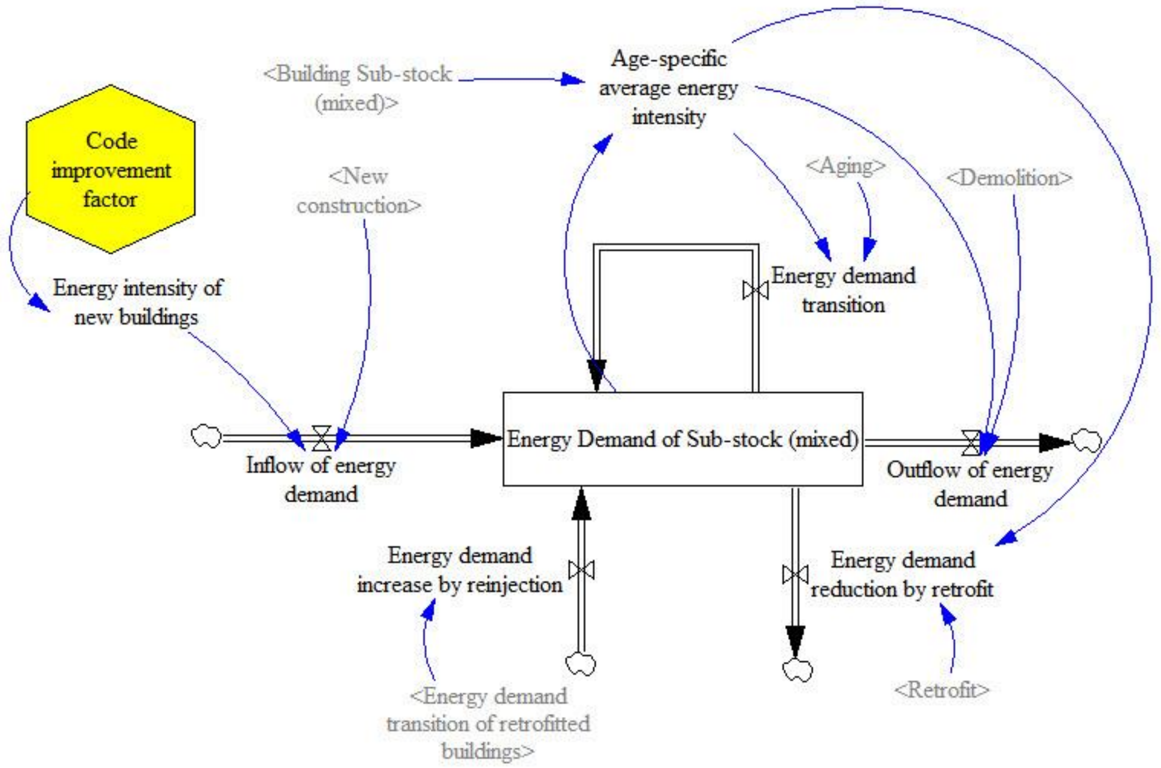

Figure 10: Dynamics of energy demand of main sub-stock of multiple-retrofits model

Similar to the settings for building stock, the (operational) energy demand of buildings is represented by using two sets of sub-stocks, with one for the main sub-stock and the other one for the sub-stock dedicated for retrofitted buildings experiencing the holding period. Compared to a regular co-flow setup, the energy demand of main sub-stock features an additional outflow of energy demand reduction due to outflow of buildings undergoing retrofit, and an additional inflow of energy demand increase due to reinjection of retrofitted buildings having survived the holding period (Figure 10). The outflow is determined by the amount of retrofitted buildings per year and the age-specific average energy intensity per year. It is useful to note that this outflow by itself is the sum of the outflows of energy demand reduction applicable to each of the age groups. As for the inflow, it is the total amount of energy demand of retrofitted buildings at all ages that survive their 10-year holding period and return to the main sub-stock of buildings. This inflow links the energy demand of main sub-stock with the energy demand of the sub-stock dedicated to retrofitted buildings, which has the typical structure of co-flow mirroring the structure of the sub-stock dedicated to retrofitted buildings themselves (Figure 11). This sub-stock is also double-subscripted to reflect the energy performance as a property of the retrofitted buildings experiencing the double-aging process. The inflowing energy demand into this sub-stock is a function of expected energy intensity of retrofitted buildings, which is a key target of policy interventions.

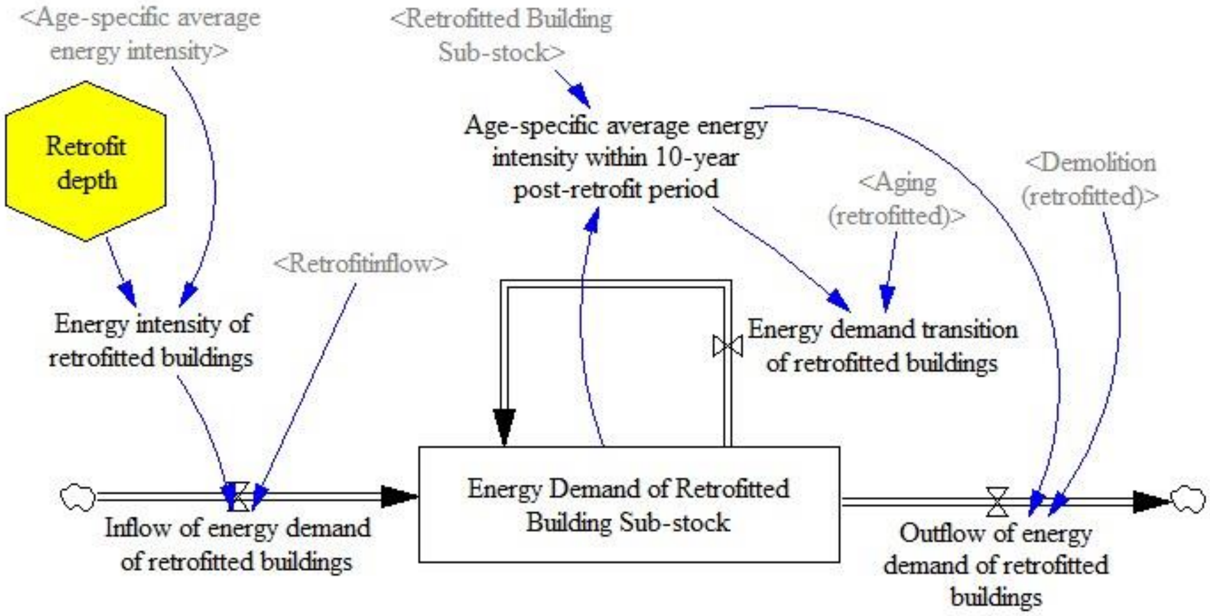

Figure 11: Dynamics of energy demand of dedicated sub-stock of multiple-retrofits model

As a simple approach, the default setting of the model is for the expected energy intensity of retrofitted buildings to be equal to the age-specific average energy intensity of existing buildings (including both retrofitted and unretrofitted buildings) minus the energy intensity reduction gained through retrofit. The gain is a percentage of the age-specific average energy intensity of existing buildings (including both retrofitted and unretrofitted buildings). The percentage, termed “retrofit depth”, represents the extent to which the energy intensity of existing buildings will be improved relative to itself as a result of retrofit. There are, of course, many factors contributing to the large variability and uncertainty with respect to energy intensity of new buildings in the future, technical potential and economic viability of retrofitting old buildings, depth of retrofit and associated costs, etc. These are context-specific factors and will need to be investigated in more detail when adapting and applying the model to a given context. The generic model presented here uses the variables "retrofit depth" and "code improvement" as simplified approximations of the impact of these factors.

The stock-wide average energy intensity of all buildings is obtained by dividing the total demand of all buildings, which is the sum of energy demand of the main sub-stock and that of the dedicated sub-stock, by the total floor area of all buildings consisting of buildings in the main stock (a mix of non-retrofitted and retrofitted buildings) and those in the dedicated sub-stock (retrofitted buildings only). The retrofit profile and retrofit depth have impacts on the stock-wide average energy intensity and total energy demand, as presented in Appendix A. Meanwhile, in the default model setup, the dedicated sub-stock for retrofitted buildings is subject to the same hazard profile as the main sub-stock, although this may not be the case in practice. Newly retrofitted buildings are unlikely to be demolished in the short term after the retrofit. There is expected to be considerable difference in stock-wide average energy intensity and total energy demand between the “On” and “Off” setting of demolition profile for the dedicated sub-stock (see Appendix B).

4 Model limitations and potential extension

It is acknowledged that the model presented here, as in any models of buildings, energy and related sectors, has been developed based on various methodological assumptions to be a simplification of the dynamic complexity of real-world building stock evolution and energy performance characteristics. These assumptions lead inevitably to limitations inherent to the model that should be taken into account when applying the model. Extensions can be made to enhance the model's flexibility and applicability.

Firstly, in modelling the effect of retrofit, we assume that building operational characteristics and occupant behaviours do not vary significantly; this is a fairly common assumption explicitly or implicitly made by many building energy models. These variations may be incorporated into future modelling with empirical data and complementary modelling approach such as agent-based modelling. Secondly, as the model's focus is on energy, our model limits itself to those energy-related retrofits. However, it is acknowledged that sometimes general renovation activities that are not directly related to energy performance will have a direct impact on building lifetime. This resultant extension of building lifetime may have a long-term impact on the interplay between the demolition of old and inefficient buildings and the construction of new and efficient buildings which together decide the stock-level energy performance. Thirdly, in the current version of our generic model, the retrofit depth is set as a single value. In reality there exist a range of energy-related retrofit activities and therefore many factors contributing to the variability and uncertainty with respect to retrofit depth. This can be taken into account through a very minor extension of the model which is to use a distribution profile to represent the share of a certain level of retrofit depth in all practically feasible retrofit depths. This extension will require empirical data. Fourthly, the holding period of the dedicated substock of retrofitted buildings is set as a constant as an intended simplification. In reality, retrofit intervals may vary due to a range of technological, economic and social factors. To take this into account, additional structures can be easily added to the model to create multiple dedicated substocks in parallel with the existing ones as has been described. Each dedicated substock is used to keep retrofitted buildings for a different holding period. This setup enables a distribution of various holding periods, which needs to be informed by empirical data.

An overview of this stock turnover and multiple-retrofits model, which presents the dynamic interplay across variables, is given in Appendix C. This is presented as a simple generic version in order to highlight some key points (stock disaggregation and multiple retrofits) rather than a fully-fledged version, which could be used for real-world applications and policy analysis. To develop the latter, additional structures and variables still need to be added to the model. For example, exogenous drivers of new construction and feedback loops enabling dynamic interplays between new construction, aging of existing buildings, and demolition of old buildings reaching their end of lifetime could be incorporated in order to model future possible trends of stock evolution. In addition, the model boundary may be expanded to cover embodied energy consumption and carbon emissions incurred in producing building materials, construction, retrofit and demolition activities. Such an extension would enable a lifecycle perspective to be taken when evaluating building stock energy performance and carbon emissions.

5 Conclusions

We present a System Dynamics model for characterising building stock turnover dynamics and tracking the trajectory of stock-level building energy performance. The model is aimed at addressing some of the fundamental structural and behavioural limitations found in previous applications of System Dynamics-based models. Specifically, the model uses an aging chain structure to represent the dynamics of the aging and demolition of buildings. The age-specific demolition rate is modelled based on the concept of the hazard function in survival analysis. The model loosens the strong assumptions made by previous models, including perfect mixing in a first-order delay in a single stock model, and perfect mixing in each delay of a third-order delay in a three-vintage model. By disaggregating a building stock into age-specific sub-stocks, the model enables explicit representations of the uncertainties associated age-specific risks of demolition and the resultant building lifetime distribution. Compared with previous models, the model offers great structural flexibility to accommodate various levels of data availability. Moreover, it offers the capacity of calibrating building lifetime distribution using empirical data on stock size. Another salient feature is that the model avoids unreasonable situations where a building is allowed to undergo multiple rounds of retrofits within a very short period of time, a building is demolished soon after being retrofitted, or a building is retrofitted soon after it is constructed and put into use.

The model is generic, transparent and therefore potentially applicable to a wide variety of contexts. Its flexibility enables adjustments to meet various requirements and settings. On the one hand, the model can be extended to accommodate increased granularity and enhanced level of sophistication, or expanded boundary of modelling. Structurally, with available empirical data, the sub-stocks of retrofitted buildings can be further divided to model various lengths of the holding period. Functionally, depending upon model purpose, additional structures and variables can be added to the model to enhance its utility, such as feedback loops linking demolition and new construction to model future stock growth, embodied energy and carbon due to production of building materials, building construction, retrofit and demolition activities, stock of existing heating technologies and possible future trends of technology mix to model carbon emissions of heating. On the other hand, sometimes building demolition is of less concern, e.g. buildings are generally long-lived and/or the period of modelling and analysis is short relative to building lifetimes. In these circumstances, the model can be straightforwardly reduced to a three-vintage or single stock structure as found in existing literature. Similarly, the multiple retrofit dynamics can be easily reduced to single retrofit or no retrofit structure, but retain the ability of avoiding unrealistic modelling results of previous models. The reduced form version of the model will be useful when the interest of modelling is in general behavioural dynamic patterns of building stock and energy, rather than in detailed representation of model structures and variables for accurate numerical values of stock or sub-stock level performance indicators.

In conclusion, we believe that our model is well placed to be used as a stand-alone model or as part of a larger model looking at building stock-level energy and carbon emissions in a variety of national or sectoral contexts. Its transparency and flexibility will enable further extensions and improvements for greater capacity in wider applications for evaluating policy interventions targeting transforming buildings towards greater energy efficiency and low carbon development.

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Appendix A: Impact of retrofit profile and retrofit depth

The impact of the retrofit profile and depth on average energy intensity and total energy demand is examined under the following hypothetical scenario where:

- Annual new buildings are built at the rate of 100 million m^2 per year
- Energy intensity of incoming new buildings decreases linearly from 20 kgce/m^2 in 2019 to 10 kgce/m^2 in 2119.
- Existing building stock size is 10,100 million m^2 in total, with each age-specific sub-stock being 100 million^2.
- Energy intensity of existing buildings is 25 kgce/m^2.
- Age-specific demolition rate of buildings is derived from the hazard function of a lognormal distribution of building lifetime, whose mean is 75 years and standard deviation is 15 years.

Firstly, at a given retrofit depth of 15%, the model is run with three levels of retrofit rate, i.e. 0.01, 0.05 and 0.10. As expected, accelerating retrofit rate has positive impact on improving stock energy performance in terms of stock-wide average energy intensity (Figure 12).

Secondly, at a given retrofit rate of 0.05, the model is run with three levels of retrofit depth, i.e. 5%, 10% and 15%. As expected, deepening retrofit intensity has positive impact on improving stock energy performance in terms of stock-wide average energy intensity (Figure 13)

Thirdly, the model is run with various combinations of retrofit rate and depth to illustrate the positive impacts of increasing retrofit rate and deepening retrofit intensity on the total energy demand of the entire building stock (Figure 14).

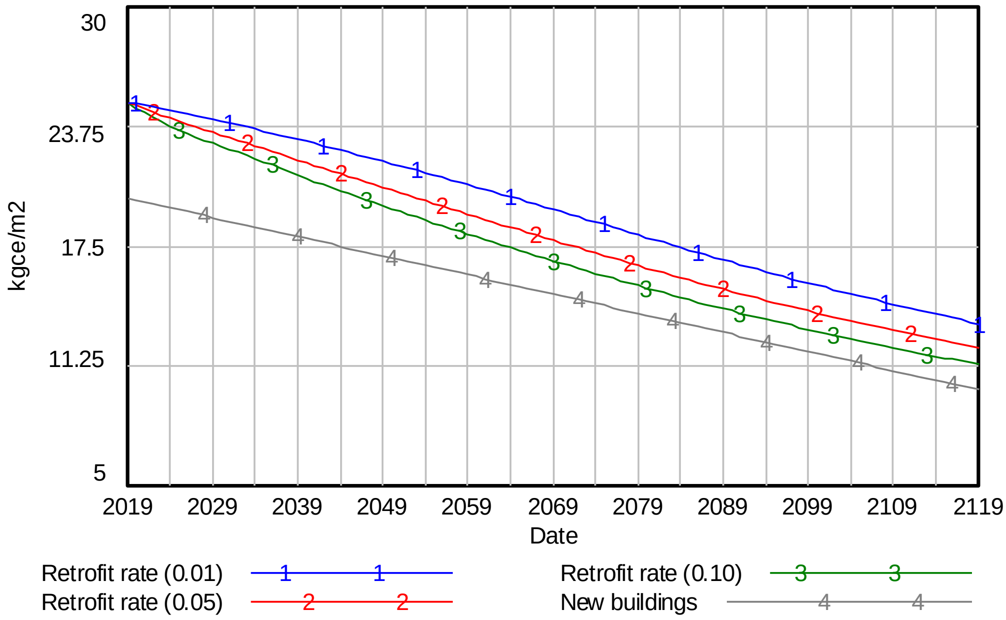

Figure 12: Impact of retrofit rate on stock-wide average energy intensity (retrofit depth = 15%)

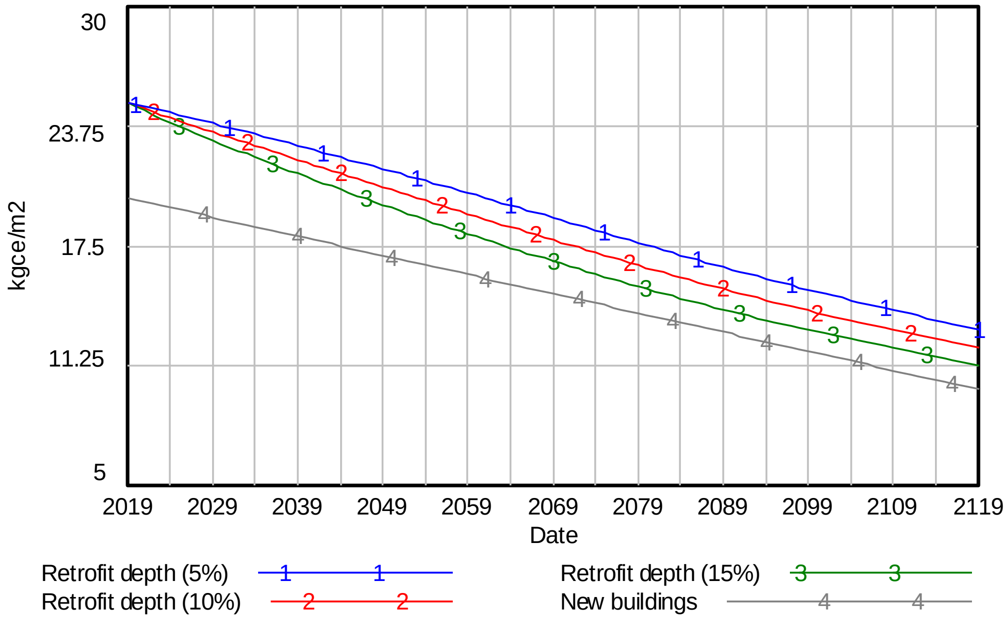

Figure 13: Impact of retrofit depth on stock-wide average energy intensity (retrofit rate = 0.05)

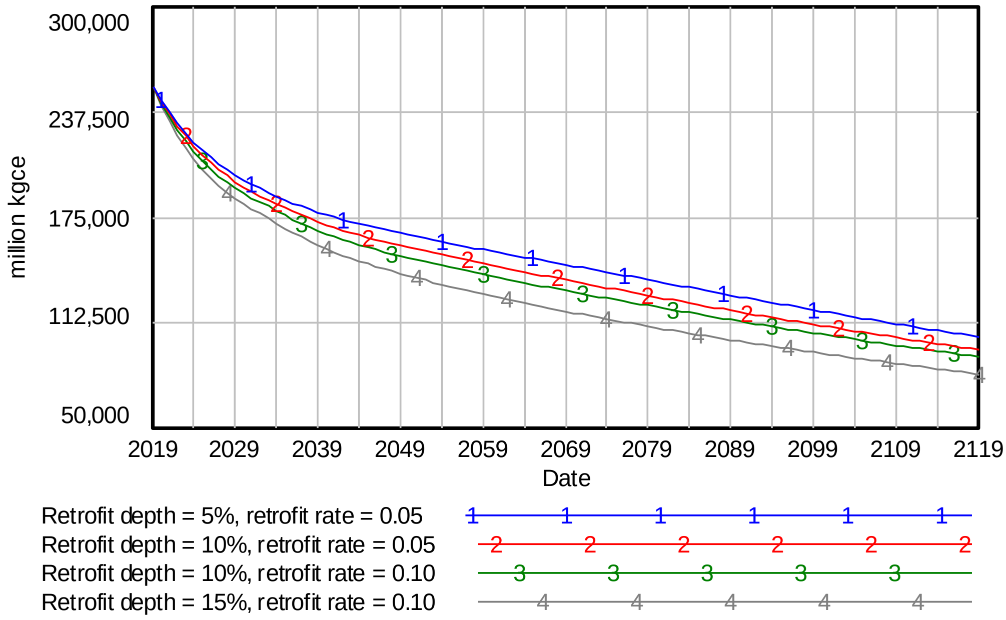

Figure 14: Impact of retrofit rate and depth on total energy demand of entire stock

Appendix B: Impact of demolition profile of retrofitted buildings in the dedicated sub-stock

In the default model setup, the dedicated sub-stock for retrofitted buildings is subject to the same demolition profile as the main sub-stock. This may not be the case in practice. Newly retrofitted buildings are unlikely to be demolished over short term after the retrofit. There is expected to be considerable difference in stock-wide average energy intensity and total energy demand between the “On” and “Off” setting of demolition profile for the dedicated sub-stock. This is examined under the following hypothetical scenario where:

No new buildings are constructed

Existing building stock size is 10,100 million m^2 in total, with each age-specific sub-stock being 100 million^2.

Energy intensity of existing buildings is 25 kgce/m^2.

Age-specific demolition rate of buildings is derived from the hazard function of a lognormal distribution of building lifetime, whose mean is 50 years and standard deviation is 15 years.

Retrofit depth is 15%

Retrofit rate is 0.10.

Firstly, the model is run with its default setup, where the demolition profile of retrofitted buildings in the dedicated sub-stock is set to be “On”. At “On”, retrofitted buildings are subject to the same demolition profile as those buildings in the main sub-stock. During the 10-year holding period, some retrofitted buildings are removed from the dedicated sub-stock due to demolition. Only those retrofitted buildings surviving the 10-year holding period will be reinjected to the main sub-stock.

Secondly, the model is run with the alternative setup, where the demolition profile of retrofitted buildings in the dedicated sub-stock is set to “Off”. At “Off”, retrofitted buildings are not removed from the dedicated sub-stock as they are not subject to any demolition. Therefore, they will be fully reinjected to the main sub-stock upon the expiring of the 10-year holding period.

The impact of “On” and “Off” is visible. In the “Off” setup, due to less demolition of retrofitted buildings, the size of overall building sub-stock is increased as compared to the “On” setup

(Figure 15). The retrofitted buildings are more energy efficient, thereby contributing to lowering the stock-wide average energy intensity (Figure 16). The total energy demand may increase or decrease depending upon the varied stock size and average energy intensity. In this case for illustration purpose only, the effect of increased stock size exceeds that of the lowered average energy intensity, therefore leading to increase of total energy demand of the entire stock (Figure 17).

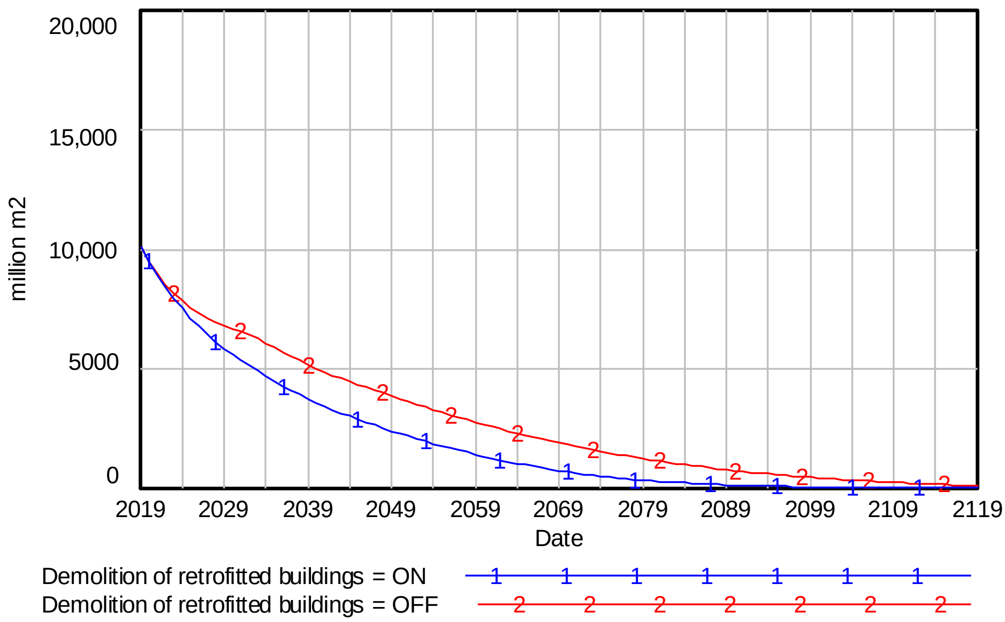

Figure 15: Impact of demolition profile of retrofitted buildings on overall stock size

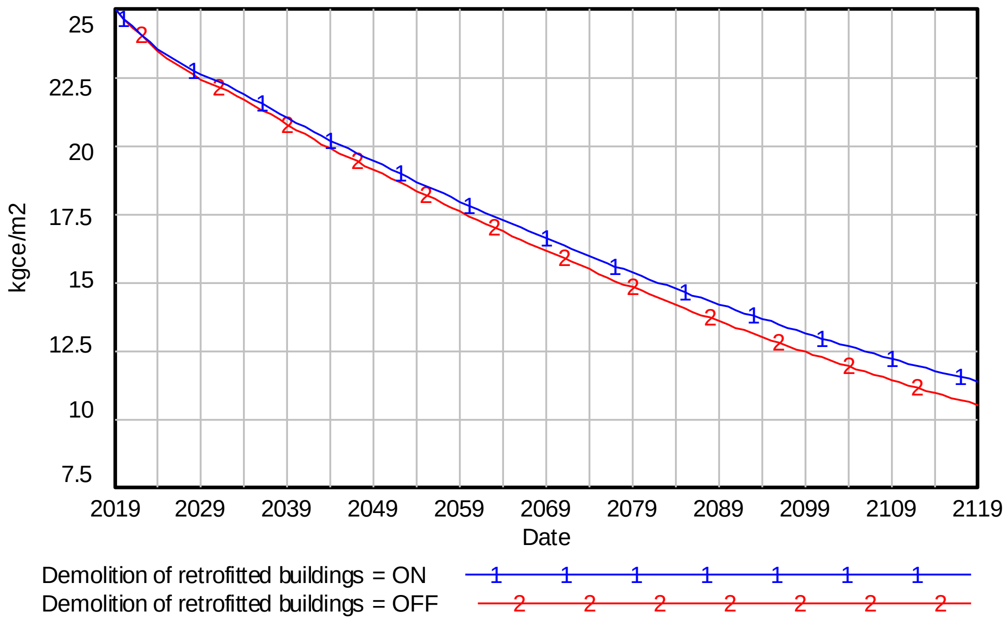

Figure 16: Impact of demolition profile of retrofitted buildings on stock-wide average energy intensity

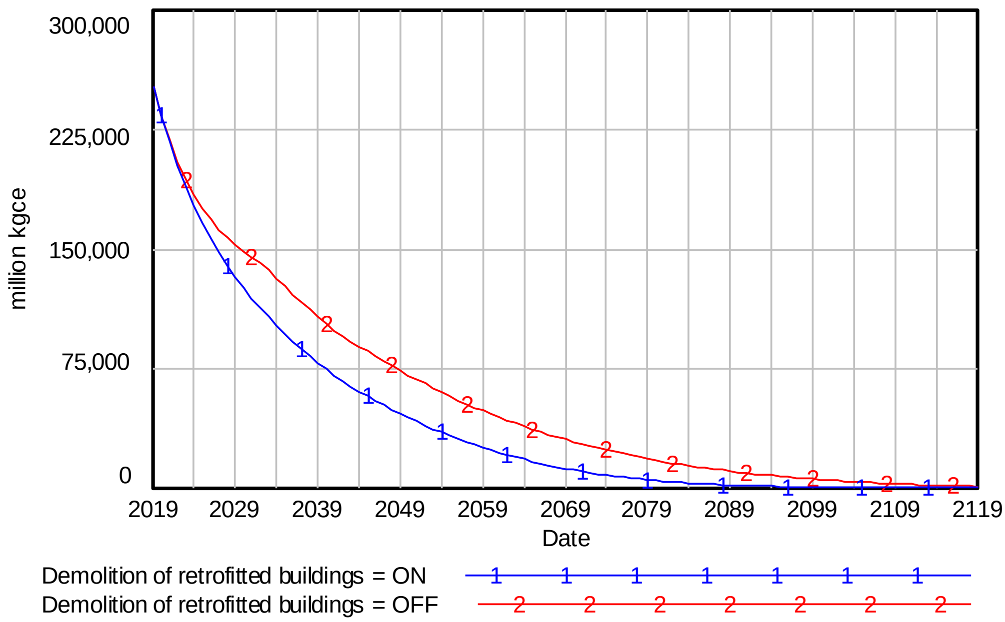

Figure 17: Impact of demolition profile of retrofitted buildings on total energy demand

Appendix C: Full model of building stock turnover and energy retrofits