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The more the better? Archetype segmentation in urban building energy modelling

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The more the better? Archetype segmentation in urban building energy modelling

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Abstract. Urban building energy modelling is gaining traction as a planning tool to support widespread decarbonization of the built environment. Building-scale models allow for the evaluation of specific emission reduction policies at an urban scale. Given the limited availability of building-by-building data on construction standard and program, aggregating building information through archetypes is key, but a poorly understood step in the urban energy modelling process. In this study, different levels of archetype segmentation are explored for the city of Oshkosh, WI (~13,000 buildings). A comparison of actual, city-level energy with UBEM simulations suggests higher levels of archetype segmentation do not necessarily lead to higher accuracy, leading to models that are both accurate and nimble enough to explore a variety of upgrade scenarios. Informing archetypal segmentation with policy-informed metrics is beneficial, but pursuing increased detail could dangerously reduce accuracy without ground-truth data.

1. Introduction

With limited time to achieve greenhouse gas reduction goals, cities are experiencing pressure to reduce building stock emissions. While deep retrofits can reduce building energy use by up to 90%, strong barriers to adoption exist due to policy gaps at the building and building-systems scale [1]. The growing field of urban building energy modelling (UBEM) addresses this issue. A bottom-up approach, UBEM is based on building characteristics rather than statistical models, enabling the evaluation of specific emission reduction pathways seen as necessary for the development of specific decarbonization policies. While UBEMs allow for flexibility and improved scenario testing of retrofit adoption pathways, limitations exist due to inadequate data and fragmented standardization [2].

As UBEMs require individual simulations of many buildings, model complexity reduction techniques are needed. In particular, clustering buildings into representative archetypes increases efficiency and addresses incomplete data by utilizing characteristic similarities of buildings [3]. Correlating building characteristics with energy use, studies have found that archetypes should be, at a minimum, defined by age and program when modelling energy use for given building footprints and heights (floor area) [4]. Particularly, a building's year of construction (or last major renovation) is an important indicator of energy use [3]. The modeller may choose to make further divisions which have been found to affect energy use, such as geometry (floor area, attics), construction-type, or census data [5,6]. This process has been standardized for widespread regional use with the development of regional archetypes, such as the European TABULA project and the US National Renewable Energy Laboratory (NREL) commercial reference buildings [7,8]. While archetypal division is found to be a viable simplification method, there is little consensus on needed segmentation resolution, particularly when considering incremental changes to energy use through retrofits [9,10]. With sufficient data, more archetypes may increase precision when it comes ot predicting energy savings from upgrading subsets of buildings even if the total predicted building energy use for a city does not change [4]. Archetypal division is therefore closely linked to use-case. For example, planning for retrofit policy rollouts might call for representing archetypes by program and location (often correlated with age). In addition to policy considerations, [4] found that additional building parameters should be considered relative to their variability within the building stock. For example, roof types in residential buildings proved to be an insignificant addition of detail. While there is a good level of understanding surrounding what changing archetype partitions should do, *in principle*, there remains a surprising lack of clarity as to how sensitive simulation accuracy is to archetype segmentation. For example, how many (and which) time divisions should a modeler pick when dividing archetype templates by age.

Currently, archetypal partitions have broadly followed historic construction standards and events. The US NREL commercial reference buildings are representative of more than 60% of existing commercial buildings. Three age groups (partitioned between 1980 and 2004) and 16 building types (only one of which is residential) result in 48 typologies per climate zone, informed by historical releases of AHSRAE standards that were adopted nationwide [7]. However, with increasing computational resources, it is tempting to increase the complexity of UBEMs by modelling at higher levels of detail as more statistical data on the building stock becomes available [9]. In response to a need for increased sensitivity to local typologies in highly detailed UBEMs, NREL's ResStock and ComStock databases were developed, characterizing the national building stock by construction decade, census zone, building type (program), stories, mechanical system, and construction type [11]. Models are created by sampling conditional probability distributions for building characteristics throughout the country, resulting in unique building profiles in almost all modelling scenarios. Even though this high granularity increases computational time and model complexity [4,9], the underlying assumption is that simulation results will become more accurate. In this manuscript we probe this assumption asking *how much can archetypes be simplified while still yielding useful UBEMs for urban retrofit adoption modelling and decision-making?* We answer this question for the city of Oshkosh, WI, for which city-level annual electricity and gas use for buildings are available.

2. Methodology

2.1. Modelling procedure.

We utilize an UBEM framework presented by Berzolla et al.*[12]* to compare two fidelity scenarios and their impacts on retrofit pathway selection. The UBEM process is a true bottom-up approach, considering building geometry (footprint and height), orientation, age, residential program, and building interactions from GIS shapefiles with building metadata. Using the UBEM.io framework to create the urban model, archetypes were assigned to each building, and the energy analysis was completed with the Urban Modelling Interface in Rhino 7 *[13,14]*. In addition to urban models, a 10x3m two-zone (core and perimeter) shoebox was considered for comparative validation, with baseline energy use estimated for each archetype. Being computationally simple, the latter approach offers a rough UBEM estimation scaling energy use intensity (EUI) by floor area *[15]*.

2.2. Case study: Oshkosh, Wisconsin.

The US city of Oshkosh, WI, was selected for a case study. With 66,000 residents and approximately 13,100 buildings (2.3 million square feet), the city is a largely residential urban area. To reduce emissions by 84% by 2050, Oshkosh is targeting a 53% reduction in carbon emissions compared to 2019 by 2035 *[16]*. Oshkosh is representative of a great number of small cities and urban residential areas in the US that aim to decarbonize their building stock, but lack resources for expensive and specialized studies *[17]*. In Oshkosh, detached single family residences (SFRs) built before 1980 make up the largest portion of the city's residential floor area (approximately 70%). The city is located in ASHRAE climate zone 5A, a "cold" climate.

2.3. Archetypal fidelity scenarios and data sources.
We compare three scenarios of archetypal detail related to building age and type: low-, mid- and high-fidelity (Table 1). The low-fidelity scenario is based on the Pacific Northwest National Laboratory single-family, newly constructed residential template, revised with local tacit knowledge of building characteristics *[18]*. This is a common and often necessary approach in practice to develop UBEMs when statistical building stock distributions are not available *[10]*. The mid-fidelity scenario is drawn from aggregated ResStock distributions for Oshkosh's census region, with 16 archetypal divisions based on residential building type and age. All scenarios consider locational context of climate zone and individual building geometry (footprint, height, and shading context). The high-fidelity scenario is also drawn from ResStock, partitioning archetypes by decade of construction to produce 36 individual archetypes. Building age divisions start at 1940, due to the scope of ResStock distributions. The GIS data was provided by the City of Oshkosh, and grid emissions factors are based on local utility historical data *[19]*.

Table 1. Archetype fidelity scenarios.

	# Arch.	Description	Data-source(s)
Low-fidelity	3	3 age divisions by building code trends *(pre-1980, post-1980, post-2000);* Residential-only	[7], tacit knowledge
Mid-fidelity	16	4 age divisions by building code trends *(pre-1940, pre-1980, post-1980, post-2000);* 4 residential programs *(SFR, townhouse, low-rise condo, high-rise apartment)*	[11]
High-fidelity	36	9 age divisions by decade *(pre-1940 to post-2010);* 4 residential programs *(see above)*	[11]

3. Results

3.1. Shoebox estimates.
Initial two-zone energy models confirm that the average and maximum calculated EUI for each fidelity scenario is approximately equivalent (within 5%), while the low-fidelity's best-performing archetype has an EUI that is significantly lower than the statistical scenarios (over 30%). This is expected, as the statistical scenarios (mid- and high-fidelity) are drawn from the same statistical distributions, and the low-fidelity models are calibrated relative to local knowledge. The highest and lowest EUI for low-fidelity varied by 80%, whereas the mid- and high-fidelity produced a 126% and 129% difference respectively.

3.1.1. Oshkosh scenario simulations. Scaling to an urban context, each fidelity scenario was modelled for all residential buildings in Oshkosh. Experiments were run on a Windows 10 computer with an Intel Core i9-9900 processor, using 32 GB of RAM at 3.10 GHz. As expected, modelling individual buildings took significantly longer than area-scaled shoeboxes, taking hours rather than seconds. With a minimum computation time of 9.4 hours for the low-fidelity model (3 archetypes), the model runtime appears to linearly increase with number of archetypes. The maximum runtime for the high-fidelity scenario was 10.3 hours (36 archetypes), with several hours of archetype preparation time.

Initial UBEM results show that increasing detail resulted in higher total energy, as seen in the shift of median building energy use in Figure 1, and overall end-use in Figure 2. This is likely a result of ResStock sample sizes; more archetype segmentations result in distributions created from smaller sample sizes and are subsequently prone to being skewed. This is evident in Figure 1, given that mid-fidelity introduces wider distributions of energy use compared to low-fidelity, but the high-fidelity scenario appears only to shift the distribution towards higher values. Accordingly, the mid-fidelity scenario provided more accurate results overall, although end-use consumption was erroneous. In this scenario, further calibration work could be done. As expected, in all cases the pre-1980 archetypes make up the largest portion of energy use, as seen in Figure 3. Specifically, the single-family home divisions built before 1940, given that this archetype makes up the majority of Oshkosh's floor area.

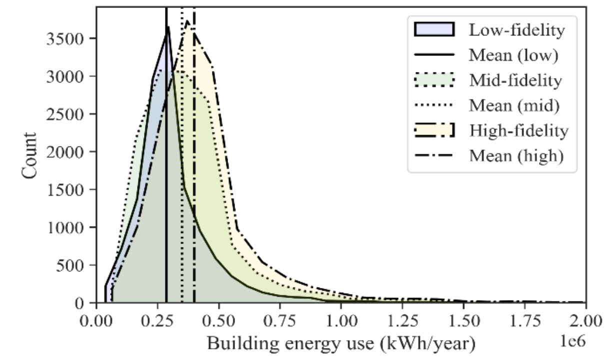

Figure 1. Distribution of building energy use.

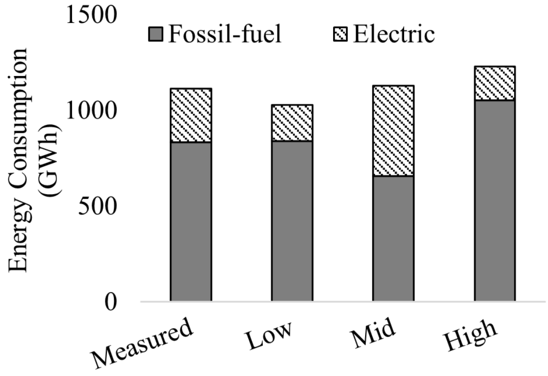

Figure 2. Energy consumption by end-use fuel.

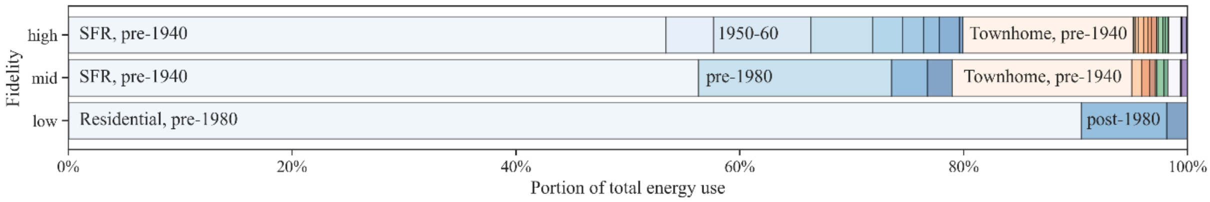

Figure 3. Breakdown of total energy use by archetype.

Considering energy use independently from area, the EUIs of each archetype were calculated. As expected in a cold climate, all scenarios resulted in heating-dominated energy end-use distributions, as seen in Figure 4. Like the aggregated results, the highest proportion of energy use was from older buildings. However, the worst performing archetypes of the mid- and high-fidelity scenarios were both the oldest and youngest groups (built before 1980 and after 2000), pointing towards the importance of choosing appropriate segmentation dates. Even so, higher fidelities show clear groupings of successive archetypes (close in age or building type) that have very similar EUI values, suggesting that a high resolution may not be necessary for energy calculations. On the other hand, when considering the optimal archetypes for retrofits, ranking archetypes by overall energy use (Figure 3) results in differing target groups. It is evident with an increase in detail to mid- and high-fidelity that the SFRs and town homes built before 1940 should be targeted for upgrades in particular, making up about 50% and 16% of the city's carbon emissions respectively. This is explored further with a retrofit scenario.

4. Upgrades

To explore the impacts of fidelity on incentive programme planning, upgrades were applied to selected archetypes to achieve emissions reduction goals. To target archetypes, conservation measures were first applied to shoeboxes and scaled by floor area to quickly estimate carbon savings for each group, then selected based on emissions reduction potential for a full UBEM simulation to simplify and shorten the modelling process. All retrofit packages were the same for each archetype, improving infiltration, lighting and equipment power density, gas furnace efficiency, and envelope R-values.

To achieve the goal of a 40% reduction in carbon emissions, as seen in Figure 5, the low fidelity scenario required deep energy retrofits of all residential buildings built before 1980. This is 88% of the residential building stock by floor area, and a mixture of privately-owned and multi-family buildings, and greatly overshoots targeted goals. For mid-fidelity, shoebox models project that the majority of savings are realized by upgrading only single-family homes built before 1980 and town homes built before 1940, comprising 84% of the residential building stock by floor area. This also shortened computation time, as a smaller number of buildings needed to be re-simulated. Given that the targeted buildings' archetypes were largely the same as the high-fidelity scenario, it was not deemed necessary to recalculate savings of the same groups.

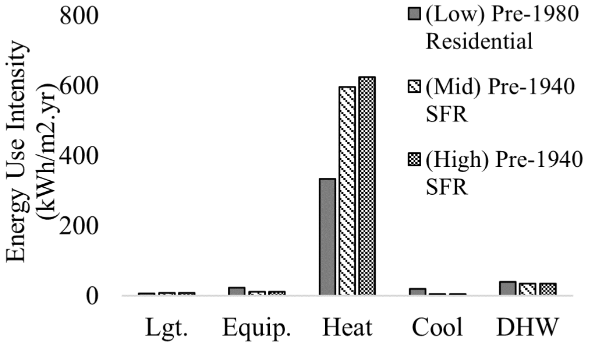

Figure 4. Baseline end-use EUI is heating dominated.

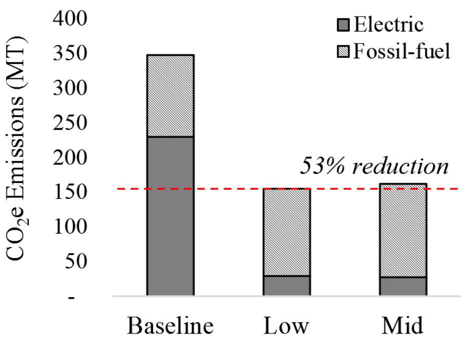

Figure 5. Upgrade results are similar across fidelity scenarios.

5. Discussion and conclusion

This study suggests that the pursuit of archetypal resolution granularity in UBEMs can be an unnecessary barrier. Particularly in cases without ground-truth energy data, higher levels of detail can introduce inaccuracies. In the case of Oshkosh, a large proportion of the floor area is a single archetype (SFR), so modelling with high resolution is unnecessary for upgrade conclusions at a policy scale. However, distinguishing between program types did have an impact on final conclusions: rather than targeting all residential buildings built before 1980, only individually-owned homes could be targeted, eliminating a bifurcated policy strategy between multi-family commercial and single-family residential buildings. Additionally, appropriate granularity is largely dependent on the local context. This is evident in the end-use distributions of archetype EUIs, as seen in Figure 4. As level of fidelity has an impact on end-use distributions, for a climate or building stock that is not heating dominated or is not dominated by a single archetype, this could result in different conclusions about target groups and energy reduction strategies. Finally, the development of building templates themselves can contribute to an appropriate number of archetypes. In most cases, calibration is needed, even when generating from large quantities of sampled data. As the calibration process is highly time consuming and iterative, project resources may inform the number of archetypes appropriate for the project. In the case of Oshkosh, while it is realistic to revise 3 archetypes, manually calibrating 36 archetypes is deemed unrealistic and unnecessary in practice. With a focus on realistic implementation in policy decision-making, we suggest that the development of archetypes take on a top-down approach in terms of precision: looking first at overall accuracy, then increasing detail within those bounds.

So, while archetypal division is largely determined by policy scope (e.g. decision-makers may wish to target smaller subsections of the building stock), detailed segmentation is often unnecessary in stock-level UBEMs, given that subdivisions are made in a context-informed manner, most importantly considering building stock distributions and historic trends. In the context of incentive policy programs, we present an approach to determine minimum viable granularity of archetypal division in an efficient manner. Acknowledging that the process of creating building archetypes is highly contextual, this involves several areas of consideration: data availability, historical context, project resources, and building stock distribution. This is especially useful considering the use-case of UBEM models. In many situations, urban energy analysis is employed as a "triage" to determine the severity and savings potential of building groups to reliably target specific populations of buildings in order of significance [2]. We conclude that archetype segmentation requires a judgement call from the modeler who needs to balance accuracy, against computation time while paying close attention to what building types and upgrades are most relevant for a given building stock.

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