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Housing stock energy modelling: Towards a model for Wales

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January 2023

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- This report for the Welsh Government looks at modelling emissions associated with the housing sector, in the context of Net Zero Wales, the Welsh Government's second carbon budget (Welsh Government, 2021).

- The Welsh Government's decarbonisation strategy calls for a reduction in carbon emissions arising from Welsh homes by 80% from 1990 levels by 2050.

- Housing stock energy models (HSEMs) have potential to underpin housing decarbonisation policy. The models calculate the energy performance and associated carbon emissions of national and sub-national housing stocks. HSEMs can broadly be divided into two types: traditional and dynamic.

- Traditional housing stock energy models (T-HSEMs) focus on modelling annual energy use and associated carbon emissions. T-HSEMs have contributed to formulation of energy-related housing policy. However, a weakness of these models is that the structure of the housing stock remains unchanged in the scenarios, whereas in practice the housing stock changes all the time.

- Dynamic housing stock energy models (D-HSEMs) aim to capture the ongoing changes that occur in the housing stock. D-HSEMs have to date been under-used but they have the potential to enable policymakers to estimate the likely economic and carbon impacts of strategies to decarbonise the housing stock over the longer term.

- Unifying traditional and dynamic approaches to housing stock energy modelling has the potential to create a more comprehensive resource to support the analysis of policies that are formulated with long-term decarbonisation targets in mind.

- The report concludes with short and medium-long term recommendations. The recommended short-term strategy is to adapt a T-HSEM that employs dynamic simulation techniques to create a Welsh Housing Model (WHM). Recommended medium-long term strategies involve further development of analytical capabilities of the WHM.

List of abbreviations

ABBSM	Agent Based Building Stock Model
ABM	Agent Based Modelling
BREDEM	Building Research Establishment Domestic Energy Model
BREHomes	Building Research Establishment Housing Model for Energy Studies
CHM	Cambridge Housing Model
CGS	Clean Growth Strategy
D-HSEM	Dynamic Housing Energy Model
EHS	English Housing Survey
ENHub	Housing stock energy hub
EPC	Energy Performance Certificate
ERR	Energy-Related Renovations
GUI	Graphical User Interface
HSEM	Housing Stock Energy Model
SAP	Standard Assessment Procedure
SDM	System Dynamic Modelling
T-HSEM	Traditional Housing Energy Model
WHCS	Welsh Housing Condition Survey

Introduction

The combination of increasing global demand for energy and strict carbon emissions targets have made the decision-making process around acquiring and using energy complex. In the context of the commitment to achieve net zero CO_2 emissions by 2050, the UK and devolved governments are interested in understanding the emissions implications of policy decisions and the interrelationships between them.

The Wales Centre for Public Policy was asked to support the Welsh Government to develop an approach to capture the carbon impact of policy decisions, including an assessment of how examples of good practice can be built upon. The Welsh Government are particularly keen to understand how measures to model or account for emissions across Government can increase awareness of the carbon impact of policy decisions.

In commissioning this report, the Welsh Government indicated a particular interest in four main questions:

1. What are the emerging trends in the housing sector with respect to decarbonisation? How might these affect the modelling of the housing sector?
2. What housing models exist and how can they inform policy options and awareness of the need to reduce emissions? How consistent are different models or approaches with each other, and what is the extent of any overlap?
3. What tools are available to capture the projected carbon emissions (from smaller-scale policy decisions)? How have these been used in other governments, nations and in private industry?
4. How can the results of sectoral or policy-based models be used to inform the broader Net Zero target? What options are available to formulate a coherent and integrated approach across government?

To address these questions, this report provides a synthesis of research on modelling strategies and related software that calculates the energy performance and associated carbon emissions of national and sub-national housing stocks. This review of Housing Stock Energy Models (HSEMs) is intended to support the formulation of housing stock decarbonisation policy and the evaluation of its effectiveness.

This review starts by summarising the housing situation in Wales, its energy performance and the related policy context. It then critically analyses different types of HSEMs; starting with an examination of traditional HSEMs, which have been employed for the last 50 years in the UK to test scenarios to reduce energy use and carbon emissions from housing, for a snapshot in time. The report goes on to discuss HSEMs that have recently emerged in Europe, which model how the composition of housing changes with time (due to construction, renovation and demolition) and the consequential impacts on carbon emissions. After discussing the advantages and limitations of both traditional and dynamic approaches, the review concludes by proposing a suite of research, development and application priorities to support Wales in developing a model which would ultimately unite the best of both approaches to support the evidence-based decarbonisation of its housing stock.

Housing stock energy use in Wales

The Welsh Government's decarbonisation strategy, Net Zero Wales, calls for a reduction in carbon emissions arising from Welsh homes by 80% with respect to 1990 levels, by 2050 (Welsh Government, 2021). At present, some 80% of energy use in housing in Wales is due to space heating and domestic hot water use, based predominantly on gas fired central heating systems. The Decarbonisation of Homes Advisory Group has recommended that the Welsh Government set a target to retrofit the housing stock to achieve an Energy Performance Certificate (EPC) band A rating; representing a median energy efficiency score of 92 or better. Reducing the demand for heating offers the greatest potential here, but this may not be realised in all cases, for reasons of cost effectiveness or of architectural heritage conservation.

Of the 1.44 million dwellings in Wales, some 70% is owner-occupied, with the remainder being split between private rental (14%), social (10%) and local authority (6%) housing providers (Stats Wales, 2020). As most of the housing stock is owner occupied this is the tenure which has been most widely studied for energy-related renovations (ERR) such as insulating the walls, roof or floor, substituting the glazing or installing a more efficient heating system.

EPC ratings for the Welsh housing stock have improved considerably, with ratings of B and C properties having risen from 5% in 2008 to 27% in 2018. However, despite improvements across all other categories, 73% of dwellings are rated D or lower. The most recent analyses of EPC ratings by the Office for National Statistics are somewhat more encouraging (Office for National Statistics, 2021). They estimate the median energy efficiency rating for all properties in Wales to be 64, corresponding roughly to the upper quartile of band D. This dataset also suggests that the proportion of properties rated C or above has increased to 37%.[1] However, pre-1900 and 1919-1929 dwellings are estimated to fall significantly short of targets, with median ratings of 51 and 55 respectively. During these periods, solid walls were the dominant mode of construction. Of the 28% of properties in Wales that are constructed of solid walls, some 82% are uninsulated; in contrast to just 32% of uninsulated cavity walls (Welsh Government, 2019).

Box 1: Housing condition surveys

The English Housing Survey (EHS) is a continuous survey that is published annually and typically involves around 13,300 household interviews and around 6,200 physical surveys. Survey results from adjacent years are normally amalgamated when a survey dataset is released to the research community, so that these then represent a discrete two-year period, including around 12,400 physical surveys. In 2017/18 a Welsh Housing Condition Survey (WHCS) was conducted, involving physical inspections of 2,549 properties across Wales. These properties were selected to coincide with those that participated in the National Survey for Wales, which involved a household interview, so that the combined result was comparable to the EHS; albeit with smaller samples, reflecting the smaller population size. As part of the WHCS, the surveyors also calculated EPC ratings (Welsh Government, 2019). These are compared to similar evaluations from the 2008 Living in Wales Property Survey, as well as to EPC datasets for the other UK nations.

The UK government's 2018 Clean Growth Strategy (CGS) set a target for all fuel poor homes to be EPC-rated C or higher by 2030, and has set an *aspiration* for as many homes as possible to be rated C or higher by 2035, where practical, cost-effective and affordable (HM Government, 2018). This includes social housing, but the Climate Change Committee, in its Sixth Carbon Budget report calls for this to be bought forward to 2028 (Climate Change Committee, 2020). Furthermore, the CGS mandates that privately rented properties should have an EPC rating of E or above to be able to be let. According to Welsh Housing Condition Survey (WHCS) data, 7% of private rental properties received an F rating.

In terms of property type (detached, semi-, terraced or flat) and tenure (social, private or owner occupied), it is clear that social housing performs comparatively well, as do

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[1] However, the level of skill and rigour employed in the execution of the WHCS surveys and EPC ratings is likely to exceed that of the ONS's EPC dataset, so that comparisons should be approached with a degree of caution.

flats and maisonettes (Table 1). This is expected, due to the reduction in surfaces (floor, roof or wall) that are exposed to the outdoors.

Table 1: Median EPC energy efficiency scores by property type and tenure for Wales

Tenure (rows) and type (columns)	Detached (33%)*	Semi-detached (29%)	Terraced (31%)	Flats and maisonettes (65%)
Social rental (56%)	67	67	68	73
Private rental (30%)	56	61	61	68
Owner occupied (23%)	59	60	59	70

Source: Office for National Statistics, 2021.

* The figures in brackets are the corresponding percentages of dwellings having an EPC rating of C or higher

To understand how the retrofit target of an EPC band A rating for the Welsh housing stock could be achieved it is necessary to use a housing stock energy model which:

- Represents the housing stock in a disaggregated manner, discriminating by age and thus mode of construction as well as by type or archetypal form;
- Represents the mode of tenure of the housing stock and, preferably, accounts for the policy measures that target these different tenures;
- Predicts the likely outcomes from policy and regulatory measures that target different property types and tenures; and
- Accounts for the fact that by 2050 the composition of the Welsh housing stock is likely to be different, as houses are demolished, renovated and (re-) constructed.

Housing stock energy modelling

The UK has a long history of developing and applying HSEMs, starting from the early post-1973 oil crisis period, with more than 30 HSEMs having been developed in the UK to date. This section describes two categories of model, traditional and dynamic, and how they have been applied. It also considers the extent to which external factors influencing housing energy use are represented, such as climate, the broader energy system and local infrastructure networks.

Housing stock energy models may have different time horizons, ranging from short- to long-term. Short time horizon applications might focus on testing the effectiveness of specific interventions in relation to specific types of houses, to illustrate how they might best be renovated to reduce their carbon emissions, say over the next three to five years. These models make no judgements about the likelihood that these actions might be taken, rather they allow the consequences of scenarios with assumed levels of uptake to be estimated. Studies to support UK housing policy have been dominated by this type of modelling which concentrates mainly on applications of building physics to model energy flows in houses. We refer to these as traditional HSEMs or T-HSEMs. In the UK, T-HSEMs have overwhelmingly been based on simplified (monthly or annual) energy balance calculations that are unable to calculate indoor temperatures and how these, and related energy flows, are affected by occupants' behaviours and the storage of heat in the building fabric.

In the context of future climate impacts and the need to decarbonise heating to mitigate these impacts, current policy encourages heat pump uptake and the decarbonisation of the power sector. However, this could negatively impact on households' livelihoods through increased operating costs, particularly if electrical energy costs rise (as they have during the recent energy supply crisis) to recover the costs from capital investments in low carbon energy generation technologies. Furthermore, thermal comfort and health may be compromised if the envelope isn't insulated to compensate for lower water distribution temperatures from heat pumps. These impacts can only be studied using modern HSEMs that explicitly simulate the transient flows of heat in buildings and their energy and carbon consequences.

Long time horizon models are more far reaching. They are concerned with the composition of the stock of houses and households and the external factors that influence them, in terms of construction, demolition and renovation. They seek to understand how national housing stocks are likely to evolve in response to scenarios to stimulate accelerated and deep renovation that complies with the 2019 amendment of the 2008 Climate Change Act to achieve net zero by 2050 (The

Climate Change Act 2008 (2050 Target Amendment) Order 2019). These policy impacts can only be revealed through dynamic simulations of the housing stock composition. We refer to these as dynamic HSEMs or D-HSEMs.

Note that these dynamic HSEMs may be thought of as an extension of traditional HSEMs, as these also calculate housing energy use and associated carbon emissions; the key distinction being that they also model how the composition of a housing stock changes over time.

This section begins with a review of simplified T-HSEMs and goes on to review recent, more sophisticated models, that transiently simulate energy use and internal conditions in houses. We then discuss D-HSEMs that have recently emerged in Europe to study the dynamic composition of the housing stock. We conclude by discussing how the virtues of these two modelling approaches could be combined to significantly strengthen their ability to support the analysis of Housing stock decarbonisation policy.

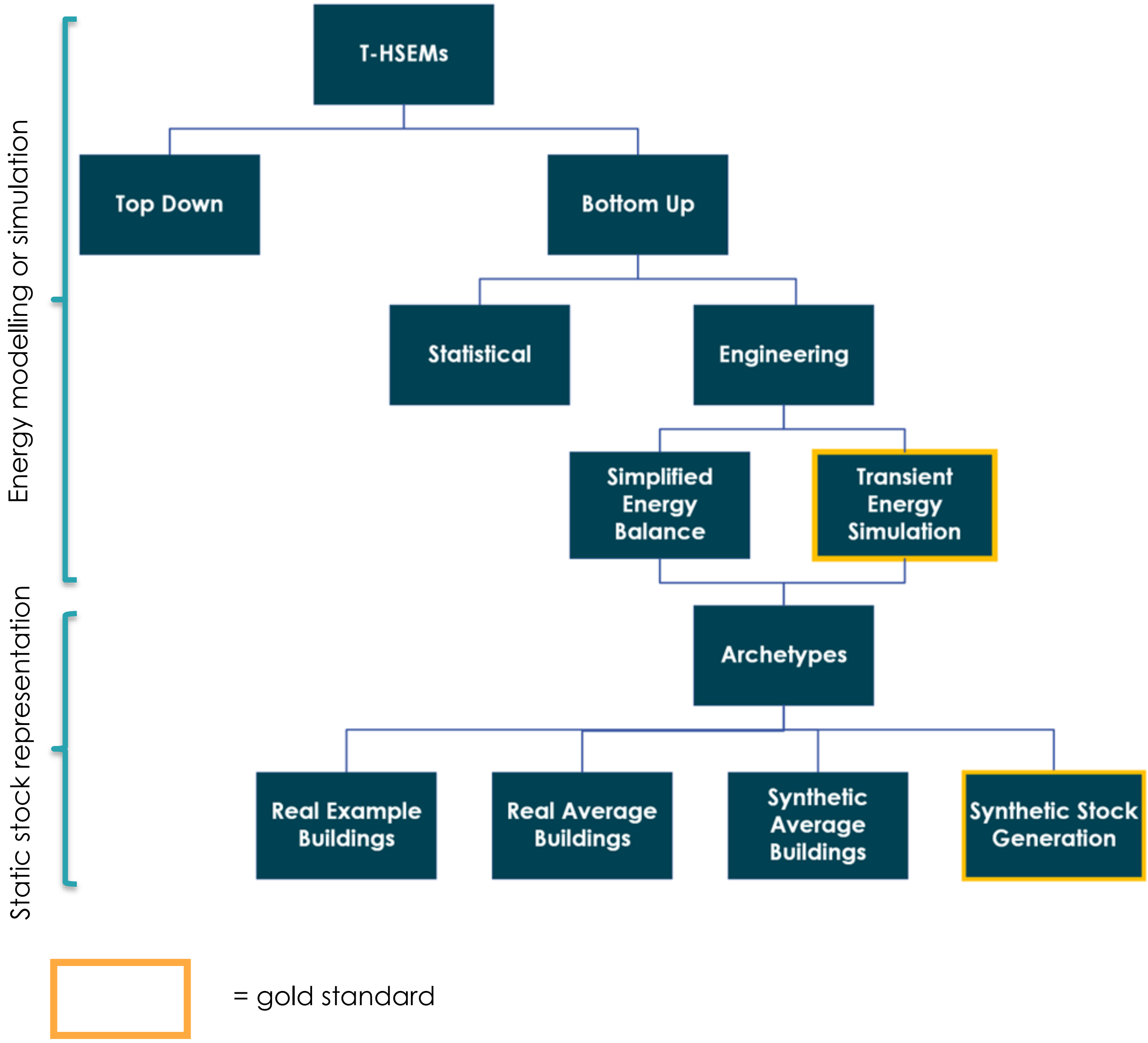
Traditional housing stock energy models

Traditional housing stock energy models (T-HSEMs) consist of two key interrelated component parts: the energy use modelling calculations and the processing of data representing the housing units to be modelled. Since it is impractical to model every individual house in a (sub-) national stock, this method clusters housing units into archetypes. In this section, we discuss approaches to energy modelling (including behavioural modelling and energy conversion modelling) and housing archetyping.

Energy use modelling in T-HSEMs

T-HSEMs can be classified as top-down or bottom-up, Figure 1. Top-down models have mostly been used to anticipate future energy supply requirements. Most T-HSEMs are bottom up, employing simplified energy balance calculations, although there exist recent models that calculate the transient flows of heat (e.g. hour by hour) in houses and the consequential indoor conditions.

Figure 1: Types of T-HSEM and their representations of the housing stock



The top-down approach to housing stock energy modelling relies on aggregate information describing historical energy use for the housing sector as a whole and how this may be influenced by macroeconomic and technological effects. This does not permit the disaggregation of energy use by types of dwelling or by dwelling use. As such these types of model do not support the testing of specific interventions and their effects in relation to specific types of property, but they do support broad sector level energy use forecasts. As such, they are mainly used to anticipate future energy supply needs.

In contrast, the bottom-up approach determines the energy use of each type of building (or archetype), potentially also of their end uses, aggregating this data through weights to determine the total energy use of the corresponding proportion of the housing stock that is comprised of this archetype. These models may use statistical or engineering techniques. Statistical bottom-up models employ detailed disaggregated data to find relationships between energy use and the buildings' features, including the characteristics of the building envelope, electrical appliances and energy (e.g. heating) systems. Engineering bottom-up models conventionally use simplified monthly or yearly energy balance models to evaluate the energy demands of housing archetypes. However, more recent T-HSEMs (e.g. EnHub and ResStock, discussed below) employ sophisticated energy simulation techniques that explicitly simulate hourly energy flows and indoor conditions.

These bottom-up *transient* engineering models are the most powerful as they calculate hourly energy use and how this is split by end uses. As such, they support the explicit modelling of a range of potential interventions and, data permitting, at any desired level of disaggregation of the housing stock, accounting also for the temporal character of energy use and indoor conditions. Coupled with recent advances in behavioural modelling, these can also explicitly account for the impacts of occupants' behaviours on housing energy use. The energy modelling and simulation techniques used in bottom-up engineering models are explained in detail in **Annex 2**.

Many of the most commonly used models in the UK are derivatives of the Building Research Establishment Domestic Energy Model (BREDEM), a simplified bottom-up engineering model. The Cambridge Housing Model (CHM) is one such model, and has recently been employed to inform the Housing Energy Fact File and Energy Consumption in the UK. BREDEM-derived models employ simplified energy balance modelling whereby the effects of internal thermal mass on the moderation of the demand for space heating are accounted for, but in a very approximate way. However, the consequences for indoor temperatures and thus for occupants' thermal comfort and the risks of overheating cannot be handled by these models. Similarly, the way in which the impact of fuel poverty plays out, in terms of balancing the cost of energy use with indoor (dis)comfort and health cannot be explicitly represented by these models. Nor can the rebound effects in terms of costs and associated energy use impacts that arise from the proposed shift towards electrified heating, in particular through the use of air- or ground- source heat pumps. Heat pumps operate more efficiently at lower temperature uplifts (the difference in temperature between the source (air-, ground-) and the distribution medium (water in pipes) and so they are normally sized for moderate uplifts. As such, this electrification of heating may result in lower indoor temperatures unless it is accompanied by sufficient insulation upgrades and/or changes to the sizes of indoor heat emitters (e.g. radiators). Furthermore, time varying energy tariffs may be introduced to encourage homeowners to use power during lower tariff periods to reduce peak demands on the power system: this would change the time profile of energy usage. Energy simulation models can explicitly simulate the interactions between these broader influences on both transient energy use and indoor conditions.

Behavioural modelling in T-HSEMs

To maintain their comfort, occupants of buildings may adjust their personal characteristics (clothing, posture, activity, consumption of drinks etc.), their environment (curtains and blinds, window openings, desk fans) and the environmental control systems that are available to them (heating, cooling, ventilation and lighting). All of these have implications for energy use. In addition, they may use a range of other energy services, for example to support cooking, working, entertaining, cleaning etc. Maier et al. (2009) identified a factor of two variation in heating demand in their study of 22 identical residential houses in Germany. Meanwhile, Gill et al. (2010) found through post-occupancy evaluations of UK eco-homes that occupants' behaviours account for a variation of 51% in heating demand between similar dwellings.

Since these adaptations take place in response to *transient* local stimuli (Haldi and Robinson 2009, 2010), they are not handled by BREDEM-type models. BREDEM-type models *do* though handle, albeit in an approximate aggregate and constant way, occupants' activity-based (metabolic) heat gains as well as heat gains arising from the use of lights and energy services. BREDEM-type models also capture intermittency in the use of heating systems as well as the heat gains (end electrical energy use) arising from the use of domestic hot water. However, BREDEM type models do not capture behavioural changes such as the use of curtains or blinds, or adjusting windows to allow for ventilation.[2]

In contrast, models such as *EnergyPlus* that simulate transient indoor environmental conditions can be integrated with stochastic models of occupants' behaviour. These models can then predict the likelihood that people will adopt behaviours to alleviate discomfort, and the energy and indoor environment consequences of these actions, as well as the likely activities and related energy services that may be called upon. Indeed, dedicated behavioural modelling platforms such as No-MASS (Chapman et al., 2018) and ObFMU (Hong et al., 2016) can be readily coupled with *EnergyPlus* or any other dynamic building energy simulation program to support comprehensive behavioural modelling, including at housing stock level.

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[2] These adaptations take place in response to *transient* local stimuli, see Haldi and Robinson 2009, 2010.

Energy conversion modelling in T-HSEMs

All T-HSEMs translate the demand for energy to heat (and cool) buildings into a corresponding energy use, by accounting for the efficiency of the systems that convert chemical (in the case of gas boilers for example) and electrical (in the case of direct electric heating or heat pumps) energy into heat. Simplified energy balance models do this using assumed constant efficiencies, whereas transient energy simulation techniques explicitly calculate the efficiency with which these energy conversions take place, depending upon the prevailing environmental conditions. As such, they are more accurate in their calculations of energy use and indoor conditions.

The final element in the jigsaw of a building's operational energy flows, once the energy demand has been converted to an energy use, is to consider any on-site generation of renewable energy. For example, by converting wind kinetic energy or solar energy into renewable electricity. BREDEM-based energy balance models also calculate these energy conversion processes by employing fixed efficiencies. In the case of solar photovoltaic panels, this calculation considers a correction to the peak output of the panel (accounting for sub-peak inefficiencies) and an overshading correction factor. In the case of wind turbines, the calculation corrects for wind speed at the wind turbine hub height, as a function of the terrain and the size of the turbine. Energy simulation techniques in contrast, calculate the transient and technology-specific conversion efficiency, explicitly (in the case of solar energy) accounting for the dynamic impacts of the local context on the energy available to be converted. This means the models more accurately determine the renewable energy that is available to be used by the lights, appliances and (if electrified) heating and hot water systems.

Housing archetypes

It is impractical to model every individual house in a (sub-) national stock, therefore this modelling method clusters housing units into archetypes. Different HSEMs employ different strategies for sampling the housing stock, with different levels of granularity used, from a single average dwelling (*BREHomes*), through a small number of categories of shape and age (*DeCarb*) to one model for each English Housing Survey (Cambridge Housing Model, CHM). This generally reflects the availability of data within the target (sub-) nation. The EU-funded Tabula project (Ballarini et al., 2014) identified three such sampling strategies:

- Real example buildings, in which a single real building is subjectively selected by a panel of experts as being representative of a particular cohort (of archetypal shape and vintage), or of the stock at large, when statistical data is unavailable;

- Real average buildings, in which survey data are analysed to identify a real example building that is a statistically sound representation of the mean characteristics of the cohort; and
- Synthetic average buildings, in which a synthetic composite building is constructed, with each geometrical, constructional and systems attribute being representative of the average from amongst the available data.

Fonseca et al. (2017) employ an alternative, fourth, strategy: using repeated random ('Monte Carlo') sampling of probability distributions describing the attributes of buildings that are surveyed in preparing individual entries to large EPC datasets. This *synthetic stock* modelling approach enables not only the average energy use, but also its distribution to be calculated.

In the UK, the CHM primarily utilises EHS data to model archetypes (one per survey), with the results upscaled, through EHS weightings to support estimations of national energy use and associated CO_2 emissions due to the total size of the housing stock that is represented by each survey entry. With more than 12,000 models this makes scenario modelling complex and time consuming; it also means that there is both avoidable duplication and gaps in parameter values that are not addressed.

Two recent T-HSEMs (EnHub in England and ResStock in the United States) share EnergyPlus as their underlying transient energy simulation engine, Box 1. While most T-HSEMs approximate heat flows in monthly or annual steps, EnHub and ResStock transiently simulate the flow of heat through a dwelling from first principles. This makes it possible to calculate how energy is used on an hourly basis and to predict the resulting indoor temperatures. (See **Annex 2**).

Box 1: Examples of alternative T-HSEMs using transient energy simulation

The simulation-based T-HSEM *EnHub* platform uses transient energy simulation (Sousa et al., 2018, 2020). It also employs synthetic stock modelling to more reliably represent the housing stock; defining archetypes that address shape, vintage, climatic region, heating system type and tenure. In this way, a synthetic stock of 1064 archetypes is generated, which is less than one tenth the size of the original EHS dataset, and in which each element retains links to its parent archetype.

Through this parsimonious archetyping strategy, the housing stock is represented with a minimum of archetypes, to more efficiently test interventions and their effects. This allows for faster modelling without sacrificing accuracy in the representation of housing stock. An important feature of EnHub is that it has been designed and developed to respect essential software engineering principles (modularity, transparency, openness, updatability etc).[3]

Further afield, and in a similar vein, ResStock (Wilson and Merket, 2016, 2018), developed and maintained by the US National Renewable Energy Laboratory, employs the same underpinning energy simulation engine as EnHub, *EnergyPlus*. This models some 350,000 archetypes, based on a combination of public and private datasets, to simulate the c.80million dwellings in the US.

Policy applications of T-HSEMs

T-HSEMs have helped policymakers to understand the extent of emissions arising from the housing stock and the potential for reducing them, despite the weaknesses discussed above. Early HSEMs were developed following the 1973 oil crisis, to shed light on how energy demands in housing could be reduced, paving the way for the introduction of conservation of fuel and power regulations, housing insulation schemes, home energy rating schemes and carbon accounting in environmental assessment methods. Since then, housing models have been frequently used to inform environmental and energy policy.

As noted earlier, BREDEM-based models have dominated this policy-related landscape. In particular in the form of applications of BREHomes (Shorrock et al., 1997) to model future housing energy use and carbon emissions based on projections of the uptake of energy conservation and efficiency measures by fitting a model to historic data, and also of assumed enhancements to the rate of uptake. Johnston et al. (2005) later employed a similar approach to examine housing carbon emission scenarios based on assumed penetration of energy conservation and efficiency measures.

More recent applications have employed the CHM to support the UK Housing Energy Fact File and Energy Consumption in the UK reports, which have themselves informed housing decarbonisation policy (e.g. the Green Deal) (Palmer and Cooper, 2013; Department for Business, Energy and Industrial Strategy 2021). Due to the nature of the underlying BREDEM model, these applications have been based on

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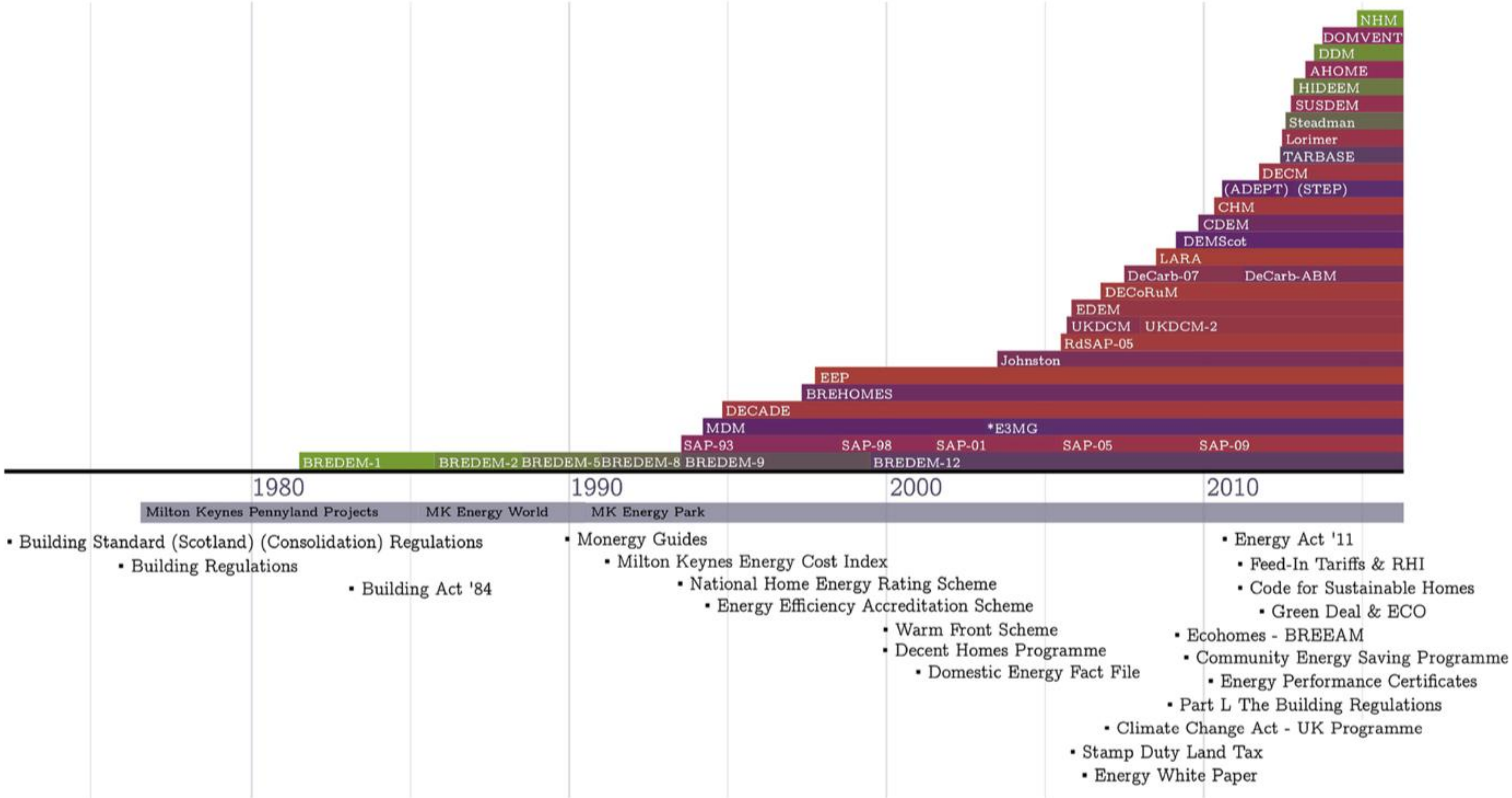
[3] See **Annex 3** for more on best practice in this area.

what-if scenarios of assumed substitutions of features of the envelope or systems of the modelled archetypes, and thus do not respond to how the structure and use of the housing stock changes over time. Also, the underpinning algorithms are not transparent and so do not facilitate assessments of how the tool should be improved (Sousa et al., 2018).

Figure 2 identifies T-HSEMs that have been developed in the UK, when they were developed and the coinciding housing-related energy policies and regulations that motivated their development and/or benefitted from their application.

Figure 2: T-HSEMs in the UK, when they were introduced and the coinciding energy policies.



Source: Sousa et al., 2017

The Standard Assessment Procedure (SAP) and its reduced version Rd-SAP are also both based on BREDEM. These calculations are employed in the building regulations, to perform EPC calculations as well as to identify candidate investments and the extent to which a house's EPC band could be cost effectively raised. This also underpinned the UK government's Green Deal.

In the United States the National Renewable Energy Laboratory has developed ResStock, as mentioned above, which simulates the (sub-) hourly demand for energy. Visualisations of results are made freely available to city, state and federal policymakers as well as to manufacturers and utilities, better leveraging the investment in developing and deploying this T-HSEM than has been the case in the UK.

The state of the art in Wales appears to be the model by Green et al. (2020). This is a simplified T-HSEM of the Welsh housing stock, drawing on EPC and WHCS data to define fourteen archetype-vintage pairings and their weights (the proportion of the Welsh housing stock represented by them). EPC data was then analysed to attribute to the fourteen archetypes, creating average dwellings with which to perform SAP calculations. Four different retrofit scenarios were considered, representing a combination of constraints and opportunities: heritage, rural, good practice and best practice, together with three power system decarbonisation scenarios (minor, significant and transformational change). The per-typology (or archetype-vintage pairing) and stock-level costs and carbon impacts of these scenarios were estimated, assuming perfect uptake.

This is a useful model, but it does not support analysis of likely impacts of alternative decarbonisation policy measures due to several drawbacks (which are common for other models too), e.g.,:

- It does not reflect the heterogeneity of the stock and therefore SAP and carbon outputs are not representative. This is due to the model's limited number of archetype-vintage pairings and the simplified energy modelling calculations employed;
- The housing stock is assumed to be static and the likely adoption of low carbon renovation strategies and corresponding (p)rebound effects is not addressed;
- The simplified energy balance model does not permit predictions of the indoor environment and comfort, which is particularly important for scenarios representing heat pumps;
- Although the power system is considered, the future climate and its impacts are not; and

- Embodied energy and carbon emissions arising from renovations are not considered

Critique of traditional HSEMs

T-HSEMs have a long history of supporting assessments of energy use in housing in England and of indirectly supporting the formulation of energy-related housing policy, discussed above. However, a weakness of these models is that the structure of the housing stock remains unchanged in the scenarios whereas in practice changes are occurring to the housing stock all the time, and as such these models are limited in the extent to which they can be used to accurately forecast the way in which housing stock and the carbon emissions arising from it is likely to evolve in the future.

T-HSEMs have overwhelmingly employed simplified energy balance methods to estimate the annual energy use and carbon emissions of the stock and of scenarios involving assumed uptake of envelope components (e.g. insulation) and system substitutions (e.g. heating system type). As such, in contrast to energy simulation techniques, they are unable to evaluate:

- Simultaneous interactions between the envelope and the heating system, and how this affects indoor conditions, such as when heat pumps replace boilers;
- The extent to which future warmer climates will impact indoor conditions, with consequential risks for overheating and related premature deaths;
- Symmetrically, the extent to which fuel poverty leads to the underheating of homes and how this impacts on indoor comfort and health; and
- The impacts of occupants' behaviours on energy use and indoor conditions and how these might change following renovation decisions (the so-called rebound effect).

This means that energy balance-based T-HSEMs are limited in their modelling potential and will face particular difficulties in meeting the challenges arising from a changing climate, changing energy and heat sources, and behavioural changes on the part of occupants. In contrast, energy simulation based T-HSEMs such as *EnHub* do not suffer from these drawbacks, so long as behavioural feedback is accounted for.

All T-HSEMs fail to consider the energy and carbon that is embedded in their construction materials and the lights, appliances and systems that are accommodated, as well as their broader lifecycle impacts. This precludes analysis of the broader environmental impacts of renovations and of whether renovation is preferable to demolition and reconstruction. They also fail to discriminate between the circumstances of households that are occupying housing archetypes, preventing them from being used to identify specific combinations, for example low income households who are in particular need of assistance as they occupy high energy- and carbon- intensity housing. Similarly, they also do not model the ways in which houses and the households occupying them are spatially clustered, and thus to spatially target where there are particular needs for local authorities to support renovations.

Furthermore, the focus on *assumed* rather than *predicted* substitutions, and how these might be influenced by policy interventions, means that T-HSEMs are limited in the extent to which they can support housing decarbonisation policy. They can highlight where decarbonisation potential in specific housing archetypes lies, but they are not able to offer forecasts as to the extent to which this potential will be realised and the time horizon needed for the changes to be achieved. This would require household investment decisions to be modelled in the shorter term. Considering longer term policy decisions and influences, it is necessary to consider how the housing stock is likely to evolve in response to population change and building degradation, how households relocate as their circumstances change and how these circumstances influence renovation decisions. In short, explicit consideration of stock dynamics becomes necessary beyond the short term.

Dynamic housing stock energy models

In contrast to T-HSEMs that focus on identifying what is possible within the constraints of the current housing stock, D-HSEMs aim to capture the ongoing changes that occur in the housing stock. These have the potential to be a powerful resource for policymakers, enabling them to estimate the likely economic and carbon impacts of their policies and strategies to decarbonise the housing stock over the longer term.

The composition of a housing stock is in a constant state of flux, as houses are demolished, new houses are constructed and existing houses are renovated, in response to changes in household circumstances, lifestyles, aspirations and demographic change. D-HSEMs which consider a longer time horizon model how the size and composition of the housing stock changes from year to year, as new houses are built, larger houses are sub-divided into flats, older substandard houses are demolished and replaced or houses are simply renovated. In this way, D-HSEMs have the potential to more effectively inform and shape policy decisions.

Demolition, construction and renovation activity also has environmental implications, due to the inflows and outflows of materials, appliances and systems. Longer term operational energy use is also influenced by climate change, structural changes to the energy system and connectivity to more localised energy infrastructure such as district heating networks.

D-HSEMs can consider how these factors evolve over time and the extent to which they influence housing energy use and associated emissions. They could, therefore, offer a more sophisticated and sensitive approach to modelling the emissions consequences of policy decisions. This section outlines the underlying principles of D-HSEMs and their advantages for policy.

Housing stock dynamics

D-HSEMs (Figure 3) have been developed over time since the model type was first introduced by Muller (2006).[4] In this model, new construction is determined by population growth linked to a corresponding dwelling occupancy density, while demolition is determined by an assumed distribution describing the probable lifetime of buildings constructed by each stage.[5] This simple model treats the stock as a single aggregate or cohort. Sartori (2016) develops Muller's modelling approach, dividing the Norwegian stock into vintages and modelling their demolition and renovation using building- and component- level lifetime distributions, fitted to statistical data. This model then assumes that renovation or demolition of the existing stock happens only as a result of deterioration of the building fabric.

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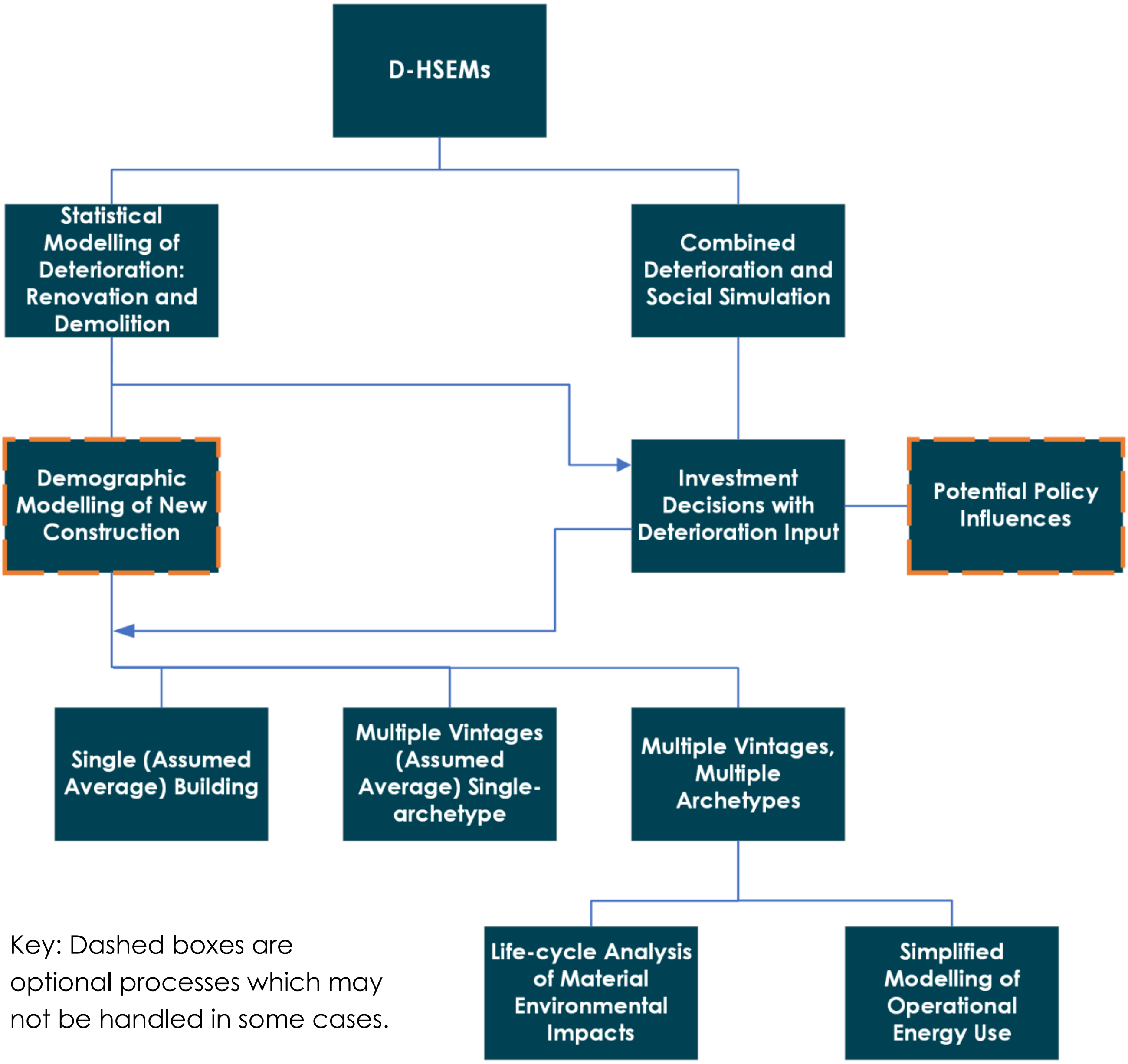
[4] Muller used a form of dynamic material flow analysis in which the size of the stock at a year *t+1* is equal to the size of the stock at year *t*, plus inflows from new (or replacement) construction at *t* less the outflows due to demolition at *t*.

[5] The Muller model was developed to anticipate the evolving demand for concrete in the Netherlands.

Figure 3: Types of D-HSEM, their representations of the housing stock and its environmental impacts



Sandberg et al. (2016), who apply this model to 11 EU countries to model stock dynamics, suggest that renovations could be linked to modelled transitions in vintage-specific energy use intensity. McKenna et al. (2013) employ this technique to model the dynamics of five archetypes and six vintages representing the German housing stock, together with its corresponding energy use; likewise Vasqez et al. (2016) to model the housing stocks of Germany and the Czech Republic, to test the effectiveness of reductions in energy use intensities applied to existing buildings through assumed renovation rates and to future new construction.

This approach is expanded upon by Heeren et al. (2013), who model the dynamics and energy performance of similar vintages representing the building stock of the city of Zurich in Switzerland. For this latter, operational energy use is modelled by a monthly energy balance calculation, complemented with life cycle analysis (LCA) of the materials' environmental impacts. This simply requires that the elements of the building envelope are associated with the corresponding entries in a database (such as the popular **Ecoinvent** database) that represent their environmental impacts. Heeren et al. (2013) complement this with scenarios addressing future power system carbon intensity. Nägeli et al. (2018) employ an approach similar to that of Heeren et al. (2013), to model energy use of a synthetic stock representing the Swiss housing stock, also accounting for renovation through a component deterioration approach. This approach provides a more detailed understanding of building deterioration by modelling how individual parts of the building fabric deteriorate, rather than assuming a constant building-wide rate. It can be further complemented with strategies to test effectiveness of reduction in energy use intensities and scenarios addressing power system carbon intensity.

This approach has been applied in the UK by Serrenho et al. (2019), who employ a dynamic material flow analysis of archetypes and vintages representing the UK housing stock, in conjunction with simplified empirical modelling of operational and embodied carbon emissions based on the SAP calculations from EHS survey data. They deploy this model to examine the feasibility of achieving national decarbonisation targets based on assumed reductions in energy use intensity and the use of low impact materials in conjunction with assumed renovation rates, as well as trade-offs between renovation and demolition and reconstruction.

These approaches are useful in that they enable the impacts of demolition, (re) construction and renovation to be modelled.[6] However, the models are based on the assumption that demolition and renovation activities are determined exclusively by deterioration (the left side of Figure 3). In practice, the causes of demolition and renovation are considerably more complex. The following sections set out some of these additional factors, and how they have been used to further develop D-HSEMs, before exploring some limitations of this modelling approach.

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[6] Indeed, Lavagna et al. (2018) highlight the importance of upgrading existing buildings rather than demolishing and rebuilding them, as the construction phase accounts for up to 40% of total life cycle impacts.

Socioeconomic drivers of housing renovation

Homeowners' decisions to invest in energy-related renovations are influenced by their views of the financial viability of these investments. These are determined by the upfront costs (influenced by the scale and complexity of the house and the scope of the investment), the costs of financing, future potential cost savings and the associated payback period as well as the amount of savings available (Wilson et al., 2018). However, Energy Related Renovation (ERR) decisions are not influenced by finances alone. Other factors include perceived (dis)comfort and environmental concerns (Curtis et al., 2018) as well as social norms or the recommendations by others (Kastner and Stern, 2015) and how these may be influenced by social networks (Friege, 2016). Decisions may also be constrained by barriers including perceived disruption, homeowners' knowledge or the availability of information with which to judge the suitability of investments and the associated trust in any advice given (Wilson et al., 2018).

Broers et al. (2019) and in a similar vein Wilson et al. (2018) outline a multi-stage process by which these decisions are made:

- Getting started: interest is triggered by one's own beliefs (e.g. about comfort or environmental concerns) or by information campaigns (e.g. on the benefits of renovation, the availability of financing or of local subsidies);
- Gaining information: through knowledge or the input from an expert, say following an energy audit;
- Forming an opinion: weighing up the factors mentioned above; and
- Making a decision and following this through with implementation.

Social simulation techniques could provide a vehicle by which the complexity of homeowners ERR decisions could be mapped onto renovation outcomes:

> **'An approach for future research is to use simulation which maps the decision-making process of home-owners on ERRs for their homes, exploring heterogeneity, perceived economical and non-economical motivations and barriers, and social impacts in different socio-spatial structures… it may result in refining existing instruments or developing new innovative instruments that would address the [low take up rates in ERR]. This could save a considerable amount of time and resource…to meet climate protection targets.' (Friege et al., 2014: 205)**

Rebound and pre-bound effects

ERR decisions are complicated by the energy-related practices of households, both prior to and after the implementation of renovations.

If a household invests in an ERR the expectation would be that the price for heating in the future would be lower, all things being equal, thus increasing the household's disposable income so that the capital cost can be recovered. However, this increase in disposable income can have the effect of increasing consumption of the energy service in question, heating in this case to raising the indoor temperature and improve comfort conditions. The increased disposable income may also afford increased consumption of other goods and services that *use* (e.g. lights, appliances) or *embody* (e.g. furniture) energy. These are referred to respectively as the *direct* and *indirect* rebound effects (Chitnis and Sorrell, 2015) and both can increase energy use and emissions. Chitnis and Sorrell (2015) estimate these effects to cause a 41% increase in domestic gas use.

In addition to this over-consumption of energy services following an ERR, there is also evidence of under-consumption prior to undertaking such an investment. For example, indoor temperatures being lower than expected, compromising thermal comfort and health and reducing energy use and emissions. Galvin and Sunnikka-Blank (2016) suggest that this causes measured energy use in Germany to be 35% lower than expected; with this gap increasing as consumption increases, and vice-versa, becoming negative in the case of low energy houses. These (p)rebound effects have been confirmed as significant through pre- and post- intervention measurement of energy use and indoor climate conditions in Welsh housing (Poortinga et al., 2018). Prebound and rebound could also be handled through social simulation.

Incorporating socioeconomic effects in D-HSEMs

There are two dominant types of models that capture social and economic effects (the right side of Figure 3): system dynamic models (SDMs) and agent based models (ABMs). SDMs represent the system being modelled as a set of aggregated interrelated component parts, simulating their dynamic evolution in terms of stocks, flows and feedbacks. They are particularly suited to top-down modelling, though sub-stocks can be defined, for example to represent housing archetypes and vintages. ABMs represent the system under consideration through sets of agents that interact with one another as well as with the environment. These agents can have different purposes and be defined at differing levels of aggregation. In the current context, they could be defined to represent housing archetypes and vintages, as with SDM, or individual houses with further agents representing the household or its members.

They also have the flexibility to represent organisations involved in construction and renovation, as well as infrastructure provision, financing, policy formulation etc.

Fazeli and Davidsdottir (2015, 2017) developed an SDM of the Icelandic housing stock, through three vintages and archetypes, to account jointly for physical deterioration and social effects as drivers for renovation, together with policies to influence energy using behaviour as well as investments in both renovation and demolition and reconstruction. With abundant geothermal resources and correspondingly low prices for heat, they found that there is inadequate incentive to change daily energy using behaviours or to stimulate renovation, but that aggressive policies to favour demolition and construction (represented simply by changing their rates) was effective in reducing future energy demand. Zhou et al. (2020) also employ SDM, this time to model the turnover of the total stock and of vintages of housing in China, with a view to, in the future, testing trade-offs between operational and embodied energy use. This however, only accounts for ageing as a determinant of demolition, construction and renovation.

Natarajan et al. (2011) reformulated their existing traditional HSEM called DECarb (Natarajan and Levermore, 2007), essentially wrapping an ABM framework around the core energy modelling engine to create DECarb-ABM. This framework was designed to represent both household agents and contractor agents; these latter being responsible for demolition and consequent rehousing of the former. This was an audacious project, but unfortunately the framework appears not to have been completed or deployed to realise its potential. More recently, Nägeli et al. (2020, 2020a) have developed a preliminary Agent-Based Building Stock Model (ABBSM), which consists of an ABM wrapped around the energy-balance model that was at the core of their former dynamic HSEM, thus replacing the dynamic MFA model with an ABM. Swiss building census data is used to generate a synthetic stock of dwellings. A deterioration process drives a demolition, reconstruction and renovation process, but the specific outcome of the renovation activity (the materials and systems adopted) is determined by a statistical (discrete choice) model, influenced by regulations, subsidies, energy prices and taxes.

ABM approaches have the flexibility to represent the stock of housing and households in a highly granular way, together with other relevant actors, including in construction, energy supply, policy and governance; but thus far this capability has not been exploited. There are clear advantages to exploiting this capability which would allow for a much greater level of detail in modelling and correspondingly improved support for policy analysis.

Household composition

In addition to these factors, there are other social, geographic and demographic factors which will influence the energy use of households and which would ideally be captured under HSEMs. The size and financial circumstances of a household determine, to a large extent, the tenure and type of house that it will occupy and where this house will be located, with both influencing its price. These choices may also be influenced by homophilic considerations; where households may wish to be co-located with households of similar social or cultural characteristics. As such, spatial clustering can emerge, which itself can reveal spatial inequalities. In particular, where low income groups find themselves segregated to less desirable locations and/or housing conditions (Stiglitz, 2012).

The data presented in Table 1, above, reveals differences in median EPC rating between modes of tenure; with social housing providers delivering better performing housing than their private counterparts. This relates to the so-called split incentive problem (Fuerst et al., 2016), where the energy costs are not borne by the owner but by the tenant, so that energy-related investments are not directly recovered by energy savings but may be partially recovered through higher rents or shorter vacancy periods. Additional incentives may be needed here, such as the UK government's recent barring of rental of housing that doesn't meet band E or better (The Energy Efficiency (Private Rented Property) (England and Wales) Regulations 2015).

Accounting for these factors requires that a three-dimensional matrix be populated; with housing archetypes and vintages represented on one axis, household archetypes on another and modes of tenure on the third. To the authors' knowledge, no HSEM has adopted such a strategy.

Spatial analysis

Spatial modelling provides the possibility to match buildings with local infrastructure provision and to better target where ERR interventions are most needed. Housing survey data can be used to generate a highly granular synthetic housing stock, offering the prospect of spatially realistic representations of housing energy performance, to facilitate the targeting of interventions to improve this performance. However, this can only be achieved if individual housing units can be paired with the corresponding element of this synthetic stock. At the (sub-)national scale, this would require mechanisms by which the archetype and vintage of individual housing units can be automatically classified, Box 2.

Box 2: Automating spatial analysis

Various attempts have been made to automate these classifications. Beck et al. (2020) used topographical data and an address database[7], to train an algorithm to classify houses by their built form (archetype), while Rosser et al. (2019) trained an algorithm using a combination of topographical, digital surface model and site boundary data to classify houses by categories of age (vintage). Robinson (2019) describes the application of these techniques to model the energy performance of the housing stock in Nottingham, by classifying every house by its archetype and vintage and using this information to pair the house with an element of the synthetic stock. Once paired, any change to an element of the synthetic stock (e.g. to improve energy conservation or efficiency) can automatically be applied to the corresponding instances within the real stock.

This approach is not perfect. The statistical techniques used are capable of predicting energy use at higher levels of spatial aggregation (e.g. at the scale of Lower-Layer Super Output Area of c.650 households or higher); therefore discrepancies at the scale of individual household are inevitable. However, such discrepancies could be avoided through crowdsourcing. For example, using a web app interface to a (sub-)national housing model, individual households could tune the characteristics representing their house to improve the fidelity of energy use predictions and to tailor the analysis of decarbonisation scenarios to their specific needs. In this way, a database of housing, household and tenure characteristics could be enriched. This in turn would enable accurate visualisation of housing inequalities and the targeting of spatially specific interventions to improve housing quality. This technique could also be matched with a Geographical Information System layer in which energy networks are represented, to help support infrastructure planning as well as to anticipate households' heating system choices.

Exogenous factors

The issues discussed above relate to the relationship between housing archetypes, modes of tenure, and the composition of the households which inhabit houses in a particular area. These account for many of the factors influencing changes to the housing stock. However, these changes can assume that external climate conditions and infrastructure networks, including national power systems, remain constant over

[7] to identify addressable domestic properties

time. To ensure that D-HSEMs can adapt to changes in these conditions over longer timeframes, consideration needs to be given to these exogenous factors.

This section therefore considers the following factors in relation to D-HSEMs:

i) Future climate projections and the corresponding impacts on space heating and cooling demand as well as overheating risk; and

ii) Decarbonisation of the power sector and the introduction of alternative fuels and their networks together with couplings to local energy (fuel/heat) networks.

Future climate projections

Global warming of between 1.5°C and 2°C will be exceeded during the 21st century unless substantial reductions in CO_2 and other greenhouse gas emissions occur in the coming decades (IPCC, 2021). Even under the optimistic scenario of the global achievement of net zero CO_2 by 2050, it is very likely that medium term (2041-2060) warming will be in the range 1.2-2^{o}C. This warming will have two consequences for building performance in the UK. It will reduce the demand for space heating and increase the risk of overheating and associated mortality, along with the likelihood that active cooling systems will be integrated into buildings, offsetting the reduction in energy use for heating.

These effects can be accounted for in HSEMs by substituting the climate files that are inputs their underlying energy models or simulations with those that relate to future climate change scenarios. For example, using the now somewhat out of date (relative to current climate change projections) **CCWorldWeatherGen** tool. Outputs from model runs with projected climate conditions can then be compared to outputs using existing climate conditions to study how energy use may change in the future. To date the only study that has undertaken this analysis appears to be that of Figueiredo et al. (2020), supporting forecasts of electricity demand for housing in Portugal. The authors conclude that space heating is expected to decrease by 33%, while space cooling shows a possible 20-fold increase.

Decarbonisation implications for energy systems

To meet the UK's commitment to become carbon neutral by 2050, the Climate Change Committee sets out a number of recommendations that have implications for this discussion:

- Decarbonisation of the power sector;
- Electrification of heating, in particular through widespread adoption of heat pumps and associated heat networks;

- Improvements in building energy efficiency;
- Phasing out of gas networks or re-purposing them to transport hydrogen; and
- Increased penetration of electrical vehicles and enlargement of charging infrastructure, combined with smart systems in homes (Climate Change Committee, 2019).

The UK government has recently launched the Boiler Upgrade Scheme to accelerate the penetration of heat pumps or biomass boilers in homes in England and Wales through a one-off grant towards the purchase and installation cost. Biomass boilers are relatively expensive to buy and install (particularly if automatically-fed) and somewhat disruptive in terms of managing fuel deliveries and feeding the boiler, if manually fed. They are, however, competitive with gas in terms of running costs and do not compromise on distribution temperatures, so that indoor comfort is not compromised. For efficiency reasons, heat pumps on the other hand normally entail lower distribution temperatures, so that if the building is not simultaneously insulated, comfort and health can be compromised. Furthermore, electricity tariffs are several times higher than gas tariffs, so that ongoing energy costs are likely to be higher, potentially leading households to further compromise their comfort. Analysis of these subtleties requires transient energy simulation.

As noted earlier, spatial modelling provides the possibility to match buildings with local infrastructure provision. This is important, as proximity to energy network infrastructure is a key determinant in heating system choices (Curtis et al., 2018). For instance, district heat systems where heating is provided through a centralised network would be more feasible in higher-density urban areas than in rural locations.

Finally, increased use of electrical vehicles and battery powered home appliances presents the prospect of using batteries for local energy storage, with charging and discharging being controlled by smart home systems that respond to time varying electricity tariffs and/or the availability of locally generated electricity through solar PV or wind turbines for example. This opens the possibility of more generalised forms of ABM to enable these energy exchanges to be modelled (Sancho-Tomás et al., 2017).

Policy applications of D-HSEMs

To date, the development and application of D-HSEMs has been undertaken by research organisations under the auspices of EU-funded research programs, through Horizon 2020, to support the achievement of the EU's 20-20-20 targets: "reducing greenhouse gas emissions by 20% compared to 1990 levels, increasing the share of renewable energy use to 20%, and improving energy efficiency by 20 %" (European Environment Agency, 2021). This is estimated to have been achieved, and the EU has now adopted a 55% net emissions reduction target by 2030. To this end, funding for the development and application of D-HSEMs to support member states' achievement of this target is likely to continue under Horizon Europe. However, to date there is no clear evidence from the literature that this work has informed member states' domestic policies.

Critique of dynamic HSEMs

D-HSEMs have thus far focussed primarily on the turnover and renovation of the housing stock from a life cycle perspective, combining embodied with operational energy use. Most studies have achieved this through dynamic material flow analysis, that represents housing turnover and renovation activity as a simple consequence of deterioration. However, the reality is more complex, with these decisions being influenced by many factors, including relocation decisions, household finances, the availability of infrastructure, perceived disruption and social influences. A small number of studies have attempted to embrace aspects of this complexity through SDM or ABM, to varying degrees of completeness and success. They have, in the main, been partial prototypes which:

- Employ highly simplified statistical or physical models to estimate operational energy use;
- Do not match housing with household structures and tenure;
- Do not spatially disaggregate housing;
- Do not consider, in any meaningful way, the (p)rebound effects arising from renovation activities; and
- Largely ignore the exogenous factors that impact on housing energy use.

In short, there does not exist a D-HSEM that comprehensively models the factors influencing the time-evolving carbon intensity of housing stocks and how this can be influenced through policy and regulation. In this context, it is important to note that the two studies that have considered future climates (Figueiredo et al, 2020) or spatial disaggregation (Robinson, 2019) have employed T-HSEM modelling techniques.

Finally, no convincing attempt has yet been made to combine the benefits of D-HSEMs with those of their traditional counterparts, with a view to embedding rigour in the simulation of operational energy use with a rigorous modelling of households' investment decisions and how these impact on embodied energy use through the consumption of materials in construction and renovation.

Box 3: Comparing T-HSEMs and D-HSEMs

- **Traditional and dynamic HSEMs model the housing stock from opposing but complementary viewpoints.**

- **T-HSEMs represent the stock as it stands now and test the impacts of assumed (or simplistically modelled) uptake of specific material or technology substitutions.**

- **T-HSEMs focus particularly on the reduction of energy use to varying degrees of rigour.**

- **D-HSEMs in contrast model how the stock might evolve (demolition, renovation, (re-)construction) over long timescales and what the life cycle impacts might be.**

- **D-HSEMs are comparatively strong on embodied energy use, but model operational, or day-to-day, energy use somewhat simplistically.**

A combination of the virtues of T-HSEMs and D-HSEMs, using sound software design principles, would offer a powerful resource to policymakers. This could enable the carbon impacts of specific policy interventions to be revealed, and when and where they would be realised. This would considerably improve the quality of evidence underpinning housing stock decarbonisation policy.

As discussed above, there are models or proposed models which respond to these criticisms and take into account the factors influencing changes in the housing stock and household composition. In particular, T-HSEMs utilising transient energy simulation can better capture indoor comfort conditions and can be adapted to model the impacts of future climate conditions. D-HSEMs using ABMs could model housing stock dynamics at a granular level, considering the factors influencing stock changes as well as the emissions associated with individual renovation decisions. To capture these advantages, a new approach to developing HSEMs will be required. In particular, uniting traditional and dynamic HSEMs could provide a comprehensive base with which to support future decarbonisation policy.

Designing better HSEMs

Developing new HSEMs, uniting the advantages of both traditional and dynamic models, needs to be long-range in scope if policies and strategies are to be effective in achieving 2050 decarbonisation targets. This evidence base is lacking at present and developing it will require a significant investment. Sound software development principles will help to reap and sustain the rewards from this investment as well as offering opportunities to develop mechanisms that can support the straightforward definition of decarbonisation scenarios and the automated modelling of their impacts.

HSEMs have thus far been developed in a largely ad-hoc way, mainly by academic and research organisations, in an environment which is not tailored to the production of commercial-strength software. As such the models tend to be used exclusively by these experts, with little regard for usability, longevity or transparency in their underlying assumptions. As well as limiting their use it also makes their update difficult. As Sousa et al. note, “current HSEMs are lacking in transparency and modularity, they are limited in their scope and employ simplistic models that limit their utility” (2018: 60). Furthermore, the scenarios that are modelled tend to be manually defined, making the process cumbersome and prone to error. This also means that an opportunity is lost to exploit the power that optimisation techniques present to search for identify policy interventions that minimise multiple objectives, including subsidy costs, carbon emissions, health and welfare inequalities.

Any investment in new HSEMs would also benefit from a mechanism to quantify the impacts of uncertainties in the data and to determine how these uncertainties are amplified into the future (in much the same way that uncertainty bands in climate change projections enlarge with time).

Following robust software engineering principles is important for achieving flexibility in the way the model can be used and updated. For example, structuring the software modularly enables new classes and methods to be added to increase the scope of software, or modes of calculation. In terms of simulation results, functionality can be developed to allow users to choose the degree of disaggregation at which they wish to analyse the energy and carbon performance of the housing stock. Good software design can also enable updates as new data becomes available. It is also good practice to have a well designed graphical user interface (GUI) and to make software openly available and accessible through a dedicated repository. The following three features have the potential to create a particularly powerful tool (see **Annex 3** for more detail):

> **Scenario definition and modelling**: This could simply involve mechanisms to identify archetypes and vintages for which envelope elements or energy systems could be substituted. More powerful would be a hybrid of dynamic and traditional HSEMs to define policy scenarios and to evaluate their impacts on energy use, carbon emissions, comfort and health. This could also allow for the modelling of exogenous factors, such as power system decarbonisation, technology improvements or climate change.

Uncertainty analysis: This involves identifying the housing envelope, systems and behavioural parameters to which housing stock carbon emissions are most sensitive and their probability distributions. This enables the uncertainty distribution of future carbon emissions to be simulated.[8]

Optimisation: Computational optimisation algorithms can efficiently search for a solution that optimises an objective function or combination of objective functions, such as cost, carbon emissions, comfort or health. This could be employed simply to identify optimal ERR strategies or the policy measures that could be put in place to stimulate these renovations.

All three techniques could be combined to model and optimise decarbonisation scenarios, accounting for parameter uncertainties. This could be an incredibly powerful resource.

[8] In principle, this feature could be extended to also address uncertainties in exogenous factors such as those noted above.

Conclusion and recommendations

HSEMs have considerable potential to underpin housing decarbonisation policy; to help to target subsidy, education and training programmes; and estimate the corresponding impacts on future emissions and employment (e.g. for heat pump installers). These models can also be used to support industry in identifying the potential market size for specific energy conservation and efficiency products and to correspondingly focus research and development efforts. They can also support utilities to anticipate and influence demands on local and national grids for heat, fuel and power through demand response to transient price signals.

The development and application of HSEMs in the UK has been dominated by traditional HSEMs (T-HSEMs). The models can help to identify where the potential for renovation measures lies, for example by modelling substitutions of elements of the building envelope or energy system, and what the impacts might be, based on assumed levels of uptake amongst homeowners.

In contrast to T-HSEMs that focus on identifying what is possible within the constraints of the current housing stock, D-HSEMs aim to capture the ongoing changes that occur in the housing stock by focussing on probable outcomes. These have the potential to be a powerful resource for policymakers, enabling them to estimate the likely economic and carbon impacts of their policies and strategies to decarbonise the housing stock.

There is a need to unify the two main approaches to housing stock (energy) modelling, T-HSEMs and D-HSEMs, to support the analysis of policies that are formulated with long-term decarbonisation targets in mind. As the scale of transformation to achieve net zero is unprecedented and the housing stock is expensive and slow to change, it is important that decisions are made using evidence that is both rigorous and joined up. In common with Sousa et al. (2017), we assert that this should be achieved using sound software development principles to ensure the longevity, accessibility and usability of the developed modelling platforms.

There is no single overarching tool that can model all the factors that influence the way in which housing stock and energy use interact and the resulting emissions. These include how the housing stock changes over time through renovation and demolition, and factors that influence renovation decisions; energy use including adjustments to maintain comfort; and exogenous factors that affect the need for and source of energy. Generally, tools have been developed with specific housing stocks in mind, often using simplified models that are empirically tuned to these stocks, and as the underlying algorithms are lacking in transparency it is not easy to assess their ongoing accuracy or how easily the tools could be applied to other housing stocks.

In England, CHM has been the most prominently used tool in recent years. However, it takes on the limitations of the BREDEM platform on which it is based and therefore does not respond to how housing stock and use changes over time. Since BREDEM has not been developed in a modular, transparent and openly accessible manner, its potential for further improvement is hindered. In contrast, the recently developed *EnHub* platform has been made freely available and offers opportunities for modelling, data and software updates to be developed and integrated. The state of the art in Wales, appears to be a simplified T-HSEM of the Welsh housing stock, drawing on EPC and WHCS data by Green et al. (2020). It is a useful model, but it has a number of limitations that undermine its usefulness and the reliability of the potential decarbonisation impacts of the renovation scenarios that it has been employed to study. In particular, it does not support direct analysis of the likely impacts of alternative decarbonisation policy measures.

Recommendations

Given the increasing urgency of developing evidence-based housing decarbonisation policies and strategies that are specific to Wales and the absence of a comprehensive HSEM for Wales, the following research, development and application priorities are recommended. They are organised by timing and likely length of the effort needed. They require an integrated approach to be taken across the Welsh Government, and a workflow to achieve this is presented in **Annex 4**. The workflow describes how these proposed short, medium and longer term developments would combine and complement one another and has the potential to produce a world leading D-HSEM platform which could guide the design and evaluation of the long range impacts of housing decarbonisation policy for Wales.

Short term: Welsh Housing Model (T-HSEM) creation

A quick win can be achieved by adopting *EnHub* (Sousa et al., 2018; 2020) and substituting the EHS dataset for England with the WHCS dataset, to create a Welsh Housing Model (WHM). This would support the transient energy simulation of a comprehensive synthetic stock, faithfully representing the heterogeneity of the housing stock in Wales. This would allow for the analysis of a greater range of renovation scenarios than has been possible to date, accounting for the corresponding impacts on energy use, carbon emissions and indoor comfort. This initial version of the WHM would provide Wales with an internationally competitive T-HSEM, on a par with the US ResStock platform.

Medium term: T-HSEM enrichment

The scope of the WHM could be enriched in the following ways over a three to five year period. These changes would create a world leading *traditional* housing stock energy modelling platform.

Tri-dimensional archetyping: Combining datasets to develop a three-dimensional matrix of archetype-vintage pairings, household archetypes (of demographic composition and socioeconomic circumstances) and housing tenure.[9]

Spatial analysis: This could include the development and application of techniques to classify houses by their archetype-vintage pairing, tenure and household type; added to a national housing GIS database. An energy network layout could also be added as well as functionality to link each house in Wales with the corresponding WHM archetype and its attribution parameters. Visualisation and analysis of housing energy performance for Wales, both spatially disaggregated and aggregated, for example by municipal ward could be included.

One significant outcome of the recommended spatial analysis capability is the geolocated identification of prospective renovation activity and the corresponding potential impacts on public financing, the local economy and employment with associated local economic multiplier effects.

Behavioural modelling: This would involve integrating a multi-agent simulation platform such as No-MASS (Chapman et al., 2018) with EnHub and enriching this with a population generator to generate synthetic households from the household archetypes and their characteristics. This would enable household members' activities and appliance ownership profiles to be modelled, together with their activity-dependent behaviours (e.g. using energy services, opening windows etc). It will also provide a rational basis for the future modelling of (p)rebound effects.

Scenario analysis: Co-design of energy conservation and efficiency scenarios, with government, industry and academic stakeholders. This would involve the

[9] WHCS, AddressBase-Plus, Census, Experian Mosaic, Council Tax Band, Landlord Registrations.

testing of these scenarios and the analysis and visualisation of their impacts at differing levels of spatial granularity (feeding back into the identification of intervention scenarios). This would benefit from the addition of cost and embodied energy modelling functionality.

Web interface / crowd-sourcing: The development of a web app interface to the WHM, providing homeowners with the means to analyse, update and test scenarios to improve the performance of their homes. This would need a mechanism to link archetypal data files with house-specific data files. It would also provide a mechanism by which the fidelity of the synthetic stock of archetypes could be enhanced, and a corresponding mechanism to periodically facilitate this.

Longer term: D-HSEM creation

In the longer term, we recommend augmenting the WHM with the features below. While these constitute a substantial investment in research and development and the use of high performance computing infrastructure, they have the potential to create a leading *dynamic* housing stock energy modelling platform. This recommendation combines the virtues of traditional and dynamic HSEMs in a comprehensive and rigorous way with which to thoroughly evidence housing decarbonisation policy and the spatial and temporal analysis of policy impacts.

Population, relocation and deterioration modelling: The synthetic households developed above could be combined with statistical modelling of their changing circumstances (such as ageing and mortality, births, income) and analysis of how these impact on relocation decisions. National population forecasts, census and housing market data could be added to calibrate this modelling. Relocation decisions are one driver of renovation decisions, which are also impacted by the deterioration in the housing stock over time. This deterioration has been modelled at two levels of aggregation: the building (for demolition) and components of the fabric and systems (for renovation).

Renovation investment decision modelling: Considering factors to determine the nature and scale of renovation activity such as deterioration of elements of the building envelope and systems (wear and tear to housing fabric) and changing household circumstances, input to agent-based investment decision modelling. In contrast to prior models, this should involve a mechanism by which elements that would benefit from being renovated are grouped and implemented as discrete jointly coordinated events.

Future climate modelling: Development of a utility to update the weather files that are inputs to the core energy simulation engine, accounting for future climate projections based on a chosen future emission scenario.

Scenario modelling and optimisation: Combining scenario definition and modelling, uncertainty analysis and optimisation as outlined in **Annex 3**.

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Annex 1: Glossary

Archetypes: In this report, we take this to refer to classifications of the shape or form of a house, such as detached, semi-detached, terraced, flat or bungalow. In the housing modelling literature however, this term occasionally has a broader definition, including classifications of age (vintage here). For simplicity, we refer separately here to archetype (form) and vintage (age).

Building envelope: the boundary between the interior and exterior of a building that facilitates indoor climate control.

Energy conservation: In the context of this report, refers to the use of measures such as envelope insulation, draught exclusion and heat recovery to reduce the rate of heat loss from a house, so that heat (thermal energy) is better conserved.

Energy efficiency: The efficiency with which energy is converted from one form to another, expressed as the ratio of the energy output (e.g. in Joules, *J*) to the energy input (*J*). For example, the conversion of chemical energy to thermal energy in a properly installed gas condensing boiler has an efficiency of 0.9-0.95.

Energy efficiency is sometimes applied at the whole building level, so that the boundary is enlarged from the efficiency of a systems (e.g. a boiler) to also consider energy conservation by the envelope and the utilisation of ambient (e.g. solar) energy. This should more accurately be termed an energy performance rating.

Energy related renovations: These may include insulating the walls, roof or floor, by substituting the glazing or by replacing the heating system with a more efficient one

Energy use: The use of energy within the geometric boundaries of a house for the provision of energy services relating to heating, hot water, lighting and electrical appliances, accounting for (e.g. heating) system inefficiencies. This is distinct from end use energy demand (EUED), which neglects these inefficiencies. Energy use is sometimes confused with ‘energy consumption’, an incorrect term that implies that energy is lost (by being consumed), in contravention of the first law of thermodynamics.

Housing stock energy models (HSEMs): Computer models that estimate national, sub-national or regional scale energy use in housing, typically through the representation of archetypes (e.g. mid-terrace, end-terrace or semi-detached,

detached, apartment), with predicted energy use from these scaled according to the total size of the stock that is represented by them.

(P)rebound effects: Where occupants consume more (or less) energy than expected following from the implementation of an ERR.

Renovation: The act or process of repairing and improving a building, to meet changing needs or circumstances.

Stochastic models: Models that account for the probability of various outcomes, in particular with respect to occupants' interactions with the building envelope and systems.

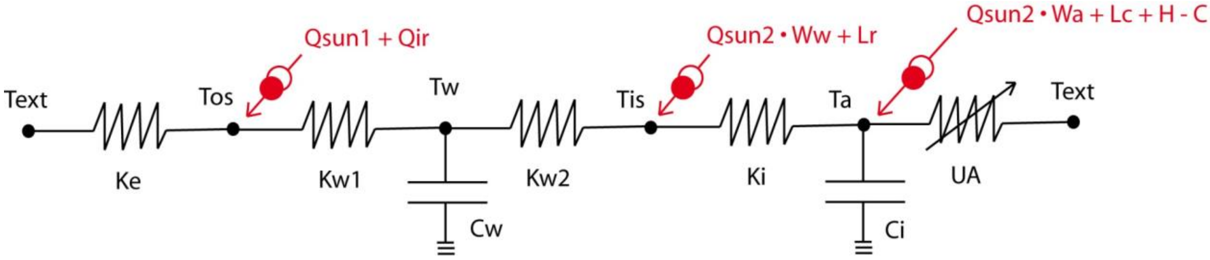
Synthetic housing stock/households: statistically reduced representations of actual housing stocks/households.

Vintage: Refers to classifications of the age of a house. For example, the English Housing Survey employs the following vintages: pre-1919, 1919 – 1944, 1945 – 1964, 1965 – 1979, and post-1980.

Annex 2: Bottom up T-HSEM engineering models

Bottom-up engineering models place a particular emphasis on heat flows. These heat flows can be represented schematically with the help of Resistor-Capacitor (R-C) network diagram, Figure A1.

Figure A1: Resistor-Capacitor network diagram of heat flows in a house with a single thermal zone



Source: Kämpf and Robinson (2007)

Analogous to an electric network, this diagram is comprised of a series of temperature nodes (*T*) that are connected to one another via resistances (*K, UA*), with some also associated with capacitors (*C*). Reading this diagram from left to right, an external air temperature node (*Text*) is connected to an outside surface temperature node (*Tos*) via a convective resistance (*Ke*) that represents the surface film resistance. *Tos* is also influenced by the net absorption of shortwave or solar (*Qsun1*) and longwave or infrared (*Qir*) radiation exchange. These radiative exchanges can in principle be influenced by adjacent buildings, for example by occluding views to the sun or sky. *Tos* is in turn connected to a wall temperature node (*Tw*), this time via a conductive wall resistance, representing the resistance to heat flow by the wall and any insulation that is integrated with it. This wall also has the ability to store (by elevating its temperature) and later discharge heat, so that it is also linked with a capacitance (*Cw*). In essentially a mirror image, this wall temperature node is linked by a similar conductive resistance to an inside surface temperature node (*Tis*), which is also influenced by internally absorbed shortwave and longwave radiation exchange; this latter representing the radiative part of internal heat gains. *Tis* is itself linked with an inside air temperature node (*Ta*) via an internal convective resistance. This internal air node is also influenced by internally transmitted shortwave radiation due to the convection of heat absorbed by glass (*Qsun2·Wa*), as well as by the convective part of internal heat gains (*Lc*) and internally convected heating and/or cooling loads (*H* and *C,* though these may also be modified to contribute to *Lr* above, if some form of radiating surface is used as the medium for heating and/or cooling). The air node may also be associated with a capacitance (*Ci*), for example to account for the storage of heat by indoor air and furnishings. Finally, our indoor air node is also connected to an outdoor air temperature node, but this time represented by a variable resistance (*UA*) to represent the dependence of advective (ventilation and infiltration) heat transfers on temperature differences, wind speeds and the extent to which windows are open (or indeed to account for mechanical ventilation systems).

This diagrammatic representation, and the underlying physical modelling, can be rendered more complex. For example, an explicit distinction can be made between the thermal effects of walls, roofs and ground floors; walls can be associated with orientation-sensitive radiative transfers and corresponding nodal temperatures; wall capacitances can be disaggregated to distinguish internal wall layers from external layers that are separated by insulation; additional thermal zones can be added, these being separated by wall resistances that can also be assigned a capacitance… etc. Indeed, dedicated transient building simulation programs, such as the widely used program *EnergyPlus* (Crawley et al., 2001) are designed to do just this; essentially translating a semantically enriched 3D representation of a building into an equivalent heat and mass flow network that transiently simulates the heat and mass flows through all key pathways in a building and the interdependencies between them. The housing stock energy hub (*EnHub*) platform (Sousa et al., 2018, 2020) employs *EnergyPlus* at its core.

Alternatively, the schematic representation of Figure A1 and its underlying physical models can be further simplified. This is the approach adopted by the Building Research Establishment Domestic Energy Model (BREDEM) and all of its derivatives (Henderson and Hart, 2012), such as the Cambridge Housing Model (Hughes et al., 2013).

BREDEM-derived models are simplified bottom up engineering T-HSEMs. They are not transient as they do not support (sub-) hourly calculation of temperatures and related heat flows. Rather, they employ assumed indoor temperature set-points and an annual or monthly energy balance to determine the corresponding heat flows, as well as assumed (e.g. heating) system efficiencies to convert these into an energy use. In performing these energy balance calculations, total heat gains for the period from solar radiation and internal sources (lights, equipment and people) are estimated. In the case of solar heat gains, these are corrected, based on an estimate of internal thermal mass (light, medium or heavy weight), to account for the extent to which these might usefully offset the demand for space heating. This is achieved using a solar utilisation factor. Any un-useful gains are assumed to contribute to a rise in indoor temperature above the assumed set-point. In a similar way, intermittent occupation and how this translates to discontinuous space heating practices are accounted for using a heating intermittency factor, which represents the discharge of heat from the building fabric, following a period its charging, when the heating system is respectively switched on and off again. So, whilst air and fabric temperatures are not resolved, the effects of internal thermal mass on the moderation of these temperatures and how this translates into the demand for space heating are accounted for, albeit in an approximate way.

The external nodes *Text* are represented as monthly averaged rather than hourly temperatures. Fabric temperatures (*Txs*) are not calculated and internal temperatures (*Ta*) are assumed. Capacitances and how their behaviours influence transient fabric and indoor temperatures are not resolved, but their effects on heat flows are approximately represented. Since fabric (or surface) temperatures are not explicitly resolved, neither are the radiative processes that influence them. However, the transmission of solar radiation and its allocation to internal walls (and other surfaces) is accounted for in an approximate way (*Qsun2.Ww*), as are the contributions of internal heat gains (including from heating systems) to indoor air temperatures. Finally, the influence of advective heat transfers on indoor air temperature are also assumed, using scheduled infiltration and ventilation rates.

Annex 3: Software engineering principles

Modern computer programming languages, such as C++ and Python offer the opportunity to improve modelling techniques, for example by social simulation modelling or life cycle analysis. Structuring the software modularly enables new classes and methods to be added to increase the scope of software, or modes of calculation. For some applications, rapid and approximate calculations may suffice, whereas for others, more computationally demanding and sophisticated modelling may be appropriate. Good software design provides for flexibility in results analysis, allowing users for example to choose the degree of disaggregation at which they wish to analyse the energy and carbon performance of the housing stock. It also provides the possibility to easily substitute datasets, as new data becomes available, so that the modelling platform can be easily updated.

It is good practice to make software openly available and accessible through a dedicated repository (e.g. GitHub), enabling other researchers to contribute to and/or benefit. Making the underlying rationale and modelling algorithms freely available would also improve understanding of scope of applicability. BREDEM-based models are notorious in this respect, with many empirical expressions for whom the source is not declared.

A well designed graphical user interface (GUI) which ensured productive and effective interactions with HSEMs would widen the pool of users beyond software developers. Although good GUIs are invariably developed by commercial software companies, excellent precedents do exist, such as the *DesignBuilder* interface to *EnergyPlus*; both the GUI and the simulation engine being leaders in their class.

Scenario modelling and optimisation

As noted earlier, carefully designed and executed modelling software brings a host of other opportunities, through additional functionality that sits at a hierarchical level above the core modelling and data management algorithms. The three most significant of these are explained below. Combining the three to model and optimise decarbonisation scenarios, accounting for parameter uncertainties would create an incredibly powerful resource.

Scenario definition and modelling: An HSEM GUI can in principle be extended to support the definition and subsequent automation of the modelling of scenarios. At the simplest level of T-HSEMs this could simply involve mechanisms to identify archetypes, vintages, envelope elements or energy systems, both conventional or renewable, that could be substituted. More powerful would be a mechanism to enrich a hybrid of dynamic and traditional HSEMs to define policy scenarios and potentially the timing of their introduction to evaluate the effects of these policies on energy use, carbon emissions, comfort and health. This in principle could also allow for the definition and modelling of changes to exogenous factors, such as power system decarbonisation, technology improvements or climate change. There is at present, to our knowledge, no example of such an HSEM scenario modeller.

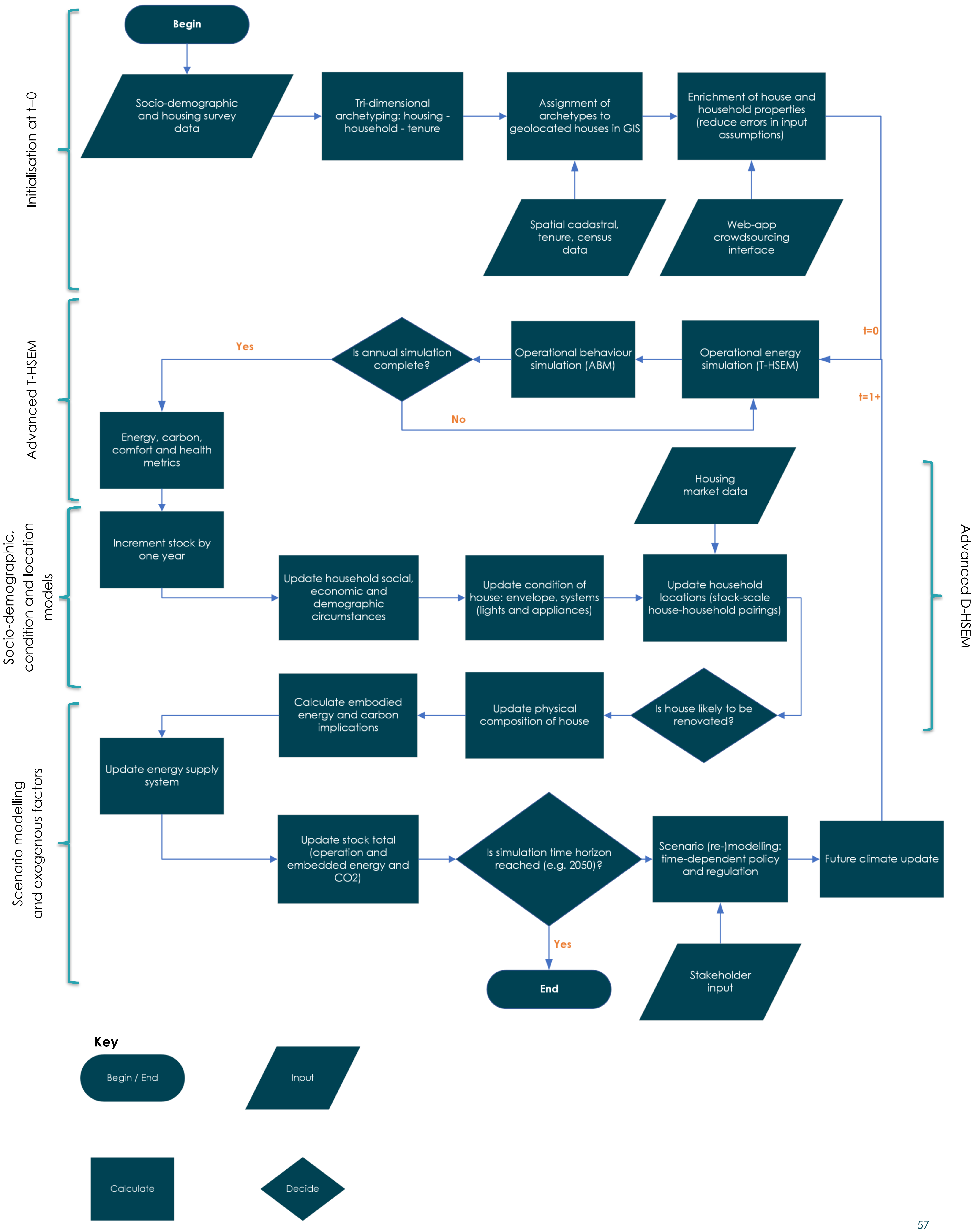
Uncertainty analysis: This involves identifying which housing stock carbon emission parameters are most sensitive and the definition of probability density functions describing them. Sampling methods can then be employed to quantify how these parameter uncertainties, and interactions between them, propagate through a simulation. Essentially then, this implies a shift from the prediction of single deterministic outcomes to distributions of outcomes, as in future climate projections. There are many instances of this being employed at the scale of individual buildings (e.g. Spitz et al., 2012, Lee et al., 2013); more recently combining energy simulation with stochastic behavioural modelling (Wate et al., 2020). However, this has not yet been employed at the (sub-) national housing stock scale.

Optimisation: Computational optimisation algorithms can efficiently search a model's parameter space for a solution that optimises a fitness (or objective) function or combination of objective functions, such as cost, carbon emissions, comfort or health. These are used to optimise the parameters of individual building designs, and more recently to optimise retrofit solutions for urban building stocks (Hey et al., 2020 and Thrampoulidis et al., 2021) but not yet at the (sub-)national scale using a bottom-up T-HSEM. However, multi-objective optimisation has been combined with uncertainty analysis at the national scale in conjunction with a top-down statistical model of the residential housing stock (Zhang et al., 2020).

Annex 4: Comprehensive D-HSEM workflow for Wales

The proposed short, medium and longer term research and development activities combine and complement one another to produce the D-HSEM workflow outlined in Figure A2 below, proceeding from top to bottom.

Figure A2: A dynamic housing stock energy modelling workflow for Wales



Initialisation: The survey data provides the inputs necessary to calibrate the recommended tri-dimensional archetyping of houses, households and the tenure of the houses they occupy. These are then matched, with the input of further (e.g. cadastral, tenure and census) data to actual houses, represented in a Geographical Information System. With further input through a web app from individual households, the statistically modelled characteristics of households and their houses can be refined, to minimise any errors in this modelling.

Advanced T-HSEM simulation: The hourly energy performance of the refined archetypes can now be simulated using transient energy simulation techniques (as with EnHub and its use of the EnergyPlus simulation engine). By complementing this with agent-based modelling of occupants' behaviours (e.g. of their use of windows, lights, appliances and heating and hot water systems), the indoor conditions and energy use can be reliably simulated. This combined energy-behaviour simulation repeats hour by hour, through to the end of the year, to produce annual energy, carbon, comfort and health metrics.

Advanced D-HSEM: The simulation then advances by one year and the households' demographic, social and economic circumstances are updated, as is the conditions of the homes they occupy. Using these updates together with the input of housing market data, some households may decide to relocate, causing an update to the matches between households and the specific property they occupy. Whether stimulated by housing relocation or not, households may then decide to renovate their homes, causing the energy and carbon impacts of the renovation activity (housing envelope products, lights, appliances and energy systems) to be calculated.

Scenario modelling and exogenous factors: Energy supply system representations may then be updated. This may simply involve modifying a CO_2 conversion factor (converting electrical energy in kWh to CO_2 emissions), but it could also involve linking houses with networks, such as district heating or Hydrogen. The total stock (both operational and embedded) energy and carbon emissions may then be updated. So long as we have not reached the end of our simulation timeframe (e.g. 2050), the time-dependent outcomes policy and regulatory scenarios, designed with appropriate stakeholder input, may then be adjusted. This may for example involve potential modifications to building regulations at certain time intervals, changes to subsidies or even assumed technological advances. Finally, the weather file that is input to the T-HSEM may be updated, reflection future emission scenarios and how these impact on global climate model simulations.

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