Alternative modelling approaches to energy performance certificates

David Jenkins[1], Sally Semple[1], Sandhya Patidar[1], Peter McCallum[1]
[1]Heriot-Watt University, Edinburgh, UK

Abstract

The requirements of energy policy, such as the Energy Performance of Buildings Directive (EPBD), has a direct effect on our use of building models and the parameters we seek to characterise. To model total energy consumption of a building is a different task to characterising the demand of that building at a transient level; to do so at scale is an additional level of complexity. With the ubiquity of Energy Performance Certificates (EPC) across Europe, there is a tendency to use this as the main vehicle for communicating building energy demand to policy. However, there is growing evidence of EPCs being applied to areas for which they were not designed to serve. By comparing alternative techniques with current methodologies underlying EPCs, this study proposes future directions for standardised energy assessment of dwellings, proposing a framework for critiquing such techniques.

Key Innovations

- An approach for critiquing new forms of energy assessment in the built environment
- New forms of building energy assessment that are cognisant of latest developments of building modelling and new requirements of such models

Practical Implications

The proposed framework suggests a new way of designing standardised energy assessments, in context of the EPBD. Using some of the proposed approaches, this allows for end-users of EPCs to have actionable information on crucial areas of building and energy system design, where traditional EPCs are not able to do so.

Introduction

Arguably, the EPBD placed building modelling at the centre of low-carbon building policy in Europe. However, the need to achieve market transformation at scale has resulted in quite simplified forms of building modelling being used to assess our buildings. Whilst this may have been appropriate for a compliance tool focussed on energy efficiency, at a time where the spectrum of modelling tools may have been narrower, new challenges (in energy system design) and opportunities (in software/hardware and data) raise questions about whether this approach is still fit for purpose.

This paper is, in part, a conceptual study, but using modelling of the authors to illustrate those concepts. It places more recent developments of building modelling, both physical and empirically-based, into the context and requirements of EPCs, noting that the questions we are asking of EPCs are not necessarily the same as in the dawn of the EPBD, 18 years ago. The role of more advanced building simulation is therefore discussed, and an approach proposed for re-evaluating what we need from standardised energy assessments.

The impact of standardising energy assessment – a review

The EPBD was introduced by the European Union in 2003 and was revised in 2010 and 2018. The recast directive (European Commission, 2010) further established the requirements for the production of Energy Performance Certificates (EPC). In particular, the EPBD states that the "energy performance of a building shall be determined on the basis of the calculated or actual energy that is consumed to meet the different needs associated with its typical use".

Within this guidance, variation already exists in terms of responses by individual countries. As noted by the Building Performance Institute Europe (BPIE, 2014), 14 EU states use only theoretical/physical methods to assess energy performance. Other states have an option for using measured energy consumption, though different criteria were used to identify which buildings could qualify for this. A report commissioned by the EU (European Commission, 2015) noted that the 28 member states of the EU had 35 calculation methodologies in place which could be used to generate EPCs for new and existing buildings. This is, perhaps, surprising for an initiative that places standardisation at the forefront, and demonstrates that the EPCs are not necessarily a common currency across different parts of the EU.

One commonality is that every EU state provides at least one calculated method for assessing energy performance, whether for new or existing buildings. For existing buildings, where not all construction details are available, most EU states provide a calculated method which uses assumed values for unknown construction details. These may be separate calculation methods or variations on the calculation method used for new buildings. Generally, all techniques can be categorised as one of the below:

- calculation using detailed construction information
- calculation using assumed construction information
- assessment based on similar reference dwelling
- measured energy consumption

Identifying flaws with current approaches

When critiquing EPCs, it is important to remember what they were originally targeted towards (and whether they achieve that purpose), whilst also noting where “mission creep” exists such that EPCs are put forward for less suitable applications.

The Performance Gap, the difference between modelled and measured energy demand, is well documented (Bordass, 2013; de Wilde, 2014). However, there is an argument that EPCs were not designed to accurately generate real energy bill estimates and, rather, are merely the result of an energy compliance tool that allows for indicative ratings of building assets (for a typical household) to be estimated. Where this argument becomes problematic is the growing use of EPCs for applications beyond basic energy compliance, such as detailed design of buildings, structuring loan repayments for energy efficiency investments, or punitive actions on homeowners based on their energy rating.

An arguably more fundamental problem for a standardised energy assessment is that of consistency. The EPBD requires that a replicable, standardised assessment can be carried out in the same way for any building. With many EPC approaches removing, or at least dampening, the impact of householder behaviour (by focussing on the building asset), some of the less standardisable aspects of residential energy use are ignored. Whilst this might imply a clear path to consistency when comparing similar buildings, studies of EPC lodgement databases suggest this is not always the case. Previous work by the authors (UK Government, 2014) using multiple assessments of a small sample (29) of dwellings show different assessors making different assessments (and models) of the same home. A study of a larger number of assessments for a single dwelling (Tronchin & Fabbri, 2012) also suggested a lack of consistency emanating from the energy assessors.

Other studies (Hardy & Glew, 2019) have taken larger databases of previously assessed buildings and identified more statistically robust variation, introduced concepts of measurement error in EPCs (Crawley et al., 2019), and looked at changes over time in those databases (Pasichnyi et al., 2019) that suggest quality control issues. With such existing variations, one might suggest that other forms of data collection and modelling could actually improve consistency in energy assessment rather than making it more difficult to control. This could involve the use of CityGML files (Rosser et al., 2019) to better describe the building stock, or efficiently determining thermal characteristics of a large community of buildings that could play a role in the energy compliance process for individual buildings (McCallum et al., 2019).

There is therefore a suggestion that, as well as designing future energy assessment for future requirements/challenges, there are already existing problems with standardised energy assessment that could be addressed by different forms of modelling and data collection.

Taking a different approach to energy assessment

The previous review touches on some of the successes and limitations of current approaches to EPCs, and the modelling that underpins that. Leaving aside, momentarily, the restrictions of the EPBD, the full toolkit available to a building modeller to help understand energy demand is vast. Even noting some of the requirements of the EPBD, there is still a broad spectrum of responses that can satisfy this initiative. Two approaches that are particularly active research areas will now be discussed – using dynamic modelling and empirical data – by proposing specific techniques developed by the authors. Whilst these might not be seen as direct replacements to EPCs, they could provide outputs that are relevant to key areas of concern in characterising future energy demand in buildings.

Dynamic simulation at scale

Although steady-state modelling is more common for EPC generation, dynamic building simulation has been used in the UK for some non-domestic building EPCs, as well as non-EPC system design.

For the residential sector, it is uncommon for simulation to be used for single dwellings at any stage. Urban-scale simulation of multiple dwellings is, however, of growing interest in academia and with different end-use audiences, such as local authorities. This provides the ability to aggregate intra-day demand patterns for sections of building stock, and opens up new applications that current steady-state models cannot speak to. These applications can involve energy network constraint issues, integration of renewable energy at different scales, use of storage, and more advanced analyses of the growing complexity of the relationship between supply and demand.

Dynamic simulation as an engine for urban energy modelling has been developed and demonstrated by several research teams. Previous work (Sola et al., 2020) has highlighted the use of various dynamic simulation tools for such applications at a timestep of less than 1hour. One of these tools, TEASER (Remmen et al., 2018), falls within the broader Integrated District Energy Assessment by Simulation (OpenIDEAS) framework, incorporating a Time Use Survey-derived stochastic occupancy model – StROBe (Baetens & Saelens, 2016). There is also a clear growth in the use of GIS data in such research (De Jaeger et al., 2018).

An approach proposed by the authors (McCallum et al., 2020) combines three key data sources, with a goal of modelling community energy demand but in a bottom-up dynamic model; where this model allows for the efficient modelling of multiple individual buildings at the same time. The data sources are the EPC register, GIS data from the UK’s Ordnance Survey, and smart meter data. Whilst challenges present themselves around, for example, underlying taxonomy of EPC and GIS data, a tested structure for this is described below.

One argument against the use of simulation methods for assessing the residential stock is the assumed increase in calculation and data complexity. However, a more involved physical or statistical calculation does not necessarily lead to unmanageable complexity on a surveyor or practitioner level. Indeed, inadequacies in the existing, manual approach to data collection, and resulting issues of assessment inconsistency, are already documented (UK Government, 2014). Therefore, an approach that uses simplified dynamic simulation at scale that incorporates "new" data with data that surveyors already collect, would be of immense value. There is still the challenge of balancing the need for scalability with the need for individual building simulations, but there are lessons that can be learned here from archetype-based stock modelling, combined with modern approaches to distributed computing.

Building archetypes, in this paper, refer to simulation models that are tailored automatically to specific dimensions and constructions, within a large group of buildings (e.g. which could be from community to city-scale). As already noted, EPC and GIS data sources can be accessed to generate such archetypes but, to achieve this at scale, efficient data mining and processing is required. Given a scenario where results from a new survey have just been logged, these direct survey records (i.e. EPC modelling inputs) could be viewed by a third-party verifier on a macro-basis against the surrounding area. Discrepancies may reflect reality but, as noted in the review, irregularities can exist due to assessor error, and these could be flagged for further attention. As well as aiding the generation of an urban energy model, this could introduce a completely new idea of accountability and quality control in energy surveying.

With regards to distributed computing, some EPC steady-state modelling approaches (such as the UK's Standard Assessment Procedure (BRE, 2019)) were developed around a somewhat dated software approach of download, install, run-on-local-machine. In addition to other perceived needs for simplification of calculation, this provided a case for computationally lightweight techniques. Many modern software packages involve either fully web-based processing or have lightweight client tools which link to server(s) via Application Program Interfaces (APIs). Moving forward in the energy assessment domain, a path can be imagined that includes server-based computations, automation, machine supervision by both practitioners and regulators, and systematic third-party verification. With the improved access to calculation processing, this could include the use of multiple simulations of different individual archetype versions, accounting for input uncertainty, as well as generating multiple archetypes tailored for a region. Other factors less aligned with traditional modelling approaches, such as occupancy patterns (with their importance in generating transient energy demand profiles, but partly stochastic, rather than deterministic, nature), could also be incorporated. This would allow for more formal uncertainty procedures to be incorporated into energy assessment methods.

During the development of building modelling, tractability issues around processing time have diminished significantly, and for dwellings computational time is trivial. The savings in manual handling and checking of data, iterating through calculations on laptops, would likely far outweigh this cost. Much of the underlying technical software already exists in the form of open source simulation engines (e.g. EnergyPlus) and batch processing and analysis libraries (e.g. Python). There would still be considerable work required to build and maintain this process and adapt to new regulations, but significant opportunities would arise from either a centralised or federated system.

A clear procedure can therefore be distilled from learning and advancements of urban energy modelling:

1. Obtain construction and geometrical data of dwelling for the target building via GIS data and automatically generate a set of building variants
2. Obtain thermal characteristics and service (e.g. heating) technology information from survey data (including existing EPC input surveys), for the purpose of generating a new EPC
3. Generate multiple occupancy profiles from available smart meter data to infer transient activity schedules
4. Run multiple dynamic simulations via an embedded calculation engine from the above input data to treat occupant-driven uncertainty
5. Although being of use for aggregated energy calculations, the existence of a bottom-up model will result in multiple individual energy consumption metrics which could be aligned to a similar standardised framework as current EPCs

Thus, an approach towards dynamic stock modelling could be repurposed for generating energy ratings at scale. The authors are currently testing this with active research projects.

Statistical treatment of empirical data

There is a growing evidence base (Ferrari et al., 2019; Zhao & Magoulès, 2012) for using empirical data, rather than purely theoretical physical modelling, to assess energy use in buildings, though limits exist for the degree to which this can be standardised. This can be seen in models such as MARKAL (MARKet ALlocation) (Taylor et al., 2014), the UK TIMES Model (Fuso Nerini et al., 2017), and the CREST demand model (McKenna & Thomson, 2016) where empirical energy data can be used (or energy inferred from other empirical data), though not necessarily focussed on the individual dwelling.

The richness of data now available through, for example, smart meter data, allows for an attempt to correlate energy demand with socio-economic class/status, dwelling properties, and appliances (Beckel et al., 2014; Gajowniczek et al., 2018). Crucially, high-resolution (e.g. 5 min and below) electricity demand data can be linked to behavioural characteristics that would not be discernible through the use of purely physical modelling. Previous work has proposed a Hidden Markov model (HMM), with a Seasonal-Trend Decomposition procedure based on Loess process" (STL), and a Generalised Pareto (GP) distribution for simulating such dynamics for high-resolution electricity demand profiles (Patidar et al., 2019). The application of STL facilitates temporal decomposition of stochastic components of demand profiles from deterministic features, noting how this differs from seasonal features. This level of information can characterise specific activities occurring at specific times in a household, which itself provides clues to causation (Torriti, 2020). Building on this, templates of activity can be developed from these causal factors which could lend themselves to a more standardised approach for energy assessment, one which attempts to account for household (i.e. occupants) as well as the building itself.

This is similar to ideas of a Domestic Operational Rating (DOR) scheme (Lomas et al., 2019), which uses daily smart meter data alongside contextual information collected from an energy/household-based survey. As we attempt to have better integration and communication between energy demand and supply in future low-carbon energy systems, there is considerable value to being able to categorise energy use in buildings in this way.

With the added complexity of large and high-resolution energy demand datasets, clustering provides an avenue to help classify such data, potentially in a standardisable way. One example of this proposed here is based on empirical data, applying a k-means clustering approach to a case-study (Fintry community (Smart Fintry, 2018)). Half-hourly data was collected for 56 dwellings over a period of six months, which then underwent a feature extraction analysis to help characterise transient demand in a useful way. Three chosen statistical features are related to cost functions (half-hourly cost of supply; non half-hourly cost of supply; cost of supply depending on time of use and consumption pattern), and three are load factor based (daily load coefficient of variation; average annual load factor; total consumption). This is informed from work elsewhere (Jang et al., 2016). There is also a weather related feature from degree day correlation. Principle Component Analysis (PCA) is then applied to these features to transform a high dimensional correlated dataset into a smaller set of uncorrelated principle components. The underlying idea is that highly correlated variables contain redundant information and thus can be mathematically transformed into a reduced number of variables. Since three cost-related variables are expected to have a high correlation, they are transformed using a PCA procedure. Similarly, three load-related variables are combined using a separate PCA procedure. Therefore, two separate PCA procedures were applied: i) for three cost function related variables, and ii) for three load function related variable. This technique has several applications but, for this study, we are interested in how transient feature identification, focussing on key “proxy” features with statistical value, followed by clustering of half-hourly demand data using those proxy variables, could be applied for purposes of energy demand classification.

The month of February 2017 is taken from the above dataset to form clusters around the three PCA components extracted from the seven annual features. Larger periods of time are currently being explored by the authors, but the month above provided a complete and reliable dataset. To test the suitability of the three PCA parameters (PC1, PC2 and PC3), the total variance was noted for cost and load functions, as shown in Table 1.

Table 1 – Results of variance from three components of PCA processes

Proportion of Variance	PC1	PC2	PC3
Cost function related	0.9799	0.01996	0.00017
Load function related	0.5364	0.2752	0.1883

Nearly 98% of the cost function related information is captured in PC1, and more than 80% of load function related information is captured in PC1 and PC2 combined. Therefore, the k-means clustering is deemed to be suitable for basing around four variables: PC1 for cost function, PC1 and PC2 for load function, and a degree day correlation variable. An elbow method is applied to obtain an optimal cluster number for the 56 dwellings, with the k-means procedure and its implementation in R (using “fviz_cluster” in the R package “factoextra” (R-package, 2020)) described elsewhere (Kassambara, 2017). Using this method, the intention is to produce household demand categories clustered into clear, distinct groups, that could inform energy classification schemes. The results of the clustering analysis are summarised in Figure 1, using Within Cluster Sum of Square (WCSS), the squared average distance of all points within a defined cluster, and Between Cluster Sum of Square (BCSS), the variation between the clusters in terms of squared average distance between all centroids. A smaller WCSS ensures less dispersion within a cluster (indicating that the cluster may be suitable for classifying the data) whereas a larger BCSS indicates a good separation achieved across the different clusters (indicating strong definitions between the clusters). A Silhouette ($-1 < Si < 1$) analysis is also carried out to measure how well each observation is clustered, where a Si value of 1 indicates observations are very well clustered, 0 indicates the observation lies in two clusters, and a negative value indicates the data is likely assigned to an unsuitable cluster.

Table 2 – Summary statistics of k-means clustering

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Size of cluster	21	22	23	14
WCSS	37.22	29.15	39.23	22.18
BCSS	188.19			
Average Si width	0.20	0.34	0.19	0.27

Figure 1 visualises these clusters for the chosen proxy PCA variables (Dim1 and Dim2). Different sensitivities, and numbers, of clusters can be proposed, but this study demonstrates the result of using four clusters for the 56 dwellings.

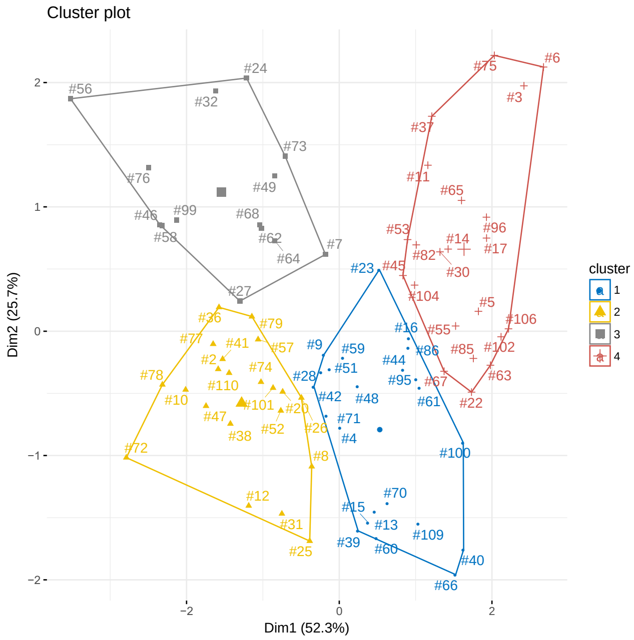

Figure 1 – 56 dwellings organised in four clusters through the application of k-means clustering approach coupled with PCA

Critiquing new methods – a framework

Having introduced two potentially useful techniques for characterising building energy demand at scale, and noting many more, there is a need to critique those methods against some criteria of suitability. For this paper, "suitability" will be based on likely future (and relevant current) requirements of energy performance assessments, though that might not be exclusively covered by the function of the traditional EPC. It is also vital, when faced with such a broad range of energy modelling options, to clearly define a purpose of assessment before setting out a framework and methodology. Table 3 takes some of these criteria (discussed below) and makes a judgement of different modelling approaches for meeting those criteria. These criteria are informed by the already discussed existing literature and the aforementioned modelling techniques. As such, they are new categories of metrics that are not directly aligned with current performance indicators, but can help discussions around what form "next-generation" assessments may take. The criteria also help distinguish different applications that are suitable for different modelling approaches, moving away from a binary definition of "wrong/right" when critiquing models and, instead, showing understanding of the importance of specific application when judging suitability of approach.

Alignment with reality (C1)

Both dynamic simulation and steady-state modelling are known to exhibit performance gaps when compared to real energy data. The advantage of dynamic modelling, however, is the ability to characterise dynamic physical processes within a building. The transient nature of air flow, heat transfer, thermal mass and occupancy behaviour can only be addressed by steady-state models through considerable simplifications and proxy coefficients. So, although all purely theoretical models should not be used as direct replacements for real energy data, dynamic models do attempt to model "real" physical processes in a way that steady-state models do not. This justifies a judgement that dynamic simulation satisfies this criteria to a medium level, compared to the low level of steady-state models. Empirical characterisation, by definition, has a stronger relationship with real energy data – though this may cause challenges for other criteria that are addressed below.

Flexible demand rating (C2)

Demand flexibility is a key part of understanding future energy system design. Whilst not traditionally seen as part of energy compliance, the ubiquity with which this topic is associated with "behind the meter" building technologies suggests a need to better account for its impact at a building level. It is not the purpose of steady-state modelling to account for dynamic aspects of energy use and, therefore, it cannot be used as a basis for understanding demand flexibility – hence the low rating proposed here for meeting this criteria. Dynamic modelling, with higher temporal resolution, can model key drivers of flexibility (e.g. thermal mass, thermal storage, and occupancy control/behaviour), though there are challenges to meeting the input requirements and may require the model to simulate at higher resolution than currently used with energy compliance (e.g. some non-domestic Energy Performance Certificates in the UK already use simulation at hourly resolution, but some aspects of demand flexibility require ~minutely resolution). Likewise, the ability of empirical characterisation to adequately reflect demand flexibility issues will depend on the resolution of collected data (e.g. from smart meters), but there is great potential to do so from high quality datasets.

Accommodates new technology (C3)

In the UK, procedures exist for quantifying the impact of new technologies (Products Characteristics Database, 2020), such that they can be accommodated within the existing SAP model. It is more difficult to judge whether a given modelling approach is actually suitable for accommodating that technology. If a model is not modelling a technology explicitly, we should question whether calibration factors and coefficients of approximation are appropriate for measures that are fundamentally dynamic in nature. Therefore, key measures currently being proposed as important for meeting low-carbon targets (such as district heating, heat pumps, onsite storage and home-charged electric vehicles) may not be well-served by steady-state models calculating/averaging over long time durations. Dynamic modelling can operate with calculation time-frames more suitable to any technology with a strong diurnal cycle of variation. This justifies a high C3 rating for dynamic modelling, as opposed to the medium rating of steady-state modelling. The suitability of using empirical data in this way could be dependent on the level of sub-metering for large numbers of buildings; however, even without this, pattern recognition techniques (Jenkins et al., 2014) could still be effective for isolating signatures from individual technologies.

Suitability for punitive action (C4)

Energy assessments have, generally, not been used to enforce actions on building owners but, rather, to advise on action. With the growing need to act to meet ever-closer carbon targets, this is now changing, with legislation being proposed to compel building owners to improve energy efficiency as a condition for selling or leasing a property. This should require a re-evaluation of the model itself, making a judgement about the fairness of doing this and what the consequences may be. For a model such as SAP, it is important to note that this is designed for generating approximate energy ratings, does not account for the household specifically, and does not accurately predict energy bills. An informed, albeit subjective, judgement might suggest the use of such a model to enforce an action would be difficult to evidence (hence a low rating for C4). Dynamic modelling could, at least, be used to explore why and when certain energy uses are higher than legislation may allow, providing some level of accountability and explanation for recommending a punitive action, even if we are still placing great reliance on a purely theoretical model. Justifying action on actual energy use (i.e. incontrovertible evidence that energy is high in a property) suggests a higher level of proof and accountability. Even a modified form of this, using generalised energy patterns from an empirical database to match a given property, would provide a stronger platform than theoretical models.

Extrapolating and standardising (C5)

With SAP (and similar EPC-relevant models) largely designed for largescale, replicable use, it would be reasonable to rank steady-state methods highly for C5. Dynamic models (rated medium) have more complex inputs and (potentially) a higher level of training required for energy assessors. However, it is suggested here that most countries are yet to test how replicable dynamic simulation can be used within a standardised framework, often using the rationale of it being too complex, and requiring too high a skillset to be used at the scale required. Some of the research presented here aims to question these arguably outdated assumptions, albeit accepting the challenges this would create. Empirical data could place an even greater challenge on standardisation; even with the suggested clustering approach of this paper, empirical data is tied to the decisions of the householder(s) within the signals generated, unlike asset-based theoretical models. There may therefore be a compromise required on either the level of standardisation, or a new approach to rating buildings that is linked to different household (as well as building) categories.

Quality of input information (C6)

Issues of consistency across different energy assessors have already been documented in this paper. Even with improved quality control, standardised energy assessment procedures, by design, have to make compromises on input accuracy (e.g. the use of generic "look-up" tables rather than building-specific, measured inputs). Dynamic simulation gives more scope for building-specific information to be collated (with more granular data required), and the data collection method in this paper suggests a way of achieving this at scale. An empirical approach to building and energy classification brings with it a higher degree of representation of individual buildings and their energy characteristics. However, this would have to be integrated into some form of categorisation technique, with causal factors, that would require the clustering method of this paper to be developed.

It could be argued, therefore, that C6 counterbalances C5; that is, achieving reliable input information for individual dwellings can create standardisation challenges.

Table 3 – Evaluated ability of different assessment approaches meeting selected criteria

	Steady-state models	**Dynamic simulation**	**Empirical characterisation**
C1 Alignment with reality	Low	Medium	High
C2 Flexible demand rating	Low	Medium	High
C3 Accommodates new technology	Medium	High	Medium
C4 Suitability for punitive action	Low	Medium	High
C5 Extrapolating and standardising	High	Medium	Low
C6 Quality of input information	Low	Medium	High

Conclusion

Through reviewing recent research, and also proposing methods developed by the authors, this study has compared established methods of standardised energy assessment with potential new forms. In doing so, a series of criteria has been proposed that judge whether key requirements of energy assessment can be met by different methods. Crucially, this framework attempts to capture likely future requirements of assessment; noting that what we once asked of energy assessment may be significantly different to the needs of today. The study concludes that the range of techniques currently on offer for assessing energy use in buildings are not necessarily well-replicated in standardised, regulated forms of assessment, particularly in the UK. More research is required to judge, and demonstrate, how these different approaches can be used to address current flaws in steady-state energy modelling, whilst reflecting on new challenges emanating from our evolving building stock and surrounding energy systems.

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