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A multi-sectoral approach to modelling community energy demand of the built environment

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ABSTRACT

This paper examines the major challenges associated with evaluating energy demand in the residential building sector in an integrated energy system modelling environment. Three established modelling fields are examined to generate a framework for assessing the impact of energy policy: energy system models, building stock models and dynamic building simulation. A set of profound challenges emerge when attempting to integrate such models, due to distinct differences in their intended applications, operational scales, formulations and computational implementations.

Detailed discussions are provided on the integration of temporally refined energy demand, based on thermodynamic processes and socio-technical effects which may stem from new policy. A detailed framework is discussed for generating aggregate residential demands, in terms of space heating demand, domestic hot water demand, and lighting, appliance and consumer electronics demand. The framework incorporates a pathway for interpreting the effects of changes in household behaviour resulting from prospective policy measures. When long-term planning exercises are carried out using this framework, the cyclic effects between behavioural change and policy implementation are also considered. This work focused specifically on the United Kingdom energy system, however parallels can be drawn with other countries, in particular those with a mature privatised system, dominated by space heating concerns.

1. Introduction

One of the challenges that has become firmly rooted at the centre of energy planning discussions is the evaluation and characterisation of temporally precise energy demands from the built environment. Traditionally, this has been approached using semi-empirical methods, by extrapolating and manipulating present-day demand data. Over the past few decades, our understanding of society's energy needs has been undermined by growing uncertainty due to innovations in policy, technology and evolution of the energy markets. Much of this innovation has been stimulated by the energy trilemma: the requirement to provide clean, affordable and resilient energy systems. This poorly understood transformation away from traditional demand behaviour means that empirical demand curves are no longer adequate for describing anticipated demands in the future.

The questions raised by such discussions are part of a much broader subject - that of long-term energy system planning. Common transition goals imposed by the energy trilemma have been emerging for incumbent infrastructure for some time, in developed and developing countries alike. Increasing pressure is being placed on national and regional administrations to create and then manage complex policy measures that ensure that investment and operational decision-making leads to outcomes that allow energy networks to deliver these common transition goals. The scale, complexity and cost of energy system expansion and maintenance means that a long-term view is a necessity, typically spanning many decades into the future.

Energy system planners and policy makers place a growing reliance on Energy System Models (ESMs) to tackle these challenges. This family of models includes Energy System Optimisation Models (ESOMs) and Energy System Simulation Models (ESSMs), the former being particularly relevant to long-term planning studies. However, existing energy networks are highly complex, incorporating myriad natural resource deposits, extraction and refinement processes, fuel imports and distribution, conversion/generation processes, transmission networks and end-use demands. By necessity, ESMs are constructed using a significant number of assumptions, introducing uncertainty into modelled

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outcomes whose origin and behaviour may often be poorly understood. Once this problem is exacerbated with the difficulties associated with interpreting future narratives, the need to handle and interpret uncertainty becomes increasingly challenging.

In light of these broad issues, this paper brings together, for the first time, a series of energy modelling techniques which speak to key questions of energy system modelling. Two specific objectives have been identified below to build a framework to address challenges around representing energy demand in the residential sector:

i. To capture aspects of the socio-technical dynamics in society, stimulated directly by future narratives, or resulting from policy implementation (i.e. to ensure that energy demand responds to change)
ii. Facilitate feedback of policy driven energy demand changes back into the integrated ESM, to ensure that long-term causal effects are considered

The first of these is intended to enhance the potential of ESMs to capture the social and behavioural interaction between society and the policy and technological changes that may occur in the future. As such, this aims to incorporate end-users as an integral part of the energy system – i.e. provide enhanced linkages for social science, to incorporate the direct effect that people and society have on energy demand from the residential built environment. The procedure adopted to allow this to happen includes a hybrid physics-integrated building model and stock model. This relies on external models which can infer transitions of behaviour in society.

The second goal, which is closely related to the above, is to facilitate a causal and cyclic relationship between the new policy instruments – the traditional *outcomes* of ESM activities – and the long-term implications of these instruments on future demand – i.e. a key *input* to ESMs. Given the public response to PV incentives in the UK between 2011-2015 (Department of Energy and Climate Change, 2015), for example, it is clear that energy policy can have a profound and rapid impact on the broader energy system. Widely discussed policy topics relating specifically to demand include electric vehicle incentives and electrification of heat, the effects of which must be recognised within models that anticipate future demands.

It is not the intention of this work to test specific policies in 'what-if' type scenarios, or to deliver case study results for multi-sectoral studies involving numerous research fields. The framework presented in this paper embeds tools which traditionally sit outside the relm of long-term energy planning; in particular, Dynamic Building Simulation (DBS) for thermal demands, and statistical tools which reproduce non-heating residential loads. This facilitates new ways to provide richer inputs to ESMs, that can challenge socio-political-technical issues.

This work fits within the wider context of the (UK) National Centre for Energy Systems Integration (CESI) (National Centre for Energy System Integration (CESI)) (EPSRC grant EP/P001173/1). The scope of this individual piece of work has been isolated from many of the wider multidisciplinary issues to explore the specific concerns (i) and (ii), detailed above. Whilst this work identifies where a number of boundaries with multidisciplinary modelling approaches lie, it is also important to recognise that these are linked with policy in different sectors. Consistency across modelling methods, and the ability to translate cause and effect across scales and sectors, should encourage harmonisation of policy that is attempting to stimulate the construction of a low carbon future.

The framework presented in this paper relies on a number of well-established research themes and aims to utilise a broad range of existing methods, along with new approaches outlined in Section 4, acting as a conceptual overarching framework (see Section 5). There are instances where specific tools can be interchanged with alternatives; there are also areas where further model development is required (this is already underway in some cases). There is a particular focus on the UK for this work; however, parallels can be drawn with other nations with mature privatised energy markets, in heating dominated climates. Aside from the nuances of UK-specific customs and behaviour associated with energy which impact model design, the low-carbon agenda for the UK (commitment to lower greenhouse gas emissions by 80% from 1990 levels by 2050 (Department of Energy and Climate Change, 2011a; Department of Energy and Climate Change, 2011b; Department of Energy and Climate Change, 2011c), along with further post-Paris Agreement strategy (Parsons and DNV GL, 2015; Department for Business Energy and Industrial Strategy, 2018)) has provided the impetus for initiatives and consortia projects (such as CESI) for a number of years. It is interesting to also note other commentary on the current upheaval of the UK energy system, including that provided in McMeekin et al. (2019).

2. Background and literature review

Three distinct fields of literature are relevant to the current discussions: energy system models (ESMs), Building Stock Modelling (BSM) and Dynamic Building Simulation (DBS). A brief account of relevant research within these areas is summarised below.

2.1. Energy System Models

A number of historical reviews of ESM application in the UK are available. Trutnevyte et al. (2016) provided a review of a series of developments in scenario modelling for the UK, between 1978 and 2002. This highlighted the use of the MARKAL (Fishbone and Abilock, 1981) model by the UK Government in the period 1994 to 1999, used to assess various scenarios in both explorative and normative contexts, up to the year 2030 (this applied the scenario classifications: predictive, explorative and normative, as described by Börjeson et al. (2006)).

The role of MARKAL in the development of energy system modelling in the UK was also described by Taylor et al. (2014), through three distinct phases of developments spanning 35 years. The first two phases predated policy interventions, targeting planning solutions for reduced dependency on imported oil following the 1979 oil crisis (largely through expansion of nuclear generation capacity), before going on to assess renewable energy technology research and development objectives in the 1990s. The third phase culminated in the binding commitment to lower greenhouse gas emissions by 80% from 1990 levels, by 2050 (Department of Energy and Climate Change, 2011a; Department of Energy and Climate Change, 2011b; Department of Energy and Climate Change, 2011c).

Following integration with a related optimisation code (EFOM (Cormio et al., 2003)), MARKAL evolved to become TIMES (IEA), which remains the principal tool for energy planning in the UK. A number of variants exist, including: TIAM (Loulou and Labriet, 2008) (a global model which incorporates a component for temperature rise, as a function of emissions), UKTM (UKTM-UCL) (the up-to-date UK model, which emerged from the wholeSEM project (WholeSEM)), and Scottish-TIMES (which contributed to the Scottish Energy Strategy (The Scottish Government, 2018)).

A number of reviews have been published over the last decade which summarise energy system modelling tools, highlighting their application to different geographical locations and scales. Jebaraj and Iniyan (2006) provided a review covering a very large number of applied studies and model developments. Connolly et al. (2010) described and compared 37 existing models in terms of various metrics governed by model type, availability/accessibility, geographical scale and temporal resolution.

In the review by Koppelaar et al. (2016), ESM application was closely linked to the related subjects of scenario classification and political decision making. The six widely accepted scenario classes (Börjeson et al. (2006)), were used: predictive forecast, predictive what-if, explorative external, explorative strategic, normative preserving and

Table 1
Model type classification of a number of common energy system models (Hall and Buckley, 2016).

Model class	Example models
ESOM: (optimisation)	MARKAL; TIMES; ESME; WASP; RESOM
ESSM: (simulation)	Anderson Model; BRE NDEEM; BREHOMES; CGEN; ENUSIM; ILEX EU-ETS; SATURN; SEEScen; UKDCM/UKNDCM; VMM
Econometric:	AMOS; DECC Energy Model; E3MG; ECLIPSE; EESyM; MDM-E3; OXERA; UKENV

normative transforming. In this context, the present work is aimed specifically at enhancing the efficacy of explorative strategic and normative transforming exercises, both of which incorporate descriptions of socio-political-technical change. A major consideration in the studies reviewed by Koppelaar was the examination of long-term pathways in policy implementation and resulting impact on the energy system. In the political decision-making context, the relevant underlying analyses were problem discovery, instrument comparison, social paradigm exploration and political paradigm exploration, the latter being of greatest interest this work.

Hall & Buckley (Hall and Buckley, 2016) identify in excess of 90 ESMs referred to in literature, proposing a framework to categorise and rationalise some of the key model attributes. A range of models which were studied is included in Table 1, listed by fundamental model classifications: Energy System Optimisation Model (ESOM), Energy System Simulation Models (ESSM) and econometric.

Pfenninger et al. (2014) identified a set of major challenges around integrated energy system modelling, which also apply to energy demand modelling in the residential sector:

1. Disparities in temporal and spatial resolution
2. Uncertainty and lack of transparency
3. Tackling complexity in real systems across all scales
4. Capturing the human dimension

The present work contributes to all four areas. A bottom-up perspective is necessary to begin to capture the complexities of real-world systems centred around the end-user, where endogenous demand modelling must be an integral part. This provides a platform to address some uncertainty and transparency issues associated with ESM. Temporal and spatial resolution concerns become a major obstacle; aspects relating to scale are also discussed here. The issues of concern in this paper represent a small part of the overall complexity and corresponding uncertainty associated with ESM, specifically associated with modelling energy demand from the residential building sector.

2.2. Stock models

Stock modelling of energy performance is an exercise in capturing overlying, simplified causations between aspects of buildings, technologies and occupants, and energy use of large groupings of buildings. The data requirements for non-domestic (such as the work of Bruhns et al. (Isaacs and Steadman, 2014)) and domestic (e.g. BREHOMES (Shorrock and Dunster, 1997) and Cambridge Housing Model (Hughes et al., 2013)) stock models can be different, with a greater degree of homogeneity of buildings in the latter, but the general principles governing model construction are the same. There is generally a requirement for:

- Data inputs, describing different classifications of building types (and potentially occupant types), which reflect technologies being used in such buildings;
- A basic understanding of climate diversity across a country/region (potentially using a national "average" climate to define weather conditions);
- An ability to change input parameters to reflect expected or realised changes in that stock;
- A steady-state calculation engine that returns estimates of energy use at (typically) annual or monthly resolution. In some cases, model output can be compared to monitored energy data from that building stock as a limited form of validation or calibration.

Whilst the ambition of scale of traditional stock modelling can limit the detail of output produced, it does allow for some indication of how different future scenarios, and policy choices, might impact on overall energy demand of a building stock. There is evidence that effective improvements have been realised in practice from retrofit schemes (e.g. for insulation or heating system upgrades) in the UK (Hamilton et al., 2013), whilst the rate of uptake raises additional questions around ownership and income (Hamilton et al., 2016). Moreover, the overall success of schemes may not be fully realised with respect to the initial indications derived from the stock model(s) (Laurent et al., 2013; Filippidou et al., 2019).

The contribution stock modelling approaches can make to modelling the performance of energy networks is less well understood. However, the ability to categorise and define large numbers of buildings is a common problem for both building energy performance modelling and more detailed energy demand profiling analysis.

2.3. Dynamic building simulations

In contrast to ESMs, a relatively small number of computing tools for Dynamic Building Simulation (DBS) are presently in use, in part due to a dominant group of packages in the commercial software sector. At the same time, there has been a rich background in open-source codes over a relatively long period, which has helped with the convergence of code development. ESP-r (Clarke, 2001) was originally developed in the 1970s, and has since been widely circulated. EnergyPlus (Crawley et al., 2001) has also long been an important application, with a very active research community.

Widely used commercial software includes IES-VE (IES), Tas (Environmental Design Solu), TRNSYS (TRNSYS), Sefaira (Sefaira) and Green Building Studio (Autodesk Green Building Studio). These are used in varying degrees within academia and industry, with IES-VE and Tas for example representing a significant share of application in the UK Building Industry due in large part to their accreditation for use with energy performance certification. TRNSYS is also widely used in industry and academic research.

Alongside purpose-built tools for direct simulation of individual buildings, research in statistical modelling and aggregated community scale energy demand is also growing. A statistical approach was used to allow recursive reprocessing of DBS results in Patidar et al. (2011). This used a single set of simulation results output from ESP-r to develop thousands of surrogate models via principal component analysis, to investigate the building's response to probabilistic climate change projections (UKCP09 (Met Office)). In Jenkins et al. (2015), the above method was combined with a Hidden-Markov Model (HMM) (Jenkins et al., 2014), which captured the effects of both aggregated demand and future climate probabilistic projection. The importance of empirically substantiated building performance metrics was exemplified in (Summerfield et al., 2015). This provided a fast evaluation tool via a Power Temperature Gradient (PTG, W/K) method, which identified a linear metric for the thermal performance of individual buildings within a stock (fabric, system and occupant associated) with respect to the mean daily temperature. A key benefit in this approach is the incorporation of inherent socio-technical aspects of energy use, whilst avoiding complex externalities that would be required for a purely model-based endeavour (these can be very difficult to calibrate).

Fischer et al. (2016) presented their bottom-up SynPRO model for energy demand (electrical, space heating and domestic water heating), applied to German building stock, validated against the Harmonised European Time-use Survey database (HETUS, temporally rich public survey records of eleven European Countries (Eurostat, 2008)) and VDI 4655 profiles (The Association of German Engineers guidelines for medium-sized combined heat and power systems (Verein Deutscher Ingenieure (VDI), 2008)). In these types of model, the space heating and domestic water heating components are treated discretely, due to the different nature of these demands.

The growth of smart-meter data availability could see such statistical techniques become more influential in our assessment and understanding of building performance, these arguably representing richer descriptions of building end-user needs and behaviours.

3. Model integration challenges

Inappropriate policy decision-making (or lack of decision) is often attributed to uncertainty in modelled results, with insufficient transparency in the models and input data, and a lack of integration between the underlying sub-models. Major integrated ESM challenges include those discussed by Pfenninger et al. (2014) (see discussion in Section 2.1). Related challenges are discussed here with a specific focus on residential energy demand. The two specific objectives identified in the introduction have been considered to build a framework to address aspects of those more general challenges, points 1 to 4, in Section 2.1.

3.1. Temporal and spatial dimensions

The degree of variation in temporal and spatial dimensions between the various models is a fundamental challenge, both in terms of detail and span. Fig. 1 depicts temporal resolution against geographical coverage, indicating the respective scales at which the example models tend to operate. Time-spans are not illustrated (this typically ranges between one year for dynamic physics-integrated models to 40–50 years for ESMs); however, it is not technically implausible to overcome this discrepancy between different model classes (i.e. to run dynamic simulations over several years or decades). Similarly, spatial detail is not shown.

In terms of energy policy, an important area of development involves models which are towards the upper-right quadrant of Fig. 1, providing system responses at sub-hour resolutions which scale well to regional or national level. Additionally, there is a strong argument for increasing the geographical coverage of physically-rich dynamic models; this is a key motivation for the present work.

3.1.1. Temporal considerations

Modern ESM methods have been transitioning away from coarse temporal schemes (characterised by cumulative energy demand by seasonal and diurnal time-slices), as the validity of that approach comes into question when accounting for large variations in output from intermittent renewable sources.

Changing relationships between people and technology also introduce requirements for improved temporal detail. These perturbations have technological elements (e.g. what cost-effect heating systems are available on the market) as well as behavioural (e.g. will lower household bills increase energy consumption through the rebound effect), which will be intrinsically linked. Two key technology groups which will offer potential to alleviate strain on the electricity grid are storage and demand response (DR). Enhancements to model temporal detail will be required to accommodate the interactions that these have on the energy system.

Improper representation of time will therefore overlook basic operational characteristics of integrated energy systems. Literature has shown that this can lead to overestimations in the uptake of renewable energy systems (Poncelet et al., 2016; Haydt et al., 2011; Ludig et al., 2011; Deane et al., 2012). Furthermore, the temporal scheme should be designed to simultaneously reflect the distinct dynamics of demand, renewable sources of supply, storage and DR, which may not coincide. Moreover, interrelationships between these factors are likely to be very complex. Whilst the referenced literature has demonstrated the merits

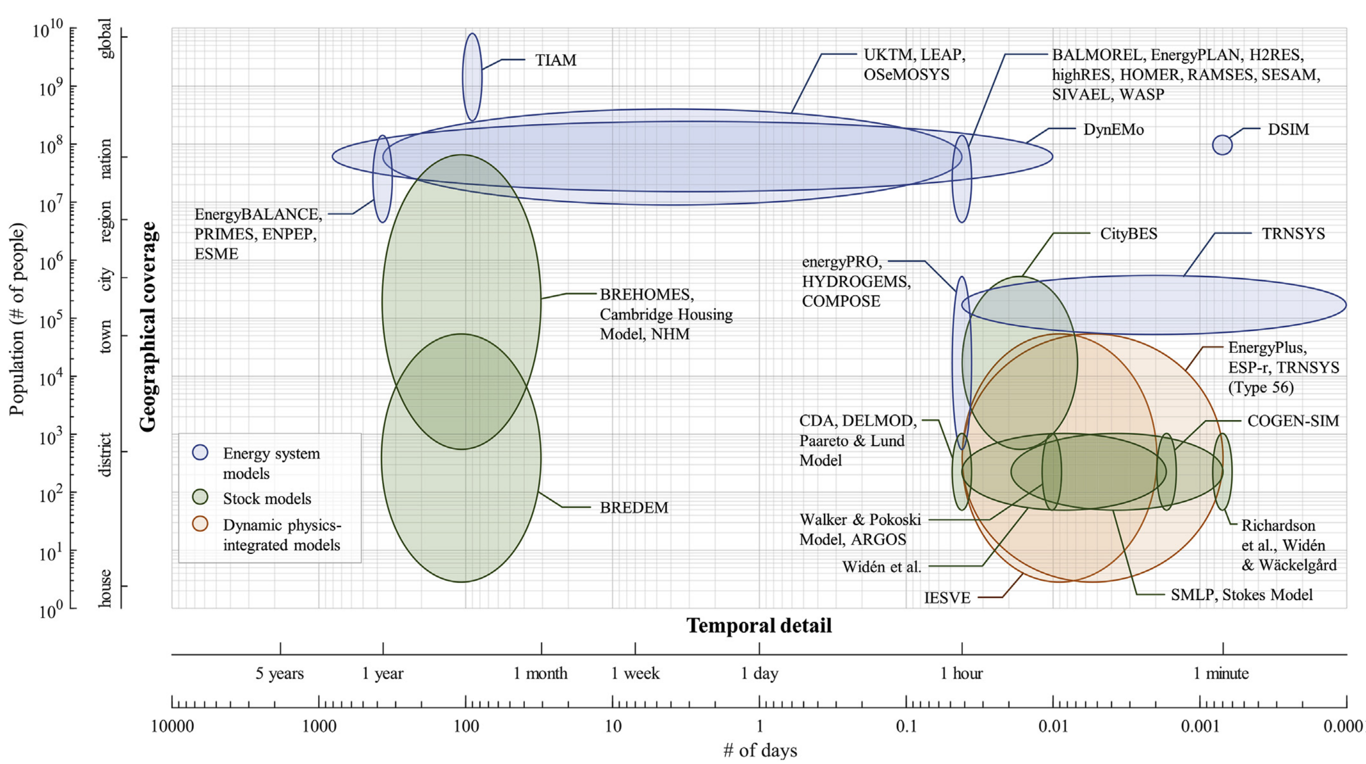

Fig. 1. Depiction of temporal detail and geographical coverage of various numerical models, within the classifications: energy system models, building stock models and dynamic thermal building simulations.

of moderate improvements in temporal detail, greater focus has been directed towards variability in renewable supply, rather than demand, with the latter being reliant on inelastic data based either on load distribution curves or representative days.

3.1.2. Spatial detail

All models discussed thus far make significant assumptions regarding spatial variability and detail of energy demands. The development of the SHED model (Quiggin and Buswell, 2016) provided an enhanced spatial representation over earlier work based on the FESA model, using three locations to adjust empirical daily trends via a climate corrected scheme. This represented a relatively small area of the UK; however, within the UK, significant spatial variation can be found in social, demographic and climatic terms.

With respect to climate, resources such as the UKCP18 (Met Office) and the PROMETHEUS database (University of Exeter) provide weather data which account for various climate change scenarios up to the year 2080. In the PROMETHEUS dataset, 45 locations were used to represent climate variation at various latitudes and around coastlines and heat islands. To capture these effects in energy demand, physics-integrated modelling is necessary.

Other spatially sensitive demand aspects include the topology and density of human geography. The energy transition is widely expected to herald a change in energy system control locus, i.e. the incumbent centralised system will be replaced by a plethora of decentralised, localised solutions. The development of an ESM approach that can access more granular spatial detail is therefore likely to be required in order that policy guidance relevant to this transition can be evaluated. Communities which are not connected to major energy infrastructure, for example, typical in rural and island locations, can be represented at a stock level. Likewise, possible sites for district heating networks can also be considered where appropriate.

3.2. Representing energy demand in scenario exercises

Various forms of scenario exercises are relevant for future energy system planning, these being predictive, explorative or normative in nature. The discussions in this paper relate to explorative strategic and normative transforming exercises (Koppelaar et al., 2016), as discussed above; these are specifically intended to test political paradigm exploration, i.e. dynamic policy approaches over a long time-horizon. In this way, predictive (forecast or 'what-if') approaches become irrelevant for the underlying objectives of this work, those being aimed at short to medium-term testing of predetermined policy measures and demand trends. Explorative external analyses, which test resilience to events which are imposed on the energy system under *fixed policy* schemes, are of reduced relevance. Normative preserving studies exclude socio-political-technical evolution over the long-term; these are also less relevant.

A key distinction between explorative and normative studies is the nature of the question being asked: what can happen, or, how can a desired target be achieved. As such, explorative and normative approaches are driven by the distinct ESM paradigms, simulation (ESSM) and optimisation (ESOM), respectively. In both cases, the energy demand patterns that feed into the ESM must reflect the input narratives which establish the state of the existing system and its future direction. Furthermore, when a long-term planning model is used to study periods spanning many decades, a large number of individual policies may arise at different times over the course of those years; evolution of energy demand as a result of preceding policy must be considered. It is proposed here that a hybrid stock-DBS model is used to translate the corresponding socio-technical inputs into energy demand timeseries.

Two important considerations are:

- That demand evaluations should be based around arrays of probable scenarios, rather than a discrete, singular vision (analogous to the UK Climate Projection approach used for UKCP18, for example);
- That our visions of our future paths are always changing – constructing an array of appropriate future scenarios in, say, one year's time, will yield a different array to that based on what we know today (National Grid identified significant inconsistencies between forecasts made in 2012 and 2013 for future installed PV in the UK (National Grid, 2013)).

  Scenarios should therefore be transparent, so that they can be understood and maintained by policy makers. Furthermore, robust tools are required to translate these scenario descriptions into quantitative demand profiles.

3.3. Techno-economic and socio-technical detail

Techno-economic detail must be considered at a range of scales, from major generator plant down to technology at the distributed level. Start-up/shut-down times, minimum turn-down and part-load efficiencies require specific treatment, usually via an ESSM. Many socio-technological factors also exist which are overlooked in ESOMs and are of particular importance in future projections of energy use; Public opinion has influenced major energy subjects in recent years, including state decisions regarding nuclear, shale gas and wind.

ESOMs tend to have capacity to optimise down to household technology level, accounting for basic boiler efficiencies for example. This enables the model to make decisions regarding technology choices and operation at a reasonably fine level of detail. However, a wide range of socio-technical issues are overlooked when addressing household technologies in such a way. Uncertainty over the simplified economic constraints in ESMs should be considered carefully; in the absence of verified and validated models for such considerations, at the very least, the following questions should be considered:

1. What age categories do the dwellings fit into?
2. What dwelling-form categories exist across the stock?
3. To what extent (a) have dwellings been renovated under an existing energy efficiency scheme, or (b) are certain dwelling types suitable for future energy efficiency retrofits?
4. What dwellings have an existing gas or district heat connection (or have access to wider infrastructure)?
5. What tenure arrangements exist for different sections of the stock?
6. What dwellings have adjoining privately owned ground (including details of area and condition, i.e. what are the techno-economic constraints for different types of ground-source heat pumps)?
7. What is the distribution of heating system age across the stock?
8. What dwellings have secondary heating systems (e.g. open/gas fires or wood burning stoves)?
9. Is thermal storage capacity available/restricted across sections of the stock?
10. Are combined space heating and domestic hot water systems feasible?
11. To what degree are heating systems incorrectly sized (is condensing mode achieved during typical boiler operation; to what degree are heat pump coefficients of performance (CoPs) affected by poor sizing)?
12. What impact on heating system efficiency is attributable to poor workmanship (e.g. poor design, poor control, lack of pipework insulation).

These questions can be asked on an individual dwelling basis, leading to an archetype approach when considered across some building stock, each designated with case specific constraints. One of the major difficulties with this approach is the number of degrees of freedom that are introduced into an overstretched archetype framework. Along with the wide range of relevant questions (or dimensions, of which there may be more), some of these questions can have a range of responses.

Increasingly erratic fluctuations in wholesale fuel costs and grid carbon intensity (and potentially doped natural gas carbon intensity) present further uncertainty questions over the ability of ESMs to optimise heating technology across the building stock. Furthermore, the true effectiveness of past energy efficiency schemes is not always clear; however, where suitable data are available, the uncertainty around varying success rates can be assessed via a DBS.

Further complex issues surround societal aspects such as fuel poverty. There have been studies demonstrating the use of analytical data procedures in conjunction with smart meter data to reveal new insight on fuel poverty (Gouveia et al., 2018). In the context of the present framework, it may be possible to apply similar methods to generate augmented building-user behavioural inputs that reflect fuel poverty. By extension, this could allow for interpretations of fuel poverty in long-term scenarios. In a conceptual sense, it may also be possible to infer trends (bad and good) in fuel poverty that result from certain scenarios or (indirect) policy. In such a way, it might be possible to be conscious of fuel poverty, to avoid worsening of the situation, without addressing it directly.

Similar arguments exist for other income related factors that affect energy usage patterns in homes, for potential rebound effects from energy efficiency programmes (where profligate behaviour results in net increases in energy consumption, see (Font Vivanco et al., 2016)), for geospatial factors, and so on. These inexhaustive points highlight some diverse areas that make residential energy demand extremely complex. It is not the intention to analyse these specific issues here; rather it is to provide a means for incorporating the response of otherwise stand-alone models into the broader long-term planning assessments dominated by ESMs.

3.4. Characterising uncertainty: calibrating assumptions, inputs and diversity

When adopting an archetype-based approach, for each M questions that can be asked for any building stock, a new degree of freedom is introduced. When the questions asked can have N_m different responses, this potentially gives rise to $\prod_{m=1}^{M} N_m$ archetypes (or in the simplest cases, where N_m is constant, N^M archetypes), which can number in the thousands. Aside from computational tractability issues (which may be overcome), fundamental concerns regarding empirical calibration of inputs and uncertainty characterisation remain the biggest obstacles in modelling energy demand in the residential building sector. The fundamental modelling question becomes: what value does bottom-up modelling provide if it raises more questions than answers?

To this end, it can be argued that the future cannot be objectively planned for purely on the basis of historic data and/or simplified steady-state demand models: socio-technical change stemming from medium to long-term trends must be considered across domestic and transport sectors in particular. If these effects continue to be overlooked, policy makers will remain restricted in their capacity to influence model outcomes; insight on real-world implications of policy changes will also remain restricted. Furthermore, it can be argued that simplified steady-state modelling approaches that do not prompt the large range of questions alluded to, do not scratch the surface of the pertinent issues. It is the nature of scenario planning exercises that a range of possible outcomes can be explored for different purposes; if we simply provided one vision of the future and continue to avoid asking complex questions, we get one answer which has dubious relevance.

By presenting policy makers with the ability to control model responses to a broader set of questions (some of which have been considered above), new policy avenues can be explored. To develop an enhanced understanding, for example, of the relationship between building defects and thermal performance (Alencastro et al., 2018) or poor heating installer workmanship/design and system performance, an 'input channel' for these concerns should be made available to policy makers, to assist when mandating new policy.

In spite of these arguments, the major concerns around empirical calibration and uncertainty characterisation still remain. Improved understanding of the discrepancies, for example, between standard U-value assumptions for solid wall constructions and measured variation in real buildings highlight some of these issues (see Li et al. (2015)). Regarding infiltration, stochastic methods examining the effects of inter-dwelling air permeability were presented in (Jones et al., 2015), which showed that overlooked air transfer mechanism between occupied properties resulted in substantially lower heat loss, introducing uncertainty. Alongside dwelling-form considerations, which are typically captured in conventional archetyping procedures (aspect ratio, external perimeter and glazing orientations), infiltration and set-point temperatures were identified in (Yusuf and Durmus, 2011) as being the most influential input parameters when evaluating energy performance of residential apartment buildings, both of which are poorly understood in real buildings.

Research activity on the subject of uncertainty characterisation is introducing new ways to capture some of the complexities of modelling future residential energy demand, across various scales. On large geographical scales, studies exist that consider long-term scenarios, constructed around both socio-technical and socio-economic uncertainty (Eyre and Baruah, 2015). At the opposing end of the scale, individual buildings have been evaluated using uncertainty approaches that investigate the sensitivities > 600 of building parameters (Eisenhower et al., 2012; Chong et al., 2015; Royapoor and Roskilly, 2015) (using non-residential cases studies).

The growing repositories of data (especially smart meter data and time use surveys) are likely to play a major role in addressing calibration issues, along with the new data analytics and machine learning approaches, which are very active area of research. The remainder of this paper is intended to justify an approach to evaluating building-user behavioural effects, in agreement with the objective outlined in Section 1.

4. Detailed demand modelling for the residential sector

The proposed demand model has three stages, detailed below and depicted in Fig. 2. Focusing specifically on a community-scale system and exploiting the bottom-up approach to demand modelling:

1. The composition of building stock in the region of interest is established first, capturing stock sizes, archetype building properties (including construction type, age, dwelling-form and the socio-technical typologies considered above), details of demographics and statistics associated with typical behavioural groups within the community.
2. Energy demands are then synthesised for the relevant archetypes using Dynamic Building Simulations (DBS) and a statistical model (Hidden-Markov Model, with Generalised Pareto distribution (HMM-GP)) to generate thermal and electrical demands, respectively. These have the capacity to capture building-user behaviour, including any foreseeable evolutions in behaviour over the long-term model horizon (e.g. up to the year 2050).
3. The resulting set of synthesised thermal demands are converted to fuel demands, based on stock descriptions of distributed heating technology (including part-load and seasonal efficiencies, and fuel type). The fuel demands are then aggregated according to the stock composition and any statistical variation in building-user behaviour, to provide diversified demand inputs for an ESM.

In the present framework, the underlying components of residential energy demand are recognised, each originating from physically distinct processes: space heating/cooling (SH/C) demand; domestic hot water (DHW) demand; lighting, appliance and consumer electronics (LACE) demand. The distinction between energy demands and

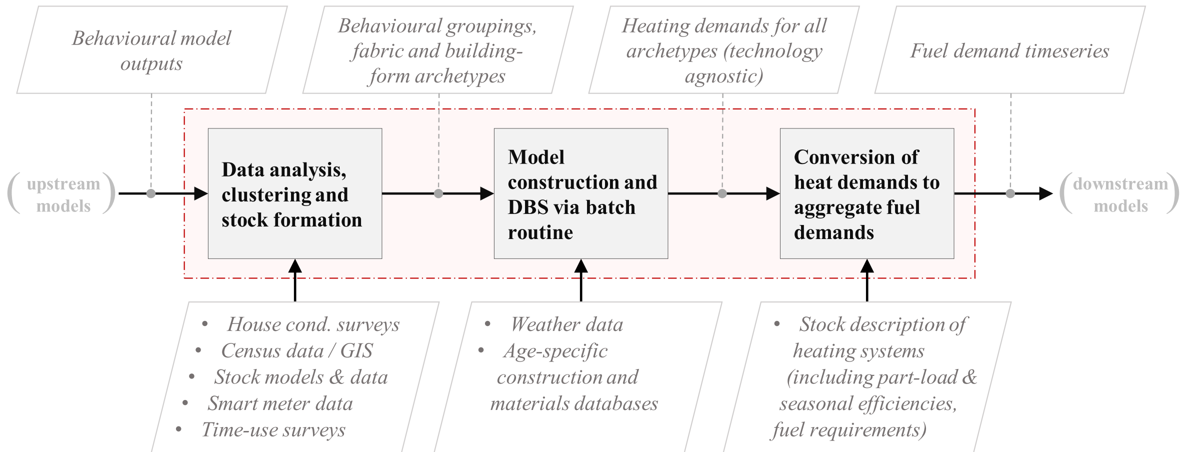

Fig. 2. Framework for evaluating residential energy demand, including three principle stages and various inputs at each stage.

descriptions of fuel usage (e.g. 'electricity/gas demand') is a necessity when modelling the discrete character of each underlying demand. This allows societal behaviour to be related to physical processes and socio-technical descriptions of the present day and future. In contrast, it is otherwise difficult to unpick specific demands for heating, domestic hot water and cooking from existing records of electricity and gas usage.

Other key influencing factors related to future energy demand include demand response, energy storage, distributed generation and prosumerism. These factors require discrete models which operate externally to the components depicted in Fig. 2. This distinction arises because the demand aspects addressed directly in Fig. 2 (i.e. demand for heat, light, energy for cooking, power for electronics etc.) are raw service demands which emerge directly from the behaviour of building-users; demand response, storage and on-site generation (which facilitate prosumerism) can be seen as disruptive technologies which impact the demand for different fuels; some of these disruptions may also influence the response of upstream behavioural models, others will not. Feedback of these more complex considerations, as well as other externalities to the model in Fig. 2, are presented later in Fig. 4.

4.1. Space heating/cooling demand

One of the specific challenges presented by SH/C demand is the delayed thermal response of building fabric and complex nature of solar gains. Both have an associated time-lagged effect which links to a range of physical variables (notably climate), spanning anywhere from a few hours to a few days.

As an approach to modelling SH/C demand in residential building stock, the authors have developed a technique to meet some of the described concerns in this paper; in essence, a dynamic, local-scale stock model. A starting point for this is to apply the following classifications to develop a set of building/occupant archetypes:

- Building fabric classification (U-values, thermal mass, infiltration, radiation);
- Dwelling-form classification (detached, terraced, multi-level, etc.);
- Building orientation;
- Occupant behaviour (daily routines, working patterns, occupant density, demographic).

Once the stock description is established, simulations are carried out using a traditional DBS tool. An earlier version of this application is described elsewhere (though outside of the ESM context) (Patidar et al., 2016). Diversity is introduced by batch processing sequential variations of the daily occupant behaviour profiles, offsetting the time-stamp of each control event (i.e. temperature set-point changes) across a range of different times. The diversified results are generated automatically using a weighted distribution centred around the typical basis response defined in the stock description. This procedure is illustrated in Fig. 3 using an example heating set point profile for a weekday, for a given household behavioural group. A small time-increment (e.g. 5 min) is applied to the reference profile, as Fig. 3(a), which is then assigned as an input to the iterative simulation routine, repeating across the pre-determined time window (2 h in the example). The corresponding deterministic results are then aggregated using a weighting, based on the probability of occurrence of each heating profile (Fig. 3(b)). Methods for extracting reference profiles and corresponding probabilities are currently being developed, using smart meter data.

4.2. Domestic hot water heating demand

DHW demand shares similar characteristics to both SH/C and LACE demands. Supply, distribution and storage aspects are generally the same as space heating demand, with simple, cheap and mature technology readily available for thermal storage, for example. Existing storage systems are commonplace, and expansion would be anticipated

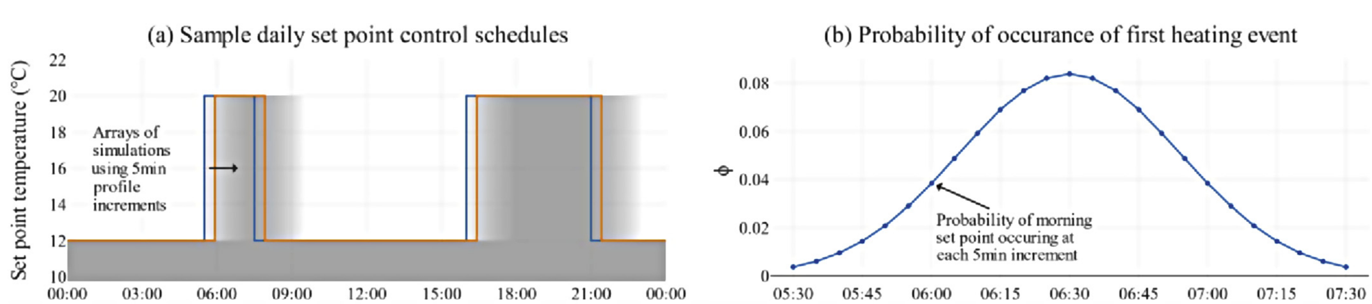

Fig. 3. Input profile diversification: (a) two sample heating system control schedules characterising the same behavioural routine, differentiated by a small time-increment; (b) probability (or weighting) of each time-incremented profile.

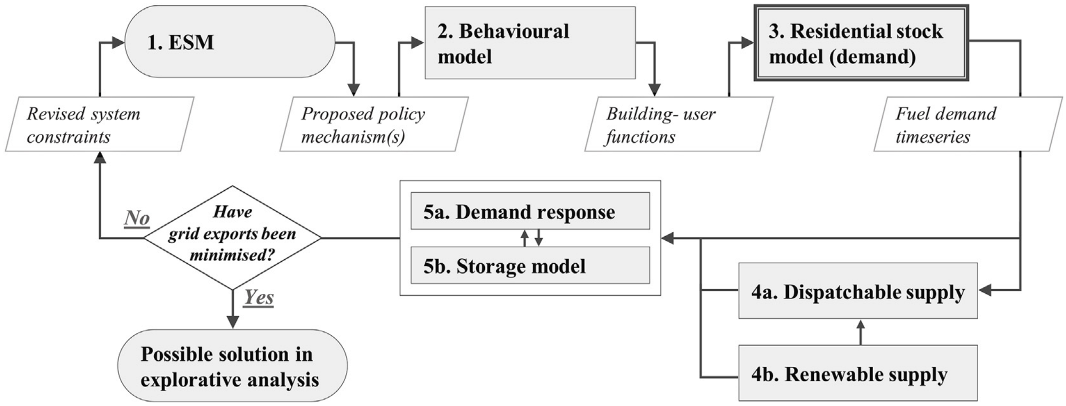

Fig. 4. A community-scale energy system with shared ownership for generation technology, with governance structure. Key outputs/inputs are identified between component models.

if demand response sees widespread deployment in the future. In contrast to modelling the thermal envelope and solar gains associated with a building, however, the dynamics of thermal stores are relativity straightforward to model. Furthermore, the principal seasonality consideration is the mains feed temperature, which again is easily captured in a model.

The socio-technical aspects of DHW demand are more closely related to the LACE demand group. Demand for both categories is on an ‘as-and-when’ basis, generally associated with stochastic patterns which repeat on daily cycles (typically having specific weekday/weekend behaviours). Each pattern depends on specific socio-technical relationships, an important example being electric shower usage on weekday mornings, which is often the largest single load in a dwelling. The specific timing of energy demand events within a dwelling depend on social factors, such as the working pattern of the household or the presence of children.

Two options are proposed here for treating DHW demand. The first allows for reduced data input by using established DHW curves (Fischer et al., 2016; Jordan and Vajen, 2001; Energy Savings Trust, 2008) for demand behaviour. This would apply in circumstances in which relatively minor changes in DHW demand behaviour are expected in future scenarios. In such cases, it may be argued that the preeminent external factor is DR, that there is negligible impact on the underlying household activities around DHW use, and that DR only affects DHW fuel consumption patterns (i.e. the use of thermal storage becomes more widespread working in conjunction, for example, with a variable tariff scheme). This would assume that people generally make no change to their normal behaviour; therefore, there is no need to explicitly model human behaviour. Despite the empirical nature of this input condition to the model (in contrast to the main arguments in this paper), the present framework would allow for new technology as the heat source and allow for changes to how DHW demand is fuelled. This would help overcome shortcomings of existing ESOMs, which should ideally have some capacity to observe the impact of widespread usage of electric showers, for example.

The second proposed method for DHW demand characterisation involves synthesising aggregated profiles of demand. Where it is argued, in contrast to above, that present day profiles are not sufficient for modelling future DHW demand, statistical methods can be used to interpret socio-technical descriptions of future scenarios. An example of this method is the Hidden-Markov Model (HMM), as has been applied to LACE type demands in (Jenkins et al., 2014), as described below. In order to apply this method, a rich set of temporally refined DHW demand data is required for all relevant archetypes.

The above approaches can capture technological changes but take no consideration of underlying behavioural change over long periods of time. Discussions presented by Shove (Shove et al., 2012) around changing hygiene practices offer further social insight which could extend the application of the present approach.

4.3. Lighting, appliance and consumer electronics demand

The use of empirical data to define electrical demand profiles has the advantage of demonstrating real causations between known properties of the buildings from which demand originates, and the energy-use itself. However, to adequately envisage different scenarios of how those buildings are used (along with the technologies within) and to more widely extrapolate any findings, this must be placed within a statistical modelling framework. The ultimate goal of linking building and operational/behavioural inputs to shapes of electrical demand profiles is an important one, with several potential applications for estimating the impact of demand response, demand-side management and energy efficiency measures in our buildings.

This paper is concerned with the conceptual approach to such modelling and its integration with other forms of modelling related to energy systems. The authors have previously developed such a model described in detail elsewhere (Jenkins et al., 2014). Therefore, although the framework of the authors is designed with a particular statistical model in mind, a more general recommendation of this work is to encourage the wider of use of such statistical models that are informed by real data, particularly where available for high-resolution electrical demands.

The aforementioned statistical model is based on a Hidden Markov Model (HMM), which has been enhanced with an additional Generalised Pareto component (HMM-GP). High-resolution electrical demand timeseries for a single building (or group of buildings) exhibits the stochastic patterns (in this case, short-period spikes in electrical demand) that lends itself to HMM, providing the model is calibrated on real sample data (i.e. to define the demand characteristics).

Previously (Patidar et al., 2016), the authors investigated the efficiency of an HMM based approach for generating synthetic electricity demand profiles at 1-min resolution. This was shown to be acceptable for predicting the majority of values in real datasets of individual dwellings, but less satisfactory for the top 1% percentile; as previously discussed, such “extreme” values can have a bearing on key features of an electrical demand profile. To address this, a Generalised Pareto (GP) distribution was fitted to the 99th percentile of the *observed* energy demand timeseries, with the fitted distribution used to sample extreme load values for the *synthetic* energy demand timeseries. This approach uses a Seasonal-Trend decomposition procedure based on the Loess (STL) process (Cleveland et al., 1990) and allows for a systematic decomposition of an electricity demand series into three distinct components: trend, seasonal and random.

In the context of future demand evaluations, a key requirement of such an approach is the ability to cope with "disruptive" technologies, such as those associated with electrified transport and heat. The proposed statistical approach means that, with the data to identify real correlations, this is both possible and flexible enough to accommodate future changes.

5. Integrated model framework

With the pretext of the modelling approaches described in the previous section, the two main objectives are addressed here. Central to this is the embedding of endogenous demand evaluations within a broader framework for explorative strategic and normative transforming analyses. An example application is presented in this section to define the externalities and application interfaces necessary to operate the demand models within the context of community energy policy assessments. The intended purpose is to capture aspects of behavioural change in society, stimulated directly from future narratives or resulting from policy implementation (i.e. ensure that energy demand responds to change).

Issues around community-scale renewable energy systems tend to stem from temporal mismatches in the delivery of renewable energy generation and demand behaviour. Understanding the long-term issues (including planning activities, constrained micro-grid issues, curtailment prevention, net import/export expenditure) requires integration of supply and demand models. Fig. 4 shows a proposed integrated model which enables long-term planning for a community with shared ownership of renewable supply systems and private-wire grid. An a priori view taken when configuring this model was that a combination of storage and DR approaches would be considered to reduce import/export costs, and that the community was motivated to act collectively to minimise these costs (i.e. households would agree to self-governed policies). The model is intended to steer an evolving policy framework over the long-term, which captures demand changes, whilst also determining generation and conversion technology mixes via the traditional optimisation approach.

The routine activities of households within the community are interpreted via the embedded demand model, which introduces behaviour driven demands; this represents a solution to the objective (i) from the introduction. Key to this approach is the upstream interface with the behavioural model. At present, assessment of temporally refined building-user behaviour is predominantly data driven; clustering techniques can be used to build a picture of routine daily cycles linked to demographic data. Community-wide behavioural change can evolve through adjusted weightings of specific demographic groups, and through adoption of technology within households (e.g. efficient heating system, storage, solar thermal heating). The response to the changes in demand patterns, which originate from policy actions generated within the model, relates to objective (ii) from the introduction. It is envisaged that a fully integrated system would incorporate a dynamic behavioural model which responds to qualitative social definitions in future narratives.

6. Conclusions and policy implications

The components of an integrated Energy System Model (ESM) represent parts of a complex system: the demands on the network; supply capabilities; distribution networks; storage; energy conversion technologies; policy mechanisms; economic and social environments. The human factor links closely with all of these components; however, unresolved questions around socio-technological issues also suggest that our interaction with new technology is complex and difficult to predict. At the same time, in light of the significant transitions anticipated in the near future around the fuelling of our heat and transport needs, we know that our existing energy network and infrastructure is likely to come under considerable strain. Making appropriate adaptations for resilience involves extremely complex policy planning analyses; the importance of this subject is unquestionable, as failure to plan ahead will increase cost and carbon intensity, as well the likelihood of outages.

A recent policy example from the UK highlights some of these challenges. The 2019 Spring Statement (UK Parliament, 2019) confirmed that the new 'future homes standard' would mandate a ban on fossil-fuel based heating systems in new homes from 2025, to reduce carbon emissions and energy costs. Regarding carbon, this will almost certainly be true; however, when combined with the simultaneous transition to electric vehicles, there is no certainty, without a broader range of coordinated commitments, that energy costs will come down. This leaves many unanswered questions, including:

- What will happen to gas prices, the gas grid and gas industry?
- How will people in existing homes be affected, along with the fuel poor and people in the rental market?
- Will there be a rebound effect if apparent energy cost drop for some homeowners for a period?
- Will there be a heightened chance of power outages, voltage or frequency issue?
- Will new nuclear plant be necessary to attain this goal?

While the environmental intent from this policy is well meaning, the reality may fall short because of limitations in integrated policy making. What is presented here is a small contribution towards facilitating multi-disciplinary policy model integration, to aid policy makers.

Demand modelling provides an entry-point for new kinds of information flows towards ESMs that otherwise become externalities with weak links (or no links) to the principal tool in long-term energy planning. The virtue of the presented framework is that modelling approaches concerning socio-technical issues like fuel poverty or rebound effects can be carried out using contemporary models from across disciplines; those methods can evolve over time from within their own research areas, with new data and new science. The value in what is being presented here is that Dynamic Building Simulation (DBS) provides a new conduit for key issues that are otherwise disconnected from an integrated ESM, including many issues already influencing policy in other ways. The examples of socio-technical effects touched on here is not intended to be exhaustive or be described in enough detailed to introduce their own complexities.

In this work, a framework for investigating future energy demand in the residential sector is examined, with the specific UK context in mind. This is informed both by physical processes within the building stock, as well as statistical processes surrounding the interaction between people, buildings and technologies. Specific approaches have been outlined for space heating demand, domestic hot water demand and lighting, appliance and consumer electronics demand. Following the formation of the stock description, based on building fabric, building form and household behaviour, large numbers of probabilistic simulations are carried out to develop temporally diverse thermal demands. These timeseries exhibit causal relationships with the energy system end-users – i.e. the shape of demands can be linked to daily behavioural routines of a diverse population. Methods for inferring underlying, distributed household behaviour from smart meter data is an area of ongoing work, which aims to calibrate this hybrid DBS-stock model. Furthermore, with respect to electricity demands, Hidden-Markov Models (HMM) are proposed for delivering diversified lighting, appliance and consumer electronics demand, by generating thousands of statistically similar results using appropriate sets of seed data.

Two objectives were considered to guide the policy implications discussed in this paper. The first of these was to incorporate a mechanism to translate behavioural signals into energy demand profiles on a community or regional scale, providing a means to interpret social parameters defined in future narratives. This process employed a building stock model, dynamic building simulations and the statistical

HMM-GP method. The second objective was to place this group of models within a framework for policy investigation studies, in a way that captures the cyclic effect of evolving demand patterns. The example given was for a community scale system with shared ownership of renewables and administrative responsibilities; policy assessments carried out using such a framework have the capacity to consider socio-political-technical change.

Preliminary work is under way to test this process for a limited geographical area. It is important to note that scalability will remain an ongoing issue, this representing a major area for development. It is the overall aim in this wider work (National Centre for Energy Systems Integration (CESI) (National Centre for Energy System Integration (CESI))) to develop advanced methods to treat the dynamic demands in more computationally efficient ways, to allow up-scaling and integration with third-party models. The impact will be the ability to inform low-carbon policy areas with consistent demand projections that, in turn, can share assumptions with other policy areas that are important to the running of our energy systems.

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