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Developing a common approach for classifying building stock energy models

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ABSTRACT

Buildings contribute 40% of global greenhouse gas emissions; therefore, strategies that can substantially reduce emissions from the building stock are key components of broader efforts to mitigate climate change and achieve sustainable development goals. Models that represent the energy use of the building stock at scale under various scenarios of technology deployment have become essential tools for the development and assessment of such strategies. Within the past decade, the capabilities of building stock energy models have improved considerably, while model transferability and sharing has increased. Given these advancements, a new scheme for classifying building stock energy models is needed to facilitate communication of modeling approaches and the handling of important model dimensions. In this article, we present a new building stock energy model classification framework that leverages international modeling expertise from the participants of the International Energy Agency's Annex 70 on Building Energy Epidemiology. Drawing from existing classification studies, we propose a multi-layer quadrant scheme that classifies modeling techniques by their design (top-down or bottom-up) and degree of transparency (black-box or white-box); hybrid techniques are also addressed. The quadrant scheme is unique from previous classification approaches in its non-hierarchical organization, coverage of and ability to incorporate emerging modeling techniques, and treatment of additional modeling dimensions. The new classification framework will be complemented by a reporting protocol and online registry of existing models as part of ongoing work in Annex 70 to increase the interpretability and utility of building stock energy models for energy policy making.

1. Introduction

Buildings worldwide are responsible for 36% of energy use, emitting 40% of direct and indirect CO_2 emissions [62]. These numbers are expected to rise due to growth in population and building floor area, increased access to energy in developing countries, and growth in energy-consuming devices. Reducing building energy use and increasing the flexibility of building operations are essential strategies for mitigating the risk of catastrophic climate change. Indeed, the International Energy Agency (IEA) estimates that buildings in 2040 could be 40%

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more energy efficient than today, with savings driven by reduced energy need for space heating, water heating, and cooling [62].

The development of concrete strategies for effectively managing building energy use remains a key challenge. Building researchers and policy makers lack data for understanding how building energy use is expected to change over the next several decades, which is essential for identifying the specific efficiency and flexibility strategies that have the greatest impact on these changes. While access to these data at both a granular spatio-temporal resolution and for the building stock as a whole is improving, gaps in data coverage, consistency, and accessibility across countries must be addressed to support setting effective priorities for building technology research, development, and deployment programs.

To address gaps in building energy use data at large scales, a group of international researchers that includes the authors is collaborating on an International Energy Agency (IEA) Energy in Buildings and Communities (EBC) Annex "Building Energy Epidemiology", or IEA-EBC Annex 70. The concept of energy epidemiology as first defined by Hamilton et al. [54] is the study of energy use in a large population of buildings. The scope of research that falls within the energy epidemiology field is broad, including both modeling of energy use in the building stock under different sets of input conditions, analyses that identify correlations between energy use and influencing variables, and testing of causal hypotheses about the effects of implementing energy efficiency measures across representative portions of a building stock.

The guiding objective of IEA-EBC Annex 70 is to improve the use of data and models of building energy use to facilitate dramatic reductions in building energy use and greenhouse gas emissions. In support of this objective, we seek to identify and compare models of large-scale building stocks and their energy use that are broadly applicable across the international buildings research community. Accordingly, this paper proposes a framework for classifying building stock energy models that builds upon existing classification approaches while acknowledging emerging modeling techniques and identifying additional dimensions that characterize the development and use of such models. The intent is for the proposed classification to serve as a common framework for quickly comparing and assessing available building stock energy models across the scales of cities, regions, and countries. This, in turn, can facilitate evidence-based decision-making to support concrete actions to reduce the energy and emissions of the buildings sector, while assisting the increasing number of global, national, and sub-national scale initiatives on sustainable development, such as the Sustainable Development Goals and the Global Covenant of Mayors for Climate and Energy, among others.

The scope of the proposed classification scheme covers models of the buildings sector that: (a) represent multiple buildings that are often geographically co-located; (b) produce energy use metrics as an output; and (c) generate out-of-sample predictions. This includes multi-sector energy system and integrated assessment models in which the buildings sector is represented. The proposed classification scheme does not pertain to models that: focus on a single building's energy use in isolation; do not yield energy use as a primary output (e.g., focus exclusively on other building performance metrics such as indoor environmental quality or water use); or are purely explanatory or descriptive in nature [134].

We begin by reviewing previous efforts to develop building stock and energy model classifications, identifying critical gaps in these existing classifications and establishing the need for an updated classification framework. We then introduce a new classification scheme that builds upon the strengths of the existing model classifications while addressing their shortcomings in the context of currently available data resources and computational capabilities. Unique elements of the classification approach are enumerated in detail along with examples from the literature that demonstrate their relevance to the task of building stock energy modeling. The paper concludes by discussing potential applications of the proposed classification scheme – including its use in related IEA-EBC Annex 70 efforts to create a registry of building stock energy models and develop a complementary model reporting protocol – as well as limitations to its future use by buildings researchers.

1.1. Summary of existing classification approaches

To-date there have been multiple efforts to classify building stock-level energy models by technique and purpose. Foremost among these is a 2009 review by Swan and Ugursal [141], which summarizes major energy modeling techniques for residential sector end uses. The Swan and Ugursal classification has gained wide acceptance among building stock modelers, as evidenced by its large number of citations to date in other studies.[1] The designation of "top-down" models, or those that begin with an aggregate view of a system that may subsequently be broken down into constituent sub-systems, and "bottom-up" models, or those that begin with a detailed representation of a system's constituent parts that may be aggregated up to the whole-system level, has long been used for many types of modeling. Swan and Ugursal [141] extended these concepts to the modeling of residential building stock energy use, identifying eight major types of modeling techniques under the general top-down and bottom-up categories (Fig. 1).

Other classification systems define the building stock energy modeling space more broadly than the Swan and Ugursal classification. For example, Keirstead et al. [66] reviewed all studies on urban energy system models, including other major energy systems such as transportation, and classified each model's purposes and category. Building stock energy modeling is a subclass of "building design" in their schema, but few details are given on the specific techniques used for this model subclass. Referring to the OpenMod initiative, Limpens et al. [76] performed an extensive review of 53 existing energy models and tools. Most of them adopt an energy systems analysis approach with the electricity sector as their main scope. Thirty-one of the models reviewed cover the "heating" sector (of which the buildings sector is a part), although half of them only do so partially (through combined heat and power). In addition to the sector coverage, Limpens et al. [76] classify the models in terms of optimization vs. simulation, "openness" (in terms of usage and source code) and time (resolution and run time).

Two other review papers discuss classification in the context of appropriateness for building energy policy making. Brøgger and Wittchen [17] adopt the general Swan and Ugursal classification, while discussing the appropriateness and accuracy of each model type in the context of European policy-making. Sousa et al. [137] present a review of building stock energy models specific to the United Kingdom, comparing and contrasting the capabilities for each, utilizing the general bottom-up and top-down divisions provided in Swan and Ugursal.

Few studies have attempted to expand upon the Swan and Ugursal classification of top-down modeling techniques. Ahmad et al. (3) perform a comprehensive literature inventory of existing data-driven building stock energy modeling studies, creating their own four classifications of data-driven modeling in the process based on specific statistical and machine learning techniques. Li et al. [75] provide a classification tree nearly identical to Swan and Ugursal, adding a few elements to the top-down branch, including "other" and "statistical" top-down sub-branches as well as a statistical modeling technique that relies on physical input variables. The majority of this review article, however, focuses on bottom-up applications and the new top-down techniques are not explored in detail in the text.

For bottom-up models, the general division between "statistical" (i.e. data-driven/black-box) and "engineering" (i.e. physics-based/white-box) models has endured in multiple works recategorizing models. For example, Nageler et al. [96] utilize the general Swan and Ugursal classification for bottom-up models. The same physics vs. data-driven model

[1] https://scholar.google.com/scholar?rlz=1C5CHFA_enUS846US846&um=1&ie=UTF-8&lr&cites=464700330571940757 (accessed 06/30/2020).

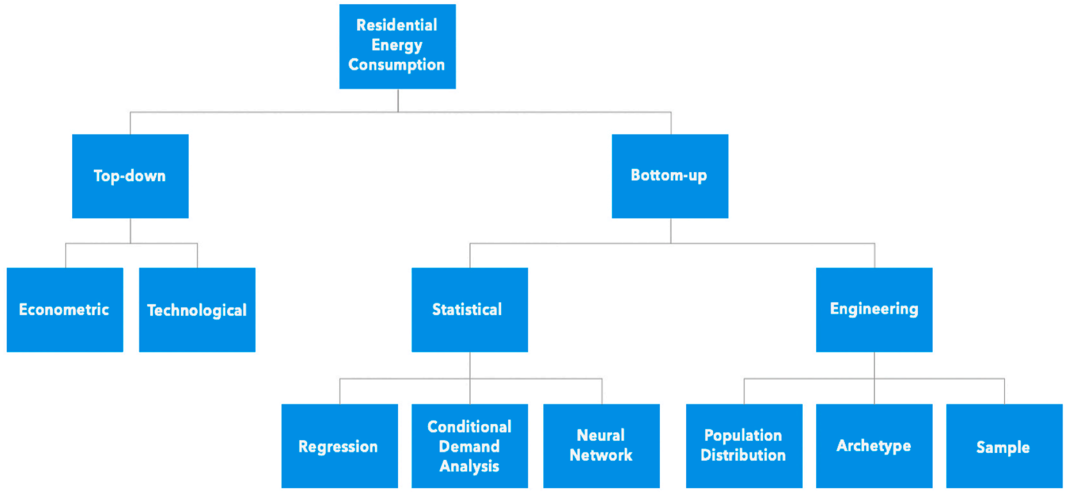

Fig. 1. Swan and Ugursal's 2009 model classification. Models of residential energy use are classified using a hierarchical tree structure that includes two main branches: one for "top-down" models, or those that begin with an aggregate view of a system that may subsequently be broken down into constituent sub-systems, and a second for "bottom-up" models, or those that begin with a detailed representation of a system's constituent parts that may be aggregated up to the whole-system level.

split is followed by Gao et al. [50] in a paper that provides an extensive review of the latter. Soto and Jentsch [136] accept the classification and comparatively review five statistical and seven building physics bottom-up energy models. Kavgic et al. [65], another heavily-cited paper, directly adopts this simplified Swan and Ugursal bottom-up division, adding in a "hybrid" category that combines data- and physics-driven approaches. Mastrucci et al. [85] also focus on bottom-up models using this general classification, but extend beyond demand modeling to include a multi-level life cycle analysis framework to account for embodied energy. This article also makes a distinction between the energy modeling portion of an assessment and the different stock aggregation methods - something of increasing importance to bottom-up models.

Other publications have expanded upon the bottom-up sub-class of models in Fig. 1. Zhao and Magoulès [166] classify methods to predict building energy consumption into engineering, statistical, neural networks, support vector machines and grey models, where the latter combines methods. Wei et al. [160] draw further on the Zhao and Magoulès [166] paper by defining white-box models as those that input detailed physical information and black-box models as those that input historical data, with grey-box models again using combined approaches. The authors also distinguish between data-driven approaches that are used for prediction (ANN, support vector machine, statistical regression, decision tree and genetic algorithms) vs. classification (k-means clustering, self-organization map, hierarchical clustering). Reinhart and Davila [116] develop one of the first overview papers specifically on the Urban Building Energy Modeling (UBEM) sub-class of bottom-up models. The paper compares published models and offers a high-level overview of approaches. Reyna et al. [118] develop an orthogonal classification focused on building interactions (building-building, building-transportation, etc.) and provide cases leveraging the Swan and Ugursal classification. Ahmad et al. [3] conduct a comprehensive review on energy-demand prediction models for buildings at urban and rural building levels. Each of these publications reference building stock energy modeling capabilities far beyond those outlined in the original Swan and Ugursal paper. The development of new approaches necessitates renewed evaluation of building stock energy modeling and the advantages and disadvantages of emergent capabilities.

1.2. The need for an updated classification

When the Swan and Ugursal classification was published in 2009, building stock energy models were limited in number and functionality. Three major developments have increased the capabilities and applications of current building stock energy models: 1) big data, enabled through advances for example in the area of utility energy data access, has increased the amount of empirical evidence that can be integrated into model development and calibration; 2) computing power has increased the availability and decreased the costs of large-scale simulation through cloud computing and access to supercomputing; and 3) as modelers adapt to increased data and computational capabilities, many models now use multiple modeling techniques to estimate both energy use and its driving variables; such models don't fit cleanly within a single category and/or include dimensions that are not captured by a high-level classification approach. These issues are detailed further here.

In the past ten years, increasing amounts of data have been collected on both model inputs (e.g., building characteristics, geospatial information for individual buildings, operational schedules, and occupant behavior) and outputs (e.g., energy use); these improved data can inform more accurate models of building stock energy with finer spatio-temporal resolutions. For example, European Energy Performance Certificates [36] and benchmarking mandates in the United States [144] are increasing data collected on building characteristics and energy performance. Moreover, while utilities have long restricted access to account-level energy use data, there is now a growing recognition that these data are essential for decision making for the public good in the face of climate change [9]. In California, for example, universities have been able to obtain account-level energy use data under non-disclosure agreements, and municipalities are also able to access aggregated utility data for their jurisdictions [22]. Access to these data allows linkages to be created through geocoding to building/parcel attributes, thereby revealing the relationships between energy use and building vintage, use-type, square footage, and socio-demographic attributes [44,111]. A transition to using such granular, empirical energy use data is dramatically improving the spatial resolution and predictive abilities of building stock energy models. Some classification systems for whole (i.e. individual) building modeling and calibration have been extended to cover these advancements (e.g. Fumo [46]), but stock-level energy modeling classification systems have not been extended to cover newer data-driven techniques.

Simultaneously, non-traditional data sources are augmenting available data on buildings. For example, remotely-sensed data such as LiDAR and satellite imagery are being used to determine external characteristics such as building height, geometry, shading, solar irradiance, and even externally-placed building equipment [52,82,92,146,163]. All generate rich detail on the building stock, but new modeling techniques are required to leverage this information in full. Such techniques include geospatial simulation models [116], which simulate all or a representative subset of individual buildings comprising a stock using whole building energy simulation engines and geospatial data; system dynamics and agent-based models [43,83], which are able to explore causal effects and interactions across modeled entities (e.g., across individual buildings, or occupants within a building); and machine learning models [8], which leverage big data resources to predict changes in building energy use at scale.

Cloud-based computing has proven to be an important enabling technology for many of these computationally-intensive models, as the cost of cloud computing has decreased and the availability of web-based resources has improved [45]. Geospatial models, for example, dramatically expand upon the single-archetype assumption of previous bottom-up engineering model classifications in their ability to represent every building in a city, region, or country explicitly at a finely grained temporal resolution. Moreover, models utilizing these big data and cloud computing resources often combine multiple techniques that don't fit neatly within the distinct "top-down" or "bottom-up" Swan and Ugursal designations, and such models may also explicitly represent additional variables that influence energy use as part of the model's structure and outputs. Additional classification categories and layers are needed to capture the proliferation of such hybrid modeling techniques for representing both stock-level energy use and its key correlates.

Beyond these gaps in existing classifications' coverage of modeling techniques and mixed modeling approaches, previous classifications also lack guidance on how to assess the transferability and quality of models along dimensions that are implicit in the high-level classification diagram. In 2009, most models were bespoke and privately stored - standalone models developed to assess a single geographical area by a single group of people for a single purpose. Increasingly, stock models have become designed for wider applicability, allowing core modeling structures to be transferred to other cities or countries by varying model input data. As model transfer is being considered, additional language is needed to appropriately communicate key characteristics of the model such as handling of time dynamics, model and input uncertainty, and the geographic and spatial resolution and extent of models. Accordingly, there is a need to identify and describe such additional dimensions to complement a high-level model classification approach.

2. Overview of proposed classification scheme

The proposed building stock energy model classification scheme (Fig. 2) establishes a flexible framework for high-level model classification that: (a) builds from existing classification frameworks while accounting for emerging simulation-based, data-driven, and hybrid modeling techniques; (b) recognizes the potential sub-layers of a building stock energy model; and (c) encourages the description of additional model dimensions that are not readily captured by a high-level classification.

In place of the hierarchical organization of existing classifications, the classification diagram in Fig. 2 groups building stock energy modeling techniques into one of four quadrants based on their design (top-down/bottom up) and degree of transparency (black-box/white-box).[2] The four classification quadrants are thus: top-down/black box (Q1), top-down/white-box (Q2), bottom-up/black-box (Q3), and bottom-up/white-box (Q4).

To illustrate how this new classification approach addresses gaps in the coverage of building stock energy modeling techniques in existing classifications, Fig. 2 includes examples of emerging data-driven and simulation-based techniques alongside established techniques: machine learning (Q4: bottom-up/white-box), system dynamics (Q2: top-down/white-box), agent-based modeling (Q4: bottom-up/white-box), and physics-simulation (Q4). Additionally, Fig. 2 designates an area between each of the four classification quadrants for hybrid modeling techniques that combine techniques across (but not within) the quadrants. Details concerning the example modeling techniques identified in Fig. 2 are discussed in the next section.

Fig. 2 shows three additional modeling layers that support the main energy layer of the classification. These supporting layers concern the representation of key energy use determinants: occupants energy-related behaviors within the modeled building stock, the characteristics of the building stock itself, and environmental context (physical conditions such as outdoor temperature and solar intensity as well as socio-economic conditions). Modeling techniques that directly represent such variables are expected to map to the same four quadrants shown in Fig. 2 for the energy layer, though specific techniques within each quadrant may be unique to the supporting layer. Where these supporting layers are only implicitly addressed in a building stock energy model, this should be noted alongside the model's classification.

Finally, Fig. 2 identifies four additional modeling dimensions that should be described as a complement to the high-level classification: dynamics, system boundaries, spatio-temporal resolution, and model uncertainty. Each of these dimensions represents an axis along which modeling approaches may vary independently of the high-level classification quadrants and layers. While such dimensions are not readily captured by a high-level classification, their description provides important context about a model that further facilitates its assessment by the research community and comparison with similar building stock energy models.

The following sections expand upon the classification quadrants, example modeling techniques, and additional model dimensions shown in Fig. 2, providing an overview of key concepts and relevant studies from the recent building stock energy literature. Collection of relevant literature sources was informed primarily by the domain expertise of the Annex 70 authors. A summary of the classification quadrants, the strengths and limitations of the modeling approaches they represent, and example literature references is provided in Table 1.

2.1. Quadrants of the classification

2.1.1. Q1: top-down/black-box

In the new classification, top-down/black-box models remain mostly unchanged from previous classification schemes. This class of models estimates building stock energy utilizing readily-available, sector-wide historic variables such as demographics or economic indicators. These models typically exclude end-use energy attribution or rely on aggregate end-use functions that link energy demand and underlying socio-economic factors. Our classification maintains two major categories of top-down/black-box modeling techniques, econometric and technological, consistent with existing classification schemes.

2.1.1.1. Econometric. Econometric models apply statistics and mathematics based on economic theory to forecast specific outcomes. For building stock energy modeling, commonly used economic indicators include demographics, fuel prices, household income, or the gross domestic product of an economy as a whole, which may be assessed at regional, national, or global scales. Econometric models were originally developed in the 1970s, stemming from the economic field, and are particularly useful for exploring high-level trends. For example, Lin and Liu [77] develop an econometric forecast of building energy consumption in China given heavy urbanization trends under three different future scenarios and estimate the rebound effect of energy efficiency. Broin et al. [19] model energy demand for space and water heating from

[2] Here, black-box refers to models in which underlying processes leading to outcomes are not directly interpretable, while in white-box models the internal model structure and influencing variables are directly interpretable.

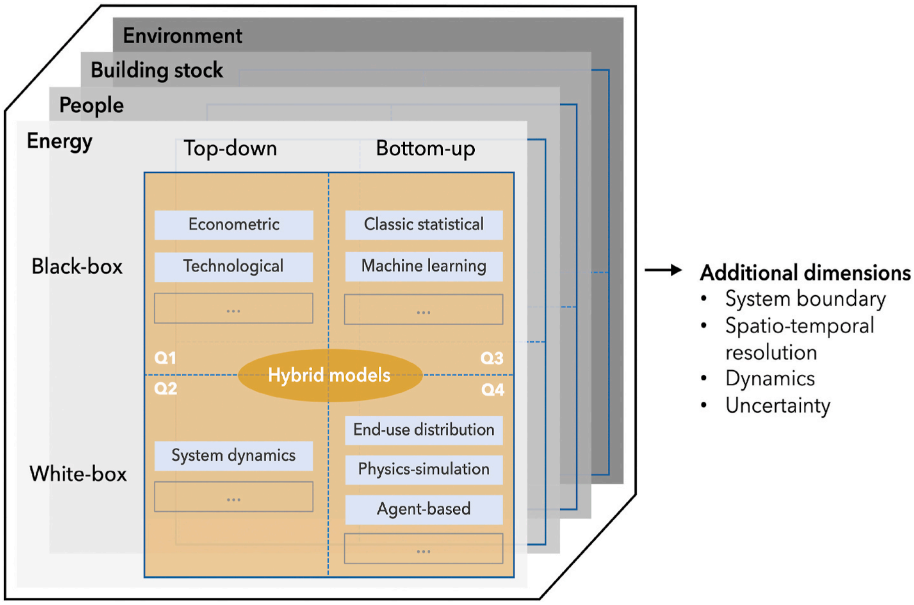

Fig. 2. An updated classification scheme for building stock energy models. The scheme builds from existing classification approaches while contributing the following changes: 1) the classification eschews a hierarchical structure in favor of a more flexible organization, grouping models into four quadrants based on whether each is top-down or bottom-up and black-box or white-box; models are tagged by their applicable quadrant(s) (Q1 for top-down/black-box, Q1/Q4 for hybrid, etc.), 2) examples of the emerging use of simulation-based and data-driven techniques in building stock energy modeling are included (e.g., system dynamics, agent-based models, machine learning) 3) hybrid models are identified that combine modeling techniques across quadrants, 4) sub-layers representing key energy use determinants (e.g., people, building stock, environment) are represented; modeling approaches for each of these determinants could be mapped to the same four quadrants of the energy layer, and 5) additional dimensions (e.g., system boundary, spatio-temporal resolution, dynamics, and uncertainty) are identified that should be described in parallel with mapping a model to the high-level classification quadrants.

Table 1
Summary of proposed building stock energy model classification quadrants, the strengths and limitations of the modeling approaches they represent, and example literature references.

Classification Quadrant	Approach	Strengths	Limitations	Example References (Modeling Technique)
Q1 (Top-down/ Black-box)	Estimate aggregate building energy use from sector-wide socio- economic and/or technological variables	Simple and computationally tractable, readily paired with other modeling frameworks(e.g., with bottom-up representations of energy demand in Integrated Assessment Models)	Typically unable to represent impacts of specific technology or operation improvements/measures; unable to represent disruptive changes to building stock energy use due to reliance on historical data	[2,19,31,41,77,112] (Econometric) [35,49,69,74,156] (Technological)
Q2 (Top-down/ White-box)	Represent physical causality at the aggregate building and technology stock level	Able to represent the complexity of building stock energy use and its components at the aggregate level, including technology and building stocks, stock flows, and the evolution of the system over time	Unable to link aggregate building energy use to building-level operations; challenging to represent spatial dimension; may require extensive data, time, and expert knowledge to fully represent system components and causal flows	[32,33,39,95,107,167] (System dynamics)
Q3 (Bottom-up/Black-box)	Attribute building-level energy use to particular energy end uses(e.g. space heating, hot water usage, household appliances) utilizing statistical analysis of historical data	Able to reveal important relationships between energy end use outputs and relevant input variables; relatively simple models with low data requirements may yield high explanatory or predictive performance	Unable to explicitly represent key dynamics influencing energy end uses in buildings (e.g., occupant behavior, heat transfer through the envelope); in certain cases require large datasets to yield good predictive performance (e.g., machine learning models)	[4,60,79,84,129,145] (Classic statistical) [5,68,104,110,110,120] (Machine learning)
Q4 (Bottom-up/White-box)	Simulate the physical relationships of processes at the building or energy end-use level	Able to explicitly represent key dynamics influencing building energy end uses, building stock diversity, and the aggregate energy effects of changes to operations at the individual building level	Require extensive data to represent detailed characteristics of the building stock and drivers of its end use patterns, computationally intensive, potentially challenging to pair with other modeling frameworks	[18,119,152,153] (End-use distribution) [1,10,93,98,135,165] (Agent-based) [11,59,65,86,100,101,136] (Physics-simulation)
Multiple Quadrants (Hybrid)	Combine elements of the modeling approaches across the four classification quadrants	May address the limitations of one modeling approach by complementing with the strengths of another; potentially more flexible in application and able to answer a broader set of analysis questions	Often more complex in design and implementation – and by extension, more difficult to communicate and replicate – because of the need to harmonize multiple modeling approaches that may concern disparate scales and variables of focus	[63,71,80,81,90,149] (Technological-econometric and end-use distribution) [142] (Machine learning and physics-simulation) [26,126] (Technological, system dynamics, and archetype)

1970 to 2005 in the residential sector of four EU countries using index decomposition,[3] econometric models, and cointegration analysis. The spatial and temporal influences on energy demand in each country from the number of households, floor area per household, and unit consumption for space and water heating are isolated. Fazeli et al. [37] explore three separate econometric techniques to forecast fuel consumption associated with residential space heating in Nordic countries. Filippini and Hunt [41] estimate a stochastic frontier function for U.S. residential aggregate energy demand using panel data for 48 states from 1995 to 2007. Dilaver and Hunt [31] forecast the relationship between Turkish household final energy consumption expenditures and residential electricity prices by applying a structural time series model to annual data over the period from 1960 to 2008. Pourazarm and Cooray [112] employ unit root tests, cointegration, and error-correction models on annual time series of residential electricity consumption in Iran for the period 1967–2009 and forecast consumption through 2020. Adom and Bekoe [2] study electricity use in Ghana across sectors using two econometric approaches – autoregressive-distributed lag (ARDL) and partial adjustment model (PAM). Hussain et al. [61] study cross-sector electricity use in Pakistan using Holt-Winter and Autoregressive Integrated Moving Average (ARIMA) models and time series data from 1980 to 2011; similar approaches are summarized in Ref. [14,64,70,123].

2.1.1.2. Technological. Technological models expand upon the inputs of econometric models to explicitly account for technological characteristics of the building stock, such as appliance saturation trends or adherence to building codes. Over the past decade, these models (and combined technological-econometric models, as reviewed in Ref. [38]) have largely supplanted pure econometric approaches. For example, the Austrian Institute for Economic Research presents a working paper exploring technology and economic impacts on residential energy demand [69]. Integrated Assessment Models (IAMs) often also derive total energy demand based on technological as well as demographic (population, population density), economic (income per capita), and climate-related inputs (heating or cooling degree days). For example, Eom et al. [35] utilize appliance efficiency trends alongside demographic and economic trends to project future energy consumption in China. Other IAMs that have technological modeling elements include: the EDGE model, which is used to explore scenarios of global energy consumption until 2100 across 7 regions [74]; the IMAGE model, which is used to explore lifestyle changes including reduced demand for space and water heating, a cap on home size, and reduced rates of appliance ownership [156]; and the compilation of results from 5 models (GCAM, IMAGE, MESSAGE, MERGE and REMIND) on energy demand scenarios that achieve a 2°C warming and well-below 2°C warming climate target [49].

2.1.2. Q2: top-down/white-box

Previous classification schemes have generally neglected top-down/white-box models, which represent physical causality at the aggregate building and technology stock level. This approach is distinct from the two existing top-down approaches that correlate economic (econometric) or technology (technological) indicators with building energy demand. In the new classification, we highlight system dynamics as an example of such a top-down/white-box modeling technique.

2.1.2.1. System dynamics. Typically, system dynamics models are characterized by: a) a conceptual diagram of the building and technology stock and its aggregate-level feedback loops and b) quantitative models of aggregate-level building and technology stocks and flows. Stocks represent point-in-time quantities of interest (e.g., the national residential building stock), while flows represent time-varying additions to or subtractions from stock totals (e.g., annual additions/alterations/subtractions to the residential stock from construction/retrofits/demolition).

There are several examples of system dynamics approaches in the building stock energy modeling literature. The Energy Policy Simulator [33] is a system dynamics model that represents the economy and energy system across the buildings sector as well as the transportation, electricity supply, industry, and land use/forestry sectors. The Simulator assesses the effects of national energy and environmental policies on emissions, cash flows, consumers, and the composition of electricity generation, among other metrics, and it has been adapted for use across multiple countries. Onat et al. [107] develop a system dynamics model of greenhouse gas emissions from the U.S. residential building stock to explore the efficacy of different policies in stabilizing an increasing emissions trend. Model variables include the carbon footprint and energy intensity of residential buildings, the number of new and existing green buildings, retrofit rate, employee travel characteristics, gross domestic product, and total population. Motawa and Oladokun [95] use system dynamics to characterize relationship between the building stock, occupants, and the environment (policy, climate, and economy) and simulate UK energy use and CO_2 emissions. Eker et al. [32] build a system dynamics framework to explore interactions between various aspects of the UK's housing stock. Causal loop diagrams are developed to assess as–built performance, retrofit rate dynamics, and the well–being of residents. Similarly, Zhou et al. [167] use a system dynamics approach to explore the turnover dynamics of the Chinese residential building stock. Finally, at the urban scale, Feng et al. [39] develop a system dynamics model of energy use and CO_2 emissions trends for Beijing between 2005 and 2030. Six sub-models comprise socioeconomic, agricultural, industrial, service, residential, and transport parameters, and flows within and between the sub-models are described using regression equations.

2.1.3. Q3: bottom-up/black-box

Bottom-up/black-box models utilize historical information to attribute building energy use to particular end-uses, assuming the conditions underlying the model prediction space mirror those of the model training space. From these relationships, building-level end use estimates can be extended to the scale of the entire building stock.

2.1.3.1. Classical statistical. Classical bottom-up statistical techniques have traditionally been used to predict either whole building or end use energy consumption, developing correlations between these outputs and key input parameters. In the new classification, this category encompasses both the regression-based and conditional demand analysis techniques identified in previous classification frameworks [141]. When covering economic inputs, bottom-up statistical models differ from the macro-econometric models of Q1 in that they enable micro-economic studies with a higher level of detail and often cover the interactions between households and individuals (e.g. building owners) and organizations [86] (e.g., in studies of the UK and Germany [14], China [79], and Denmark [73]).

Bottom-up statistical models are found across national, regional, and urban scale studies of building stock energy use. At the national scale, Santin et al. [129] utilize bottom-up statistical techniques to identify the relative importance of building characteristics and occupant behavior to stock-level residential energy consumption in the Netherlands. Liu et al. [79] study the effect of a new type of urbanization on energy consumption in China through a spatial econometric analysis. At the urban scale, Howard et al. [60] develop a regression model for end-use building energy consumption in New York City, linking consumption to specific locations throughout the city. Mastrucci et al. [84] statistically downscale city energy use to the building level for Rotterdam using linear regression. Some studies also use bottom-up statistical techniques

[3] Decomposition approaches are noted in multiple other studies (e.g., Ref. [21,58,117]).

to support energy utilities, developing forecasts of day-ahead energy demand that inform utility-scale management, control and verification strategies. For example, Akpinar and Yumuşak [4] predict household natural gas consumption in the Turkish Sakarya Province by using a sliding window technique with multiple linear equations to select the most suitable data set sizes, based on data from 409 days containing meteorological conditions, customer numbers, and holidays. Tian et al. [145] investigate local variations in energy use intensity for electricity and gas in London using geographically weighted regression, a mixed model, and a Bayesian hierarchical model.

2.1.3.2. Machine learning. Machine learning techniques aim primarily at predictive accuracy, utilizing a wide range of algorithms to find patterns in rich but large and unwieldy datasets. The primary difference between machine learning models and classical bottom-up statistical techniques is the former's nearly-exclusive focus on predictive accuracy, while the latter are often also used to identify relationships between variables and test their significance (i.e., statistical models are commonly used for inference). The new classification generalizes related models identified in existing classifications (e.g., neural networks in Ref. [141]) to a broader set of machine learning techniques.

Machine learning models of building stock energy use have seen a large increase in the literature over the last decade, though they are rarely used at the regional and national scales due to their heavy data and computational requirements (see reviews in Ref. [7,121]). At the urban scale, Tso and Yau [147] compare classical statistical regression techniques to decision trees and neural networks to evaluate the accuracy in predicting energy consumption in Hong Kong. The results indicate that all three models are valid for this type of prediction, with the decision tree and neural network performing slightly better in the summer and winter, respectively. Robinson et al. [120] use multiple machine learning methods (linear regression, gradient boosting regression, and random forest regression) to estimate the energy use of the commercial building stock in different U.S. metropolitan areas based on floor area, principal building activity, number of floors, and heating/cooling degree days. Zhang et al. [164] use a similarly wide range of machine learning techniques to model electricity and natural gas consumption in U.S. homes, complementing a separate analysis of transportation-related energy use. Papadopoulos et al. [109] use an unsupervised learning algorithm to cluster buildings in New York City based on their energy use. Kontokosta and Tull [68] develop a predictive model of electricity and natural gas use at the building, district, and city scales using training data from energy disclosure policies and predictors from widely-available property and zoning information. Three different machine learning algorithms (least squares regression, support vector machines, and random forest) are fit to the city's energy benchmarking data and used to predict energy use for every property in New York City. Nutkiewicz et al. [104] propose a network-based machine learning model to learn the hidden energy connections and interdependencies between buildings at multiple scales (e.g., individual building scale, community scale, and urban scale), tested for US commercial buildings. Papadopoulos and Kontokosta [110] use a gradient tree boosting method to develop a building energy performance grading method; this method has shown improved performance over linear models in predicting hourly and annual building energy use at the urban scale. Finally, Al Tarhuni et al. [5] use random forest and deep learning neural network approaches to predict the monthly natural gas consumption of hundreds of university-owned student residences in the U.S. Midwest from readily accessible building geometry, energy system characteristics, and energy consumption data.

2.1.4. Q4: bottom-up/white-box

Various forms of bottom-up/white-box models have been expanded over the last decade. This class of models simulates the physical relationship of processes at the building or end-use level. In the new classification, we note advances in this area afforded by high-performance and cloud computing along with simulation-based techniques.

2.1.4.1. End-use distribution. This approach models the distribution of energy demand per end-use or appliance type to calculate total end-use or appliance energy consumption at scale – generally without accounting for interactions between end-uses. Standalone end-use distribution models are uncommon in the existing literature, as these models are often combined with other modeling techniques to form hybrid approaches. The U.S. RECS and CBECS surveys rely on end-use distribution models to apportion whole building residential and commercial building energy use collected from billing data across contributing energy end uses [152,153]. Engineering estimates are made of the expected consumption of each end use, and these estimates are entered as inputs to regressions with measured total building energy use as the dependent variable, to calibrate the end use attributions. Reyna and Chester [119] utilize appliance distribution modeling combined with detailed physics-simulation of the thermal envelope to project residential building demand under different climate change scenarios in southern California. Broin et al. [18] pair exogenously derived assumptions about annual changes in energy carrier mixes, improvements in appliance efficiency, and construction rates with an end use-disaggregated model of energy demand in EU residential and service buildings, estimating total useful energy demand in new and existing vintages of these building types across a multi-year time horizon.

2.1.4.2. Agent-based models. Agent-based models (ABMs) represent causality at the individual building or district level, constructing stock-level building energy use outcomes in a bottom-up manner. ABMs use software representations of individual buildings and/or decision-maker agents that have heterogeneous attributes as well as rules for interacting with other agents and their physical or economic environments. Aggregate stock and energy outcomes emerge from individual-level behaviors – that is, macro-level outcomes are determined by the micro-motives of agents with endogenous behavior rules. In many ways, agent-based models are the bottom-up analogue to top-down system dynamics models; like system dynamics, agent-based techniques have not been highlighted in previous classifications.

ABMs have gained in popularity across many applications, and there are several notable examples for the buildings sector. Zhao et al. [165] developed the Commercial Buildings Sector Agent-based Model (CoBAM). CoBAM considers U.S. commercial buildings of different types and in different climate zones as adaptive agents that are evolving internally and interacting with energy efficiency regulations, which in turn dictates the evolution of building energy use over time. In another study focused on the residential sector, Moglia et al. [93] use an ABM to model the uptake of low carbon and energy efficient technologies and practices by households, considering both the influence of social networks and the decision rules of several different agent types that extend beyond homeowners. This study adapts the decision-making algorithms of an earlier ABM published by Sopha et al. [135], which was used to model uptake of energy efficient heating in Norway. Similarly, Nägeli et al. [98] develop an ABM of the building stock that uses a decision model to simulate building renovation and heating system substitution decisions of building owners coupled with a physics-based model to simulate the resulting energy demand over time. Azar et al. [10] use an ABM framework to calculate the thermal comfort and energy use of multiple buildings on a campus in Abu Dhabi. Their model consists of three sub-models: people movement, thermal comfort, and energy consumption. Abdallah et al. [1] evaluate the impact of a non-intrusive energy messaging intervention on energy use in the Belgian residential sector using an ABM that represents daily energy-related occupant behaviors, peer pressure effects on energy use, and the effects of messaging interventions.

2.1.4.3. Physics-simulation. Physics-simulation models are a new category in this classification that encompasses both the archetype modeling technique of previous classifications and emerging geo-spatial models, recognizing the common reliance of both on physics-based simulations of whole building energy use. Archetype modeling (also referred to as "prototype" modeling) is a well-established physics-based approach that simulates the energy performance of a single building or collection of buildings that represents a larger segment of the building stock; results can be scaled up to represent total sector energy use in a defined geographic area. Pure archetype approaches are plentiful, including ResStock [100] and the *Tabula* project [11], along with similar models compiled for the UK in Ref. [65], for Germany in Ref. [136] and worldwide in Ref. [87]. Recent advances in computing and data have allowed improvement of the traditional, single-building archetype approach to include modeling of hundreds or thousands of representative buildings (e.g., ResStock), sometimes even modeling every individual building in a given geographic area (e.g., ECCABS [86]).[4] As such, the methodologies used to generate the building archetypes may be diverse, including artificial reference buildings [88,91], statistically sampled reference buildings [87], synthetic buildings [97,98], or data-driven approaches [6,139].

Geospatial modeling, which uses building energy simulation in combination with spatial representation and modeling in geographic information systems (GIS), is a rapidly developing physics-modeling approach that holds promise for generating information required for energy and emissions-related policy making and planning by actors such as municipalities and utilities already using GIS-based decision support. In this approach, geodatabases are developed that link building attributes and simulated energy use to common geographical references such as parcels or building footprints. Commonly, archetype-based energy simulation is performed using software such as EnergyPlus for representative buildings (e.g., CityBES [59]). Results are applied to actual buildings corresponding to the archetype in the stock – in some cases using actual building geometries (e.g., Ref. [150]). Less commonly, buildings are simulated individually (e.g., AutoBEM [101]).

Multi-module models that integrate more than one of the bottom-up/white-box approaches above typically focus on electricity use, distributed renewable energy and other demand/supply interactions. For instance, Sandels et al. [127] forecasts electricity load profiles hourly for a population of Swedish households living in detached houses with a model constructed of three separate modules: appliance usage, domestic hot water, and space heating. The latter module represents the thermodynamic aspects of the buildings, weather dynamics, and the heat loss output from the aforementioned modules. Subsequently, a use case for a neighborhood of detached houses in Sweden is simulated using a Monte Carlo approach. Similar approaches are used by Nyholm et al. [105], where heating demand estimates from the ECCABS model are supplemented with hourly profiles for electrical uses, using a statistically sampled description of Swedish households with electrical heating. This approach is further developed into the EBUC model in Ref. [122], which adds a district heating (DH) module, and in the MOSAIC method [67], which uses a bottom-up simulation approach to determine current and future consumption and production load curves for an area, calibrating estimates by comparing simulated load curves with observations.

2.1.5. Multiple quadrants: hybrid models

In practice, many models use mixed approaches that cross the quadrants of Fig. 2 and thus fall into the hybrid region shown in between the quadrants.

Examples of building stock energy models with hybrid elements are prevalent in recent years. For example, NEMS, an integrated multi-sector energy modeling framework developed by the US EIA, uses a technological-econometric approach (Q1) to develop a long-term forecast of growth in the building and technology stock, which is combined with bottom-up appliance distribution models (Q4) to estimate the energy use intensity of new and existing building stock vintages [149,161]. Scout [71], a buildings sector-specific US model that draws its baseline energy use scenario from NEMS, adopts the same Q1/Q4 modeling approach. In the Canadian CHREM model, machine learning (Q3) is used to predict occupant–driven domestic hot water and lighting energy use, while an archetype model (Q4) is used to predict space heating and cooling energy use [142]. gTech [90], another Canadian model, merges the capabilities of the previously developed CIMS hybrid energy-economy model (Q1/Q4) [63] with other top-down modeling approaches. Sandberg et al. [126] use a hybrid model to simulate the long-term housing stock energy use in Norway, using technological (Q1) and system dynamics (Q2) techniques to simulate the development of the stock and an archetype approach (Q4) to estimate demand. Colloricchio [26] adds an econometric component (Q1) to Sandberg et al.'s housing stock model (Q2), applying the hybrid model to a case study of the residential sector in Italy.

Prominent multi-sector energy system models such as MARKAL and TIMES similarly combine bottom-up functions for disaggregated energy demand (Q3) with top-down representations of macro-economic effects on the energy system (Q1) [80,81]. TIMES has been adapted for use across several countries in recent years, sometimes to investigate energy use in the buildings sector. For example, using the Global TIMES model, Wang et al. [159] simulate the transformation pathways of the global energy system under 2-degree and 1.5-degree climate targets, analyzing the features and challenges of building sector transition pathways in 14 high, middle, and low income regions. Seljom et al. [132] use a stochastic TIMES model with an explicit representation of uncertainty in the electricity supply and building heating demand to demonstrate that the Scandinavian energy system is capable of integrating a large amount of zero-energy buildings with intermittent PV production. Cayla and Maïzi [23] develop a TIMES-Households model that represents household daily energy consumption and equipment purchasing behavior with a focus on the French residential building and transport sectors. Shi et al. [133] use China TIMES to model the future energy consumption and carbon emissions in building sector and find that, including renewable energy used in buildings, China's building sector can reach a relatively low-carbon future with more consumption of low- and non-carbon fuels. In general, demand sectors in TIMES models – including energy use in buildings – have often been handled with a limited degree of detail [132]. This can be problematic since a too coarse description of energy demand may lead to unrealistic results, with small price changes leading either to no impact or sudden technological changes [23]. Furthermore, the benefits of energy savings on the wider economy [72] and behavioral preferences or "rebound" effects [128] are typically disregarded.

Many of the above hybrid models rely more heavily on one of the classification quadrants from Fig. 2 than others – TIMES, for example, is a primarily bottom-up framework that "reaches up" to capture certain effects of the larger economy on the energy system [80]. Making the classification quadrants and the conceptual differences across them explicit in the proposed scheme mitigates the loss of information that would result from simply adding a hybrid branch to the hierarchical organizations of existing classifications.

2.2. Additional model dimensions

Given the increasing sophistication of building stock energy models, the high-level classification quadrants and layers of Fig. 2 may be insufficient to communicate important contextual details about the chosen modeling approach. Accordingly, we propose that a model's treatment of at least four additional dimensions should be described in

[4] This advanced kind of archetype model is sometimes labeled urban-scale building energy modeling (UBEM) in previous literature [116], although the approach can be applied to other land use types besides urban land uses.

parallel with its mapping to the high-level classification quadrants of Fig. 2; these additional dimensions are described below.

2.2.1. System boundaries

In building stock energy modeling, the collection of buildings studied can be conceptualized as a system that is bounded in time and space in a manner consistent with principle modeling questions and applications. System boundaries are identified at the interface between the entire modeled system and the external environment, as well as at the interface (s) between modeled sub-systems. (Fig. 3). Choosing and communicating appropriate boundaries for the modeled system and sub-systems represented by a building stock energy model is critical to ensuring the interpretability of model outputs. Here we present further considerations regarding the definition of a building stock energy model's spatio-temporal scope, as well as other aspects concerning a model's overall extent and sub-system boundaries.

The spatial scope of a model is the geographical area covered in the study. Spatial scope could be a given neighborhood (e.g. Cuerda et al.; Sartori et al. [28,131]), city (e.g. Ouyang et al. [108]), region (e.g. Galante et al.; Reyna and Chester [48,119], country (e.g. Mata et al.; Sandberg et al.; Nägeli et al. [89,97,126]) or countries (e.g. Urge-Vorsatz et al.; Building Performance Institute Europe (BPIE); Vásquez et al.; Mata et al. [20,89,151,157]). Combinations are not unusual – e.g., Hargreaves et al. [56] integrate regional and urban [55] modeling with the DECM model at the building scale to forecast how spatial planning policies would affect the suitability of retrofitting and decentralized supply and how this would vary between area types.

The temporal scope of a model is the year(s) or time period under study. Static models commonly describe the energy use in a specific year (e.g. Cuerda et al. [28]), whereas long-term dynamic models may describe the development over long time periods up to 50 or even 100 years (e.g. Sandberg et al.; Berardi [13,125]). Other models serve as an archival repository of historical consumption data and are continually updated [111]. The temporal scope may therefore cover both historical and future development of the modeled building energy system.

The system boundaries of a building stock energy model may be defined by more than spatio-temporal considerations. Building stock energy models are often used as part of a larger, multi-sectorial modeling frameworks such as the partial-equilibrium NEMS [149] and MARKAL/TIMES models [80,81] and general equilibrium Integrated Assessment Models [35,49,69,74,156]. Within the buildings sector focus, model application may also be limited to a subset of the building stock – e.g., residential (Csoknyai et al. [27]), non-residential building stock (Lindberg et al. [78]), or the public housing stock (Gagliano et al. [47]). Depending on the desired outcome, specific energy end uses might be targeted in the analysis. Some studies focus on operational energy use only (e.g., heating, cooling, domestic hot water), while others adopt a life cycle perspective and therefore include other phases of energy use and emissions such as manufacturing, transportation, construction and demolition in the analysis.

In addition to addressing these considerations about a model's overall system boundary, modelers should describe any subsystems within the model and the boundaries that determine their spheres of influence. Typical subsystems represented in building energy stock models include energy demand, occupants, physical building characteristics and systems, and environmental context, as suggested by the modeling sub-layers shown in Fig. 2. Outdoor conditions such as weather are usually treated as inputs to the model, although some parts such as detailed solar radiation and local wind pressure modeling could be included as separate subsystems. Extended models may include representations of the electric grid, transportation systems, and macro- and micro-economic processes, among others.

2.2.2. Spatio-temporal resolution

The spatio-temporal resolution of a building stock energy model is the level of disaggregation with which key model information and results are represented. Each model has a fundamental unit of observation at which calculations are done, across both space (e.g., 'a house', 'room-based', 'meter-based,' etc.) and time (e.g. hourly, 15-min., annual). While a system boundary represents the highest geographical or temporal aggregation of a model and therefore serves as an upper limit on a model's spatio-temporal resolution, the model's unit of observation is the lower limit of its spatio-temporal resolution.

Many building stock energy models study the energy demand within a given spatial boundary without any details about the location or distribution of the buildings within the geographical area. The spatial resolution is therefore equal to that entire area, even though the unit of observation might be a single dwelling. Other models have a high spatial resolution and tie building energy use to specific locations – e.g., through the use of geographical information systems (GIS). The geocoded model results are then commonly presented in maps which adds important additional information about the distribution of the energy use (e.g. Mastrucci et al.; Stephan and Athanassiadis; Möller et al. [84,94,138]). Where multiple data layers are incorporated, each layer may have a different spatial resolution (e.g., census tract, zip code) and therefore the analytical methods used to map these layers to a common spatial unit is an important model attribute.

The temporal resolution of building stock energy models concerns the time step that is used to generate results. In the studies previously mentioned with longer temporal scopes, energy simulations are typically carried out per year (e.g., Giraudet et al. [51]). However, studies also demonstrate higher time resolutions (e.g., per minute or hour as in Sartori et al.; Reyna and Chester; Mata et al. [87,119,131]). A model's temporal resolution determines the type of questions that it can answer – for example, an hourly resolution is needed to investigate demand-side energy flexibility strategies, as clear diurnal variations occur in building loads; a monthly resolution is relevant for the study of total heating and cooling demand; and an annual resolution is appropriate for studying building renovations.

2.2.3. Dynamics

Treatment of dynamics in building stock energy models can be described along the lines of the three supporting variable layers of Fig. 2: 1) building usage/occupant behavior, 2) building stock, and 3) context/environment. In practice, these variables may be tightly connected in the model implementation (e.g., building stock dynamics are affected by changes in the model context).

Occupant/building use dynamics include the number of occupants (e.g., evolution of family composition, number of visitors on the premises, aging, typical occupant interactions), occupants' energy-related behaviors over time (e.g., adjustment of thermostat set points and other controls, movement to and from different spaces), and changes in appliance ownership trends (e.g., type of HVAC equipment, number of TVs, etc.). For multi-family or commercial buildings with centralized control systems, operator decision-making would also fall into this category of dynamics.

Building stock dynamics refer to changes in the stock such as building demolition, renovation, and new construction, as well as the effect this has on the building stock composition, installed equipment, and resulting energy and environmental impacts. Changes to the building stock may be represented using both static and dynamic approaches (Fig. 4) [85]. Static models assess building stocks at a defined moment in time (e.g., for a single year). Such point-in-time snapshots may be assessed in a *status quo assessment* or a *comparative assessment*, where the latter compares the current state with a hypothetical future state (e.g., after the implementation of certain energy efficiency measures). In contrast, dynamic models capture the evolution of building stocks and their energy use over time by modeling processes such as new construction, demolition, retrofits and replacement of technologies. Such analyses can be focused on historic development (*ex-post*), on forecasting future development (*ex-ante*) or a combination of both.

Context/environment dynamics concern changes in the energy system

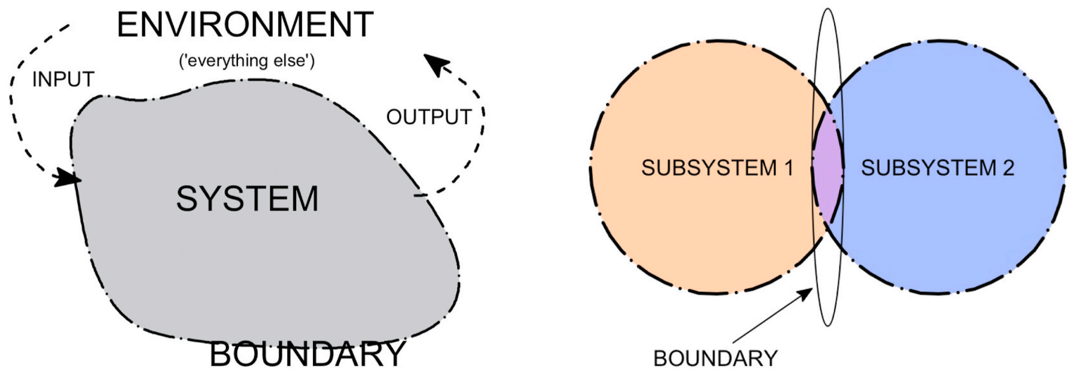

Fig. 3. Relationship between the modeled system and its environment; the overall system boundary is represented as a conceptual line between the two (left). Interrelationship between two subsystems within a larger system, with a boundary defined at the interface between the two subsystems (right) [124].

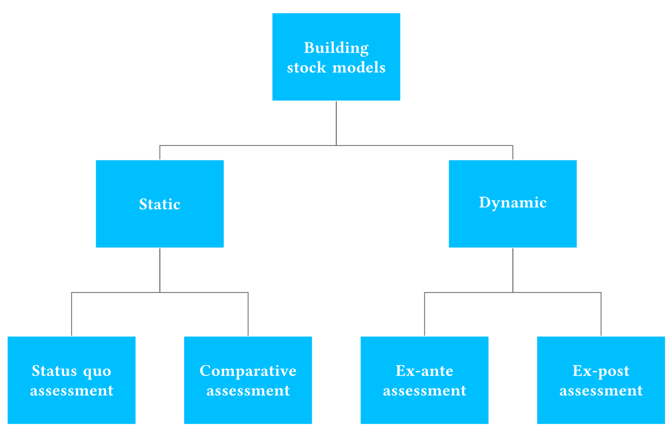

Fig. 4. Approaches for representing changes to the building stock may be static (assessing stocks at a specific moment in time) or dynamic (capturing the evolution of building stocks over time); each approach is suitable for different types of modeling assessments.

that result in (for example) altered greenhouse gas emission factors (e.g. changing electric generation mix), changes in energy prices, population growth, structural changes in the economy (e.g. growth of certain economic sectors) or the impact of climate change on building energy demand – e.g., via rising temperatures and day-to-day weather conditions.

Transparent descriptions of how each of these types of dynamics is handled in building stock energy models are crucial for assessing the quality of model outputs. For example, as described in Sartori et al. [130], it is often the case that policy roadmaps and other studies use time-resolved inputs on energy and emission intensities, but represent changes in the building stock using fixed rates for construction, demolition and renovation, which may be overly simplistic. Alternatively, renovation rates may be assumed to increase rapidly in order to reach stock-level energy efficiency goals. Sandberg et al. [125] demonstrate how unrealistic assumptions about renovation dynamics can result in model outputs that overstate future energy savings potential.

2.2.4. Quality assurance

It is essential to understand the limitations of a building stock energy model's predictive power. No model can be a perfect representation of the system it aims to emulate, and all models inevitably contain uncertainty [114] which should be quantified as part of the model quality assurance process. Uncertainty can be defined as "any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system" [158]. It is to be expected that as the systems being modeled increase in scale and complexity, the uncertainty in the model will also increase. Consequently, it is inevitable that building stock energy models will contain a considerable number of uncertainties. While some applications of building stock energy models, such as in early design, actively seek a range of possible options, it is common to see building stock energy model outputs expressed as a single value [24]. Such point values may yield misleading impressions about the certainty of model insights when used to support energy policy decisions.

In the literature, several different classification schemes focused specifically on model uncertainty have been introduced [15,106], but a general consensus in terms of uncertainty classification and related terminology does not appear to exist [115]. Although there is a lack of agreement on the detailed categorization of sources of uncertainty, a review of 20 existing uncertainty classification schemes highlighted a broad pattern with sources of uncertainty being grouped according to whether they related to model inputs, the model itself or model outputs (Fig. 5).

A review of the treatment of uncertainty in the literature relating to large scale building energy models undertaken by Fennell et al. [40] concluded that Uncertainty Analysis (UA) and Sensitivity Analysis (SA) are not common practice in building-stock energy modeling and that if UA and SA are performed, only a few parameters are assessed and methodologies are not standardized. In addition, although the literature suggests that model uncertainties are likely to be a significant source of overall uncertainty, the review did not identify any studies which addressed this source of uncertainty.

Parallel Annex 70 work is underway to address the lack of evidence in the published literature on the treatment of uncertainty in building stock energy models. A wide range of research teams are participating in this work with a diverse range of modeling approaches. The initial phase of the work is focused on input uncertainty. Each model will be evaluated stochastically based on shared sets of uncertain inputs. A range of different sensitivity analysis techniques will be applied to each model to explore how model attributes such as geographic scale and degree of aggregation affect the performance of different techniques.

Finally, we note that model validation is an additional aspect of quality assurance, in which model outputs are compared to measured values. The review undertaken by Reinhart and Davila [116] suggests that when aggregated city-scale building energy use data are used for validation, individual building model errors tend to average out and overall errors are in the range 7%–21% for heating loads and 1–19% for total energy use intensity. However, simulation errors may be much higher for individual buildings in the stock, which is not reflected in the aggregate validation statistics. In addition, Reddy et al. [113] highlight the high dimensionality of many classes building stock energy models, underscoring that small validation error only indicates that a local minimum has been achieved, and that model accuracy is not guaranteed through aggregate validation alone. Validating against multiple external data sources can potentially improve confidence in model accuracy, but this is not always possible. Moreover, for building stock energy models

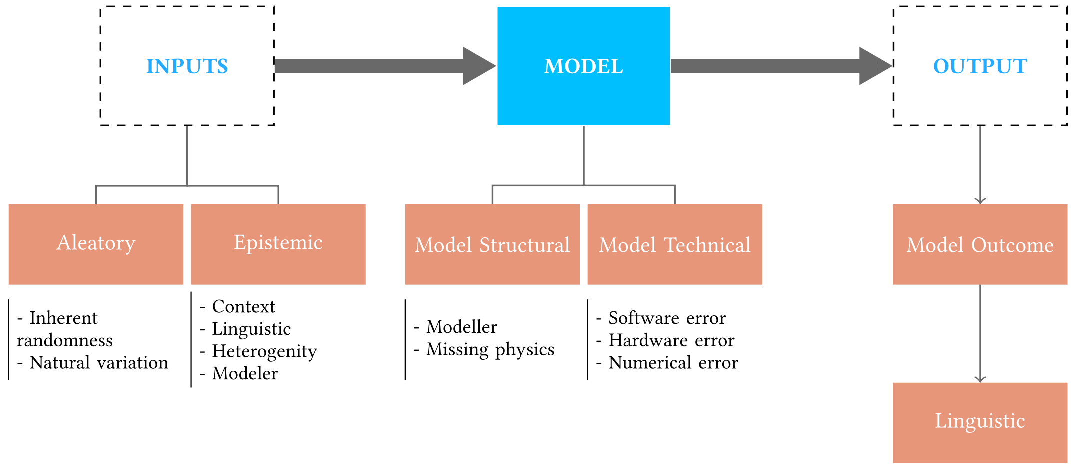

Fig. 5. Sources of model uncertainty identified in existing uncertainty classification schemes. Sources of uncertainty may be grouped by whether they relate to model inputs, the model itself, or model outputs.

that project out into future years, validation data will not be available at all to compare model outputs against. Complementary model uncertainty assessments can help address these shortcomings.

3. Discussion

The model classification approach presented in this paper provides a formal framework for comprehensively surveying, assessing, and demonstrating use cases for the wide range of building stock energy modeling approaches that have been published in recent years, as well as those that will be published in the years to come. At a conceptual level, the classification quadrants introduced in Fig. 2 encourage quick comparisons across building stock energy models, including those that apply to different regions and building stocks of interest. Such comparisons support stronger international collaborations around building stock energy modeling, which are needed to find pathways for long-term reductions in building energy use and emissions that can contribute substantially to global climate change mitigation efforts. At the same time, this paper's classification scheme provides avenues for communicating richer technical information about a model, by including supporting modeling layers in the high-level classification structure (buildings, people, environment) and by encouraging modelers to describe their handling of additional modeling dimensions that are not captured by the high-level structure.

Within Annex 70, the new classification scheme is being used to generate metadata for organizing models in an online repository. Models in the Annex 70 repository will be summarized in terms of the following attributes:

- general purpose and application,
- model classification quadrant (top-down/bottom-up, white-box/black-box per Fig. 2),
- modeling technique (system dynamics, statistical, machine learning, archetype, etc. per Fig. 2),
- inclusion of additional layers (buildings, people, environment)
- treatment of additional dimensions (system boundaries, spatio-temporal resolution, dynamics, and uncertainty), and
- accessibility of the model and supporting data sources.

Table 2 shows examples of how key models from each of the Annex's participating member countries are being described in terms of high-level attributes.

3.1. *Challenges for building stock energy model classification and complementary efforts*

The large number of new building stock energy models that have been published over the last decade collectively represent a variety of modeling methods and outcomes. While the proposed classification framework establishes a common language by which researchers may effectively communicate such models, we acknowledge that no classification scheme can list or fully characterize all possible techniques for modeling building stock energy use. Indeed, this was not the aim of our effort; rather, we provide a general, multidimensional, and extensible framework onto which particular techniques or combinations of techniques may be mapped, even if these techniques are not explicitly called out by the classification diagram in Fig. 2. As the research landscape around building stock energy modeling continues to change, we anticipate the need to revise our classification diagram accordingly, much as we have adapted elements of existing classifications published over the last decade.

Moreover, while the classification scheme presented herein is intended to facilitate quick model comparison and assessment, it is not designed to yield deeper insights into a model's design and execution that are needed to accurately reproduce its use across the research community. Mapping between research question and modeling approach is complex and informed as much by practical considerations of data availability, expertise of the modeling team, and access to computing resources as by methodological drivers. Additional details will be needed on overall model objectives (e.g., simulation vs. optimization vs. accounting), model licensing and usage rights, model analysis components and sub-components, guidance on running the model, and a model's input and output data structures, among other items. To address this limitation on the classification scheme's application, IEA-EBC Annex 70 is developing a complementary reporting protocol for building energy stock modeling. This reporting protocol is distinct from the classification scheme in its stronger emphasis on capturing the technical details needed to fully understand how a model works, but draws upon the classification framework to establish model metadata - much as the Annex 70 model repository is doing. Other fields have successfully deployed reporting protocols,notably health care [12], and the intention is to have modelers use the protocol to frame any publication that presents a building stock energy model, enabling its

Table 2
Sample mapping of building stock energy models from IEA-EBC Annex 70 member countries to this paper's proposed model classification scheme.

Country	Model Name	Model Use	Model Classification Quadrant	Additional Details
Belgium	Delghust Model	Assessment of the effect of energy saving measures in terms of reducing energy consumption in relation to costs in the residential sector	Q4 *physics-simulation*	Model documentation [29, 30], and application [16]
Canada	E3MC	A macroeconomic model used to develop projections for Canada's National Communication and Biennial Reports to the UNFCCC and Canada's Emissions Trends reports	Hybrid: Q1 *econometric* to simulate macro-economic trends and Q2 *system dynamics* to simulate energy demand	Model documentation [34, 143] and application [53]
	CityInSight	Assessment of energy, greenhouse gas emissions and financial impacts of changes in land use, building type, building code, fuel mix, equipment, renewables, district energy, and behavior to support municipal energy and emissions planning	Hybrid: Q2 *system-dynamics* to simulate building stock evolution and Q4 *physics- simulation* to simulate energy demand per unit stock	Model summary [140]
Netherlands	Vesta MAIS	Assessment of the effect of energy saving measures in terms of reducing CO_2 emissions, energy consumption, investment costs and energy costs Assessment of the effect of changes in heat supply and policy instruments including taxes, and subsidies	Q4 *physics-simulation*	Model documentation [42], GitHub repository [155], and application [154]
Norway	RE-BUILDS	Assessment of the long-term development of the Norwegian residential building stock, including its stock dynamics and renewal in terms of new construction, renovation and demolition. Assessment of long-term development in energy demand in the stock due to different development paths in various scenarios	Hybrid: Q1 *technological* to estimate the total dwelling stock size, Q2 *system dynamics* to simulate stock dynamics and Q4 *physics-simulation* to estimate the energy demand per building archetype across the simulated stock.	Model documentation [126, 130], and application [125, 126]
Sweden	ECCABS	Assessment of potentials and costs for energy savings and CO_2 emissions reductions of the long-term transformation of a building stock	Q4 *physics simulation* building-specific calculation of energy savings, and *agent-based* market share of technologies and constrained investment and retrofit rates	Model documentation [87], and application [86,89]
Switzerland	ABBSM	Assessment of the dynamics of national building stocks and its energy- and climate-impact over time. In particular how building ownerÂ's decisions to retrofit the building envelope and replace heating systems under different policy interventions affects this development.	Q4 *physics-simulation* to simulate energy demand, and *agent-based* to model building stock dynamics	Model documentation and application [98,102,103]
United Kingdom	SimStock	Assessment of the effects of different policy choices on city-level energy consumption including peak demands. Heat exposure can also be evaluated.	Q4 *physics-simulation*	Underlying philosophy [25]
United States	Scout	Assessment of national energy, cost, and CO_2 emissions impacts of U.S. building energy efficiency and flexibility to assist in R&D program design	Hybrid: Q1 *technological- econometric* to model building and technology stock size and dynamics and Q4 *end-use distribution* to model energy use per unit stock	Model documentation [148], GitHub repository [57], and application [71]
	ResStock	Assessment of the impact of energy efficiency measures in the residential sector, providing detailed information on energy time-series, cost-effectiveness, technology, building type, and location.	Q4 *physics-simulation*	Model documentation [100], GitHub repository [99], and application [162]

effective use outside of the context for which it was developed.[5]

4. Conclusion

This paper introduced a new framework for classifying models of building stock energy use at the urban, regional, and national scales. The classification scheme, which was developed as part of IEA-EBC Annex 70, builds upon previous approaches for classifying building stock energy models while addressing the need to update these approaches, given the availability of richer datasets on the building stock, expanded computational power, and the advent of modeling techniques that take advantage of these resources. Accordingly, the updated classification scheme accounts for newer modeling techniques, establishes a more flexible high-level classification structure, and accounts for additional model dimensions that are not captured by this high-level model classification exercise. Specifically, the scheme uses a multi-layer quadrant structure to classify modeling techniques based on their design (top-down or bottom-up) and degree of transparency (black-box or white-box), also accommodating hybrid modeling techniques. We provided guidance on the description of four additional model dimensions – system boundaries, geographic and spatial resolution, dynamics, and uncertainty – alongside the high-level quadrant structure and modeling layers. A selection of existing literature studies was summarized that exemplify the relevance of the high-level classification elements and additional model dimensions to the building stock energy modeling field. We concluded by discussing the practical utility of the classification scheme in promoting more effective sharing and assessment of models across the international research community, including the use of the scheme to develop an online model registry and reporting protocol for Annex 70.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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[5] In the absence of such reporting guidance, modeling techniques that fall *in principle* into the white-box quadrants of our classification may be perceived *in practice* to be black-box due to poor understanding of detailed model elements among researchers that are not part of the core model development team (due to too many equations, disparate input datasets, unclear variable relationships, etc.).

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