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Review

Modeling urban building energy use: A review of modeling approaches and procedures

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ABSTRACT

With rapid urbanization and economic development, the world has been experiencing an unprecedented increase in energy consumption and greenhouse gas (GHG) emissions. While reducing energy consumption and GHG emissions is a common interest shared by major developed and developing countries, actions to enable these global reductions are generally implemented at the city scale. This is because baseline information from individual cities plays an important role in identifying economical options for improving building energy efficiency and reducing GHG emissions. Numerous approaches have been proposed for modeling urban building energy use in the past decades. This paper aims to provide an up-to-date review of the broad categories of energy models for urban buildings and describes the basic workflow of physics-based, bottom-up models and their applications in simulating urban-scale building energy use. Because there are significant differences across models with varied potential for application, strengths and weaknesses of the reviewed models are also presented. This is followed by a discussion of challenging issues associated with model preparation and calibration.

Contents

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1. Introduction

Over the past several decades, the world has experienced unprecedented urban expansion, which was primarily due to the rapid population growth and migration from rural to urbanized areas [1]. Although global urban land is about only 0.45–3% of the world's total land area [2–4], global urban population has increased from 2.29 billion in 1990 to 2.86 billion in 2000, and to 3.96 billion in 2015. Meanwhile, the percentage of urban population to total population increased from 42.9% in 1990 to 51.6% in 2000, then to 54% in 2015. It is projected that urban population will continue to grow, accounting for approximately 66.4% of the world's population by 2050 [1].

While rapid urbanization motivates economic and social development, it also leads to significantly increased energy consumption and greenhouse gas (GHG) emissions. For instance, in 2008, only half of the world's population lived in urbanized areas; however, they consumed almost 67% of global energy [5,6]. This proportion is projected to increase to 73% by 2030 [7]. In the United States (U.S.) alone, the electric power consumption was reported to increase from 4050 kWh per capita in 1960 to 12,988 kWh per capita in 2013, a growth of over 200% or 4.16% per year [8]. As over 80% of world energy is currently being derived from fossil fuel resources such as oil, coal, and natural gas, this rapid increase in energy consumption may lead to economic vulnerability (e.g., external supply shocks) for countries importing these resources, eventually increasing the risk that climate change poses to the global community. In order to address these issues, efforts have been made to emphasize on exploring new energy sources, developing renewable energy resources and infrastructure, and improving energy use efficiency [9–14].

In response to these challenges, many countries have proposed and/or developed plans for reducing energy consumption and GHG emissions, including the two largest carbon emitters, China and the U.S. The Chinese government proposed the 13th five-year plan (2015–2020), which calls for a 15% reduction in energy consumption per unit of GDP, and a 18% reduction in carbon emissions per GDP by 2020 [15,16]. The Obama administration in the U.S. proposed a GHG emissions reduction goal that used the 2005 emission level as the baseline, i.e., a 17% reduction by 2020 and a 26–28% reduction by 2025 [17]. In order to meet the goals, several new emission standards have been proposed to reduce emissions from power plants and vehicles. Efficiency standards were also updated frequently for buildings and appliances [17–20]. Similarly, the European Union has developed goals for reducing energy consumption and GHG emissions. Compared to 1990, the level of GHG emissions is expected to be reduced by 20%, 40% and 80–95% in 2020, 2030, and 2050, respectively [21]. Furthermore, at least 20%–27% of energy consumption is expected to be from renewable energy, and energy efficiency will increase by 20% and 27% in 2020 and 2030, respectively [21].

While the goals of reducing GHG emissions are often set at the national level, major actions have to be taken at the city scale. This is mainly because the city's relatively rich energy use information can facilitate the identification of economically efficient options for enhancing energy efficiency and thereby reducing GHG emissions of the region to which the city belongs [22]. In fact, many municipalities, particularly in North America and Europe, have set goals of reducing GHG emissions that are more aggressive than those mandated by the state or federal governments. For instance, the City of Boston proposed a reduction goal of 25% by 2020 and 80% by 2050; the numbers for the City of New York and the City of San Francisco were set to 80% and 40% by 2050 and 2025, respectively. Boston, Chicago, Los Angeles and 17 other U.S. municipalities have joined the City Energy Project aiming at reducing building energy consumption and GHG emissions [23]. Copenhagen, Bristol, and Växjö are leading more than 6,000 European cities, which have signed up the Covenant of Mayors, a voluntary commitment to cut 28% in CO_2 emissions, 8% more than the EU's climate action target for 2020 [24–26].

The major sources of GHG emissions in the U.S. for example, are electricity generation (30%), transportation (26%), industry (21%), residential and commercial heating (12%), and agriculture (9%) [27]. Although emissions characteristics of industry and transportation sectors vary inconsistently across cities, electricity and gas usages remain mainly accountable for emissions from buildings in cities with their usages particularly susceptible to climate feedbacks [28–34]. Residential and commercial buildings account for over 40% of the total energy consumption and over 72% of electricity consumption in the U.S [35]. In order to effectively manage and reduce building energy use and GHG emissions, it is essential to understand not only the current status of building energy use, but also the historical energy use and its future trends. Therefore, numerous energy modeling approaches have been proposed in recent decades to analyze building internal energy flows and ultimately the origins of the energy consumption at the city level.

The aim of this paper is to provide an up-to-date review of urban-scale building energy modeling, including both top-down and bottom-up approaches. We also assess their key purposes, strengths and limitations with the highlights on recent progresses in temporal resolution improvement and model calibration. The comprehensive knowledge of modeling assumptions and their effects on prediction outcomes will provide essential guidance to researchers in the field of buildings energy analysis who explore modeling approaches suitable for their specific purposes. For instance, the spatial and temporal resolution of a model is pivotal to its application to performance evaluation at the national or local scale. In addition, we take, as an example, the physics-based bottom-up approach, one of the most popular energy modeling approaches to explain its basic procedures (modeling preparation, calibration, validation, and simulation) for energy simulation. As there are significant differences across models taking the approach, their strengths and weaknesses are also analyzed in this review. Finally, we put forward several issues and challenges associated with modeling inputs and calibration, suggesting possible solutions for using physics-based bottom-up models to simulate urban building energy use.

2. Urban building energy modeling approaches

Urban building energy models take two distinct approaches: top-down and bottom-up. The top-down models treat a group of buildings as a single energy entity, where energy consumption is often estimated at the building sectoral level without considering differences among individual buildings or end-uses. In contrast, bottom-up modeling approaches focus on individual buildings and end-uses, so that energy consumption is modeled for individual end-uses within the buildings, which can be aggregated to the urban, state, regional, or national scale. An overview of urban building energy modeling approaches is shown in Fig. 1, and the characteristics of all reviewed models are summarized in Table 1. The following sections provide detailed discussions.

2.1. Top-down approaches

The top-down approaches typically represent energy consumption by establishing a long-term relationship between the sector's energy use and the associated major drivers [e.g. changes in gross domestic product (GDP), energy price, population, household size, technologies and practices, weather condition, etc.]. The

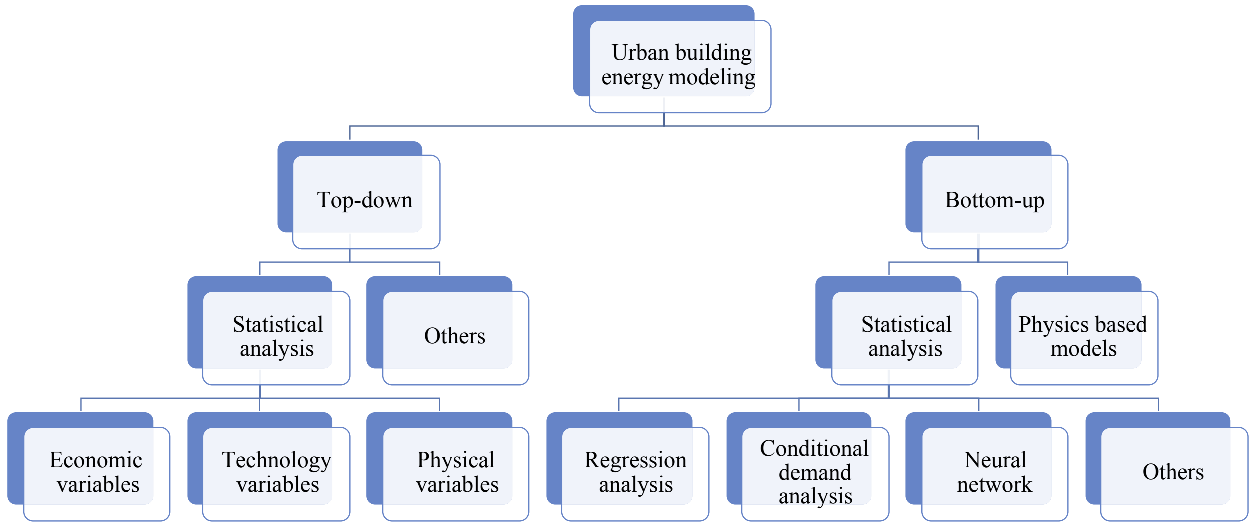

Fig. 1. Hierarchy of the urban building energy modeling approaches.

advantage of this broad category is that it often employs energy-economy interactions, thus being capable of modeling energy use under various socio-economic scenarios. It also allows for taking into consideration both socio-demographic and market economic factors. Additionally, the top-down approaches typically use relatively straightforward methods for implementation by relying on a limited set of input information, such as aggregated socio-economic data. As the emphasis is given to the energy-economy interaction, detailed information about the types of energy-consuming technologies utilized in the subject buildings and their detailed energy consumption data are usually not required. Due to its simplicity, the top-down approaches have been widely used for estimating urban energy consumption. One of the earliest attempts was made by Hirst [36] to model city-scale annual residential energy use in the U.S. using an econometric regression model. In particular, multiple socio-economic variables were selected and applied in this model to estimate household energy consumption. Other driving factors including demographic and technological characteristics were also considered in their model. The socio-economic variables of the model capture the change in social policies and human behavior, whereas the technological variables reflect the difference in the efficiency of various end-uses. Nesbakken [37] tested the sensitivity of energy use to household income and energy prices in Norway based on an econometric model. Similarly, Bentzen and Engsted [39] simulated energy consumption for Denmark using a simple regression model. Both studies discovered a tightly coupled relationship between energy consumption and income and energy price.

Table 1
Characteristics of top-down and bottom-up approaches.

Approaches	Advantages	Limitations	Literature
Top-Down Models	1) Both long-term socio-demographic and market economic effects considered 2) Detailed technology description and actual energy consumption not required 3) Limited input information often with aggregated economic data	1) Past energy-economy interactions used to predict future energy consumption 2) Long term historical data required 3) Lack in technological details	Hirst et al. (1977) [36] Nesbakken (1999) [37] Ozturk et al. (2004) [38] Bentzen & Engsted (2001) [39] Zhang (2004) [40] Thuvander (2005) [41] Labandeira et al. (2005) [42] Lowe & Oreszczyn (2010) [43]
Bottom-Up: Statistical Models	1) Both socio-demographic and marketeconomic effects considered 2) Simulation of energy use at end-use and/or building level 3) Variations in individual end uses considered	1) Billing, weather, and/or survey data required 2) A larger number of sampling subjects required 3) Possible multicollinearity to be addressed 4) Simulation results highly dependent on historical consumption trend; prediction well outside of bounds of training data not reliable	Tonn & White(1988) [44]; Douthitt (1989) [45]; Fiebig et al. (1991) [46]; Parti and Parti (1980) [47]; Sorooshian & Kerwin (1984) [48]; Pratt et al. (1993) [49]; Cetin et al. (2014) [50]; Cetin & Novoselac (2015) [51]; Bauwens et al. (1994) [52]; Lafrance & Perron (1994) [53]; Aydinalp-Koksal & Ugursal (2008) [54]; Lins et al. (2002) [55]; Park et al. (1991) [56] Peng et al. (1992)[57] Aydinalp et al. (2002) [58]; Aydinalp et al. (2003) [59]; Aydinalp et al. (2004) [60]
Bottom-Up: Physics-Based Models	1) Socio-demographic and economic information not required 2) Simulation of energy use at different temporal scales 3) Variations in individual end uses considered	1) Detailed physical and technological measures required 2) Socio-demographic and market economic trends not captured 3) Intensive computational effort required	Cerezo et al. (2014) [61]; Dickson et al. (1996) [62]; Shorrock et al. (1991) [63], Shorrock & Dunster (1997a &b) [64]; Shorrock et al. (2005) [65]; Johnston (2003) [66]; Johnston et al. (2005) [67]; Boardman et al. (2005) [68]; Natarajan & Levermore (2007) [69]; Firth et al. (2010) [70]; Farahbakhsh et al. (1998) [71]; Snakin (2000) [72]; Hirsch (1998) [73]

In addition to economic variables, physical factors such as weather/climatic conditions have also been incorporated in some of the top-down models. Summerfield [43] compared the total residential energy consumption of the U.K. in 1970 and temperature variations. Multivariate linear regression was used to analyze the relationship between household energy consumption, outdoor temperature, and energy price. Their findings revealed that, with a temperature increase of 7 °C in the heating season, the average household delivered energy dropped about 1 MWh/year. Zhang [40] incorporated climate variation to calculate and compare residential energy consumption in China, Japan, USA, and Canada. In their study, the consumption of electricity, coal gas, liquefied petroleum gas, and natural gas were jointly used to estimate overall residential energy consumption. Labandeira [42] also demonstrated the importance of utilizing various factors, including demographic, economic, and climate variables, to estimate detailed building energy consumption in Spain. Their research employed seven regression models to estimate the consumption of electricity, natural gas, propane, automotive fuel, public transport, and food.

2.2. Bottom-up approaches

The bottom-up approaches, which represent energy consumption based on detailed end-use information, can be categorized into two types: statistical versus physics-based methods. The former usually takes building energy use values from sample buildings to analyze the relationship between end-uses and total energy use. The statistical method is similar to the top-down approach in terms of its ability of incorporating socioeconomic factors [74]. However, the method uses more detailed and often disaggregated data, which typically represent energy consumption data for individual buildings. The second, physics-based method simulates energy consumption based on the physical characteristics of individual buildings, such as building geometry, non-geometric features (e.g., heating, ventilation and air conditioning (HVAC) systems, usage patterns, and building envelope), and user characteristics.

The bottom-up statistical method simulates urban building energy use based on long-term historical data including energy consumption and economic indicators, such as GDP [74]. Urban area is one of the most important variables for urban building energy use modeling as urban area is a key measure to evaluate the size of a city and also served as a parameter to calculate energy consumption. The past and current urban areas information obtained from government sources can serves as baseline data for undertaking a statistical simulation of the total size of future urban areas. The major limitation is that as statistical urban areas are simulated, the spatial variation of urban areas cannot be determined. In contrast, the physics-based model is not considered to be capable of simulating urban areas, given that the model utilizes as inputs existing technological knowledge, such as building type, building area, building geometry and non-geometry information. Nevertheless, the physics-based model can address such limitation by incorporating information of past and current spatial variations in urban area and building areas obtained from GIS techniques. Future urban area is then simulated with a spatially explicit model, such as the Cellular Automata model [75].

2.2.1. Statistical methods

The bottom-up statistical method used for urban energy modeling projects energy consumption based on billing information, survey data, and socio-economic variables. While there are many possible approaches in this category, they can be classified into three groups: (a) regression analysis, (b) conditional demand analysis, and (c) neural network analysis.

The regression analysis employs data about historical energy use and socio-economic forces to predict future energy consumption. Sensitivity analysis is used to determine the influence of major forces, followed by goodness-of-fit tests to assess model performance. Tonn and White [44] proposed 30 different regression models to examine the relationship between electricity use and wood fuel use, equipment and lighting, heating, and indoor temperature in Hood River, Oregon. In their study, occupant behavior was also considered using data obtained from 300-question surveys. Several of the regression models achieved high performance with R^2 over 0.8. They also found that ethical consideration of energy consumption was more important than economic variables for the prediction of energy use, showing that ethical motivations, including what they call “rural ethic”, “conservation ethic”, and “voluntary simplicity ethic”, had major effects on building energy use [44]. In addition, Douthitt [45] developed a model based on around 370 data records of fuel price, fuel consumption, climate conditions, and building prototypes with around 370 data records all collected from Canada to simulate the energy use of space heating. The author found a positive, statistically significant correlation between energy use and the subsidies provided to low-income households. In addition, to identify regional energy conservation potential, change point models have been proposed and widely used [76,77]. For instance, Raffio [78] developed a regression model with three “energy signature” coefficients, including weather independent energy use, the building heating or cooling coefficient, and the building balance-point temperature, from which the building characteristics and coefficients were identified. To give an example, weather independent energy use associates with hot-water heater retrofits via lowering the setpoint, replacing low-efficient, and fixing leaks, and the variation in the balance point temperatures associates with the preferred temperature at which a household switches between cooling and heating. Buildings that have high heating or cooling coefficients are significantly influenced by weather and thus can be a target for energy efficiency retrofits. In the model, the coefficients were used to identify average, best, and worst energy performers and to examine how the building energy performance has developed over time, all of which can be used to evaluate energy savings potential.

Conditional demand analysis (CDA) is another powerful statistical technique for modeling building energy use. Unlike typical regression analysis, CDA runs regression based on end-use appliances belonging to each building and requires very detailed information about appliance ownership (e.g., unit energy consumption and utilization rate) and/or building characteristics (e.g., population, conditioned area, heating method). Such detailed information are often obtained from building owner surveys and utility data. Model performance is strongly correlated with the number of variables employed. An early CDA approach was taken by Parti and Parti [47] for analyzing residential electricity use in San Diego. In their study, a regression method was used to estimate the utilization rate of of residential appliances (e.g. dishwasher, freezer, and TV set) and thus to project the level of energy consumption, based on surveys of 5,286 households and utility provided monthly electric billing data. Aigner et al. [48] applied the CDA approach for modeling energy consumption of end-uses at the fine temporal resolution of one hour. They obtained 15-minute level data from more than 100 households, developing 24 regression models to estimate energy use of appliances in each hour of the day. In order to generate realistic results, they imposed restrictions, such as the use hours of dishwasher, cooking, and laundry. Another important work was done by Pratt [49] who conducted an examination of almost 300 houses in the End-Use Load and Consumer Assessment Program (ELCAP) for residential homes in the Pacific Northwest. Cetin [50] and Cetin and Novoselac [51] studied the use patterns of residential appliances and HVAC systems of several hundred households. They found significant differences between single family and multi-family homes and between user-dependent and user-independent appliances. Fiebig [46] revised the standard CDA model in a conditional coefficient framework using utility meter data. This work considered the household variation in energy-use intensity of different appliances. In particular, using utility meter data obtained from 348 households as the benchmark they found that the revised CDA model is a significant improvement over the standard approach. Other popular mathematical approaches, such as Bayesian analysis, have also been successfully applied to integrate meter data into the CDA approach for urban-scale energy modeling [52]. The CDA approach has also been widely used in estimating energy use at various scales. Lafrance and Perron [53] analyzed the electricity consumption of the residential sector in Quebec, Canada, using a CDA regression method with electricity billing data and appliance information, as well as other inputs, such as heating equipment, weather conditions, and water heater characteristics obtained from almost 100,000 households. The study revealed that electricity consumption was highly dependent on household dwelling types (single family, duplexes, triplexes, buildings with 4–9 apartments and buildings with over 10 apartments). The CDA approach was found to effectively represent urban-scale heating energy use for residential buildings using multiple sources, including wood, electricity, and gas. The approach has also been applied to a national-level residential energy use analysis in Canada [54]. Based on the residential energy use data collected from 8,000 households in 1993, Aydinalp-Koksal and Ugursal [54] proposed three CDA models to represent the residential energy consumption of electricity, gas, and oil in Canada. Additional variables, such as burning efficiency of natural gas or oil, average indoor temperature, conditioned area, number of occupants, number of windows, and other building-related variables, were also included in their analysis to improve model accuracy. In a case study for residential buildings in Brazil, Lins [55] proposed a CDA model based on the monthly energy consumption data collected from over 10,000 households. They indicated significant differences in energy use across the study areas, demonstrating the importance of considering regional differences and appliance ownership for robust predictions. In their study, electricity consumption for lighting and refrigeration, for example, accounted for 61.8% and 41.9% of total consumption in North and South Brazil in 1989.

In addition to the conventional and CDA-based regression methods, artificial neural networks (ANN) is another statistical approach frequently used for modeling building energy consumption at the city scale [79,80]. Aydinalp [58] applied ANN for modeling energy consumption in Canadian residential buildings, in which different ANN models were developed for estimating energy use of appliances, lighting, and cooling. In order to improve model performance, 55 variables including information about appliances, heating system, and population were considered. Overall, energy consumption and meter data from 741 households were used for model training with the remaining information of 247 households used for validation. Compared with an engineering model [R^2: 0.780, CV (coefficient of variation): 3.463], the best ANN model achieved a substantially higher performance with R^2 of 0.909 and CV of 2.094 [58,59]. Aydinalp [60] extended the ANN model developed by Aydinalp [58] to predict space heating and domestic water heating energy use in Canada. Following a similar procedure, two separate ANN models were developed, achieving an R^2 value of 0.91 and 0.87, respectively.

2.2.2. Physics-based methods

The physics-based bottom-up methods simulate building energy use based on the physical characteristics of the subject buildings and the thermodynamic principles that govern how a building interacts with the environment. The approach does not require knowledge of socioeconomic factors and can also be completed without the use of historical energy consumption data. It is the only type of modeling approach that does not require historical data. However, one major limitation is the requirement for intimate knowledge of a large number of physical parameters. They include a full suite of information, such as building shape, glazing, orientation, thermal properties of buildings envelope, types and performance characteristics of HVAC systems, ventilation rates, thermostat set points, occupancy rates and schedules, internal loads, etc. The collection of basic physical parameters therefore may take more than 30% of overall energy modeling effort in this case [61]. Since the physics-based methods simulate energy use with the combination of building physical data, survey data, and climate condition data, they can be used not only for modeling of existing buildings but also for assessing the performance of future infrastructure that is yet to be constructed. This feature makes the methods promising to predict future urban-scale energy consumption and thus appropriate to be used in energy models that forecast GHG emissions and provide support for informed decision-making. In addition, the physics-based methods simulate building energy use based on the physical characteristics of individual end uses at the annual, monthly, daily, hourly or in some cases, sub-hourly scales. In addition, energy models taking the physics-based approach are capable of assessing the impact of energy efficiency improvements [81,82]. Building energy performance is known to be strongly associated with solar exposure, weather condition, buildings morphological characteristics, and buildings structure. These parameters are all needed to be set at the early design phase of energy modeling to provide relevant information and support for potential users. Passive solar design that considers solar energy capture and usage is already integrated into physics-based models to improve energy efficiency and overall net energy use. Major components of the passive solar design include optimizing building envelope, building shape, building-to-sun orientation, building shading devices and thermal mass. These physics-based models consider all of these components as major input parameters for modeling building energy use [83].

One of the most widely used physics-based models for projecting building energy consumption at the city scale is the Building Research Establishment's Domestic Energy Model (BREDEM) [62,63,84]. The model is updated annually, acting as a key part of the Government's Standard Assessment Procedure in the U.K [85]. The BREDEM modeling framework have been extended to other physics-based models to simulate residential energy use. They include the Building Research Establishment's building model for energy studies (EREHOMES) developed by Shorrock and Dunster [64,65,86], the Johnston model developed by Johnston [66] and Johnston [67], the UK Carbon Domestic Model (UKDCM) developed by Boardman [68], the DECarb model developed by Natarajan and Levermore [87], and the Community Domestic Energy Model (CDEM) developed by Firth [70]. While these models employ the same BREDEM modeling framework, they exhibit significant differences. In particular, buildings are categorized into from 47 house prototypes in the CDEM model, 1000 categories in the BREHOMES model, 20,000 dwelling types in the UKDCM model, and 8064 building prototypes for 6-year bands in the DECarb model. Given the complex and often unknown relationship between energy consumption and various input data, it is necessary to explore uncertainty in energy modeling. However, among the five models, only CDEM has been tested with uncertainty analysis. Firth [70] identified key input parameters and their corresponding sensitivity for the urban building energy models. In addition, different baselines are used for modeling energy consumption. The UKDCM, DECarb and Johnston model use 1996 as the base year for predicting energy use up to 2050. The BREHOMES model uses 1993 as the base year for projecting energy use to 2050 [65], and the CDEM model has been used only for estimating energy use in 2001 based on the climate data between 1971 and 2000.

In addition to the BREDEM model, the physics-based approach has been taken by the Canadian Residential Energy End-Use Model (CREEM) to evaluate the impact of different energy efficiency strategies on energy use and carbon dioxide emissions in Canada [71]. In the CREEM model, 8,767 houses were classified into 16 prototypes based on building types (single-detached, single-attached), space heating fuels, building age (pre-1941, 1941–1960, 1961–1977, post-1977) and regional location (Western Canada, Prairies, Central Canada, Atlantic Canada) to simulate annual energy use under two scenarios: the R-2000 standards and the NECH standards [88]. The CREEM model has been considered effective in assessing the reduction of residential energy use and emission from different energy efficiency measures. The major limitation of this model is that it only considers single-detached and single-attached houses, meaning almost 40% residential buildings, including multi-family apartments, condos, duplexes, townhouses, and high-rise-apartment are ignored.

Another energy model used to assess heating energy efficiency and GHG emissions was proposed in Finland by Snäkin [72]. The model employs statistical data, such as fuel and energy use, demographic variables, and building parameters to explore energy conservation options and alternative heating and fuel choices. All dwellings are aggregated into several groups based on basic building type, heating type, fuel and energy sources, and building age. Although the model is useful in identifying potential improvements in heating energy efficiency, it does not consider behavioral and temporal variations arising from the characteristics of occupants and equipment usage, which reportedly have significant impacts on energy use [74,89].

In the U.S., numerous models have been developed for modeling building energy use. DOE2 is a popular physics-based model developed by Hirsch & Associates, along with the Lawrence Berkeley National Laboratory [73]. It simulates energy consumption using building geometric (e.g. envelope, building geometry, areas, glazing), non-geometric (e.g. HVAC system, occupancy schedule, usage patterns), and environmental (e.g. weather data) parameters. The DOE2 model can represent most building features, such as shading, envelope, building mass, the dynamics of different heating and cooling controls, and the impact of natural lighting on thermal demands. Therefore, it has been widely used to provide accurate predictions of individual end uses (e.g. lights, HVAC systems, etc.) and of whole-building use. However, challenges remain, because using DOE2 requires an in-depth understanding about the model, its underlying assumptions, and its interface, as well as significant professional training and skills. To address this issue, a graphical user interface, Quick Energy Simulation Tool (eQUEST), has been developed. eQUEST combines the building creation wizard, the energy use calculation wizard, and the modeling results graphical display module based on an enhanced DOE2.2 model [90,91]. The eventually projected energy use is directly presented in the graphical display module, and can also be downloaded for a more detailed analysis. Heiple and Sailor [92] used eQUEST for simulating energy use intensity of 18 building prototypes in Houston, TX to project citywide building energy use by incorporating information about building floor space, number of floors. Moreover, Zhou and Gurney [91] modeled energy use and CO_2 onsite emissions of Indianapolis/Marion County, IN by coupling the energy use intensity of 30 building prototypes from eQUEST with information on floor areas and floor numbers from GIS dataset.

Another most widely used energy simulation engine is EnergyPlus [93], which builds on the most powerful features of DOE2. Compared to DOE2 and eQUEST, EnergyPlus has a refined temporal resolution of energy modeling (sub-hourly) and improved modeling principles to integrate dynamic solvers that take into account the thermodynamics of the building and building systems (building shell and HVAC system). Cerezo Davila [24], for example, employed EnergyPlus to simulate building energy use intensity of different building types, generating building energy use at high spatial and temporal resolution for the city of Boston. Several other studies have simulated building energy use by incorporating passive design and solar energy features. Hachem et al. [94] investigated the potential of electricity generation by building-integrated photovoltaic (BIPV) systems for single family housing units in Canada. In particular, they proposed an integrated design methodology for residential neighborhoods to be considered at the early stages of the housing design process. In particular, several important parameters, such as the orientation and shape of housing units and unit density, were used as inputs for EnergyPlus. Hachem also [95] explored the impact of key design parameters on both energy use and GHG emissions of a large-scale solar community. In this study, building energy performance, neighborhood types, street design specifications, and the relative location of commercial centers to residential areas were all included as design parameters to account for their combined effects and interactions. The study simulated building energy use for individual neighborhoods prototypes within the vicinity of Calgary, Alberta in Canada, highlighting the importance of adopting high-energy efficiency measures at the early stage of energy modeling. In addition, Nault et al. [96] proposed a new meta-model for evaluating the performance of the early design neighborhood project utilizing simple geometry and irradiation based parameters. Their results suggest that the proposed method has the potential to be used as an essential engine in the early design phase.

2.3. Geospatial techniques in top-down and bottom-up approaches

With the advances in geospatial techniques, the need for integrating such techniques in building energy use study is gaining much importance. This is mainly because geospatial techniques could be integrated with energy use models to provide support for estimating and investigating spatial and temporal variations of urban building energy use.

Geospatial techniques can be integrated with the top-down approaches to downscale urban building energy use from the city level to the group or individual building level. For example, Tornberg and Thuvander [41] developed a GIS-based urban energy model to decompose the total consumption of electricity and gas at the individual building stock level in the city of Goteborg, Sweden. While energy use was presented at the building group level, its detailed spatial pattern allows for informed decision-making in government and real estate management contexts. Delmastro et al. [97] took Centro Residenziale Europa of Turin as an example, evaluating the demand for heating in the buildings based on the actual energy consumption data. Enabling geo-referencing and representing building blocks, GIS techniques served as a crucial tool to distribute energy consumption, emissions, and energy saving information across the study area.

Geospatial techniques have also been commonly used in the bottom-up models to upscale building energy use from the individual building level to the city scale. The bottom-up models, which allow for simulating energy use at individual level with a high temporal resolution, can represent, if combined with geospatial techniques, the energy use of hundreds, thousands, or even more buildings at the city and regional scales. Mastrucci et al. [98] introduced a GIS-based bottom-up statistical approach for estimating citywide residential building energy consumption. In their study, the GIS database of the Rotterdam city served as the major information source for representing residential buildings throughout the entire city. Having started with modeling energy use for individual buildings, geospatial techniques are now being used to generate building energy use at the city level and thus to provide a support for investigating the spatial variation of citywide building energy use. Ma and Cheng [99] integrated the GIS technique with data mining methodology to model building energy use intensity for 3,640 multi-family residential buildings in the City of New York. In their study, the site energy use intensity was estimated with prepared features, such as building, demography, economy, and education, using support vector regression, artificial neural network, and elastic net. Based on the estimated site energy use intensity, citywide energy use was generated in combination with geospatial technique. Mattinen et al. [100] integrated a bottom-up approach and a GIS technique for modeling and visualizing the energy consumption and GHG emissions of residential sectors. Specifically, the bottom-up approach was taken to estimate energy use and GHG emissions of individual residential buildings, in which the GIS technique was employed for mapping building energy uses in the whole residential sector and visualizing the spatial pattern of these estimates. Yu et al. [101] proposed an improved two-step floating catchment area approach to estimate building energy use and reflect its heterogeneity within the city. Building energy use was estimated using the GIS data and technique, in combination with tax lot data, such as building type and floor area. With the spatial data of the whole city, the building energy use of the entire city was generated with energy deficit and surplus areas identified to support the planner's decision making [101]. Fonseca and Schlueter [102] introduced an integrated model of dynamic demand prognosis in a geospatial framework for characterizing the spatial and temporal patterns of building energy use in city districts. In particular, the two bottom-up approaches, statistical and physics-based, were integrated to determine the spatial and temporal variability of energy services in both standing and future residential, commercial, and industrial buildings. In the study, geospatial techniques served as tools to map building energy use from individual buildings to the whole city district.

Recently, studies have been conducted to model urban building energy use by coupling bottom-up physics models with GIS techniques. Zhou and Gurney [91] modeled urban building energy use and CO_2 emissions for Indianapolis-Marion County, IN through integrating their energy use model, eQUEST, with GIS techniques. In their study, several important datasets, including building footprint and building parcel data, were prepared and processed using a geospatial technique that allows the investigation and visualization of citywide building energy use and its spatial and temporal variations. Gurney [90] modeled CO_2 emissions down to each individual building, further examining the spatial variation of entire urban landscape of building emissions with the support of geospatial techniques. Davila et al. [24] developed an Urban Building Energy Model (UBEM) to estimate the citywide hourly energy demand at the building level. The EnergyPlus model was used, instead of eQUEST, to simulate energy use intensity for each individual building, in combination with geospatial techniques, which were employed to calculate final building energy use and to upscale the energy use to the city level.

3. Procedures in physics-based bottom-up models

While numerous approaches have been proposed for modeling buildings energy use, the physics-based bottom-up models have become most popular due to their high temporal resolution. These models are capable of supporting the development and evaluation of new technologies installed to improve buildings energy efficiency. Fig. 2 shows the general procedures of using physics-based bottom-up models for simulating urban building energy use. In particular, several aspects of the building environment need to be considered in model preparation, including information on buildings geometry (e.g. shape, and window opening ratio), buildings non-geometry (e.g. construction, material, and occupancy schedule), and weather conditions (e.g. temperature, wind, and solar radiation) [25]. Moreover, such models need to be calibrated before being applied for final energy modeling.

3.1. Model preparation

Buildings geometry generally consists of building shape, floor area, height, and roof characteristics. If not known, it requires multiple sources of data collection using GIS and remote sensing techniques [24,25]. In recent years, the citywide GIS data has become more easily accessable to the public. In the U.S. local government agencies (typically the Department of Urban Planning and the Department of Transportation) collect data on building footprints. The data is often available online for large cities and is downloadable free of charge. Total building floor area can be calculated by combining the GIS database of building footprints and buildings height information from LiDAR (Light Detection and Ranging) data which use remote sensing techniques. In addition, county assessors' databases contain building parcel data, which provides information on building type, age, heating system, and other building characteristics.

Compared with buildings geometry data, buildings non-geometry data are relatively difficult to collect. As there are thousands or even hundreds of thousands of buildings in a large city, it is impractical to collect non-geometry data for all buildings [24]. Therefore, it is necessary to use building prototypes to represent different groups of similar buildings throughout the study area. In general, building prototypes can be defined using several parameters, such as building shape, size, age, thermal properties, etc. Shimoda [103] simulated residential energy use in Osaka, Japan with 20 identified building prototypes. In particular, based on building shape and floor area, 1,128 residential buildings were classified into 10 types of detached homes and 10 types of multi-family houses. Mastrucci [98] estimated residential energy savings for the city of Rotterdam, Netherland with 26 building

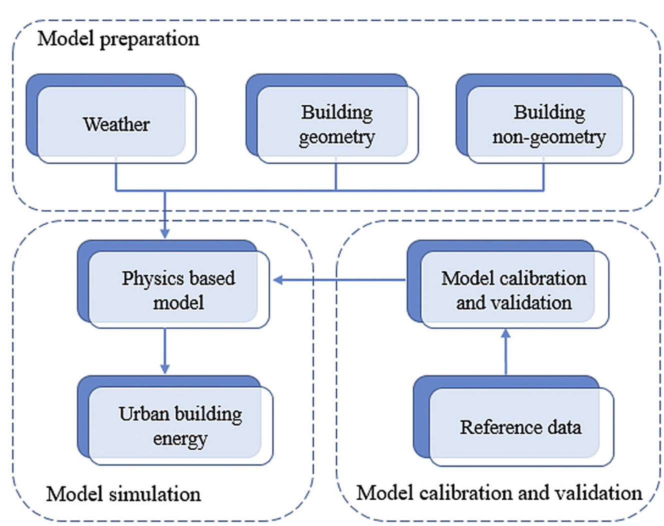

Fig. 2. Flow chart of urban building energy modeling using the physics-based bottom-up model.

prototypes. Specifically, based on building shapes, they classified buildings into detached homes, semi-detached homes, rowhomes, maisonette, flat-galerij, and flat-portiek types, which were further classified based on building age into 26 building prototypes [104].

The methods of heating have also been considered in defining building prototypes. For their urban energy model, Heiple and Sailor [92] defined 11 commercial building types and 2 residential building types using building shape and age information, followed by further categorization into 30 building prototypes according their heating methods (primary heating, electric or non-electric). In addition to the above studies conducted at the urban level, works have been done also at the regional and national level. For instance, Dascalaki [105] modeled residential energy use in Greece by grouping 2,514,161 buildings into 24 building prototypes based on building shape, age, and four climate zones. Famuyibo [106] pointed out the importance of representing construction methods and thermal variations in buildings prototype classifications. Mata [107] proposed an approach to grouping buildings into building prototypes based on building shape, age, climate conditions, and heating systems, demonstrating its effectiveness in cases of four European countries, that is, France, Germany, Spain and the U.K.

In additional to buildings geometry and non-geometry data, weather data is another important input for energy modeling. Several different weather datasets have been commonly used [108]. Typical weather data includes important weather parameters, such as air temperature, wind speed and direction, solar radiation, and humidity, which have direct impacts on buildings energy demand. The Test Reference Year (TRY) is one of the earliest hourly weather datasets derived from weather data (1948–1975). It includes most of important weather parameters, such as dry- and wet-bulb temperature, pressure, wind speed and direction [109]. However, it does not provide solar radiation information. Energy models using the TRY data thus need to calculate solar radiation itself before determining the final energy use. In order to overcome the limitation, the Typical Metrological Year (TMY) weather database was generated by the National Climatic Data Center (NCDC) and Sandia National Laboratory (SNL) in 1981. The TMY database include 12 months of hourly weather data with each monthly weather data selected from those between 1952 and 1975 to represent the average conditions over the period of study. Solar radiation information was included in TMY data for 234 locations throughout the U.S. (26 locations with observed solar radiation data, and 208 locations with calculated solar radiation data) [110]. More recently, the TMY3 dataset produced by the National Renewable Energy Laboratory (NREL)'s Electric Systems Center provides data for 1,020 locations with their solar radiation information coming from satellite data. The TMY4 dataset will rely on climate reanalysis data and satellite data to provide all weather parameters, enabling a wide range of weather data unrestricted to the location of weather stations.

Besides weather data available in the U.S., weather data have also been made available in other countries and widely used in modeling energy use. For example, the International Weather Files for Energy Calculation (IWEC) developed by ASHRAE covers 3,012 worldwide locations outside the U.S. and Canada. The ASHRAE has also collaborated with the White Box Technologies to provide web access to the ASHRAE IWEC2 datasets by county or region. In addition, the WATSUN data developed by the WATSUN Simulation Laboratory and the University of Waterloo cover 49 locations in Canada [111]. Moreover, the European Test Reference Year (ETRY) weather data have been created using the TMY methodology from NCDC with SNL providing weather data for European locations [112].

3.2. Model calibration, validation and simulation

Energy modeling consists of dozens, even hundreds or thousands of input variables, depending on the model under consideration. Model performance relies heavily on the professional experience and judgment of the users and the quality of inputs provided. This consideration, combined with variabilities in building use, occupancy rates, plug loads and other sources can lead to significant differences between the predicted energy use from a model and the actual consumption. In an event where significant differences are observed, the calibration of the employed energy model through adjusting the input parameters becomes crucial. Two statistical indices, the mean absolute error (MBE, Equation (1)) and the coefficient of variation of root mean square error (CVRSME, Equation (2)), have been widely used for evaluating the model performance, as recommended by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers [113], International Performance Measure and Verification Protocol [114], and the Federal Energy Management Program [115] (see Table 2). The two indices are given by

$$MBE = \frac{\sum_{i=1}^{j} S_i - M_i}{\sum_{i=1}^{j} S_i} \quad (1)$$

$$CVRMSE = \frac{\sqrt{\sum_{i=1}^{j} (S_i - M_i)^2 / j}}{\bar{S}} \quad (2)$$

where, S and M are the monitored and modeled energy use for each model instance i, and j is the total number of data recorded (the size of j is 12 for monthly simulation and 8,760 for hourly simulation).

Numerous studies have been conducted on the calibration of building energy models. Among them, four main approaches have been widely applied, including: 1) manual calibration with the assistance of iterative and pragmatic intervention, 2) manual calibration using graphic representations, 3) the special test and analytical approach, and 4) the mathematical approach [116]. Manual calibration relies on the modeler's professional experience, as input parameters are manually modified based on the user's knowledge and expert judgment. For example, Pan [117] developed a building energy model based on a range of survey-collected data (building geometry, operating schedules, historical utility data), in which the CVRMSE of electricity and gas was 24.9% and 64.4% respectively before calibration, which was significantly higher than the acceptable criteria. Based on the energy consumption analysis and on-site survey, they modified inputs for internal loads, occupancy schedule, and HVAC system, and eventually, the monthly CVRMSE of electricity and gas in 2004 dropped to 4.71% and 8.92%, respectively. Such kind of calibration approach has been widely accepted and applied in numerous studies [117–122].

Rather than comparing the modeled value with the monitored value as in the case of iterative manual calibration, time-series and scatter plots can be generated with the graphical representation technique to illustrate model fit. One early attempt by Haberl and Bou-Saada [123] analyzed hourly differences between estimated and monitored energy uses using a 3D plot, in which the modeled data, the reference data and their difference were the three corresponding axes. The study found the technique highly effective in adjusting time-associated variables, such as occupancy schedules. Bronson [124] calibrated hourly building energy use using 3D graphics. Calibration signature analysis is another type of graphic-based calibration method, in which a signature is defined as the normalized graphical representation of the discrepancies between modeled and monitored energy uses. The approach was first

Table 2
Calibration criteria in buildings energy use modeling.

	Index	ASHRAE Guideline 14 [113]	IPMVP [114]	FEMP [115]
Monthly	MBE (%)	5	20	5
	CVRMSE (%)	15	–	15
Hourly	MBE (%)	10	5	10
	CVRMSE (%)	30	20	30

introduced by Kandil and Love [125] for energy model calibration. A two-step calibration instruction has also been provided by Liu and Liu [126] for simplifying energy model calibration using calibration signatures. They developed an office building energy model, calibrated it with monitored data, and conducted the second calibration based on a calibration signature to identify variables to modify. The calibration signature approach can effectively improve the modeling accuracy of heating and cooling energy use with multiple HVAC systems as it can help users assess the impact of input variables by indicating a set of parameters that need to be modified.

While manual calibration approaches have proved effective in improving the accuracy of building energy models, it can be time-consuming to perform. It is thus worth to consider calibrating energy models with the assistance of computers and multiple analytical and mathematical methods. One promising approach is to calibrate energy models based on special tests and analytical methods, such as the Primary and Secondary Term Analysis and Renormalization method (PSTAR). The PSTAR was initially developed by Subbarao [127], and was later revised by Burch [128] and Balcomb [129]. The method concerns hourly building energy modeling and performance analysis using a short-term monitoring data. In PSTAR, buildings energy consumption is considered as the sum of heat flows with the primary and secondary terms defined by a re-normalization approach.

Automatic calibration approaches can also be taken based on either mathematical methods or analytical methods. One example is applying the Bayesian method to calibrate building energy models. As the uncertainty of input parameters can significantly influence model performance, such prior uncertainty is considered and reconciled in a Bayesian calibration method through probabilistic sensitivity analysis that matches modeled and monitored energy uses [130–132]. Optimization techniques provide another solution for automatic calibration. In this case, energy models are coupled with optimization methods to achieve automatic calibration [133], in which an objective function, defined as discrepancies between modeled and monitored energy uses, is utilized to calibrate the model. One example is the universally feasible statistics-based calibration method proposed by Sun and Reddy [134]. In their model, the impact of input parameters on building energy use was analyzed, followed by reorganization of all input parameters based on recognition analysis and eventual model calibration using mathematical optimization. This method was revised by Farhang and Ardeshir [135] and also by Taheri [136] with the improvements in the selection process of the parameters. Several other mathematical methods and softwares, such as Monte Carlo and GenOpt, have also been applied to the optimization technique-based automatic calibration [116,137]. Although the effectiveness of coupling energy modeling with optimization techniques has been proven, it also brings other challenging issues, such as increased computational burden and analytical complexity. For example, simulation and data analysis need to be conducted for both energy modeling and optimization procedures.

In order to reduce model complexity and thus to improve efficiency, the meta-modeling approach has been proposed by Eisenhower [133] for building energy modeling and calibration. The first step of this approach is data sampling, in which only a limited number of parameters, not all of them, are selected as samples to be used in the simulation and optimization procedures. As meta-modeling works with the essential characteristics of a building under consideration, it can be considered as one of the fastest methods [133].

3.3. Challenges

While the physics-based bottom-up methods have proven to be effective and received great popularity, some challenges remain, especially in the preparation and calibration of models. Specifically, Typical Meteorological Year (TMY) has been widely utilized as weather data in the models for energy use simulation. While the TMY data is freely available in many regions globally, it is simulated weather data, so that it does not typically match the actual year-to-year weather data, not presenting extreme weather events and future weather predictions. Urban heat island effects and other local microclimatic phenomena, which are likely to cause high variation of urban weather patterns within a city, are not provided either [138,139]. Therefore, improvements should be made in collecting high-density weather data through direct observations and generating spatially-varied data that take into account spatial patterns within cities.

Although most studies have so far focused on energy modeling of past or present performance, the prediction of energy use in future climate scenarios can inform decision making by governments and private sectors [140]. Given that building energy use is highly correlated with surrounding climate conditions, climate change may have a significant impact on building energy consumption [141]. Huang and Gurney [142] analyzed the relationship between climate change and building energy consumption in 925 U.S. cities, showing a substantial increase of building energy use in summer and a significant decrease in winter. They also reported that the variation of the impact within climate zones is greater than the variation across climate zones, which indicates a potential bias arising from examining climate-zone scale variations only with a limited number of sampled locations and also highlights the importance of evaluating the impact of climate change at local scales. Xu et al. [143] examined the impact of climate change on building heating and cooling energy use in California. Their forecasting results indicated that over the next 100 years electricity usage for cooling would increase by about 25% under the IPCC's most likely carbon emission scenario (A2) and the number would jump to 50% under the IPCC worst-case carbon emission scenario (A1F1). Wan et al. [144] assessed the impact of climate change on energy use in air-conditioned office buildings in subtropical Hong Kong, reporting that, compared to its 1979–2008 numbers, average annual building energy use would increase by 6.6% and 8.1% by the end of 21st century under the scenarios of low and medium radiative forcing levels, respectively. It follows that an accurrate representation of future weather conditions with the consideration of different Representative Concentration Pathways (RCP) scenarios from Intergovernmental Panel on Climate Change (IPCC) or scenarios from other climate prediction methods would be essential. As such, the top-down models, which represent long-term socio-demographic and market economic influences, have been frequently employed, although they lack in technological details to provide concrete policy suggestions.

Another challenging problem concerns model calibration. Rigorous model calibration is a key ingredident to superior performance in building energy modeling. Most of the exant studies have used on the national average building energy use data from U.S. EIA as the reference for model calibration. While the EIA's survey data is easy to access, models calibrated with the data may become unreliable as the spatial heterogeneity of energy consumption may result in significant energy use variations between specific locations and the national average. Billing data from utility companies may be an alternative instrument for improving model calibration, although such data is not widely available to the public.

4. Conclusions

In this paper, the top-down and bottom-up approaches for modeling urban building energy use are summarized and their strengths and weaknesses in a variety of applications are discussed. This review also focuses on the popular and widely used physics-based bottom-up models by providing a summary of the basic procedures using these models for simulating urban building energy consumption. Given the important role that geospatial techniques can play in modeling the citywide building energy use, this review also provides a summary of studies that apply geospatial techniques for top-down or bottom-up building energy use modeling. Finally, this review discusses challenges associated with model preparation and calibration.

The top-down approaches are simple to implement because of limited input requirement for establishing building energy models. Generally, the statistical methods are used to analyze building energy use based on market, economic and socio-demographic data. As the data are usually collected at the regional level, the top-down approaches are widely used for city, regional, national or other large-scale energy use modeling. However, the advantage of the top-down approaches comes with a price. In particular, the top-down approaches require long-term historical data of urban-scale energy consumption and socio-economic indicators. Modeling of building energy use is based mainly on the long-term analysis of the relationship between energy consumption and economic indicators. Given that socio-economic and physical conditions are likely to change over time due to, for example, new developments within existing urban areas and climate change, significant errors in the projection of future energy consumption may arise [74,89,145]. In addition, the top-down approaches are also incapable of representing the impact of new construction on existing buildings. For instance, high-rise buildings can shade near-by low-rise buildings energy use. However, such impacts cannot be fully represented as only a limited set of variables can be used in the top-down approaches. Moreover, the top-down approaches can only simulate and report energy consumption at the aggregated level, although building energy consumption is highly complex and subject to many physical factors and individual end-uses. Thus for those applications of energy modeling that can benefit from more details results, the top-down approaches may not be the most ideal.

The bottom-up approaches provide a much more detailed predictions of end-use and whole-building energy consumption. Instead of modeling the buildings sector as a whole, the approaches address individual buildings and/or their individual end-uses. The basic bottom-up approach is to apply statistical techniques to establish the relationship between billing and survey data and market economic and socio-demographic data, thus projecting energy consumption based on the derived relationship [89]. While the bottom-up statistical methods has gained popularity, they also have weaknesses. For instance, the methods are not suitable for identifying opportunities to increase building energy efficiency as they do not allow for high temporal (e.g., hourly or sub-hourly) energy consumption data [146,147]. Hourly or sub-hourly energy consumption data, as compared to lower frequency data, improve the capability of assessing the impact of energy-efficient technologies. Such high resolution data can provide timely information for characterizing energy use patterns, so that detailed end-use energy costs can be determined and existing problems can be identified.[148,149]. The physics-based bottom-up methods are suitable options for high resolution data. The methods represent building energy use solely based on detailed building information and surrounding weather conditions, with no requirement for historical data as inputs. The most distinct advantage of the physics-based bottom-up methods is that energy use is simulated for each end-use by fuel type at a relatively high temporal resolution (daily, hourly, and/or sub-hourly). Consequently, the methods can provide detailed energy use response information to establish a solid foundation for evaluating new technologies with, for example, improved energy efficiency in reducing building energy use. Moreover, compared with other approaches, physics based models can include passive solar design as a measure to improve energy use efficiency. In these models, the shading structure and geometry of a building can be defined all within a single energy modeling framework. Other objects, such as contruction materials, internal mass, and infiltration, can be easily defined directly in such physics based model. To sum up, the top-down approaches are suitable for analyzing and predicting aggregate-level, long-run building energy demand based upon historical data. In contrast, the bottom-up statistical approaches are well positioned to analyze energy demand at the individual building level usually supported by utility bill and survey data. The bottom-up physics based approaches are the proper choice for analyzing detailed energy demand of individual buildings or their end use services based on a detailed, comprehensive representation of technologies. The bottom-up physics based approaches thus allow for assessing the impact of new technologies on buildings energy use.

With the development and broad application of geospatial techniques, there is an increased demand for applying GIS techniques in building energy use studies. Specifically, the top-down approaches have been used to represent regional energy use in combination with GIS techniques, which enable the allocation and dissemination of spatial and temporal data. In addition, GIS techniques have also been coupled with the bottom-up approaches to scale up the simulated building energy use from the individual building level to urban, regional or even national level. In addition, given the numerous applications of the physics-based bottom-up models, we have also reviewed their general procedures for simulating urban building energy use found in the literature. We hope the review presented here can open a new avenue of research that facilitates the next generation of urban building energy use modeling.

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