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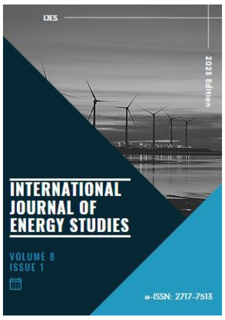

Review Article

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A comprehensive survey of the urban building energy modeling (UBEM) process and approaches

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Highlights

- A comprehensive and recent study of the various modeling approaches and modeling process used for urban building energy modeling
- A systematic literature review of the various modeling approaches and model building process used in this field
- Eliminating the confusion about concepts such as conceptual confusion, which tool serves for which purpose, and revealing studies on where the bottlenecks in these issues are in general

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ABSTRACT

Fossil fuels increase the emission values of greenhouse gases such as CO_2 in the atmosphere and cause global warming and climate change. At the same time, fossil fuel reserves are facing depletion in the near future, and energy supply also has an important dimension such as national security and foreign dependency. All these show that turning to renewable energy sources and developing solutions and policies for energy saving has become a necessity both globally and locally. For such reasons, modeling of urban structures, which have a great contribution to energy consumption, and simulating the energy demand on an urban scale are of great importance for the effective use of energy. Research on this has shown that UBEM (Urban Building Energy Modeling) is an effective solution to these problems. However, UBEM contains different technical problems for implementation. Due to its versatility, various concepts related to this field lead to complexity. With this increasing complexity, there is a growing need to compile concepts from a holistic perspective. In this study, it is aimed to create a solution to these challenges. For this purpose, a comprehensive and up-to-date research of various modeling approaches and model creation process used in urban building energy modeling has been conducted. Studies on these approaches are summarized and a systematic review of the literature is made. At the same time, the study is in the nature of guiding and forming the general knowledge level with the basic concepts that should be known to those who will work on UBEM.

Keywords: Urban building energy modeling, UBEM, UBEM approches, bottom-up approches, urban energy modeling

1. INTRODUCTION

Urban areas have great potential in terms of global climate change with the application of energy efficient methods. Because the energy consumption rates originating from cities will continue to increase in parallel with the rate of urbanization. Today, more than half of the world's population (57%) lives in urban areas, and the proportion of people living in urban areas is projected to reach 68% by 2050 [1, 2]. Globally, the energy demand of buildings accounts for one-third of total final energy consumption [3]. Urban areas account for 40% of final energy consumption and are the source of 70% of greenhouse gas emissions [4].

UBEM-Urban Building Energy Modeling is an important area where studies should be carried out and knowledge on this subject should be increased. Because the world is in a bottleneck due to finite energy sources and their negative effects on nature. For this reason, energy efficient measures in urban areas, which have a large share in energy use, have great potential.

UBEM is a bottom-up method that simulates the thermal performance of newly built or existing cities and neighborhoods [5]. UBEM is an effective simulation method that can be used to reveal the energy use of buildings and to take actions such as policies and precautions for this, and to provide various analyzes such as determination of peak loads [6, 7, 8]. The recent interest in urban building energy modeling continues to increase [9]. UBEMs are also supportive for the design of energy efficient cities when used effectively [10]. However, current approaches have limitations in representing a realistic UBEM and assessing energy use for these scales. Because cities are complex structures like an organic system by nature. It is in the form of self-organization rather than planning developments. Therefore, obtaining a true representation of these systems is challenging, as they are in complex interactions with many factors [11, 12].

UBEMs are created from a lot of data related to building systems. Establishing a reliable UBEM for larger scale regions causes some difficulties in data processing [13]. The accuracy of the data and tthe process of data processing have an impact on the effective use of UBEM. On the other hand, the two main challenges in the UBEM process are the lack of existing data and the difficulties in detecting stochastic data [14, 15]. A UBEM created in high resolution allows for detailed urban building energy analyzes where decision makers can better read the space [16].

In this study, it is aimed to create a solution to these difficulties by making a holistic examination of the conceptual confusion that UBEMs contain due to their multidisciplinary nature. For this purpose, a comprehensive literature review of various modeling approaches and modeling processes used in this field is presented. In terms of bottom-up methods, UBEM approaches are generally examined under three headings as Physics-based dynamic simulation, reduced-order calculation and data-driven methods. This study provides a systematic review of the literature on UBEM approaches, reviews recent work, and provides initial guidance to describe the process.

2. UBEM APPROCHES

UBEMs represent multiple networks of energy-related relationships of large-scale fields. Many methodologies and tools have been developed for use in UBEMs. Of these methodologies and tools, it is a great challenge for users to choose the one that best suits their complexity, accuracy, usability and data processing needs [17].

There are generally two different techniques for UBEM as top-down and bottom-up. Although they serve the same purpose, they follow different methods in doing so. Therefore, there are differences between the results obtained.

Top-down models use an estimate of total building energy consumption and other relevant parameters to correlate energy consumption with characteristics of the entire building sector. It acts on total energy consumption trends and macroeconomic indicators. It considers a group of buildings as a single energy asset and is often used at upper scale for energy demand projection [18, 19, 6]. Bottom-up models, on the other hand, calculate the energy consumption of individual residences or residential communities and estimate these indicators to represent them at the top scale, taking into account individual houses and their end-uses [18, 19]. Bottom-up methods are more suitable for constructing the energy model of urban buildings in terms of different climatic conditions, as local temperature, radiation and wind speed can directly affect the thermal physics of the building environment [20].

Many tools have been developed for the bottom-up approach, which is the most widely used when creating UBEM. Three of these tools that are in common use are: Physics-based dynamic simulation method, reduced-order calculation method, and data-driven method. Basic limitations in UBEM tools; the use of aggregate data to reveal energy consumption, the generalization of the status quo in the data-driven method, the superficial handling of the building system and the urban region, and the ignoring of the internal conditions and the effects of buildings on each other [12, 21]. UBEM tools are summarized in Table 1.

Table 1. UBEM tools by spatial scale [22]

Approach	Tool		Developer	Calculation method	Target Users
Physics-based dynamic simualtion method	CityBES	Web-based data and computing platform to evaluate energy performance of buildings	LBNL	EnergyPlus	Urbanist, policy-maker
	MIT UBEM Tool	Tool for city-scale hourly energy demand load calculation	MIT	EnergyPlus	Urbanist, policy-maker
	UMI-Urban Modeling Interface	Urban modeling interface to analyze the energy consumption of neighborhood scale	MIT	EnergyPlus	District energy manager
	Virtual EPB	Automated building energy modeling with machine learning analysis using high-performance computing	ORNL	EnergyPlus	Urbanist, policy-maker
	Tool by Columbia University	Tool for analyzing energy consumption at the community-scale through calibrated building energy models	Columbia University	EnergyPlus	District energy manager
	Tool by Cambridge University	Tool for analysis of building energy consumption for community-scale and display emission map	Cambridge University	EnergyPlus	District energy manager
	UrbanOPT	Modeling tool to integrate energy loads and renewable energy at the district-scale to develop	NREL	EnergyPlus, OpenStudio	District energy manager
	COFFEE	Utility customer optimization tool for use in improving energy efficiency	NREL	EnergyPlus, OpenStudio	Utility program
	CitySim	Decision support tool for urban energy planners and partners in minimizing energy consumption and emission	EPFL	CitySim Solver	Urbanist, policy-maker

	SEMANCO	Semantic tools for carbon minimizing in city planning	FUNITEC	Tool specific simulation engine	Urbanist, policy-maker
Reduced-order calculation method	SimStadt	Urban energy tool for city-wide energy consumption analysis	Hochschule für Technic Stuttgart	Reduced order model of ISO/CEN origin	Urbanist, policy-maker
	Energy Atlas	Spatial-semantic representation of urban structure containing information on energy demand	Tecnisch e Universitat München	Reduced order model of ISO/CEN origin	Urbanist, policy-maker
	LakeSIM	Modeling tool for infrastructure by assisting in analyzing the energy efficiency of new city block development	ANL	Reduced order model of ISO/CEN origin	Urbanist, policy-maker
	Tool by Georgia Institue of Technology	A tool for building energy modeling with GIS-Geographical Information System at city-scale	Georgia Institue of Technology	Reduced order model of ISO/CEN origin	Urbanist, policy-maker
	OpenIDEAS	Open-source framework for integrated district-scale energy evaluation	KU Leuven	Reduced order model of Modelica origin	District energy manager
	TEASER-Tool for Energy Analysis and Simulation for Efficient Retrofit	Tool for multi-building energy performance assessment	RWTH Aachen University	Reduced order model of Modelica origin	District energy manager
	City Energy Analyst	Computational framework for analyzing and optimizing energy systems in neighborhoods and city scales	ETH Zurich	Tool specific calculation modules	Urbanist, policy-maker
Data-driven method	UrbanFootprint	Planning tool to be used to access land use, policies and resources in different sectors	Calthorpe Analytics	Private datadriven solution	Urbanist, policy-maker
	Tool by New York University	A web-based tool to visualize energy benchmarking and predict energy demand	New York University	Data-driven regression model	Urbanist, policy-maker
	CoBAM	Tool to predict the adoption of energy-efficient technologies in building stocks	ANL	Data-driven regression model, Reduced order model of ISO/CEN origin	Policy-maker

2.1. Physics-Based Dynamic Simulation Method

Geometric and textural modeling of large-scale areas in digital environment is challenging and can be accomplished with simulation tools capable of advanced 3D modeling [23]. Bottom-up Physics-based dynamic simulation method is a new method compared to other tools, but it takes its infrastructure from BEM. However, there are several differences between the two tools. The physics-based dynamic simulation tool takes into account heat transfer in buildings and in the relationships of systems in buildings to each other. Bottom-up physics-based UBEM tools, which deal with the numerical representation of relationships with buildings and the environment around them, can analyze the energy consumption of buildings with detailed spatio-temporal clarity [17].

More efficient than statistical methods, physics-based bottom-up UBEM tools enable users to concretely evaluate retrofit strategies and energy supply options. Thus, it contributes to the determination of more effective policies and energy management [24]. Data-based method tools are also widely used in modeling energy in urban buildings. However, the lack of a physics-based engine in these vehicles has some limitations when considering design or retrofit scenarios [25].

The Physics-based dynamic simulation tool is commonly used in urban building energy modeling. However, due to the usual uncertainties associated with the determination of the energy demand of buildings at the city-scale, interrelating spatio-temporal human activity trends and socio-technical factors will improve the results of these tools [6]. Studies on the Physics-based dynamic simulation tool have been extensively researched and are summarized in Table 2.

Table 2. Summary of Physics-based dynamic simulation method studies

Source	Platform/tool	City/Region	UBEM objective
Nageler et al. [26]	IDA ICE	Gleisdorf, Austria	To provide a validated methodology for building modeling in urban areas based on publicly available data
Mohammadiziazi et al. [27]	-	Pittsburgh, Pennsylvania	Estimating the average annual intensity of energy use for different types of use through the identification of commercial-use archetypes
Davila et al. [28]	EnergyPlus	Boston, Massachusetts	To develop a city-wide UBEM based on GIS datasets and a dedicated library of building archetypes
Zarella et al. [29]	EnergyPlus	Padua, Italy	To demonstrate the reliability of the lumped-capacitance model in assessing the demand for heating and cooling at the urban level
Abolhassani et al [16]	EnergyPlus	Montreal, Canada	To propose a workflow to automatically extract, collect, and preprocess energy-related parameters from open-source data to enrich UBEM
Ali et al. [30]	EnergyPlus	Dublin, Ireland	To develop a hierarchical approach-based methodology for GIS-based residential building energy modeling at regional scale.
Vermeulen et al. [31]	CitySim	Paris, France	Using an urban energy simulator called CitySim in combination with a hybrid evolutionary algorithm
Polly et al. [32]	URBANopt	-	Explaining DOE's efforts to develop URBANopt, which will expand its open-source building modeling platform to zero energy zone scale
Lu et al. [33]	UMI	Vancouver, Canada	Integrating the outputs from CIMS, a non-spatial economic model, with buildings in UMI, a spatially open urban building energy model (UBEM)
Hong et al. [34]	CityBES	Manhattan, New York	To introduce CityBES, a web-based platform for supporting efficiency programs at the district or urban-scale.
Madrazro et al. [35]	SEMANCO	-	To conduct a detailed review of the SEMANCO project
Li [36]	UWG	Manhattan, New York	Integrating UWG and UBEM and quantifying Manhattan's building energy use by considering the local microclimate
Reinhart et al. [37]	UMI	Boston, Massachusetts	To offer UMI, which allows users to carry out operational energy, daylight and walkability assessments of entire neighborhoods

2.2. Reduced-Order Calculation Method

The working principle of the reduced-order calculation method is based on simplification of building systems and the relations of these systems with each other. This method, which is one of the urban building energy modeling tools, uses simple input and output information that requires a suitable model structure and normative values of the model parameters, allowing a rapid presentation of the energy consumption of a building. The Resistor Capacitance (RC) model is a common model form in many Reduced-order calculation methods. This tool is a first-order energy model based on the normative method, metastable state heat balance equations [34].

Although the bottom-up Reduced-order calculation method is less preferred than the other urban building energy modeling tools (Physics-based dynamic simulation method and Data-driven method), this tool is becoming more preferable day by day as it combines the advantages of the other two tools. Among these advantages, the use of a physical building increases the interpretability of the problem. In addition, the properties of the building can be determined by optimization techniques such as genetic algorithms. Therefore, the frequency of needing detailed building data is reduced [6]. Many studies have been done on this subject. However, studies usually bring local solutions. Studies on the reduced-order calculation method are summarized in Table 3.

Table 3. Summary of Reduced-order calculation method studies

Source	Platform/tool	City/Region	UBEM objective
Schiefelbein et al. [14]	OSM	Bottrop, Germany	To offer an urban energy modeling approach based on open source GIS datasets to reduce input data uncertainty and simplify city district modelling
Fonseca et al. [38]	CEA	Zug, Switzerland	To explain CEA, a computational framework for the analysis and optimization of energy systems in neighborhoods and urban areas
Heidarinejad et al. [39]	OpenStudio	United States	To create quickly reduced-order building energy models at the urban scale, using a systematic summary of the simplifications required for the representation of building exterior and thermal zones.
Prataviera et al. [40]	EUReCA	Padua, Italy	To offer a new open source tool for city-scale simulations
Nouvel et al [41]	SimStadt	Ludwigsburg, Germany	To introduce SimStadt, the urban energy simulation platform developed to support users in the planning of the energy transition at the urban scale
Maccarini et al. [7]	Modelica	Køge, Denmark	To provide an open-source tool to automatically transform 3D building models into ready-to-run Modelica models for urban energy simulations
Muehleisen & Bergerson [42]	UrbanSim	San Francisco, California	To explain the combination of UrbanSim with the ISO model to predict energy use and greenhouse gas emissions in an urban area
Kaden & Kolbe [43]	Energy Atlas Berlin	Berlin, Germany	To focus on city-wide forecasting of energy demands of buildings using the existing official geobase in Berlin and statistical data integrated with Energy Atlas Berlin
Li et al. [44]	GIS	Manhattan, New York	To create an city-scale building energy model that combines a reduced-order energy model with GIS.
Baetens et al. [45]	OpenIDEAS	-	To review the development of the OpenIDEAS framework, an open framework for integrated region energy simulations consisting of IDEAS, StROBe, FastBuildings, and GreyBox
Guo et al. [46]	GIS	Weyhe, Germany	Proposing a GIS integrated framework based on a low-level dataset and a custom-built library of archetypes to produce satisfactory results with a reasonable simulation time
Remmen et al. [47]	TEASER	Bonn, Germany	To demonstrate TEASER's capabilities at the building, neighborhood and urban scales by presenting its methodology and package structure

2.3. Data-Driven Method

Data-driven urban building energy modeling tools use simple comparison or more complex regression models to determine energy consumption. Building design and operational parameters are used to correlate with energy use. This tool relies on measured data such as hourly electricity data and energy usage density databases for benchmarking [34].

Data-driven tools combined with engineering or physics disciplines have the potential to increase modeling speed and computational efficiency, although modeling detailed energy consumption requires a lot of time and effort due to its complexity. Data-driven methods have the ability to integrate occupancy and socioeconomic factors into the creation of building archetypes and measuring the effects of these influential factors on urban energy consumption [10, 12]. However, data-driven methods have pros and cons and offer different performance in different situations [6].

Urban building energy modeling tools separately have a number of shortcomings. However, the data-driven method is the most widely used of these tools. Along with newly developed methods, studies are also continuing on combining data-based tools with machine learning [48, 49, 50]. Studies researched on the data-driven tool are summarized in Table 4.

Table 4. Summary of Data-driven method studies

Source	Platform/tool	City/Region	UBEM objective
Papadopoulos & Kontokosta [51]	XGBoost, GREEN	New York	To develop a building energy performance rating methodology using machine learning, city-specific energy use, and building data
Wang et al. [52]	CRECM, Statistical method	China	To develop a city-level REC calculation model
Fonseca & Schlueter [53]	GIS	Zug, Switzerland	To present an integrated model for the characterization of spatial-temporal building energy consumption patterns in neighborhoods and urban areas
Ma & Cheng [54]	GIS, Big Data, Regression	New York	Proposing a GIS integrated data mining methodology framework to predict urban scale building EUI, including preprocessing, feature selection and algorithm optimization
Kontokosta & Tull [55]	OLS, SVM, RF	New York	To develop a predictive model of energy use at building, district and city scales using education data from energy disclosure policies and predictors from widely available property and zoning information
Nutkiewicz et al. [48]	ResNet, Machine learning	California	To propose a new DUE-S framework that combines a network-based machine learning algorithm (ResNet) with engineering simulation to better understand how buildings consume energy at multiple temporal and spatial scales in a city
Alhamwi et al. [56]	GIS, Regression	Oldenburg, Germany	Modeling urban energy requirements, i.e. local electricity consumption and on-site renewable energy generation, using only open-source data and models
Abbasabadi et al. [57]	k-NN, ANN	Chicago, Illinois	To provide an integrated framework for UEUM that localizes energy performance data, considers the urban socio-spatial context, and captures both urban building operational and transportation energy use with a bottom-up data-driven approach
Ali et al. [58]	Deep learning	Dublin, Ireland	To develop a general methodology for optimizing residential energy retrofit decisions at urban scale using data-driven approaches
Hu et al. [10]	ST-GCN, Graph neural network, Time-series prediction	Atlanta, Georgia	Propose a new data-driven UBEM to synthesize the solar-based building dependency and space-temporal graph convolution network (ST-GCN) algorithm
Perwez et al. [59]	CBS, BSEM, Machine learning	Japan	Introducing a new hybrid model by integrating spatial and synthetic modeling approaches to facilitate simultaneous consideration of multiple building-oriented elements
Li et al. [60]	PCA	Jiangsu, China	To generate an urban building dataset of 539 residences and 153 public buildings to extract building morphology factors as determinants
Pasichnyi et al. [61]	Statistics, EPC	Stockholm, Sweden	Presenting an approach to using rich datasets to develop different building archetypes depending on the urban energy issues being addressed
Kristensen et al. [62]	SFH’s	Aarhus, Denmark	To demonstrate the application and performance of a newly proposed stochastic archetypal building modeling and calibration framework for constructing generally applicable physics-based bottom-up prediction models of district heating-provided buildings
Real et al. [63]	ME	Norway	Creating a nonlinear mixed-effect method of finding random differences in buildings with the same model

Dall'O' et al. [64]	Regression, GIS	Lombardy, Italy	To develop methods and strategies that accelerate the movement towards better energy sustainability at the urban level
Yang et al. [65]	CART, SFA	New York	Proposing DUE-B, a data-driven UrbanEnergy Benchmarking method for buildings using recursive partitioning and stochastic boundary analysis
Ali et al. [66]	Statistics	Dublin, Ireland	Creating a multi-scale archetype development methodology through different data-driven approaches
Wang et al. [67]	k-NN, SVR, LSTM	Jiangsu, China	To build five typical data-driven urban building energy forecasting models at the neighborhood scale.
Pasichnyi et al. [68]	Grey-box	Stockholm, Sweden	To present a data-driven approach to strategic planning of building energy retrofitting
Wang et al. [69]	LSTM	Jiangsu, China	Proposing an automated low-energy urban design framework, from simulation to data-driven technologies in urban building energy models
Nutkiewicz et al. [50]	Deep learning	Sacramento, California	Creating a DUE-S model by estimating the impact of various building energy improvements on city scale
Zhao et al. [70]	CoBAM, Statistics	United States	To propose an ABMS simulation method to predict the energy performance of multiple building stocks over time
Robinson et al. [71]	XGBoost, SVM, LR	Atlanta, Georgia	To present a technique for estimating commercial building energy consumption from a small number of building features by training machine learning models on national data from CBECS
Rahman et al. [72]	RNN	United States	Provide a recurrent neural network model to make medium- to long-term predictions of electricity consumption profiles in commercial and residential buildings at one-hour resolution
Williams & Gomez [73]	LR, RT, MARS	United States	To present a large-scale study applying statistical learning methods to predict future monthly energy consumption for single-family detached homes using building characteristics and monthly climate data
Pedersen et al. [74]	Regression	Norway	To provide a load estimation method that predicts heat and electric load profiles for various categories of buildings
Mastrucci et al. [75]	Multiple linear regression	Rotterdam, Netherlands	To determine the real energy consumption profile and savings potential of large housing stocks with a GIS-based bottom-up statistical approach

3. UBEM DATA TYPES

Deficiencies such as a standardized language, data collection process, and a set of test cases for verification prevent the widespread use of UBEM methods [17]. Technical and legal barriers to access to data, structural uncertainties and insufficient resources are among these deficiencies [76]. The ease of access to the detailed public building data required for use in UBEM is not valid for every country, which will cause critical errors such as inaccurate reading of urban energy use, as it may cause some simulation errors [77,78]. In this study, bottlenecks in the modeling process were examined under the title of UBEM Data Types. The issues to be examined were determined as follows; CityGML and IFC incompability, LOD, Archetypes, Uncertainty and calibration, Energy dynamics between buildings and urban microclimate.

3.1. CityGML and IFC Incompability

Developing an urban-scale dataset of the current building stock is an important step in automatically generating UBEM and analyzing its performance. Most cities in Europe and America have a fair amount of public data on creating UBEMs. However, this is not the case for other countries. Besides having public data, data can be in various forms without standardization and there is no common key to perform data matching [79]. The planning process, on the other hand, is two-level city/neighborhood scale and building scale, and in the first, GIS is used with CityGML as an open source 3D format. The second one applies the BIM creation process and the IFC format is an open source file format. Different data formats and data exchange takes place at both levels [80]. However, the inconsistencies in the current urban energy consumption data and the inability to integrate scalable building modeling tools to the upper scale caused a disconnection between BIM and UBEM [30]. That is, there are different approaches and basic standards for building and neighborhood scale models, namely IFC and CityGML incompatibility. The existence of mixed databases that make it difficult to create UBEM, the separation of two methods semanticly, the use of a different terminology between formats make data exchange and integration difficult [17, 80]. IFC is generally a 3D format on a one-dimensional surface and does not provide geographic information [80]. CityGML is an open data model and XML-based format for storing and exchanging virtual 3D city models. It is a universal topographic information model that describes available object types and attributes in different models [81].

There are two common methods for exchanging data between CityGML and IFC formats. The first method is to perform the integration via ADEs. This is the figural representation in separate XML schemas that refer to CityGML schemas. ADE is a kind of extension of the CityGML format for specific application areas. Indicates additions to the CityGML format, such as the number of residents of the building or the definition of new object types. It can be defined for one or several CityGML modules, providing high flexibility in adding additional information. However, this combination is not semantically ideal. It cannot be applied to existing models and integration is only in the context of data transformation [80, 81, 82, 83].

The other method is one-way conversion of IFC building format to CityGML format. Attempts are made to establish a connection between both GIS and BIM environments by creating a CityGML extension for IFC data called GeoBIM extension implemented in the open-source BIMserver [80, 84].

3.2. Level of Details (LODs)

In UBEM, sufficient geometric data is needed to represent buildings in a three-dimensional virtual environment. Even so, due to the lower level of detail in the existing data, open data models are often lacking in basic data, such as building geometries. This shortcoming in the heating loads analysis affects the energy consumption results [85]. Figure 1 shows components representing a typical building within the GIS data model.

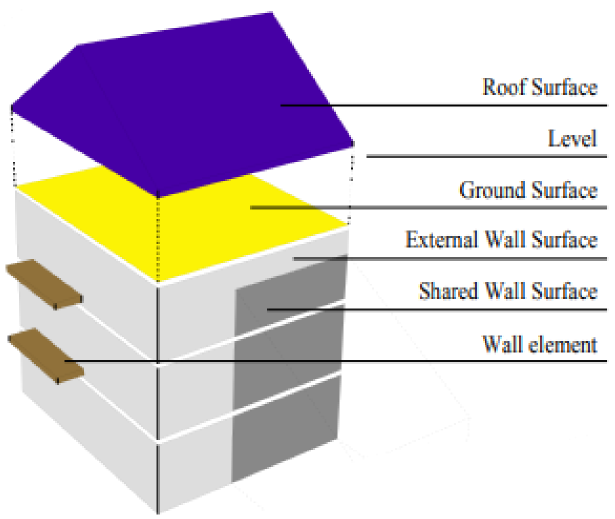

Figure 1. Components that represent a typical building within the GIS data model [86]

The creation and representation of 3D city models for urban areas requires great effort. The abundance of data that needs to be processed makes it difficult to work on this data and quickly make its 3D virtual representation. Detailed visuals cause operations in the virtual environment to occur at a low speed. The solution for these is provided by performing the modeling at various levels of detail (LoD: Level of Detail) for the purpose. With levels of detail, communication, sharing and display between complex and large-scale urban building energy models can be realized more quickly. The concept of scale for 3D buildings is expressed in levels of detail (LOD), and each of the LODs represents a specific level of generalization [23]. CityGML includes five consecutive Levels of Detail (LOD) where objects become more detailed with the LOD increasing both in terms of their geometry and thematic differentiation [81]. CityGML's five Levels of Detail, along with accuracy requirements, are specified in Table 5.

Table 5. LOD 0-4 of CityGML with its accuracy requirements [81]

	LOD0	LOD1	LOD2	LOD3	LOD4
Model scale description	regional, landscape	urban, region	urban district-scales, projects	architectural models (outside), landmark	architectural models (interior)
Class of accuracy	lowest	low	middle	high	very high
Absolute 3D point accuracy (position / height)	lower than LOD1	5/5 m	2/2 m	0.5/0.5 m	0.2/0.2 m
Generalisation	maximal generalisation (classification of land use)	object blocks as generalised features; > 6*6 m/3 m	objects as generalised features; > 4*4 m/2 m	object as real features; > 2*2 m/1 m	constructive elements and openings are represented
Building installations	-	-	-	representative exterior effects	real object form
Roof form/structure	no	flat	roof type and orientation	real object form	real object form
Roof overhanging parts	-	-	n.a.	n.a.	yes
CityFurniture	-	important objects	prototypes	real object form	real object form
Solitary Vegetation Object	-	important objects	prototypes, higher 6 m	prototypes, higher 2 m	prototypes, real object form
PlantCover	-	>50*50 m	>5*5 m	<LOD2	<LOD2
…to be continued for the other feature themes					

In CityGML format, the same object can be represented in different LODs at the same time. This enables analysis and 3D representation of the same object at different resolution levels. These are LOD0, LOD1, LOD2, LOD3 and LOD4. LOD0 is a 2.5D Digital Terrain Model on which an aerial image or a map can be overlaid. LOD1 is a block model consisting of prismatic buildings with flat roofs. A building in LOD2 can also accommodate a variety of roof types, various surfaces, and landscape elements. LOD3 represents models with detailed wall and roof types, balconies, partitions and ledges along with high-resolution textures. At the same time, detailed landscape elements and transportation objects are also a feature of this level. LOD4, on the other hand, is a level of detail added to LOD3 for interior structures (room, interior door, staircase, furniture) for 3D objects [81]. Five Levels of Detail are visually represented in Figure 2.

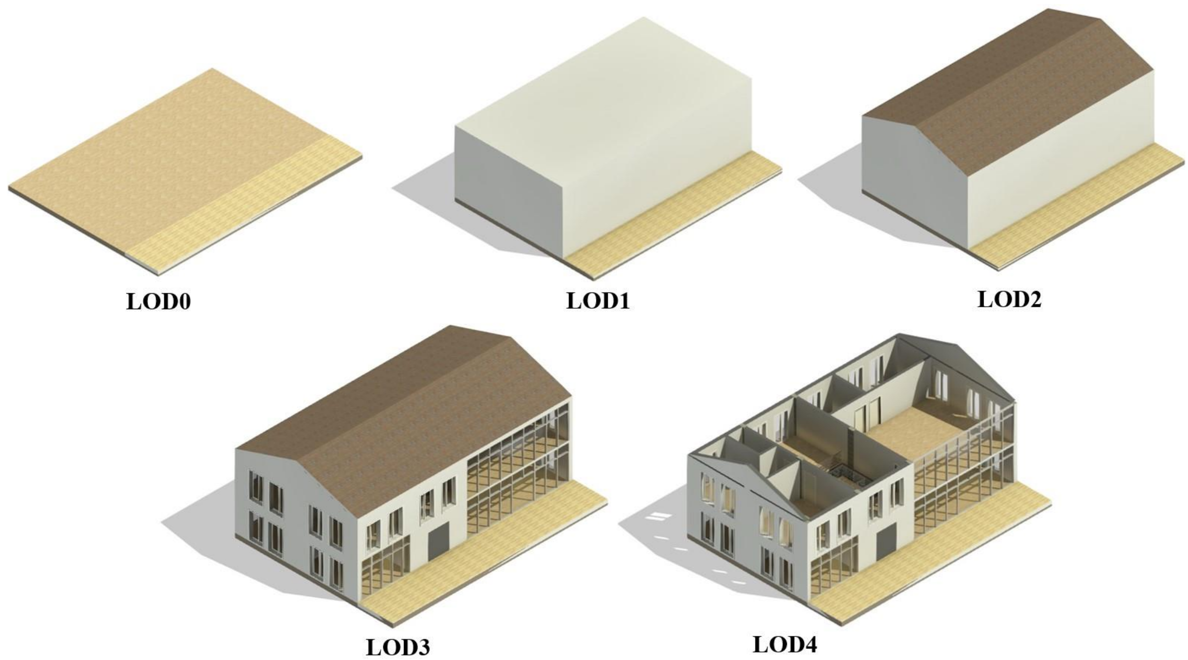

Figure 2. Representation of five Levels of Detail (LOD)

3.3. Archetypes

In UBEMs, the greatest uncertainty is associated with the definition and detail of archetypes that represent a building stock with high accuracy, nd groups of buildings are classified as "archetypes" in a standard way to reduce the simulation data requirement required [87, 88]. Archetypes provide a reduction of the data required in the formation of energy models of urban buildings [89]. The main reason for needing this archetypal solution is to cluster the building stock in a representative typology. Each model corresponding to a typology can be created with a minimum set of parameters such as the net floor area or the number of floors [90]. Considering the large number of data inputs needed for energy modeling of urban buildings, the archetyping solution can speed up the process. However, the lack of data revealing detailed building and energy consumption trends leaves the process to deterministic assumptions and the user's decision-making initiative. The resulting simplification can result in an inaccurate representation of urban energy demands [91]. The lack of archetypal templates and metered energy data often used may mislead the strategies to be developed for the energy demands of cities within the current workflows. This is one of the obstacles to the effective use of UBEM [28].

3.4. Uncertainty and Calibration

Obstacles to the efficient implementation of UBEMs are uncertainty about the data and the challenge of accessing quality, open energy demand data. Deterministics also cast doubt on the accuracy of UBEMs. Calibrating a UBEM to estimate its accuracy in analyzed building energy consumption, as well as model uncertainty due to insufficient data on thermal properties of buildings, or to reduce the error rate, is not suitable for many cities. Most of the time it can not be carried out. [87, 92]. However, additional data and Bayesian calibration can be used to reduce the uncertainty in the predicted parameter values in UBEMs [89]. Bayes ensures the accuracy of the analysis where there is measured data for comparison with the analysis result. Uncertainty analysis can provide a distribution of possible demand values at the building scale, which can be useful when users do not have reference consumption values [14]. While uncalibrated physics-based modeling methods are very likely to contain errors, models using Bayesian calibration have consistently detected lower errors in hourly temporal resolution [93].

3.5. Energy Dynamics Between Buildings and Urban Microclimate

Current UBEMs lack the ability to evaluate a network of relationships (microclimate, GBIs, LCA, etc.) that can have a significant impact on determining building energy consumption. In order to do this, it is worked by combining with various software, but a complete unification has not yet been achieved. This makes it difficult for the modeler to manage input-output between different software [17, 48]. Current urban building energy models often causes in long simulation time due to high data processing and local climate effects are ignored. Because these models use a single weather file for an entire city for efficiency reasons [20]. However, the heat exchange between buildings and the surrounding environment can greatly improve both the determination of the building's energy consumption and the simulation results for the heat island effect and outdoor comfort conditions [17, 94, 95]. At the same time, incorporating the urban local microclimate into

UBEM when assessing the building's thermal response and resistance to extreme weather conditions is crucial to obtain realistic simulation results [96]. To further develop UBEMs, effects such as microclimate need to be integrated with other urban models [76]. It is necessary to leverage this information to improve UBEMs by integrating influences such as mutual shading and microclimate into the modeling process. It is necessary to ensure that the simulation engines include this in calculations and do so with acceptable computational accuracy in UBEMs [97].

4. CONCLUSION

Urban building energy modeling approaches are an area that every country will have to adapt to day by day. UBEM will enable energy consumption trends in urban areas to be revealed in order to determine future plans and strategies in this area. In this study, a comprehensive and up-to-date research of various modeling approaches and model creation process used for urban building energy modeling was conducted. Due to the multidisciplinary nature of UBEMs, it is aimed to create a solution to these difficulties by making a holistic examination of the conceptual complexity involved. In terms of bottom-up methods, UBEM approaches are generally examined under three headings as Physics-based dynamic simulation, reduced-order calculation and data-driven methods. These UBEM methods analyze some of the relationships related to buildings in depth and examine some parameters superficially. Therefore, it is important to choose the appropriate method that serves the purpose. The outcome of the study is that it helps to eliminate confusion about concept confusion and which tool serves which purpose. At the same time, it is to reveal the key information that the user should know about the subject and the studies on which issues are usually the bottlenecks in these issues. In this regard, it is intended to guide users such as urban planners, architects, building modelers and decision makers.

UBEM has problems such as the lack of building stock system and data sets, the need to create an extra algorithm according to the selected vehicle, and the difficulty of obtaining some of its current data. Most cities in Europe and America have reasonable public data on establishing UBEM. However, this is generally not the case for other countries. There are problems with the standardization of data. Therefore, a UBEM suitable for every region is not yet available. It is also necessary to establish a link between different tools where impacts are evaluated, such as microclimate, UHI and interactions between buildings. The creation of hybrid models from the three UBEM tools examined in this study (reduced-order calculation method, data-driven method and physics-based dynamic simulation method) and their combination with machine learning have great potential for UBEMs to deliver realistic results.

NOMENCLATURE

BEM	Building Energy Modeling
IDA ICE	IDA Indoor Climate and Energy
UWG	Urban Weather Generator
OSM	OpenStreetMap
CEA	City Energy Analyst
EUReCA	Energy Urban Resistance Capacitance Approach
StROBe	Stochastic Residential Occupancy Behaviour
XGBoost	Gradient tree boosting
CRECM	REC Calculation Model at the City Level
REC	Residential Energy Consumption
EUI	Energy Use Intensity
OLS	Ordinary Least Squares
SVM	Support Vector Machine
RF	Random Forest
ResNet	Residual Network
DUE-S	Data-driven Urban Energy Simulation
k-NN	k Nearest Neighbor
ANN	Artificial Neural Network
UEUM	Urban Energy Use Modeling
ST-GCN	Spatio-Temporal Graph Convolutional Network
CBS	Commercial Building Stock
BSEM	Building Stock Energy Model
PCA	Principal Component Analysis
EPC	Energy Performance Certificates
SFH’s	Single-Family Houses
CART	Classification and Regression Tree
SFA	Stochastic Frontier Analysis
DUE-B	Data-driven Urban Energy Benchmarking
SVR	Support Vector Regression

LSTM	Long Short-Term Memory
CoBAM	Commercial Buildings Sector Agent-based Model
ABMS	Agent-Based Modeling and Simulation
CBECS	Commercial Buildings Energy Consumption Survey
RNN	Recurrent Neural Network
LR	Linear Regression
RT	Regression Trees
MARS	Multivariate Adaptive Regression Splines
CityGML	City Geography Markup Language
IFC	Industry Foundation Classes
ADE	Application Domain Extensions
BIM	Building Energy Modeling
LOD	Level of Detail
GBIs	Green and Blue Infrastructures
LCA	Life Cycle Assessment
UHI	Urban Heat Island

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DECLARATION OF ETHICAL STANDARDS

The authors of the paper submitted declares that nothing which is necessary for achieving the paper requires ethical committee and/or legal-special permissions.

CONTRIBUTION OF THE AUTHORS

Melik Ziya Yakut: Wrote the manuscript.

Sinem Esen: Wrote the manuscript.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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