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Urban energy use modeling methods and tools: A review and an outlook

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A B S T R A C T

Urban energy use modeling is important for understanding and managing energy performance in cities. However, the existing methods and tools have limitations in representing a realistic urban energy model and supporting energy performance evaluation at urban or neighborhood scales. In addition, there is a lack of an integrated approach for modeling and analyzing different components of urban energy use. The existing methods and tools for assessment of urban energy use often reduce the urban energy use definition to operational energy of buildings, ignoring other essential components such as transportation energy, and embodied energy of buildings and infrastructure. In addition, reliable and accurate urban energy prediction remains a challenge as methodological uncertainties that are embedded in the common methods are often not considered. This, in turn, affects the suitability of these approaches for decision-making purposes. The key limitation of data-driven methods stem from the use of aggregate data for energy use estimations and generalizing the status quo. In simulation-based methods, oversimplification of the urban context and failure to account for occupancy and human-related factors, and urban microclimate and inter-building effects are the major limitations. The present article provides a review of the current modeling methods, tools, and techniques in urban energy use modeling. It examines the strengths and limitations of each and presents an outlook for a future urban energy use modeling (UEUM) approach that could capture different components of urban energy use through a bottom-up hybrid data-driven and simulation-based techniques to build upon the strengths of the two methods while reducing the modeling uncertainties.

1. Introduction

Rapid urbanization increases demand for energy and consequently Greenhouse Gas (GHG) emissions in cities [1]. To support climate action plans and achieve more sustainable and resilient cities, understanding and managing urban energy use is essential [2]. Accurate representation of existing urban energy profiles can significantly help in early-stage energy driven planning, design and optimization as well as the application and evaluation of energy efficiency policies [3–5]. However, the limited information on energy use by urban buildings, transportation, and infrastructure with high temporal and spatial resolution makes it a challenging task. Urban scale energy modeling aims to tackle this challenge via generating the essential quantitative energy information data through utilizing different approaches such as simulation engineering-based or physics-based models and data-driven methods including statistical and artificial intelligence-based techniques [6–8].

Despite the immense attention on developing urban energy use modeling tools and methods with the potential to identify sustainable paths toward energy management of cities, they still have limitations to present a realistic urban energy model [3,9,10]. This is due to methodological uncertainties embedded in these methods and tools. Modeling urban energy use is a challenging task because of the complexity of urban systems, lack of data, and extensive amount of time and modeling effort which is required for an accurate urban scale modeling [10–12]. For instance, a broad range of variables of urban form, technological, and human-related factors are required to be determined to model different components of urban energy use such as building operational energy, transportation energy, and building and infrastructure embodied energy. However, the required data representing building stock, urban spatial patterns, occupant behavior, and mobility patterns among other related contextual information are often missing or have limitations in terms of quality. The available tools for urban energy modeling often focus on a singular component of urban energy use rather than an integrated approach, while these components are interrelated at different levels. Accordingly, the question remains how to enable an accurate, time efficient, and feasible approach for integrated urban energy use modeling.

The main objectives of the present article are to provide a review of key methods and tools for urban energy modeling and highlight

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Nomenclature

AI	artificial intelligence
AHC	agglomerative hierarchical clustering
ANN	artificial neural network
CART	classification & regression tree
CDR	conditional demand analysis
CNN	convolutional neural network
DNN	deep neural networks
ELM	extreme learning machine
GP	genetic programming
HMR	Huber M-estimation regression
k-NN	k nearest neighbor
LR	logistic regression
ML	machine learning
MLP	multi Layer perception
MLR	multi linear regression
NLR	non-linear regression
OLS	ordinary least square
PR	polynomial regression
RBF	radial basis function
RF (RDF)	random forest (random decision forest)
RNN	recurrent neural networks
SLFN	single layer feed-forward neural network
SLP	single layer perception
SLR	simple linear regression
SVM	support vector machine
SVR	support vector regressor
ABMS	agent-based micro-simulation
CAD	computer aided design
EE	embodied energy
EIO	economic input-output
GIS	geographic information systems
GSE	general spatial equilibrium
HVAC	heating, cooling, and air-conditioning
UEUM	urban energy use modeling
SVF	Sky View Factor
LCA	life cycle analysis
PB	process-based
RC	rule-based computation
RUC	random utility choice
SSA	static spatially-aggregate
UBEM	urban building energy model
UHI	urban heat island
EIA	Energy Information Administration
GDP	gross domestic product

limitations and strengths associated with each. The novelty of this review article is a comprehensive review on essential elements of urban energy use including building operational energy, transportation energy, and building and infrastructure embodied energy and an in-depth study on data-driven and simulation-based methods. The article also aims to envision an outlook for future urban energy modeling tools. It proposes an integrated urban energy use model that captures multiple leading contributors to urban energy use through a hybrid simulation and data-driven based approach. A hybrid model of two methods could provide the opportunity of coupling the strengths of both methods and including factors which each model alone cannot incorporate. For example, there is an opportunity to achieve more realistic building archetypes, occupancy-related factors, and microclimate effects through applying data-driven models, which simulation-based methods often have limitations to meet. An integrated urban energy model that enables modeling components of urban operational and embodied energy can provide a more holistic image of urban energy use and help understand the interrelation between various components and the trade-offs between the different planning and design strategies to achieve more sustainable cities.

2. Urban energy use modeling approaches and methods

In the present article, urban energy use is composed of four key components: building operational energy, building embodied energy, transportation energy, and road and infrastructure energy. Building operational energy here is defined as the energy used for heating, cooling, lighting, and operating of appliances of buildings. Building embodied energy comprises the total energy that it takes to construct, maintain, and demolish buildings and their associated transportation [15]. And, transportation energy includes the energy used by urban residents via different modes of travel (such as bus, car, train) for different purposes such as commuting to work. The road and infrastructure energy include the embodied energy used for construction, maintenance, and operation of the roads and infrastructure in a city [16].

Most existing methods for modeling and analysis of energy consumption in cities reduce urban energy use to urban building operational energy. Transportation is another leading contributor to urban energy demand [167], without consideration of which urban energy use reduction cannot be effectively achieved [13,17]. However, there exists a limited number of methods and tools that quantify the effects of planning strategies on urban spatial patterns, travel demand, and transportation energy use. Indeed, urban transportation energy modeling is associated with high degrees of complexity and uncertainty, mainly because of the complex nature of urban systems and multi-faceted transportation models that depend on factors such as land use patterns, travel behavior and human activity [19,20].

A comprehensive urban energy use estimation also needs to take into account the life cycle effects of material flows in the city, in addition to building operational and transportation energy use. Assuming that the consumption of goods and products remain the same across various neighborhoods within a city, embodied energy of buildings, roads, and infrastructure can vary and has to be accounted for. The existing urban energy estimation tools and methods often ignore the effects of embodied energy. Indeed, previous studies on embodied energy commonly emphasize on representing energy tracks for distinct materials or single buildings [21], without expanding the microscale to a larger urban context.

There exist numerous studies that attempt to examine these individual components of energy consumption in cities. Modeling and estimation of these components individually without an integrative approach is suboptimal and lacks the needed comprehensiveness in an urban energy prediction model. An integrated approach is therefore required to achieve the future energy efficiency and emission reduction goals. Urban energy use models can provide insight on existing profiles of energy use in cities, help forecast and predict future urban energy demand and supply, and compare alternative scenarios of urban development with regard to their energy use implications.

Swan and Ugursal [6] classify the existing methods of building operational energy use estimation into two key types of methods: the top-down models and bottom-up models. Urban scale energy use modeling approaches are also categorized into the same classifications [19,23–25]. Top-down models examine cities at a macro scale. They are not concerned with individual end-uses; rather, they treat the built environment as an energy user and utilize historical aggregated energy data to understand how energy is used in cities [6]. The strengths of top-down approaches are in their inclusion of - techno-socioeconomic effects, reliance on available aggregate and historical energy data, and the opportunity that they present for longitudinal studies over a prolonged period of time. In previous studies, top-down methods were used to extract the relationships between urban energy use and macroeconomic, demographic, and technological effects. Bianco et al. [26], for example, examine the influence of economic and demographic factors such as population and gross domestic product (GDP) per capita on yearly electricity use in Italy by using historical data. This study developed an urban energy use predictive model based on various regression methods. In another study, Lin and Liu [27] investigate building energy consumption in China by developing a macroeconomic approach that investigates how urban building energy use is affected by macroeconomic factors. The key limitation in top-down models is about the use of aggregated data for energy use estimation and the generalizing of the existing conditions. Hence, this type of models is less reliable for investigation of urban energy supply-demand.

Unlike top-down models, the bottom-up approach localizes energy use studies and considers urban attributes at the microscale of individual units, i.e., individual buildings or a collective set of buildings. This model extrapolates the energy use estimation of individual end-uses to regional and national scales. Hence, this approach is built upon a microscale framework that relies on extensive data to examine the energy consumption of each user [29].

The present review article mainly focuses on bottom-up approach, which is the dominant and the most applied approach for urban energy use modeling [3,6]. The Bottom-up approach is classified into two main groups: simulation-based engineering models and data-driven models, including statistical and artificial intelligence-based models. Simulation-based models are easily adaptable to be linked with design programs such as building information modeling (BIM) tools to aid designers at an early stage design process or assessing the different energy efficiency strategies such as retrofit analysis. Also, they enable application of renewable energy resources in modeling. The main limitations of simulation-based models often stem from the simplification of building system, urban context, and influential factors such as occupancy and urban microclimate effects [30,31]. For an urban building energy use modeling, they often rely on a limited number of archetypes to enhance speed and reduce the computational effort required for urban scale modeling which affect an accurate representation of urban energy use, building stocks, urban settings, and human-related factors across a city.

On the other hand, data-driven based bottom-up method relies on actual empirical energy data and allows for a more realistic representation of urban energy use if sufficient data are available, and adequate variables are incorporated in the model [32–34]. The accuracy and reliability of this model mainly depend on the availability and quality of large data sets and explanatory variables. The limitation of data-driven models stem from often relying on the aggregated data; yet, a limited number of datasets provide disaggregated building and transportation energy data at building and household level. Chen et al. in Ref. [35] study the available public data sources and the capabilities of the current data standards for urban building energy use modeling for major cities in the U.S. The results suggest that there are adequate public data for most cities in the U.S. to support urban building energy use modeling. However, the existing data are provided without standardization and without a common identifier , which makes applying and merging different large datasets a challenging task. It should be noted that the data-driven models are considered as not being cost-effective when data is not available. In addition, they have limitations in terms of modification of different design scenarios. Fig. 1 shows the common methods for urban energy use modeling and summarizes the limitations and strengths of each model. These approaches are discussed in section 2.1 and section 2.2 in detail.

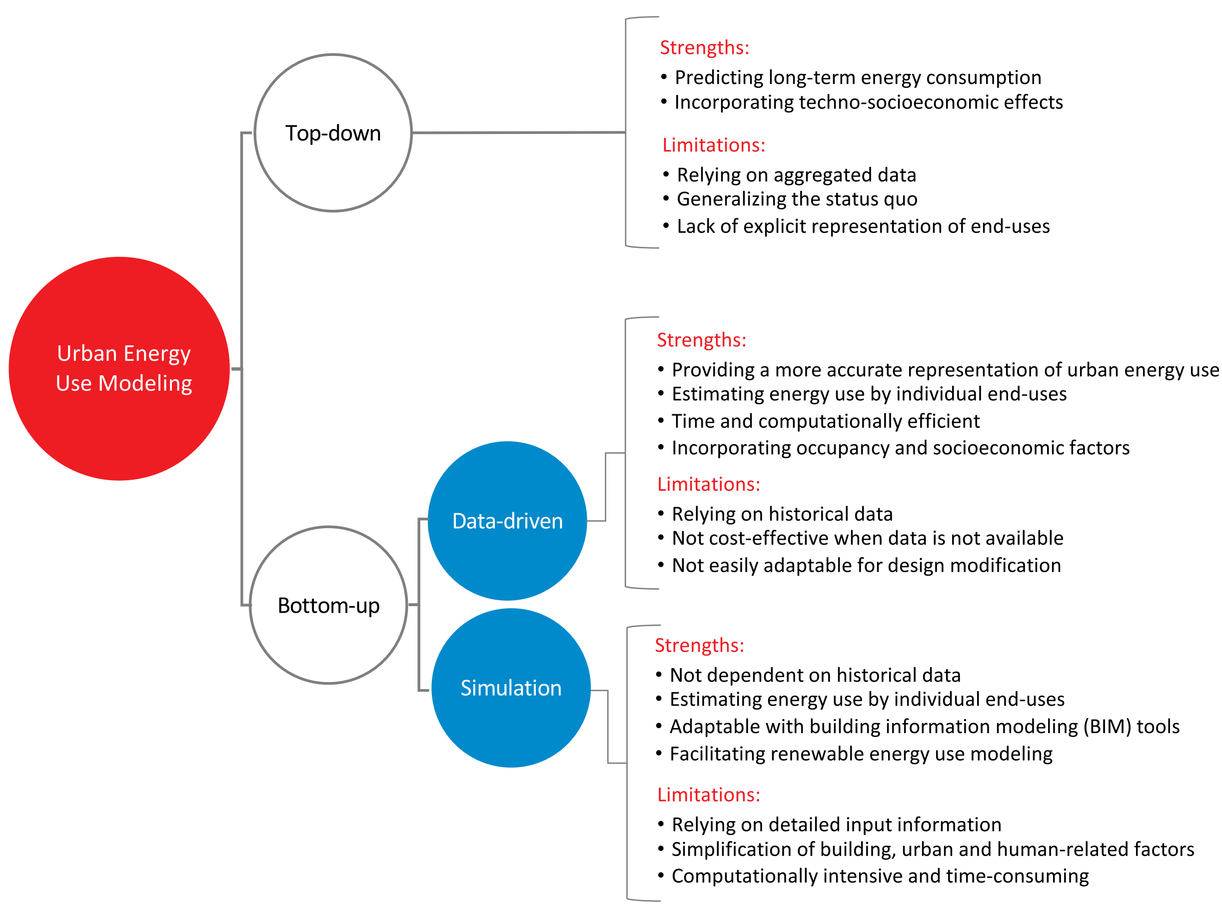

Fig. 1. Comparison of common urban energy use modeling approaches.

2.1. Data-driven models

The data-driven models use large sample sizes of government-, utility-, or locally-provided operational energy datasets and apply statistical and artificial intelligence techniques to mathematically associate the characteristics of end-uses with its energy use. Once the mathematical relationship is identified, the model can then estimate the energy use of individual end-uses. If sufficient variables are incorporated, the data-driven models can present a more accurate representation of urban energy use, as compared with urban-scale simulation-based approaches. This model has also the potential to account for variables such as occupant behavior which cannot be easily captured in simulation-based models. The data-driven models, however, rely on survey-based questionnaires that often times do not cover all variables at building, neighborhood, or city scales. The advantages of the data-driven model may, therefore, be compromised because of datasets with missing data or insufficient variables.

The most common data-driven models apply statistical and artificial intelligence (AI) simulation manily based on machine learning (ML) methods to model energy use of urban buildings and transportation through automatically "learning" the patterns in energy data, as a training dataset, to fit the model and find the mathematical relationship between energy use, and effective factors such as building characteristics, urban attributes, and occupancy features. This method is pursued in two key steps: 1) identifying statistical patterns in data, and 2) predicting from those patterns. Previous data-driven studies on urban energy use modeling have utilized statistical based algorithms such as simple linear regression (SLR), multi linear regression (MLR), non-linear (polynomial) regression (PR), conditional demand analysis (CDR), Huber M-estimation regression (HMR), and AI-based algorithms such as artificial neural networks (ANNs), support vector machine (SVM), k-nearest neighbor (k-NN), random forest (RF) or random decision forest (RDF), and classification and regression tree (CART) as well as clustering techniques for instance k-means (KM) clustering and agglomerative hierarchical clustering (AHC) algorithms [36–38]. Fig. 2 presents the most common data-driven models applied in previous studies.

2.1.1. Statistical models

The SLR and MLR algorithms are widely utilized for modeling energy-use of both building and transportation sectors. These models are easily interpretable and appropriate for demonstrating the relationships between predictor variables and building energy use [39] as well as transportation energy use [40]. The linear regression is one of the

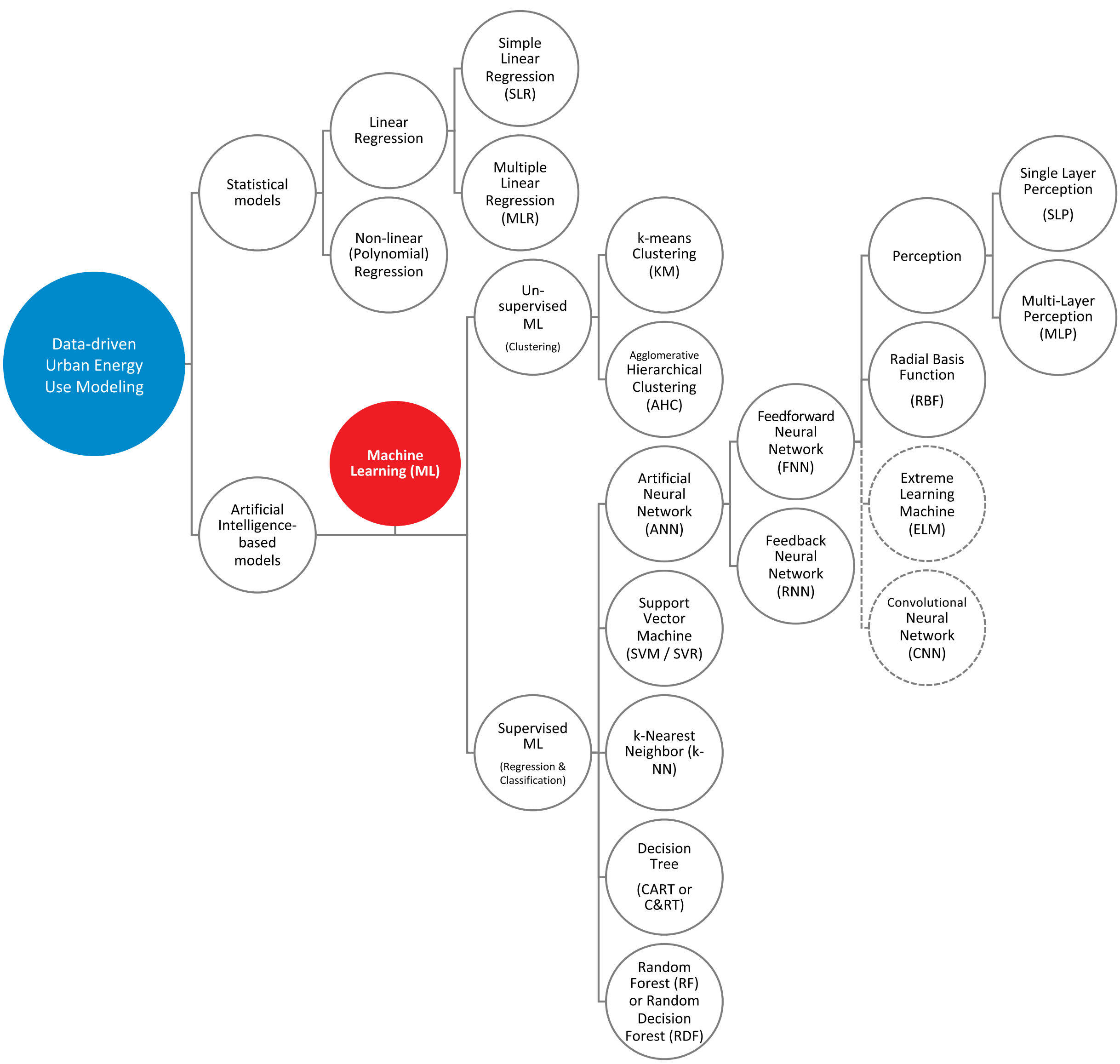

Fig. 2. Data-driven approaches for urban energy modeling.

common algorithms for energy use modeling and prediction, which is applied where the unknown variables for a model need to be estimated. This method is widely applied in the energy consumption prediction models for its computational effectiveness, sufficient precision, and simple design [4,41,42].

Kontokosta applies the MLR to estimate energy use of urban buildings through using New York City Energy Benchmarking (2011) dataset [43]. In another study, Kuusela et al. also utilize MLR method to predict energy consumption using building attributes at the neighborhood scale [44]. Dagnely et al. [45] evaluate the accuracy of the linear regression with ordinary least square (OLS) and SVM methods through an autoregressive model showing that both methods can provide an acceptable performance accuracy level. Kontokosta and Tull [4] compare the linear regression with OLS, RDF, and SVM algorithms in a data-driven city-scale energy predictive model for buildings in New York City, finding that the linear regression with OLS method has superior performance than the RDF and SVM at city level generalizing.

However the MLR algorithm is widely used for energy use prediction because of its simplicity and interpretability, this model is not capable of capturing non-linear and complex patterns [41,46]. The coefficient in MLR is interpreted as how a unit of change in a predictor causes a unit of change in target variable, but it provides only information about value of the change the direction through a positive or negative sign. This model is not capable of capturing the real-world non-linear and complex patterns [47].

Another recent study by Cheng et al. [48] compares PR and ANNs algorithms on a variety of datasets and indicates that in all cases the PR provides results at least as good as, and often better than, ANNs [48]. The Logistic Regression (LR) is also used in the building energy-related studies for classification problems when the outcomes are not continuous such as retrofit analysis or defining classes of data. For example, Marasco and Kontokosta applied LR for retrofit purposes [49]. The CDR algorithm is also applied to forecast the energy use of buildings at urban scale [50]. In another study on energy use prediction of buildings in New York City, Howard et al. use HMR algorithm. In this study, the urban building energy use prediction is applied at a ZIP code level resolution [51].

2.1.2. Artificial intelligence-based models

Artificial intelligence (AI) algorithms for urban energy use modeling rely mainly on machine learning (ML) techniques and are classified into two major groups: a) classification and regression, known as supervised models, including algorithms such as ANN, SVM, k-NN, CART, RF; and b) clustering algorithms, known as unsupervised models, such as k-means and AHC algorithms [52,53]. Unlike the supervised models, the unsupervised techniques have no response (Y) variables.

ANNs [54] are among the most remarkable classification and regression models, inspired by biological neural systems. ANNs create a network of nodes and layers and allow capturing nonlinear patterns in the model [55]. ANNs are commonly categorized into two main classes in terms of connection patterns: feedforward neural network (FNN) and feedback or recurrent neural network (RNN) of which the FNN is the most common-use model in energy prediction problems. FNN is divided into two subsets: 1) single-layer perception (SLP) and multi layer perception (MLP) and 2) radial basis function (RBF) networks in which MLPs are more popular networks among others [56]. SLP includes no hidden layers, while MLP comprises of at least a single hidden layer. Extreme learning machine (ELM) [57] is a single layer feedforward neural network (SLFN) in which the bias and weights of the input layer are captured randomly in training the data. This character enables ELM networks to perform the task [extremely] faster than the regular networks [57,58], however the accuracy of predicted values is not guaranteed to be higher than the regular MLPs. Indeed, ELM is a proper choice for quickly generalizing the tasks in applying big data which can be a good fit for urban scale problems. Fig. 3 illustrates the diagram of an MLP-ANN with single hidden layer and components of a node within the network. The ANNs perform based on experience with no explicitly for determining mathematical correlations between variables. Thus, ANNs are not programmed for a specific task, but rather, they are trained during the learning process by using actual data, then predict the outputs.

Sajjadi et al. in Ref. [59] use ELM for multi-step time-series for heat energy prediction and compare the model against the regular ANNs and generic programming (GP). The findings of this study confirm a higher level of accuracy, generalizability and time efficiency of ELM model. In another study [60] MLP-ANN was applied for operational energy modeling for office buildings and report a high level of prediction performance for the proposed time-series model. Hong et al. [61] also apply MLP-ANN for energy benchmarking for educational buildings in the UK. In case that ANNs consist of more than one hidden layer, the network is called deep neural network (DNN). The convolutional neural network (CNN) is one of the most preferred models in deep learning which has potentials in less-preprocessing of input data through scaling down the number of parameters. This means that the input variables are not fully connected to the subsequent layer (Fig. 4). CNNs are commonly used in solving actual world problems. Nutkiewicz et al. [62] apply CNN model to propose a hybrid data-driven and simulation-based model for incorporating microclimate effects in urban energy use modeling. They have applied the framework for a campus case study. Rahman et al. [63] use time series RNN model for hourly energy use prediction indicating that the model provides higher accuracy compared with the regular MLP model at an individual building level.

SVM [64] is another promising ML model, which is used for solving non-linear and classification problems [65]. The SVM defines a

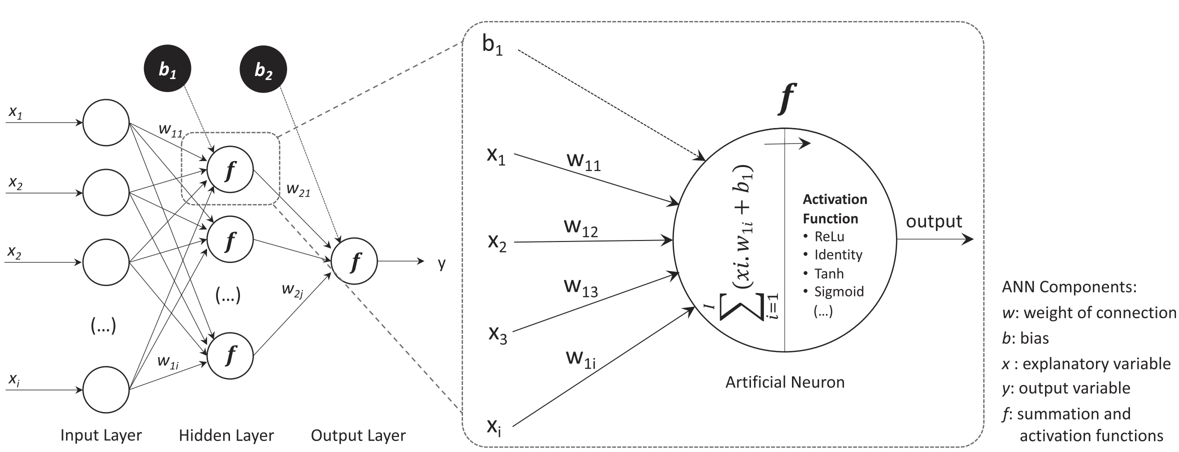

Fig. 3. Schematic of the single-layered MLP-ANN (left) and a node components (right).

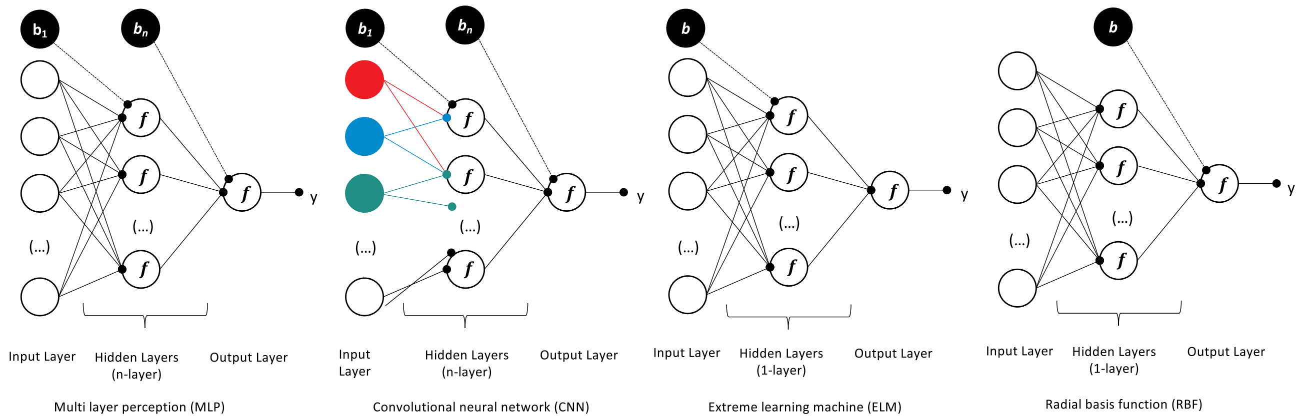

Fig. 4. A schematic of the morphological differences between four feedforward neural networks: MLP, CNN, ELM, and RBF (left to right).

hyperplane in an N-dimension space in which the data points are classified. Out of many possible locations for the hyperplanes, the one that can provide the widest margin (street) between the class of data is the expected answer. Then, through the optimization process, this margin is iteratively maximized (Fig. 5). The SVM has also been used in literature to predict urban building operational energy use. Li et al. [66] apply a hybrid model of SVM using an optimization algorithm to forecast the energy use for a smart community. The method couples the SVM model with genetic algorithm optimization and grid-searching. The results confirm the accuracy of the hybrid SVM compared with the conventional SVM model. The SVM model which is applied for solving regression problems is usually called SVR [67].

Liu and Chen [68] compare the effectiveness of SVM and ANNs in energy use prediction; the results of this study suggest that the SVM prediction performance is higher than ANN methods. Another previous study by Fernandez and Penya [52] tests the effectiveness of the AR, PR, ANN, and SVM algorithms in energy use prediction. They report that ANNs and SVM against their complex configuration show almost the same effectiveness compared with the other algorithms.

k-NN [69], C&RT [70], and RDF [71] algorithms also stand as well-established ML algorithms which allow classification and regression problems when non-linear and complex patterns are expected to be solved. The k-NN model is mostly used where 1) a deterministic probability distribution of a data is no available; 2) the train data is noisy; and 3) the data is high-dimensional. Fig. 6. (Left) illustrates a simplified k-NN classification process for two classes of features in 2D space at spot x between the two. Fig. 6. (Right) shows the schematic model of RDF comprised of n number of trees.

In a previous study, Tso and Tau [72] use CART model to predict the electricity demand for four types of residential building in Hong Kong, China based on survey-based data. The results show that the CART model has better performance relative to those captured through the regression and MLP-ANN models. Bogomolov et al. [73] develop an energy demand predictive model for reducing the primary energy generation and distribution costs for the Trentino province, Italy, in which the behavioral dynamics of users are scrutinized. An RDF model as a non-linear time series regressor on a daily-basis seasonality uses massive telecommunication (600 million features) and energy use data to forecast the daily-mean and peak daily electricity consumption. The outcomes indicate that the performance of RDF model is strikingly higher than the conventional baseline approaches in solving regression problems for large scale and time series data.

In another research, Al-Qahtani and Crone [74] develop a multivariate k-NN regression model for a time-series data in predicting the electricity demand in the UK. The outcomes were evaluated by using the empirical electricity data. It was found that the accuracy of the outputs via k-NN application is higher than those captured through utilizing common mathematical methods. Valgaev et al. [75] apply k-NN for forecasting the electricity consumption for urban buildings under the "Smart-City-Demo-Aspern" project in Vienna, Austria. By using the aggregated data, the electricity use of individual buildings was predicted and compared with the existing predictive techniques. Three typologies of urban buildings (housing, dormitory, and kindergarten) were tested for the project. The k-NN forecaster showed 7% and 23% more accuracy for predicting the electricity of the dorm and school, respectively, compared with the existing Individual Load Profiles (ILPs) model. Unlike the above two typologies, it was found no discrepancies in using the k-NN for the housing sector.

Abbasabadi in Ref. [76] developesan integrated data-driven framework for urban energy use modeling (UEUM). This framework is tested for the city of Chicago. It evaluates the accuracy of six well established algorithms including MLR, NLR, RDF, k-NN, CART, and ANN. The result of this research suggests that k-NN compared with the other algorithms can significantly provide a higher level of accuracy and prediction performance. CART and ANN performed as the next high predictive preperformance models. The results show that applying

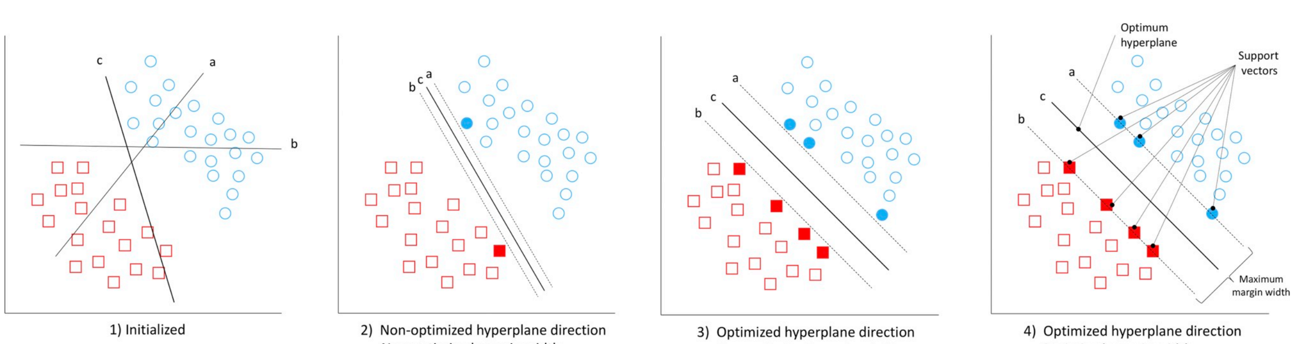

Fig. 5. A schematic of SVM optimization for two classes.

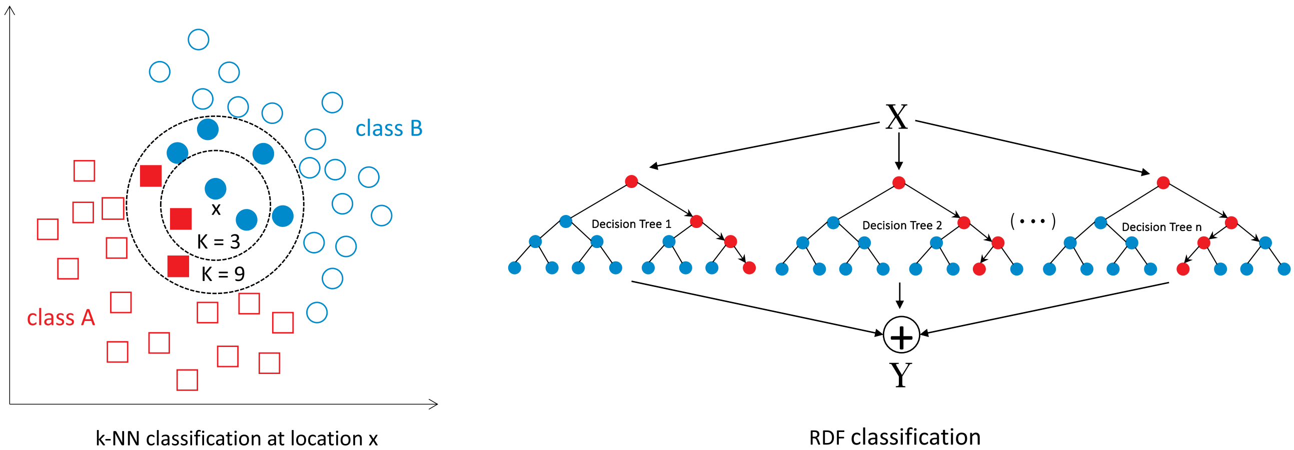

Figure 6. (Left) A schematic of k-NN for two classes based on given k = 3 and k = 9; (Right) A schematic of RDF for n number of trees.

advanced machine learning techniques, using disaggregated individual building level energy data, and considering the influential factors related to urban spatial patterns can improve the accuracy of an urban energy prediction model.

k-means [77] and AHC [78] are two common clustering models. The previous studies on urban energy modeling used k-means algorithm to extract building archetypes representing groups of buildings with certain similarities [79]. Gao and Malkawi [80] apply k-means for urban building energy benchmarking using aggregated CBECS (2008) data to extract more information on typical typologies for the U.S. commercial buildings. AHC forms a hierarchical model through merging data into clusters in a bottom-up process in which the combined data again are merged into larger groups and so forth. Guillaumet et al. [81] use AHC model to develop an urban building energy modeling framework and capture additional components for generating building archetypes based on electricity consumption. The method was tested on a set of 883 single and multifamily buildings. The results indicate that where sufficient data is available, the data-driven approach can provide more accurate results than deterministic approaches.

In sum, data-driven models using artificial intelligence techniques can increase the accuracy of the urban energy use prediction through relying on advanced methods that enable capturing non-linear and complex patterns and using high temporal and spatial resolution data. The data-driven models provide decision-makers with a tool that can help in both planning and engineering phases of urban energy modeling. However, they have limitations when adequate data is not available. Table 1 shows a summary of data-driven algorithms used in previous studies for urban energy use modeling.

2.2. Simulation-based engineering models

The simulation-based engineering models use simulation techniques, thermodynamic principles, and construction, climatic, and system data to estimate energy consumption. However, to achieve time and computational efficiency, urban scale energy modeling relies on a domain simplification. For urban energy use modeling, the geometric information and physical characteristics data are mainly obtained from geographic information systems (GIS) and CityGML as an open source and standard data model for 3D modeling of the city [84,85], while non-geometric data inputs, such as building HVAC and construction systems, are obtained through various assumptions according to typologies of buildings, known as "archetypes" [86]. Each archetype would represent buildings with similar physical and occupant characteristics and construction systems. Buildings with the same typologies would demonstrate similar physical behavior and environmental interactions. Then the building massing in the 3D models are converted into a group of thermal shoebox models for building energy simulation [87]. This reduced-order model, known as simplified model, is used for energy use modeling at urban scale [31,88,89].

The reduced-order approach is developed based on several assumptions of the temporal and spatial characteristics of buildings and energy systems [31,88,89]. Some studies such as [90] suggest that applying a reduced-order model compared with a more detailed one result in a limited loss of accuracy. While, in some previous studies has been suggested that energy use modeling accuracy differs from a realistic prediction though un-calibrated models [91,92]. An approach can be introduced into the simplified archetype process to provide more diversity through adding stochastic variations which can increase the model prediction accuracy [93]. Ghiassi et al. [93] utilize cluster analysis and sampling techniques for building operational modeling at urban and district scale to provide higher resolution. It enables dynamic numeric simulation and stochastic models for energy modeling of Vienna, Austria. Kristensen et al. [94] propose a hierarchical archetype calibration for urban scale building energy prediction. This model avoids oversimplification of archetype establishing through a multi-level and real-time modeling and calibration through applying Bayesian approach.

Apart from building and thermal characteristics, the urban context impacts the accuracy of urban energy modeling [95–97]. The interaction between the individual buildings and the city has been shown to impact the accuracy of operational energy use estimations at both building and urban scales [98,99]; however, it is often times overlooked. The estimation methods are also founded upon assumptions which increase the level of uncertainty, mainly in dense urban areas with high-rise buildings which microclimate effects are more evident [100]. The interaction between urban spatial patterns and microclimate impact energy use in cities in many ways such as urban heat island (UHI) effects [101,102], the waste heat from buildings air-conditioning systems [103], mutual shading among buildings, and affecting wind flow and dispersion within and over groups of buildings [104–106]. The extant literature tends to examine energy use either at the scales of individual buildings or collection of buildings of limited archetypes that do not often incorporate actual urban context effects.

Bueno et al. [103] investigate how to incorporate the influence of urban microclimate, the UHI, in urban building energy use through a reduced-order method known as resistance-capacitance network model which applies a quasi-steady-state heat balance. Li et al. [107] introduce a reduced order GIS-based urban energy model which estimate monthly heat energy through using the Urban-EPC simulation engine. This study integrates GIS to estimate an urban-scale building energy use through incorporating urban context such as UHI effects for Manhattan, New York City. GIS has the potential to provide model inputs either as general building information, or connecting to the particular archetypes for more detailed and specified systems. In another study, Fonseca and

Table 1
Data-driven algorithms for urban energy use modeling.

Source	ML model	Energy System	City/Region	Outcome
[59]	ELM	Heat energy	Serbia	ELM's showed higher speed, accuracy of prediction and capability of generalization is higher than MLPs.
[60]	MLP	Operational energy	China	High level of energy prediction accuracy was reported
[61]	MLP	Operational energy	UK	Improvement in energy consumption benchmarking
[82]	CNN + Simulation	Electricity	California	The relationship between individual building and surrounding context is evaluated.
[63]	RNN + LSTM	Electricity	Austin	Higher prediction accuracy relative to the MLP for the single building, but no significant result for residential buildings
[66]	SVM + GA	Operational energy	A smart communy	Higher accuracy relative to a regular SVM
[68]	SVM	Operational energy		Higher accuracy than MLP
[52]	SVM, ANN	Operational energy		No significant privileges against the conventional statistical models where no sufficient historical data is available
[75]	k-NN	Electricity	Vienna, Austria	More accuracy in predicting the electricity for the dorm and school but no changes for residential sector relative to conventional models. Three typologies of urban buildings (residential, dormitory, and school) were tested using k-NN.
[74]	k-NN	Electricity	UK	Higher prediction accuracy compared with the univariate k-NN and conventional statistical benchmark models
[72]	CART	Electricity	Hong Kong	Higher but not significant prediction performance relative to MLP and regular regression models
[4]	MLR, RDF & SVM	Electricity and natural gas	New York	The linear regression with OLS provides better performance than SVM and RDF for energy prediction, generalizedfor city level
[73]	RDF	Primary energy source	Trentino, Italy	RDF have strikingly higher performance than the baseline approaches in solving regression problems
[79]	k-means	Electricity	Zurich, Switzerland	k-means clustering embedded in ArcGIS used for characterizing energy demand patterns
[5]	k-means	Electricity	Shanghai	New-occupant behavioral patterns extracted
[80]	k-means	Energy efficiency benchmarking	Commercial buildings across the U.S.	k means clustring was used For classification of existing archetypes andmore features were captured for the existing archetypes for the U.S. commercial buildings
[81]	AHC	Electricity	Engordany, Andorra	The accuracy of the AHC model for capturing more features in generating building archetypes can be increased relative to deterministic approaches if the size of data is sufficient.
[76]	MLR, NLR, RF, k-NN, CART, & ANN	Operational energy	Chicago	k-NN compared with the other algorithms showed a higher level of accuracy and prediction performance.

Schlueter [108] introduce building energy use patterns in district context using GIS for data input, analyzing, visualization and disseminate results. Duanmu et al. [109] propose an hourly energy use prediction model through estimation of individual building cooling load and accumulating the results for large-scale urban buildings.

According to the literature, occupancy factors are among the important determinants of urban energy use [110–113]. Urban energy use of buildings and transportation are also affected considerably by urban spatial patterns and the occupancy and socioeconomic factors [114]. Previous studies quantify the impacts of occupancy on energy use at individual building scale [110–112,115] or city and national scales mainly through top-down approaches using aggregated data [114]. The actual energy use may deviate from the original design conditions because of oversimplification of the model, incorporating incorrect assumptions in estimation of occupancy behavior [116–118]. Guy and Shove [117] criticized the conventional assumptions of scientists and energy policy-makers regarding energy use and built environment which ignores the sociological analysis in the model. They suggest an alternative model which incorporates building technology and various contextual factors such as techno-economic conventions and cultural adaptation aspects.

Happle et al. [118] provide a review on building energy modeling at urban scale through incorporating occupant behavior factors. They discuss three common categories of modeling approaches including: deterministic space-based, stochastic space-based, and stochastic person-based methods; and propose an activity-based multi-agent model that incorporates occupant behavior in urban energy use modeling. The results of this review show that current occupant behavior modeling tools account for an individual building level analysis rather than an urban scale building energy use modeling. And the existing methods and tools rely mainly on building archetypes with deterministic space-based occupant behavior models. Person-based and stochastic space-based modeling are not available for all building types while they allow for a more realistic energy use modeling.

In conclusion, while simulation-based models can account for variables that are not typically captured in energy surveys and data-driven methods, they are built with some building and occupant assumptions that increase the uncertainty for urban scale energy modeling purposes.

3. Urban energy use modeling tools

The urban energy use modeling tools are developed to help understand and manage energy use in cities. The existing tools often model different components of urban energy use (e.g. building operational energy, transportation energy, and building embodied energy) independent from one another. They also provide different levels of spatio-temporal resolutions. To date, only a limited number of tools exists to estimate energy use in urban or neighborhood contexts in an integrated manner. The existing tools often apply a bottom-up approach, either as data-driven statistical model or simulation-based engineering model, according to their data input. The GIS is commonly used as the platform in urban energy use modeling [120,121]. The GIS-based energy model allows the integration, analysis, interpretation, and visualization of data with a geo-spatial reference of building stock and infrastructure in urban scale. Flexibility and extension capability of GIS is suitable for a multi-variable analysis within an urban landscape through assessing energy usage/emissions and renewable energy generation potential, as well as heat transfer characteristics and energy use associated with different spatial patterns of the city [122]. The existing urban energy use simulation tools, such as CitySim, EnergyPLAN, E-GIS, Urban Building Energy Models (UBEMs), Urban Modeling Interface (UMI), and City Building Energy Saver (CityBES), rely on the estimation of the energy use at city scale through a GIS-based platform, 2D GIS and/or 3D GIS using CityGML.

The 2D GIS-implemented energy tools are composed of six components: inputs (thermal, physical, context, occupant, etc.), assumptions, baseline models, calculation engine, data exchange module, and GIS platform [119]. Quan et al. [95] introduce a GIS-based platform for building and urban energy use modeling that integrates various data input including the physical building characteristics, mutual shadings, microclimate effects as well as occupant behavior in the GIS environment and employs the Urban-EPC simulation engine to forecast the energy consumption of building stock at urban scale. The method used in their study is verified in Manhattan, New York City.

The 3D GIS energy models are in their initial stages of development. They rely on open semantic formats such as CityGML. CityGML [123] provides storing and interchanging of the city 3D models based on an XML format. The CityGML can be employed for either analysis or visualization purposes. It has been applied in many fields, including planning and energy simulation. In many of the urban energy use modeling tools, the potential of using CityGML platform is not totally appropriated, and it is mostly applied for representing physical characteristics of buildings and urban infrastructure and visualization porpuses [119]. For the purpose of urban energy simulation, CityGML can be extended with an Energy Application Domain Extension (Energy ADE), developed within an international consortium of urban energy simulation and modeling experts [124,125]. The Energy ADE enables a detailed model for energy simulation considering building physics and occupant behavior at individual building level and city scale [126]. Kaden and Kolbe developed a method for building energy demand calculation at urban scale through using 3D GIS model of Berlin (LOD2 building model) as well as other statistical data as input data. This study estimates the energy consumption for electricity, heating, and domestic hot water for building level in a city-wide scale. It uses the Energy Atlas Berlin, that is based on CityGML format and provides the data for the common urban spatio-semantic information model as well as energy use data.

The existing tools can be categorized into two groups of tools in terms of incorporating different urban energy components. The first group of tools models urban energy use by focusing on urban energy use main components including building operational-oriented urban energy use modeling tools, transportation-oriented urban energy use modeling tools, and embodied-oriented urban energy use modeling tools separately.The second group, integrated urban energy use modeling tools, integrates these components and in some cases, expand the modeling to other aspects including application of renewable energy and water consumption management and waste reduction. The next section of this article presents some examples from each group of existing urban energy analysis tools.

3.1. Building operational-oriented urban energy use modeling tools

The UBEMs, UMI, CityBES, TEASER, and HUES are some examples of tools that apply simulation-based methods with a building operational-oriented modeling approach. UBEMs [86] calculates hourly building energy use at the urban scale. The GIS shapefiles including building footprint, tax parcel data, and property tax records as geometric input are used in the tool to visualize energy consumption in each neighborhood. In addition to geometric data, UBEMs involves various data inputs such as construction systems and materials, as well as certain internal loads and consumption schedules through introducing ‘archetype’ which represents building classes with similar characteristics for each building type.

Developed by RWTH Aachen University [127], TEASER is an open source tool for urban energy modeling. TEASER is a Python-based platform which supports CityGML. It is an object-oriented, functional and structural program that provides an interface for data acquisition, data enhancement, data manipulation, as well as possibility of generating Modelica code. The tool supports geometric and spatial information, building construction characteristics, zoning, and general user behavior. CityBES [128], as another example, is a web-based computing tool which enables citywide building energy use simulation using a bottom-up approach. This tool uses CityGML to represent the 3D models and uses EnergyPlus as the energy simulation engine and employs the LBNL Commercial Building Energy Saver Toolkit to support retrofit analysis.

Holistic Urban Energy Simulation (HUES) [129], developed at Empa and ETH Zurich, is a platform for energy modeling at building and urban scales which applies a multi-model ecologies method. There are two types of modules that HUES supports: (a) energy demand/supply and (b) energy system. The energy demand/supply module refers to models and databases for energy demand calculation and/or renewable energy potential estimation. For example, the GIS-based heat demand database in this module is used to simulate the annual energy use for heating and hot water for Switzerland residential buildings. The energy system module addresses the design optimization and energy system operation at a building to a city scale. Another urban energy use simulation tool, SimStadt automatizes the thermal energy demand of buildings. This tool employs CityGML and incorporates the CityGML's Level of Details (LoD) and allows an enhanced analyzed city 3D model. SimSadt uses CityGML with Energy ADE, a domain extension for energy use simulation [124,125].

SEMANCO [130] is a web-based platform that provides access to various available energy data sources to help stockholders and urban energy planners in energy analysis using existing data as an alternative to simulation methods. It introduces a semantic energy information framework that allows a multi-scale analysis for evaluation of energy consumption at building, neighborhood, and region levels [131]. In addition to data structuring, this framework and its tool enable determining energy indicators, evaluating various methods for carbon emissions reduction and forecasting energy consumption of buildings in urban areas [130]. The platform has been developed for three case studies, including Manresa, Spain, Newcastle, United Kingdom, and Copenhagen, Denmark.

The Cities on Power (CoP) [132] project aims to reaffirm Local Action Plans of the European Union to encourage European cities to increase the use of renewable energy sources in urban areas through developing new financial and organizational tools which enable estimation of energy derived from solar panels and geothermal. Also, it provides insight into economic values and estimates when the residents' investment would return. Through a financial assessment, it triggers fostering clean energy development in cities. The energy cost estimation element is suggested to be extended to urban energy modeling tools to stimulate energy efficiency intervention either on buildings or transport sector. DECoRuM is another toolkit that enables urban building energy use modeling and GHG emissions and Cost-benefit analysis [133]. DECoRuM is a GIS-based tool and helps planners to develop carbon reduction plan through enabling energy modeling and monitoring energy efficiency improvements and cost-benefit analysis. It also enables assessing the potential for citywide application of solar energy systems.

Combined Energy Simulation and Retrofitting (CESAR) [134] is another tool developed by Empa which deals with modeling the building and urban energy demands at different scales through a bottom-up approach employing statistical and clustering techniques as well as EnergyPlus as energy simulation engine. This tool is capable of handling 3D geo-based data in mapping out energy demands. Wang et al. [135] employ CESAR for modeling energy demand in three case studies in different scales (urban, suburban, and rural) in Switzerland.

CitySim developed at the Swiss Federal Institute of Technology Lausanne (EPFL), is another urban energy modeling tool which provides decision support to minimize energy and emissions by simulating the energy demand of building stock at city level [136]. CitySim models urban building energy use, while considering the stochastic nature of occupants' presence and behavior, urban climate effects and energy supply from renewable energy sources [136]. CitySim employs a reduced order energy model which simplifies zoning and HVAC system

[137]. Walter and Kampf in Ref. [137] validate the results from CitySim using the Building Energy Simulation Test (BESTEST) protocol and suggest that the CitySim simplified model is comparable to the detailed simulation tools.

Urban microclimate influences building energy demand for heating and cooling in addition to impacting outdoor thermal comfort and human activities. There are simulation tools to model urban microclimate effects. For example, Computational Fluid Dynamics (CFD) is one of the tools for microclimate effect assessment which enables resolving the transfer of heat and mass as well as the interaction between individual buildings [138]. The Urban Multi-scale Environmental Predictor (UMEP) is an open source GIS-based tool which enables assessing urban climate, outdoor thermal comfort, wind flow, and urban energy use [139]. UMEP allows for interacting with spatial information and using different data sources which are accessed through QGIS, a GIS open source platform. ENVI-met as a 3D nonhydrostatic microclimate modeling tool enables the simulation of surface-plant-air interactions. This tool uses EnergyPlus as the simulation engine which is coupled with the CFD to measure the urban microclimate effects and building energy use thermodynamics [140]. TownScope is also a GIS-based urban energy assessment tool that helps in understanding the effect of urban microclimate on energy usage of buildings [141,142]. This model assesses three main domains including solar access analysis, thermal comfort assessment, and urban open space availability. RayMan is another available microclimate tool for modeling of mean radiant temperature and thermal indices [143]. This tool takes complex urban structures into account and is proper for several urban studies application. For example, the tool enables modeling of Sky View Factor (SVF), shadow and radiation changes as well as estimating the thermal indices for human biometeorology.

3.2. Transportation-oriented urban energy use modeling tools

The existing transportation energy modeling tools rely on either data-driven, mainly regression analysis of aggregate or disaggregate data derived from land use and travel demand patterns in the city through both top-down and bottom-up methods, or simulation based models. A broad range of data inputs is required for transportation energy modeling including household travel demand, fuel type, the related technologies, and time of energy consumption, as well as other factors such as zoning and real estate and market data [144]. In addition, transportation energy modeling requires additional data on econometric models, energy prices, demographic characteristics, and human behavior factors [144]. To date, there is a few numbers of tools for transport energy use modeling [145]. The available transport modeling tools mainly enable vehicle flows and traffic behavior modeling rather than transportation energy use modeling [145,146].

The available transportation related tools are commonly based on four major systems [19]: static spatially-aggregate (SSA) models, general spatial equilibrium (GSE) models, agent-based micro-simulation (ABMS) models, and extended activity-based models. The SSA model, as a spatially aggregate model, is a static model which fails to consider the realistic relations of land use and transportation system [19]. MUSSA [147] is an example of the SSA model. The GSE is also a spatially aggregate system and does not consider the behavioral factors. However, this model integrates the components more accurately. TRANUS [148] is one example of GSM modeling approach that analyzes urban energy demand. The ABMS model combines the strengths of micro-simulation and the disaggregate modeling of behavior and land use processes [19]. Integrated Transportation and Land Use Package (ITLUP) is based on disaggregate residential and employment allocations modeling. This tool uses extensive data input of demographic and economic profile of households and employment information and travel demand patterns including public and private modes. This tool supports various network assignment algorithms through using a multinomial logit (e.g. split sub-model and trip assignment sub-model) [149]. The agent-based approaches are linked to human activity and travel decisions by individuals which includes a wide range of methods such as Simple State Transition (SST) [150], Random Utility Choice (RUC) [151], Rule-based Computation (RC), and hybrid models [152].

The commonly available tools do not allow transportation energy modeling directly. They allow land use and travel demand modeling without energy consumption modeling. Transportation modeling tools usually rely on a GIS-based platform. STREAM [153], EnergyPLAN [154], and Energy Proforma [155] are among few available tools that allow modeling transporatation energy use along with building operational energy demand. The mentioned tools will be discussed in 3.4. Integrated urban energy use modeling tools section. In conclusion, the major source of uncertainty in transportation modeling stems from 1) the lack of data availability; 2) the complexity of the overall urban system; and 3) instability of agent behavior.

3.3. Embodied-oriented urban energy use modeling tools

Embodied energy (EE) estimation is a key challenge in urban energy use modeling. There exist limited tools to capture EE of buildings, particularly at an urban scale. EE estimation is also a challenge because there exist differing methodologies to quantify it, including process-based (PB) life cycle analysis (LCA), economic input-output (EIO) LCA, and process-based or EIO hybrid analysis methods. Process-based hybrid method is suggested to be the most appropriate method of EE estimation at urban scale as it captures not only direct embodied energy of construction materials but also indirect overhead embodied energy added by factories and equipment [16].

There are also various sources of uncertainty that affect the accuracy of EE analysis. A major source of uncertainty is the lack of transparent and temporally, technologically, and geographically-representative data that are sometimes used in EE estimation. For accurate estimation of EE in the process-based LCA, not only bill of materials data are needed but also other inventory data (e.g., quantity of electricity that is used in manufacturing of certain building component, the type of power plant used to generate that electricity, the type and amount of fuel used in transportation of that building component to construction site, etc.) are required, and they must accurately represent what is practiced in construction, maintenance, and demolition of the building under study in its specific geographical location. Collection of such data is a huge undertaking that is often beyond the researcher's resources. The researchers, therefore, tend to rely on existing private or governmental inventory databases for EE estimation and LCA studies. These databases are founded upon national and regional averages and sometimes do not properly represent the settings of a certain study. While building construction raw materials extract from various regions, limited inventory databases are available to provide accurate information for EE estimations. Also, the limited data provided by non-transparent protocols increase the uncertainty of the model. In sum, the accuracy of EE estimations is significantly affected by accurate inventory data availability for EE modeling [156].

Davila and Reinhart [28] introduce a framework and a CAD-based tool for embodied energy evaluation of buildings at urban scale. This tool is an extension for Rhino3d to model the cumulative embodied energy based on a simplified design 3D massing model connected with a custom online material database. The tool has the potential to be coupled with EnergyPlus to estimate the operational energy as well. Lolli et al. [157] propose a parametric analysis tool (PAT) that allows both building operational and embodied energy use estimation, as well as embodied building material emissions assessment. This tool can accommodate a building scale analysis.

Stephan and Athanassiadis [158] propose a bottom-up approach for quantifying embodied energy of buildings in Melbourne, Australia. The model applies a disaggregated approach in building geometry quantities, construction assemblies for each archetype. Also, the model uses a hybrid technique to estimate the embodied energy and associated emissions as well as water consumption. Quinn et al. [159] propose a framework and a web-based GIS tool for estimating the urban energy of buildings at urban scale using simplified urban typologies based on built area ratio, plot ratio, building average height, window to wall ratio, vertical structure ratio, and density of partitions factors. In a study, Quinn and Fernandez [160] propose a framework for estimating material usage of road infrastructure through identifying a road scaling pattern and its variation of material usage based on the distance from the urban center. This approach captures road infrastructure properties mathematically using data from 40 U.S. cities.

Currently few software tools allow for modeling of EE at the urban scale. Tools such as Athena Impact Estimator allow for EE modeling only at the scale of building or smaller. In other tools such as Tally, the opportunity to model urban building embodied energy exists from a theoretical perspective. However, the process-based LCA methodology that Tally replies upon for modeling of EE and other environmental impacts suffers from truncation errors due to boundary conditions [15,16]. The Green Design Institute at Carnegie Mellon University developed an economic EIO-LCA method to estimate the energy resources of materials and emissions through a web-based platform [161]. This tool uses national economic input-output models and other open data.

3.4. Integrated urban energy use modeling tools

There exist few tools that enable an integrated urban energy use modeling through capturing various urban energy components including building operational energy, transportation energy, and building and infrastructure embodied energy. EnergyPLAN is one of the available integrated tools that estimates the hourly operational energy systems including heating, cooling, electricity, as well as energy required for operation of the industry and transportation at national level through an input-output model [154]. This tool is developed by the Sustainable Energy Planning Research Group at Aalborg University and founded upon technical analysis (e.g. demand and capacity analysis and economic optimization). This tool has been applied in many areas such as modeling renewable energy application through a demand-supply balance. As an example [162], use EnergyPlAN to evaluate the possibility of renewable energy systems application for Denmark. STREAM [153] is another tool which is open source and applies a bottom-up approach and allows simulation of the energy systems including transportation, as well as the energy demand for electricity and heat. This tool enables energy reduction and decarbonization evaluations for different development scenarios.

UMI [163] is another tool that applies a simulation-based method to enable the modeling and evaluation of energy and environmental performance in neighborhood and city scales. The tool is a Rhino-based environment that employs EnergyPlus engine. UMI provides the possibility of the energy calculations for both operational and embodied energy; also it allows daylighting and neighborhood walkability analysis.

Energy Proforma [155] is another web-based energy assessment tool, developed by the Massachusetts Institute of Technology's Department of Urban Studies and Planning, to address a data gap and enable modeling the energy use and carbon emissions based on the neighborhood design characteristics. This tool captures three main components of urban energy use, including building operational energy use, transportation energy use, and embodied energy use. In addition to assessing energy consumption and carbon emissions in neighborhood context, it examines how renewable energy can be applied in cities. Energy Proforma uses SketchUp and the CityGML Sketchup Plugin. The Energy Proforma can be integrated with the Sustainable Communities Assessment (SCORE) tool to enable assessing sustainability-related issues at neighborhood scale for several capital types such as natural, economic, social, and cultural capitals [155]. Table 2 shows a list of turban energy use modeling tools including urban building operational energy oriented, ransportation and embodied energy-oriented modeling

Table 2
Urban energy tools; Operational Energy (OE); Embodied Energy (EE); Transport Energy (TE).

Source	Tool	Type			Modeling Approach	Spatial	Output
		OE	EE	TE			
[155]	Energy Proforma	×	×	×	Data-driven model	City	Building operational energy demand and operation of the industry and transportation
[130]	SEMANCO	×			Data-driven model	City	Building operational energy demand
[164]	EnergieAtlas	×			Data-driven model	City	Building operational energy demand
[5,154,162]	EnergyPlAN	×		×	Simulation/Engineering model	City	Building operational energy demand and operation of the industry and transportation
[86]	UBEMs	×			Simulation/Engineering model	City	Building operational energy demand
[163]	UMI	×	×		Simulation/Engineering model	City	Building operational and embodied energy use; walkability sore; daylighting
[128]	CityBES	×	×		Simulation/Engineering model	City	Operational energy use; retrofit strategies
[136,137]	CitySim	×		×	Simulation/Engineering model	City	Operational energy use; solar generation, transport choice, and other energy efficiency standards
[127]	TEASER	×			Simulation/Engineering model	City	Operational energy demand
[129]	HUES	×			Simulation/Engineering model	City	Operational energy demand
[124,125]	SimStadt	×			Simulation/Engineering model	City	Thermal energy demand
[153]	STREAM	×		×	Simulation/Engineering model	City	Electricity, heat and transportation
[166]	Tally		×		Process-based LCA model	Building	Embodied energy and other environmental impacts

tools.

4. Conclusion and envisioning a future framework for urban energy use modeling

Urban energy use modeling is essential in urban energy management and understanding of energy performance of cities. However, the available methods and tools for energy performance evaluation in urban contexts often reduce the urban energy use to operational energy of buildings, ignoring the urban transportation energy and embodied energy over the buildings and urban infrastructure life cycle. In addition, accurate urban energy performance modeling and prediction remains a challenge due to the methodological uncertainties embedded in these methods and tools. As discussed in the previous sections, the urban energy use modeling is a challenging task due to the complex nature of cities and their dependency on a broad range of factors for providing an accurate representation of real-world urban energy system. This is time-consuming and computationally expensive. The main limitations of urban scale energy modeling stem from either the use of aggregate data for energy use estimations and generalizing the status quo in data-driven models or oversimplification of building system and urban context and failure to account for the intra- and inter-buildings and urban microclimate effects as well as occupancy related factors in simulation-based models.

To properly model energy use at urban scale, an integrated framework is required to be developed to capture different urban energy components: (a) building operational, (b) building embodied (c) road infrastructure and (d) transportation energy use through a bottom-up hybrid data-driven and engineering based energy modeling at multiple scales. Such modeling framework could provide a more comprehensive representation of urban energy use and be built upon the strengths of the two bottom-up models to reduce the uncertainties associated with each. Fig. 7. illustrates the conceptual framework for integrated-hybrid urban energy use modeling.

This framework would take advantage of the advent of big data technology and energy disclosure laws for buildings which improves transparency and enables employing data streams at the actual building level along with the development of advanced artificial intelligence (AI) techniques to extract localized archetypes. The localized archetypes which represent actual variations of buildings in a city would be used as input for simulation-based models. While the application of detailed energy use modeling needs an extensive amount of time and effort, data-driven techniques have the potential to help increase speed and computational efficiency for urban scale modeling. Another application of data-driven methods into development of hybrid models is incorporating microclimate effects through utilizing data such as local weather data which reduces the uncertainties of the simulation models significantly.

In a hybrid model, the data-driven approach can also aid in incorporating the occupancy factors, which is an overlooked area in urban energy modeling. For example, urban scale occupant behavior modeling is not currently happening based on existing studies and available tools, but rather, it is still executed at the individual building level. As discussed in section 2.2., the current models mainly rely on archetypes with deterministic space-based occupant behavior models. Data-driven approaches provide the opportunity of incorporating occupancy and socioeconomic factors into constructing building archetypes and quantifying the impacts of those influential factors on urban energy use. Machine learning based algorithms such as ANN and SVM, among others which gained significant attention, especially in developing smart buildings, has the potential to be applied for urban scale occupancy modeling. It can also help incorporate occupancy factors to optimize energy load through HVAC control, lighting control, learning user preferences and increasing occupants comfort level through collecting data based on detecting the presence of occupants, counting the number of people, and tracking their movement. Using the extracted localized archetypes reduces the subjectivity in modeling and increases the accuracy of the model.

Such urban energy use model would present an integrated tool which considers different components of urban energy use and applies strengths of data-driven and simulation-based approaches to increase the accuracy of the urban energy use estimation. Moreover, it provides the opportunity to modify the model and propose energy-driven planning, design, and optimization, as well as evaluation of the different

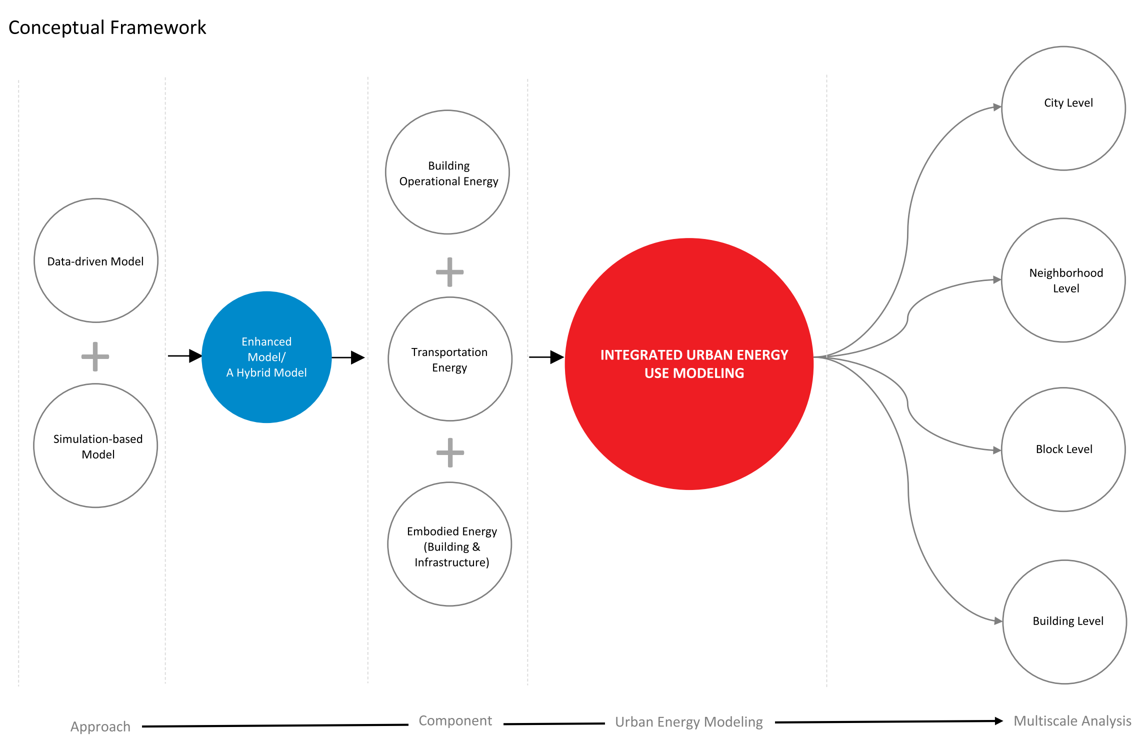

Fig. 7. The conceptual framework for future integrated urban energy use modeling tools.

energy efficiency strategies at multi-scales of building, block, neighborhood, and city levels. This model has the potential to help contextualize the methods corresponding to local features, quantify performance from a multi-dimensional perspective and explore the design and planning strategies to increase the energy performance of built environment.

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