City-scale energy modeling

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Comparative review of city-scale energy modelling approaches

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Abstract

Buildings are responsible for more than 40 % of global CO2 emission and use approximately equally percentage of global energy. Therefore successes in this sector can support significant positive change in the total consumption and emission. Nowadays we can see the importance of having a tool for facilitating energy-efficient thinking at pre-design stage of retrofitting and in case of new buildings as well. In response to those global challenges, building energy modelling (BEM) is a continually developing discipline. Global, nation-wide, city and district scale models are having an increasingly important role, when the methodology is not focusing on detailed individual building energy models, but complete systems based on more buildings and synergies between them. This tool can support decision makers (in the field of utility development projects and development of support strategies) in retrofitting existing urban areas and designers in developing planning regulations and choosing between design options regarding to basic geometrical decisions, window-wall ratio on the facades, orientation. These urban models are divided into two main categories: “top-down” and “bottom-up” models. The aim of both approaches is channelling data sets which are the base of large scale models.“Top-down” building stock models link building energy demand and supply to macroeconomic variables and predict future energy use relying on statistical data. However, while using „bottom-up” methodology, single building energy demand and consumption are extended to group of buildings with similar geometrical and technical characteristics. Through the review of research literature, this paper is focusing on exploration of modelling methodologies and comparison of urban energy models and simulation platforms linked to them. As a conclusion, those fields are presented which the existing methods could not deal with because of the lack of data input or too complex calculations. In this way, we explore the current technical shortcomings of the designated topic and the possible directions of further progress in the subject.

1. Introduction

1.1. Climate and urban dimensions

In 2015 at the Paris climate conference (COP21), 195 countries adopted a global climate deal. This was the first time when an universal, legally-binding climate deal was applied.[1] One of the aims is to keep the increase of global temperature well below 2°C. Until now 97 parties have ratified, and this agreement will enter into force in the fourth of November in 2016.[2] According to the Hungarian national strategy the goal for 2020 is to reduce the energy consumption in Hungary by 18% (Hungarian Government, 2014). The building sector accounts for nearly 40% of the energy consumption worldwide (European Commission and Eurostat, 2013; Eurostat, 2015), and as occupants spend more time in their homes (Pérez-Lombard, Ortiz, and Pout, 2008) this will only increase. The building sector has the greatest potential, to reduce CO2 emission (UNEP, 2009). For reaching these numbers, it is an absolute necessity to construct accurate models, to help municipalities, and evaluate policies. To efficiently deal with these problems, such models are needed, which are dealing with energy consumption at urban level, but are capable to address energy reduction opportunities at building level. (Reinhart and Cerezo Davila, 2016)

1 EUROPEAN COMMISSION AVAILABLE: HTTP://EC.EUROPA.EU/CLIMA/POLICIES/INTERNATIONAL/NEGOTIATIONS/PARIS/INDEX_EN.HTM [ACCESSED:26-OCTOBER-2016]

2 UNITED NATIONS AVAILABLE: HTTP://UNFCCC.INT/PARIS_AGREEMENT/ITEMS/9444.PHP [ACCESSED: 26-OCTOBER-2016]

1.2. Large scale modeling approaches

The building energy modelling can be divided in two different investigation scales. One is the micro, and the other is the macro scale (Fabbri & Tarabusi, 2014). Macro scale generally means, that the indicators and the data are applied on an aggregated level, globally or continentally. The micro scale, however, reflects to a single device, or a single building unit. These scales were adopted from meteorology studies, where there is a third scale, which is in between the primary scales. Yamada and Koike (2011) state that the extension of this scale is between 100- 300 km (meso-scale alpha) and 40 km (meso-scale gamma). By means of building energy modelling, it can be interpreted as anything between micro and macro scale, or between continents and buildings, belongs here.
In the recent years there has been a significant growth in the number of energy models. Energy modelling started to grow approximately from the early 1970s. The beginning of the computer use in the 1960s indicated that more complicated calculation methods had been applied for different problems. At that time, the Top-down modelling was ahead of the Bottom-up modelling, because the simple simulation technologies, based on heat-mass balance equations, were developed in the 1970s too. The other big indicator was the Arab oil embargo at 1973. A lot of countries had to build new building energy policies in. The building sector was the biggest energy consuming sector, so models and ideas emerged here.
The top-down-bottom-up debate first came into the view during the efficiency-gap debate in the 80-90's (Grubb, 1993). From the 1990s on, the bottom-up method started to gain more space. That had a lot to do with the rise of the PCs. As the computational performance progressed, the growth between building energy modelling software accelerated. It indicated the evolution of the bottom-up and the Hybrid models, with the exponentially bigger computational needs.

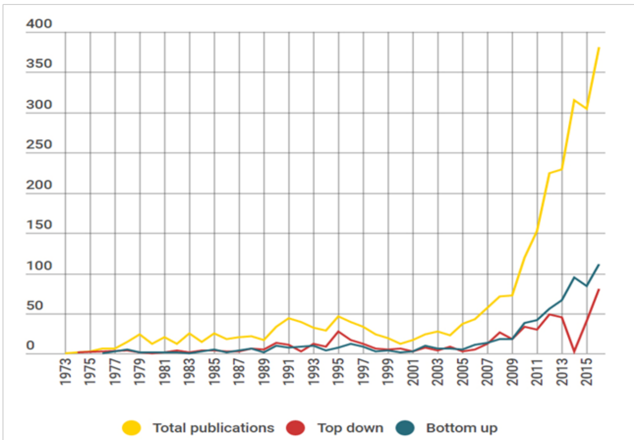

Fig.1. showing the distribution of papers depending on the year of appearance

The first search resulted in 2698 elements, the search for the Bottom-up resulted in 696, and the search for the Top-down resulted in 536 elements. The progress in the recent years is clearly visible in this and also in (Keirstead, Jennings, & Sivakumar, 2012). The progress accelerated somewhere near 2003, and from 2009 it has become more gradient.
In 2014 it occurred, that no Top-down models were available. This is a strange result and for this reason, this would need further investigation.

1.3. Energy modelling in building group scale

The approaches in BEM also differ with these scales. Goy and Finn (2015) claim, that there are two ways of investigating approaches: a small scale, and a large scale. The small scale reflects to less than five-, while the large scale to more than five buildings. For small scale the methodologies could be divided into three ways: white boxes, grey boxes, and black boxes. (Foucquier et al., 2013)

1.3.1. White-box approach

By energy modelling in small scale which means less, than five buildings according to Goy and Finn (Goy & Finn, 2015), three merely different approaches can be separated. The first approach is the White-box modelling (Foucquier and Jay, 2013; Li and Wen, 2014). This is a so-called forward modelling technique (Wang and Xiao, 2012), which means, it needs a big amount of physical data from the building envelope. As shown in Fig.2. the icons in the small circles represent the different types of statistical data like energy consumption, number of occupants etc.. If this icon is pale grey, then it is not available, when it is black, it is available. This deterministic approach models the building with detailed physics-based mathematical equations. The model could either be dynamic, which are capable of modelling building dynamics like thermal dynamics of envelope, or system dynamics (Wang et al., 2012), or steady-state, which is a static model, and only can calculate the dynamic effects, with correlation factors (Wang et al., 2012). Dynamic methods are more accurate, but they have more complex calculation methods, whereas steady-state models are less accurate, but easier to calculate (Li and Wen, 2014; Wang et al., 2012).

A group of detailed physics based mathematical equations, create a simulation engine. For this engine, the typical input data includes four groups of parameters (Wang et al., 2012): weather data, detailed description of building, detailed description of building components, detailed description of systems. These datasets are from measurements, and traditionally this method do not use any statistical data.

There are three main groups of simulation engines: CFD (Computational Fluid Dynamics), Zonal methods, and Nodal (also known as Multizonal) methods (Foucquier et al., 2013).

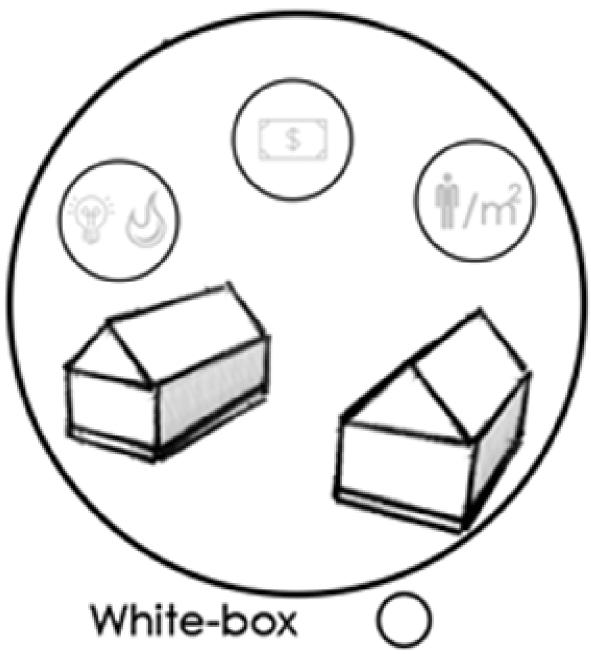

Fig.2. White-box model

Some example of engines, by approaches are the following according to Foucquier et al. (2013).

CFD method: FLUENT; COMSOL Multiphysics; MIT-CFD; PHOENICS-CFD. Zonal method: SimSPARK; POMA. Multi-zonal method: TRNSYS; EnergyPlus; IDA-ICE; ESP-r; Clim2000; BSim ; BUILDOPT-VIE.

1.3.2. Black-box approach

The Black-box method is another approach of modelling. This so-called inverse-modelling technique (Wang et al., 2012) uses some form of regression to calculate energy indicators. This model needs on-site measurements over a certain period of time, and over different conditions, to create representative, and trained model (Li and Wen, 2014). This method is mostly used when the physical parameters of a building is not known (Fig.3.). The great power of this method is that, it does not need heat transfer equations, and it needs less building parameters, than the white box approach does (Foucquier et al., 2013).

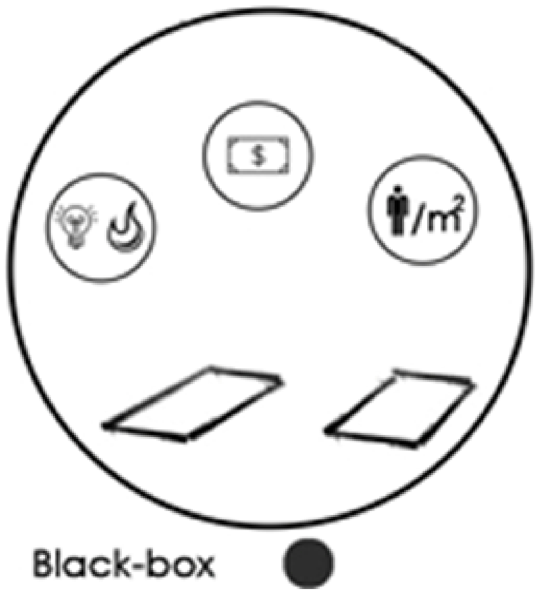

Fig.3. Black-box model

The most used computational techniques for Black box modelling are: Linear Multiple Regression (LMR); Artificial Neural Network (ANN) and Decision Trees (DT); Genetic Algorithms (GA); Support Vector Machines(SVM) (Foucquier et al., 2013).

1.3.3. Grey-box approach

The third method is the Grey box modelling. This approach is used, when the building characteristics are not well known, or it could also be used, to eliminate the weaknesses, of each previously mentioned model (Fig.4.) (Foucquier et al., 2013). This method is also referred as the hybrid method (Foucquier et al., 2013), for the simple reason, that it contains attributes of the white box model, and also the black box model.
According to (Foucquier et al., 2013) there are several ways to couple these two approaches: Using machine learning, as physical input estimator; build a learning base, with White-box approach, then use statistics, to implement a learning model; and to use statistical data in fields, where White-box data is less efficient.

Fig.4. Grey-box model

Nowadays, modelling urban energy systems is a continuously developing field (Christoph F. Reinhart & Cerezo Davila, 2016). The simulation of building energy use is no longer reliable and efficient enough assuming isolation from the urban context such as microclimatic impact and energy system in which the building operate.

The model of an urban energy system is neither feasible nor useful without taking into consideration the buildings that it serves. Thus we are interested in exploring the state of the art of this area.

In our study we seek to answer the following questions. What are the capabilities of existing urban energy modelling tools ? What are the current technical shortcomings of these models? In which directions they should be further improved is order to cover all the energy related issues in city-scale modelling?

2. Methodology

2.1. Methodological summary

In order to have an accurate picture, the discussion of this study builds upon a literature review and a critical revision linked to comparative tables. (See the methodology on Fig.5) Firstly, a research of existing related city-wide models with the scope of energy modelling was done in the scientific database of ScienceDirect . Secondly, the collected studies distinguish approaches by their scale. There is access from building or building group scale and there is another way from large scale modelling as it is revealed from the literature review. In order to better understand the topic we explored both methodology, which is shown in the following sections. Building Energy models (BEM) are divided into three parts (white, black and grey boxes) while urban energy modelling platforms are further separated in two subgroups by their nature (top-down and bottom-up modelling approaches). We present the application fields of white, grey and black box techniques in the Discussion. The comparative analysis of large scale models is presented in Section 2.2. Here, aspects of the comparison are defined, based on collection of viewpoints from the workflow of each model, and list of aspects from the overview of literature. Results are stated in Section 3.0.

Finally, the most highly cited, diverse seven models has been separated for a deeper look at their capabilities and compared with each other by their input, workflow and abilities for satisfying energy related sustainable aspect we set up in Section 2.2.3. To sum up, the aim of the study is to demonstrate a critical review of current methodologies and their shortcoming in different layers in order to support the development of further efforts in this field of urban design.

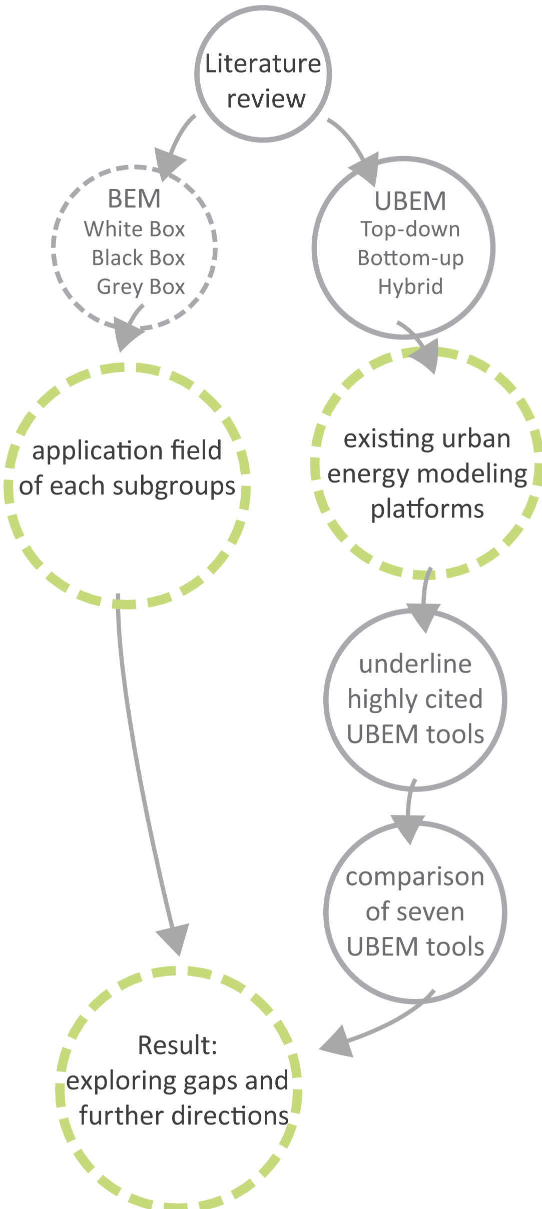

Fig 5. Research method

2.2. Detailed methodology

2.2.1. Comparative analysis of top-down models

As it is mentioned in the introduction, the top-down method treats the building sector as a big black box. The most commonly-used indicators are macroeconomic indicators like: fuel prices, GDP, employment rates, annual mean income, etc.; climatic conditions, housing construction/ demolition/renovation rates, and data on technological appliances (Johnston, 2003; Swan and Ugursal, 2009).

There are two ways of top-down modelling: econometric and technological. Econometric modelling is based on prices, incomes (Balaras et al., 2007; Coffey et al., 2009; De Santoli et al., 2014; Howard et al., 2012; Labandeira and Rodriguez, 2005; Siller and Imboden, 2007) while technological modelling is based on consumption, and life cycle stage of technological appliances (Young, 2008). Also, there are a few models, which use both ways (Swan and Ugursal, 2009; Tornberg and Thuvander, 2005)

The top-down models investigate long-term changes and transition in the energy sector. They fit the historical data accordingly. Mostly, these models use some already existing databases, but it is not rare to estimate missing data, as well (Johnston, 2003; Kavgic et al., 2010; Swan and Ugursal, 2009)

The reliance on historical aggregated data can be either a positive or a negative attribute. Positive, because it provides inertia to the model, and simplicity to the calculations method. Also, it is easier to collect aggregated data, then non-aggregated (Swan and Ugursal, 2009). Negative, because it assumes, that values in the future remain valid, which can cause big discrepancies (Hourcade and Ghersi, 2006). Although as Swan and Ugursal (Swan and Ugursal, 2009), housing sector rarely undergoes paradigm shifts, these errors may not be so significant. Further negative point is, that econometric models are not capable to model discontinuous advances in technology. The technological flexibility is much lower than in case of bottom-up models. Also, while constructing policies, policy makers are often pushed towards building specific aspects, like technology, or envelope, and top-down models face lack of details to identify these key areas.

In Table 1, we created a framework, based on the literature review. The following aspects were identified: „scale";"building type"; „method"; „input data"; „validation". Under the „scale" point, we specified scales from country, to neighbourhood. In the „building type" scale, residential, commercial and public, mixed use, industrial and other buildings were specified. The „method" category was split into two, econometric, and technological. Under „input data" occurred a so wide variety of inputs, that only simple inputs, and estimated data was identified as subgroups. In the last point „validation", we investigated, whether or not the models was validated.

2.2.2. Comparative analysis of Bottom-up approach

The data in the bottom-up method has to be non-aggregated. We can only speak about this kind of approach, if the input data is given for a specific unit of the system. According to the available information, it is possible to separate three different groups of this method.

The first group is called the statistical method (Kavgic et al., 2010; Swan and Ugursal, 2009), also there are references for it as the data-driven method (T. Hong et al., 2016; Tardioli and Finn, 2015).

Tardioli and his co-workers states (Tardioli et al., 2015), that this kind of model is a black-box approach (Fig.6.). Every building itself is a black-box, and the output of these boxes are used as input (energy consumption, energy bill information, meteorological data, energy price, building geometrical features, building thermal features) for calculating the result.

These type of historical data is used to aggregate energy consumption for the meso-scale. There are a few types of calculation methods which can be applied to process this data.

Tardioli and his colleagues (Tardioli et al., 2015) made a literature review on this topic, in which they separated four mainly different calculation methods: statistical and regression based methods such as multiple linear regression (MLP) (Nouvel et al., 2015) ; Artificial Neural Networks (ANN) and Decision Trees (DT) (Hong et al., 2013; Wijaya et al., 2014) ;Support Vector Machines (SVM) (Humeau and Aberer, 2013; Shabunko, Lim and Mathew, 2014; Wijaya et al., 2014); and clustering based method (Arambula et al., 2014; Gao and Malkawi, 2014; Heidarinejad et al., 2014). They also grouped these data according to the question they are entitled to answer: forecasting prediction, benchmarking, energy mapping and profiling.

According to this sample, the forecasting prediction can be done by all four above mentioned methods. As for benchmarking, the same can be stated. For energy mapping only the statistical and regression based, and the clustering based methods provides solution. As far as profiling is concerned, it is only the clustering based method. So the only calculation method, which can be used for all the above mentioned four tasks, is the clustering based method. This method is about making groups in a system, from its own elements, where the elements in a group have similar features, and they are different from the elements in other groups (Tardioli et al., 2015).

It is however, a big question, what is that amount of clusters that helps the method? Would it be better to calculate the results for every building, aggregate and then numerate them? In (Humeau et al., 2013; Wijaya et al., 2014) Humeau et.al. did two analysis on the percentage of errors with different numbers of clusters, and it occurred, that if every building is treated as a separate cluster, the percentage of errors is much higher, than in the case, when the whole sample is treated as one cluster. The optimal number of clusters is defined as approximately ten, but it is only true for these two models. It is also stated, that if the number of the sampled buildings is varying, this optimal number will also change (Humeau et al., 2013; Wijaya et al., 2014).

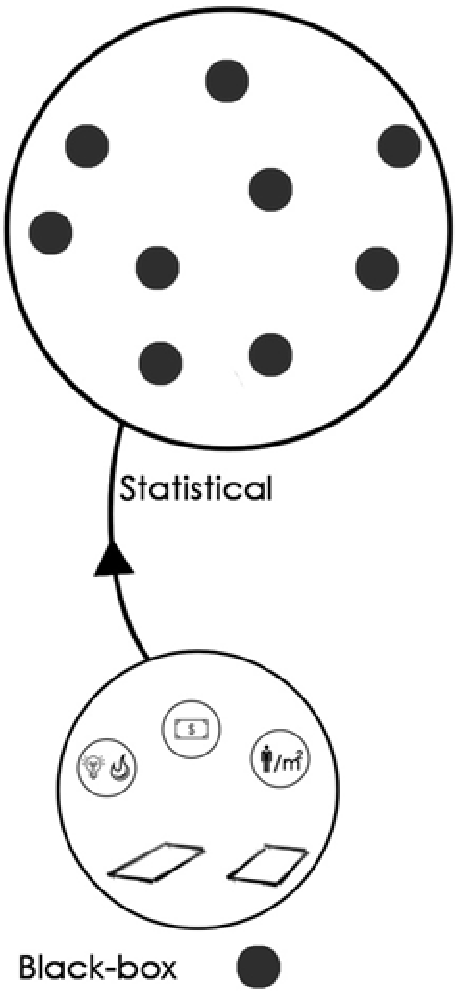

Fig 6. Statistical approach

According to Hong and his colleagues (T. Hong et al., 2016) these methods have a major gap, when it comes to assessing the future Energy Conversion Measures (ECMs). The shortage is, that this kind of model cannot take integrated effects of ECMs into consideration.

The second group is the engineering method (Kavgic et al., 2010; Swan and Ugursal, 2009). There are references for this process as physics-based method in the literature (T. Hong et al., 2016; Tardioli et al., 2015) and it is also mentioned as the analytical method (Fonseca and Schlueter, 2015). As this approach contains white-box modelling only (see on Fig.7.), it requires the most detailed inputs. By this process heat transfer and thermodynamic relationships in a building are calculated. Buildings are usually categorized by features, like the above mentioned clustering. Buildings with the same properties are represented by the same sets of inputs, in an archetype (Davila, Reinhart, and Bemis, 2016).

Also there are two more techniques: calculation based on distribution, in which the end-uses are calculated separately, and calculation based on sampling. This allows for capturing a wide variety of houses in a neighbourhood, but this technique requires a large database (Swan & Ugursal, 2009). The most common inputs are the followings: efficiency of space heating systems, areas, and thermal characteristics of different dwelling elements, such as walls, doors and roof for instance.

In this process the calculation is carried out by a simulation program which usually based on heat-mass balance equations for example : EnergyPlus[3] , BREDEM (Anderson et al., 2008).

This approach has a lot of potential. According to Swan et.al.(Swan & Ugursal, 2009) the only way to evaluate impact of new technologies is this method.

It is capable, unlike the other methods, to model on-site energy generation in both active, and passive ways. The greatest shortcoming of this concept is the lacking information about occupancy behaviour.

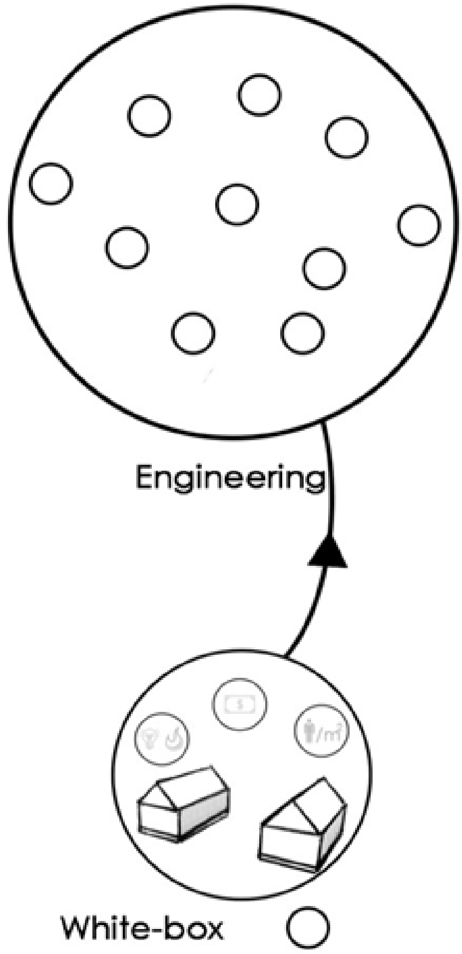

Fig 7. Engeneering approach

To address the shortcomings of both statistical and engineering method, the so called hybrid method (Kavgic et al., 2010) or UBEM (Urban Building Energy Model) (Davila et al., 2016) had been made. These models combine the advances of both methods, they consists of a statistical, and a physics based component (see on Fig. 8.)

The statistical part is used generally, for estimating the annual energy consumption data, and then the estimation of space heating, and cooling loads are accomplished with a simulation software. This way the first method is responsible to implement, and deal with the occupant behaviour, as this is aggregated from real historical data, and the second part is responsible to address the effect of implementing new technologies(Kavgic et al., 2010)

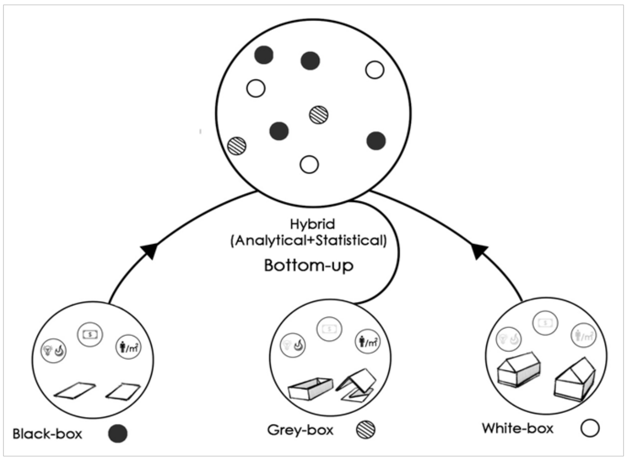

Fig 8. Hybrid approach

In the recent years, models with the best performance, and lowest level of uncertainty has been made with the concept such as (Davila et al., 2016; J. A. Fonseca, T. Nguyen, 2016; Swan, Ugursal, & Beausoleil-Morrison, 2013). For example in the Canadian Hybrid Residential End-Use Energy and GHG Emissions Model (CHREM) (Swan et al., 2013) for the statistical part, a calibrated neural network model was adapted to estimate the annual consumption of the loads mainly influenced by occupant presence.

For modelling the space cooling, and heating load the ESP-r [1] simulation package was implemented. With this package the impact of technological progression has been assessed.

To examine these models, Table 2 was created, where the different aspects was defined, by the literature review. Under the „scale" point, three different scales were identified: the City, the District, and the Neighbourhood.

By „building type" Single, and Multi-family, Commercial and Public, Mixed use, Industrial, and Other buildings were specified.

In the point „method" the above discussed Bottom-up, and further separated the Statistical, Analytical, and the Hybrid (Analytical and Statistical) methods were specified.

The next point is the „geometrical data". It was split into two categories, existing and self-built. Both have the same sub-categories, which are the CityGML Levels of Details (Gröger & Plümer, 2012; Wate & Coors, 2015), Built Environment and Topography.

At the point „meteorological data" we examined which data file they use, and whether they calculate with microclimatic phenomena or not. Data files could be acquired from General-, or Regional Circulation Models (GCM,RCM)[1], or from historical data like Typical Meteorological Year(Crawley, Huang, & Berkeley, 1997; Jentsch, James, Bourikas, & Bahaj, 2013) (TMY1,TMY2,TMY3) and Weather Year for Energy Calculations (Crawley et al., 1997) (WYEC) or any other format.

From microclimatic phenomena the Urban Heat Island effect (UHI), the effect of green surfaces, and local wind patterns were taken into consideration.

Under „building physics" we examined how the model handles the buildings: with archetypes or each building individually.

In the next point, „building control", we investigated whether to take, or not to take into consideration the building control like BMS, or the Occupant Behaviour(OB).

Next the „simulation platform" was assessed. Here, the main modelling software was defined like EnergyPlus, ESP-r,CitySim and Simstadt.

According to the literature review, the „simulation type" could either be dynamic, or static(steady-state).

Last but not least, under the „validation" and „sensitivity analysis", we examined, if the models carry out validation and sensitivity analysis, or not.

1 University of Strathclyde, "ESP-r," 2016. [Online]. Available: http://www.esru.strath.ac.uk/Programs/ESP- r.htm. [Accessed: 23-October-2016].

1 IPCC Intergovernmental Panel on Climate Change Available: http://www.ipcc-data.org/guidelines/pages/gcm_guide.html [Accessed:25-10-2016]

work source	scale				building type(NR)						method		Inputs		validation	
	Country	City	District	Neighbourhood	residential		Commercial and public (c&p)	mixed use(mu)	Industrial(I)	other(o)	Top-down				Yes	No
					Single family (SF)	Multi family(MF)					Econometric	Technological	Input Data	Estimated Data		
Siller et al., 2007	x				x	x					x		-Population, -Relative demand according to Building Type, -ERA per flat, -Total demands of Flat, -Total Demand of ERA*, -Hot water demand per capita, -Specific energy demand for hot water generation, -Final energy consumption for heating -Final energy consumption for hot water *Described in the paper	Heating system	x	
Young 2008	x				x	x						x	-Retirement ages of appliances -Household size -Household location -Household income			x
Labandeira et al., 2005	x				x	x					x		-Aggregation of goods -Prices of goods -Expenditure on goods - Educational level of household head -Geographical location of home -Ownership -Household head Working/Not working -No. Household members by age -Trend variables from database.	Stock of appliances , and level of usage		x
Tornberg & Thuvander, 2005		x			x	x	x	x	x	x	x		-Parcel key -Building key - Year of construction -Use of the building -Address -Delivered kWh gas -Delivered kWh electricity -Delivered kWh district heating -Code for section -Code for metering district -Real estate name -Heating energy. Inlc hot water kWh/m2year -GIS data	Heating system, and energy carriers by age class applied from statistics /Aggregated data applied as Non-aggregated/		x
De Santoli et al., 2014		x								x	X		-Building composition in number,type , dimension. -S/V data (Surface/Volume ratio) -Energy performance of envelope -Global seasonal efficiency of thermal plants. -Heating consumption			x
Coffey et al., 2009;	X						x				x		-location -building type -size -age -life cycle stage -floor area -energy use intensity (EUI)by fuel type -maintenance cost	User inputs: -rates of new construction -retrofit rates -demolition rates -expected improvements	x	
Howard et al., 2012		x			x	x	x	x	x	x	x		-Reference year for HDD and CDD -Use of the building -Building floor area -annual energy consumption	Fuel oil consumption	x	
Balaras et al., 2007	x				x	x	x	x	x	x	x		-Total energy consumption per building type - Construction periods -Type of heating system -Average efficiency of heating system -Climatic zones -Energy Conversion Measures (ECM's) information	-Annual growth rate of dwellings -number of permanent resid. Dwellings - floor area for buildings in each category	x	

Table 1. Comparison of top-down models

work source	scale			building type						method			geometrical data											
										bottom-up			existing						self-built					
	City	District	Neighbourhood	Single family (SF)	Multi family(MF)	Commercial and public (c&p)	mixed use(mu)	Industrial(i)	other(o)	Statisctial	Analytical	Statistical +Analitycal	2,5D LoD0*	LoD1	LoD2	LoD3	Built environment	Topography	2,5D LoD0*	LoD1	LoD2	LoD3	Built environment	
Braulio-Gonzalo, Juan, Bovea, & Ruá, 2016		x		x	x							x				x	x	N/A						
J. A. Fonseca, T. Nguyen, 2016	x			x	x	x	x	x				x										x	x(Built by a digital elevation model)	x
Hong, Chen, Lee, & Piette, 2016	x			x	x	x						x	x	x	x	x(Integrated City GML, also har…	x	x						
Dascalaki, Balaras, Kontoyiannidis, & Droutsa, 2016				x	x					x			x(defined by archetype)											
Ghedamsi, 2015;	national-level			x						x					x									
Shimoda, Asahi, Taniguchi, & Mizuno, 2007	x			x residential								x	no information available											
Eicker, Nouvel, Duminil, & Coors, 2014;		x					x				x		x	x										
Giovannini, Pezzi, Di Staso, Prandi, & De Amicis,2014	x			x residential						x			x											
R. Nouvel, Zirak, Dagtageeri, Coors, & Eicker, 2014;	x						x			x			x	x										
D. Robinson et al., 2007	x 50-500 buildings	x										x					x	x						
Romain Nouvel et al., 2015;		x		x	x		x					x		x	x									
Davila, Reinhart, & Bemis, 2016;	x			x	x	x	x	x	x			x	x				x							
Swan, Ugursal, & Beausoleil-Morrison, 2013	Country			x	x							x												

Table 2. Comparison of bottom-up models

	meteorological data											building physics		building control			simulation platform	simulation type		validation		sensitivity analysis	
	Model-based		Historical			Green surfaces		Local wind patterns		UHI effect (Urban Heat Island effect)		**Sets of inputs representing a group of buildings with similar properties(Archetypes)	Individual sets of inputs for every building	No	Yes			steady-state	dynamic	Yes		Yes	No
Topography	GCM***	RCM***	TMY	WYEC	Other	Yes	No	Yes	No	Yes	No				BMS	OB							
							x		N/A		x	x		x			EnergyPlus with Design Builder Interface		x	x			x
	Obtained from Meteonorm 7.0					N/A		N/A		x		x				x	Python v2.7 (open-source programming language)		x	x		x	
			x				x		x		x		x			x	EnergyPlus+Openstudio		x			x	
					x		x		x		x	x		x			TEE-KENAK(Official Greek National Software)	x		x			x
					x(HDD from 2008)		x		x		x	x		x				x			x		x
					x		x		x		x	x				x	calculation models		x	x			x
					insel 8 (monthly outside dry bulb temperature (DIN V 4108-		x				x	x				x	calculation (standardised in the ISO 13790)	x		x		x	
							x				x	x					calculation based on ISO 13790 and ISO 15316	x		x			x
		x					x		x		x	x				x	Simstadt	x		x		x	
						x		x			x					x	a JAVA based GUI, EA and CitySim		x(reduced)				x
							x		x		x	x				x	Simstadt			x			x
			x				x		x		x	x				x(variable related to peak occupancy)	EnergyPlus		x	x			x
				x(CWEC Canadian Weather for Energy Calculations)			x		x		x	x				x	ESP-r		x	x			x

There has been an approach which states, that the Top-down, and the Bottom-up are not mutually exclusive approaches, but they are complementary approaches (Kim and Loch, 2014). So an energy model could only be the best, if it contains the two approaches. Hourcade et.al. (Hourcade et al., 2006) pictures it in a 3 dimensional coordinate system, where the 3 dimensions are macroeconomic completeness, microeconomic realism, and technological explicitness. The pure Top-down models are moving in the plane created by the macroeconomic completeness axis, and the microeconomic realism axis. However, the pure Bottom-up models are moving in the plane created by macroeconomic realism, and technological explicitness. If a model changes just enough to move out from its original plane Fig.9., Hourcade et al. in (Hourcade et al., 2006) considers it as a hybrid model.

So according to their statement (Hourcade et al., 2006), there are four different hybrid models available:

1. Top-down based model, which abandons the conventional macroeconomist toolkit, and applies representation also for energy end-use technologies, and technology adaption, described by Bottom-up method.
2. Top-down based model, which is more disaggregated and uses Leontief (Lopes and Neder, 2016) fixed-input ratios to include some reduced form of a Bottom-up model.
3. Bottom-up based model, which includes top-down variables like: functions, for clear markets, final goods and services based on changes in cost of production, etc. (Hourcade et al., 2006)
4. The fourth is called by him as a „Holy Grail". This type of model contains a fully developed Top-down, and a fully developed Bottom-up models, with all of their characteristics.

Davila et al. states in (Christoph F. Reinhart & Cerezo Davila, 2016) that Top-down modelling is less-suitable to examine more integrated scenarios, and Nouvel et al. states in (Nouvel et al., 2015) that this approach is inappropriate to model energy transition. Therefore for examining of the state of art, we picked seven models from the Bottom-up table for comparisons, and deeper analysis.

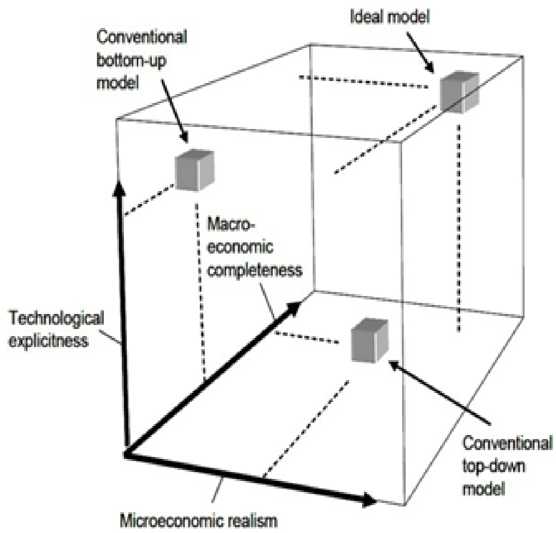

Fig. 9. Figure of the Hybrid models (Hourcade et al., 2006)

2.2.4. Overview of the seven models

Reinhart states that urban building energy modelling tools have three main pillars: data input, thermal modelling and validation. (Christoph F. Reinhart & Cerezo Davila, 2016) According to the state of the art, there are models with individually developed workflows as stand-alone software, at the same time models based on existing simulation tools can be also found, where additional effort has to be made to harmonize the work of embedded platforms and process reliable simulation results. In our paper, the following design supporting city-scale energy modelling tools are highlighted from all the collection presented in previous tables as these are the most complex and profound platforms based on different concepts or even built on each other.

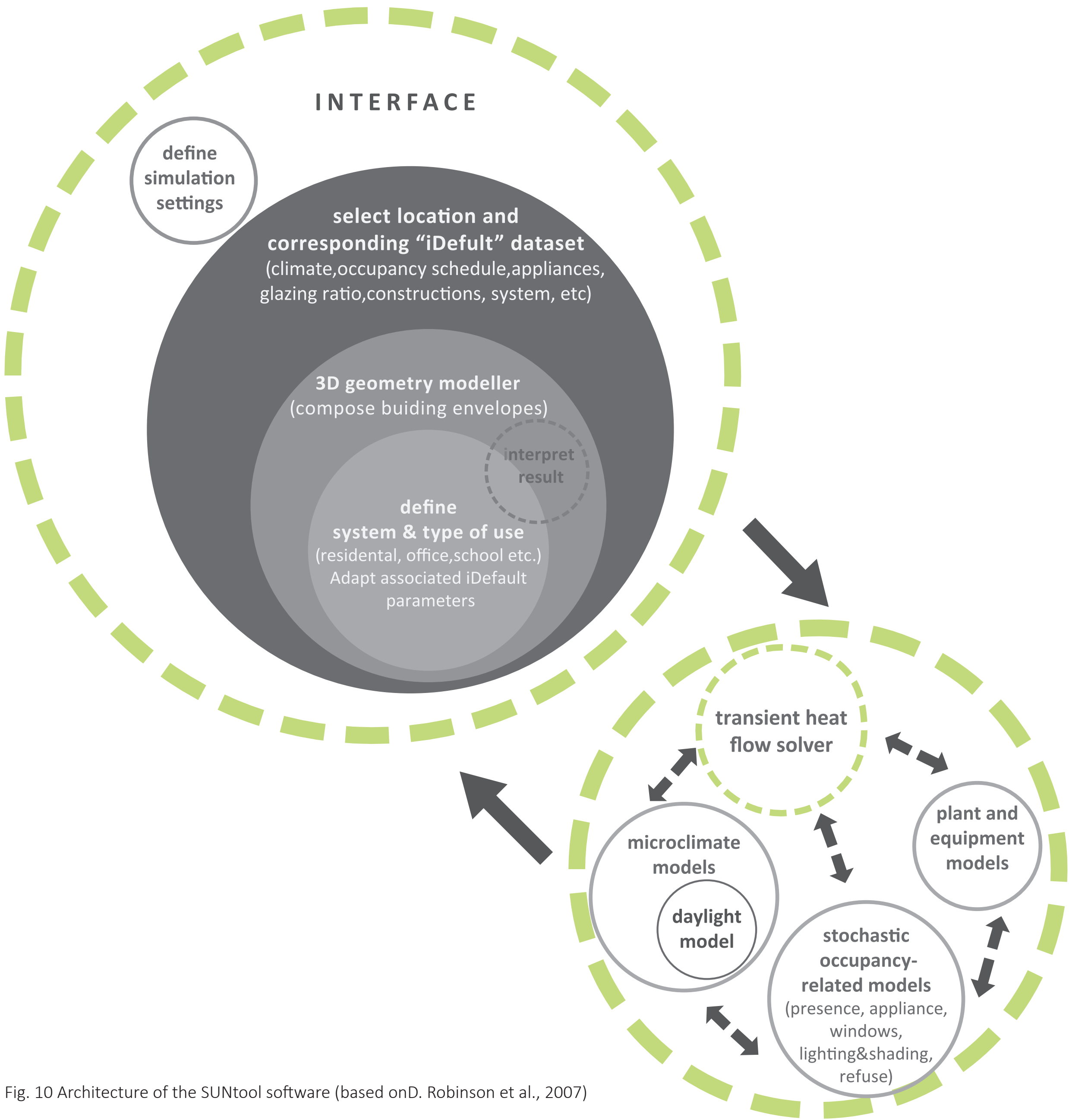

Fig. 10 Architecture of the SUNtool software (based onD. Robinson et al., 2007)

Started in 2001 Project SUNtool, Sustainable Urban Neighbourhood Modelling tool, (D. Robinson et al., 2007) (see on Fig. 10.) was developed firstly, in order to help designers in the pre-design stage to create more sustainable urban neighbourhoods. Maintaining the scale of 50-500 buildings this framework is based on simulation of resource flows (energy, waste and water) taking into consideration the microclimate conditions (Darren Robinson & Stone, 2004) and the effect of human behaviour. (J. H. Kämpf & Robinson, 2007) SUNtool has been documented in several publications, applied in Greece and Switzerland, however, the software has not been officially published.(C.F. Reinhart et al., 2013)

As occupants' behaviour has important impact on building's energy balance, this model gives particular attention to this matter. Using quarter-hourly profiles, occupants presence can be set. Much attention is paid to window openings, lights and shading devices, electrical and water appliances, as well. (D. Robinson et al., 2007)
There are two reasons why it is becoming interesting to model weekly waste flow with the help of statistical data.
On one hand, it is a key indicator of sustainability, on the other hand energy can be produced through incineration.(D. Robinson et al., 2007)

Inside the Graphical User Interface there are optional settings. Here, the Fuel/Plant Library allows user to choose from, or even create fuels and those equipments belong to them.
These properties have to be linked to building and district energy centres.

This design support tool has a complex workflow. Firstly, the global location of the site has to be selected using the user interface (developed in Java). It is assigned to climate data and an intelligent default dataset, which includes detailed information of each building as age and type of use, that can be further detailed (such as default properties of built-in HVAC systems can be overridden).
After this, building geometry has to be defined (rendered with Microsoft DirectX for Java3D). Decentralised or connected to a central energy centre, renewable sources and water processing technologies may also be chosen. Then from GUI containing all relevant data via XML files C++ objects can be generated and sent to the solver Fig.10.
For microclimate, thermal, stochastic (as user presence for instance) and plant models, an instance is created in order to store information for the internal connections of each model. The structure of the solver contains four layers for the four models with different workflows with distinct degree of complexity. The results of simulations of each four models are fed back to the GUI as an XML file.
SUNtool is the first integrated dynamic model which is based on physically rigorous analyses of communication between the urban environment and the building energy consumption. However, according to Robinson, it has several shortages discussed below. (D. Robinson et al., 2007) Meanwhile internal water appliances by buildings are modelled, neither rainwater storage, nor black or grey water flow are presented. The energy production of renewable sources are also not supported, as stated in the study. Life cycle cost analysis is not included.

CITYSIM

The aim of the research project started in 2006, (J. Kämpf & Robinson, 2009) was to support the environmental design of urban master plans dealing with non-domestic buildings as well. This urban scale energy model uses SUNtool (Darren Robinson & Stone, 2004)
Fig.11. solver as a reduced dynamic thermal simulation platform. It applies properties of a shortwave and longwave radiation model which considers obstructions to both sun and sky as well as reflections from adjacent obstructions and uses them as input. The prediction of interior lightning rate and internal temperature, for instance, is meaningful information for calculating the occupants' behaviour. CitySIM (J. H. Kämpf & Robinson, 2009) is a developed version of SUNtool (J. H. Kämpf & Robinson, 2007). It was found out to support a more reliable and more comprehensive city-wide simulation process, than SUNtool had had before.
To deal with the large number of parameters, such an optimised model should be taken into account, Kämpf and Robinson in 2008 developed a hybrid algorithm of the CMA-ES and HDE methods. Fig12 (J. Kämpf and Robinson, 2009).It has been used to manipulate the geometry of city blocks in order to optimize their form for active and passive solar energy utilization. CitySIM is based on the following three parts: a graphical user interface, a database containing technical specification of groups of buildings, and a solver.
The framework is similar to the previous version, (D. Robinson et al., 2007) however, this is more detailed. The GUI (graphical user interface) allows to draw and edit the new buildings' geometry within an urban context in order to support designers in evaluating different massing concepts while the spatial opportunities on the

and urban settlements are also taken into consideration.

In common with SUNtool the database contains default values related to technical characteristics including constructional and occupational information as well as appliance and system's specification. After grouping all buildings into archetypes, there is a further opportunity to specify these settings in case of having more precise information or individual elements.

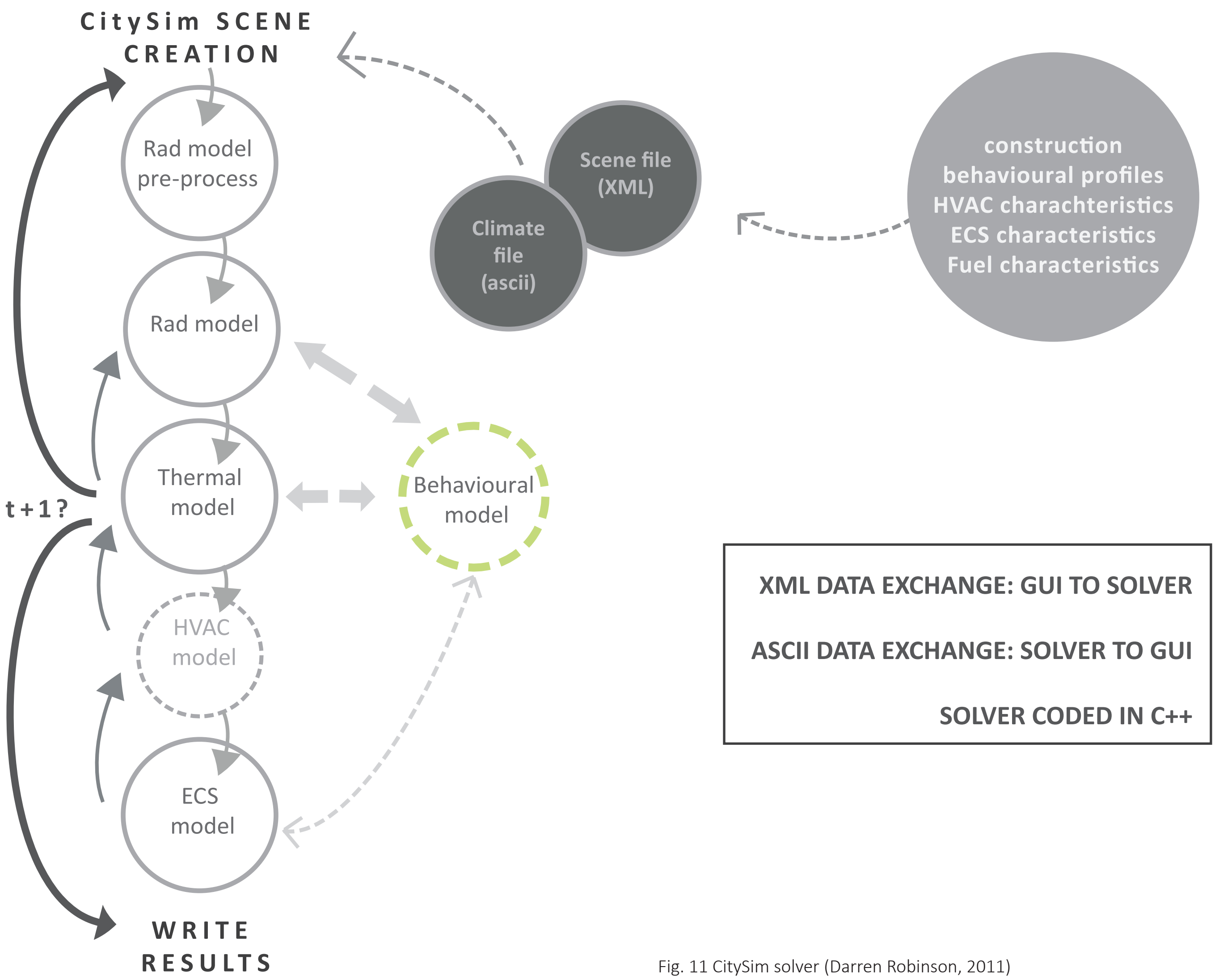

Fig. 11 CitySim solver (Darren Robinson, 2011)

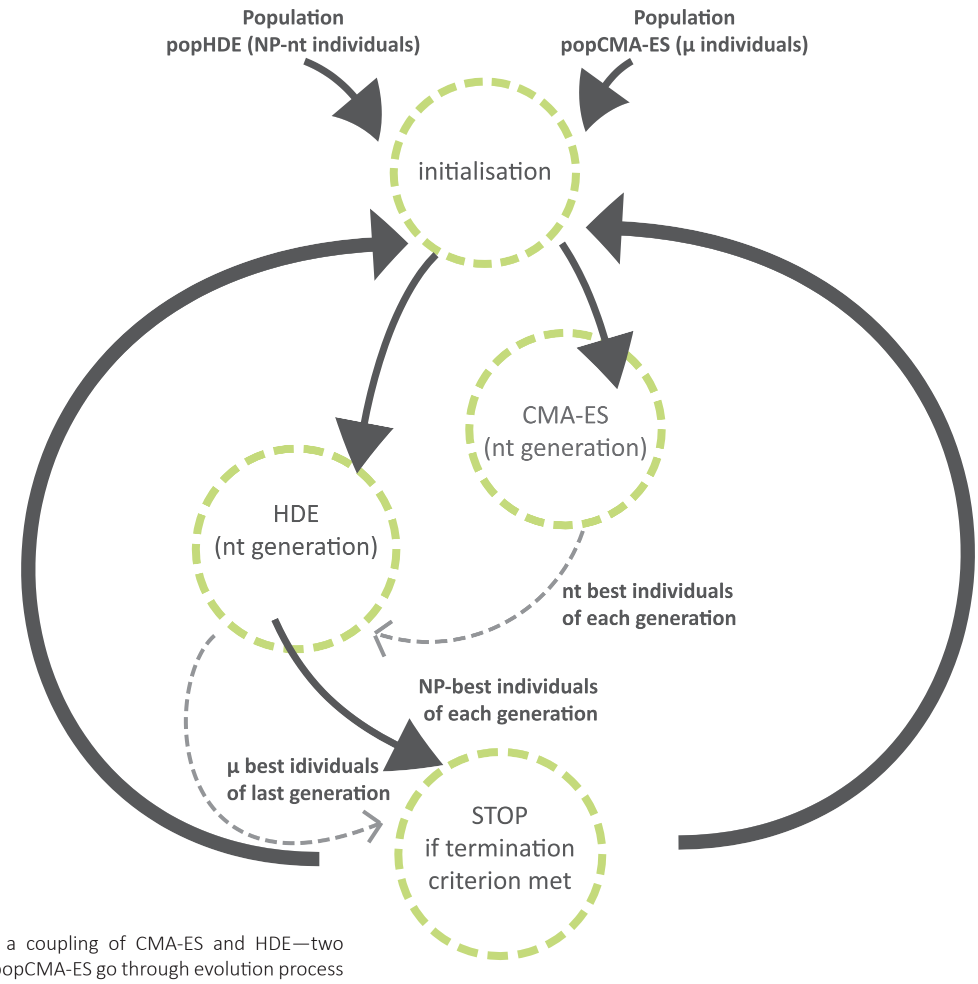

Figure 12 The hybrid algorithm, a coupling of CMA-ES and HDE—two distinct populations popHDE and popCMA-ES go through evolution process (red solid lines) exchanging individuals (blue dashed lines) (J. H. Kämpf & Robinson, 2009)

After that the building is associated with an Energy Centre according to its HVAC system, energy sources and appliances. It can also be an element of a District Energy Centre, which means more information is provided about heating, cooling and power demand. Location and climate information is set by the user.

The link between the information from GUI and the database is in an XML file, which contains all the values previously set as we could see by the previous model, SUNtool. The solver reads the XML file (defined by the C++ objects describing the buildings, zones and associated plant systems).

The solver runs the simulation for each hour and each thermal zones.

The result is described by an ASCII file and sent back to the GUI to graphically present it.

Urban scale modelling contains the necessity of computerised algorithms. Therefore through matching CitySIM structure with a hybrid method has the opportunity to reach relevant data. With developing the hybrid approach EA (evolutionary algorithm) (J. H. Kämpf & Robinson, 2009) the solver can infer the missing physical properties from the available data. At this stage the process uses a black box model.

In the pilot project of the district of Matthäus in Basel, (J. Kämpf & Robinson, 2009) 13 parameters were described via EA, glazing ratio, window U-Value, position of the insulation of the walls and insulation thickness for instance. As a result, the ideal heating and cooling demands of the group of buildings (26 buildings in the above mentioned case study) has been calculated. Moreover, 20% demand reduction has been established in case of changing a small amount of design parameters.

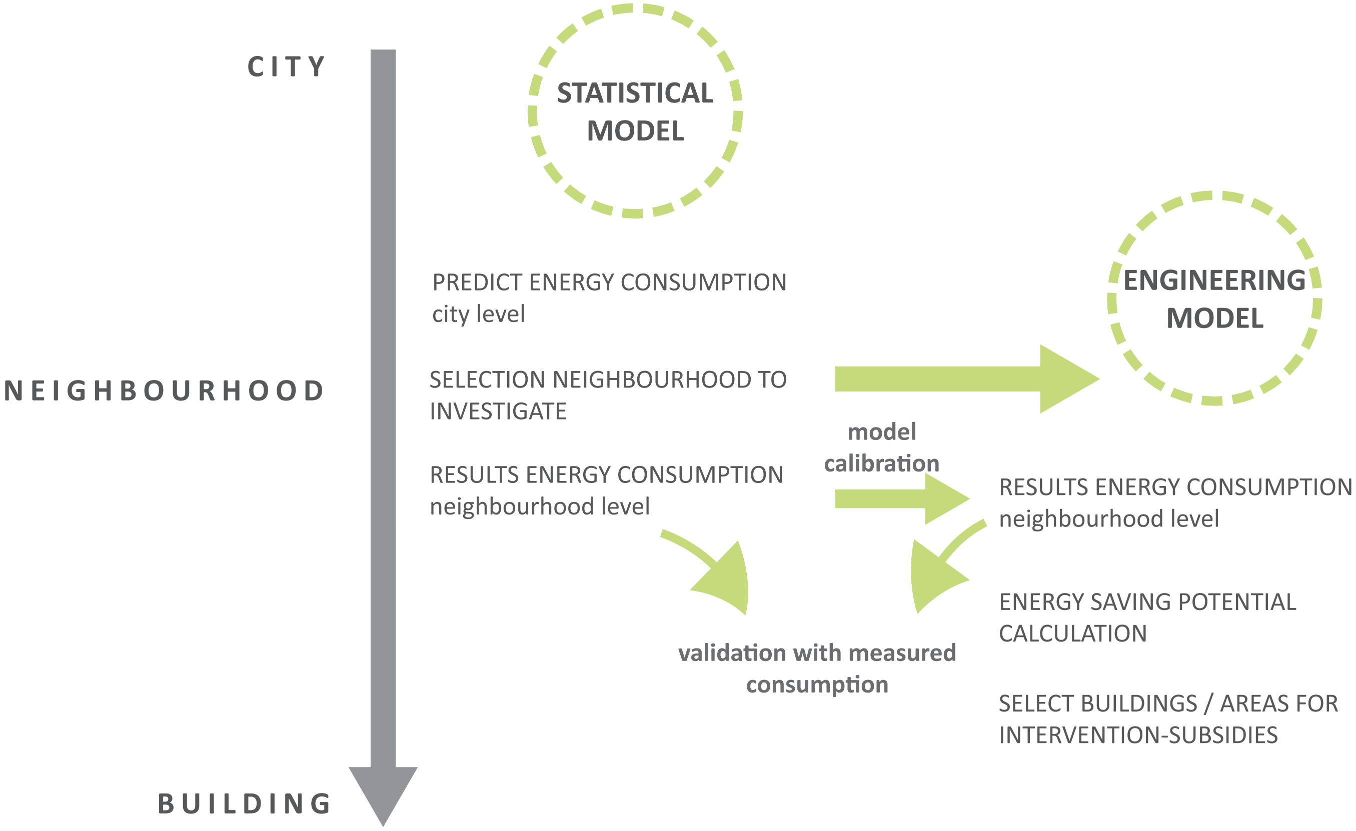

Fig. 13. Structure of the hybrid model (Nouvel et al., 2015)

Simstadt

The model from Nouvel et al. (Nouvel et al., 2015) is also a hybrid method based in Rotterdam. In their research paper they calculated the energy use with two different bottom-up methods. (statistical and hybrid.) The latter approach contains analytical, and statistical parts. The aim of this model was to develop a framework which could combine the statistical and the engineering (or analytical) model for improved predictions.

The gas consumption was calculated with a multiple linear regression to define the energy saving potentials. Although without dataset about refurbishment, the statistical model itself cannot predict the energy savings, it is estimated with benchmark values.

The analytical part is brought to effect with Simstadt urban energy simulation platform. This project is one of the reference studies for the platform.

The visualization is carried out in CityGML 3D in which there are five LoD-s (Level of Details).

This platform calculates the heating demand based on quasi-static monthly energy balance, and every building is modelled as a single isothermal zone. Furthermore, this platform is able to simulate PV potential, and urban wind flows.

Also there is a new framework, which merges statistical, and analytical approaches on Fig 13. The statistical approach is used to predict energy consumption at city level, to select the neighbourhood in which there is the biggest necessity of the energy saving. This data is also used as a validation at the end of the process. Then the analytical model is used to model the selected part of the city. So, basically with black boxes they allocate which zone uses the most energy, to this end data is assigned with zip codes to location, and then they model that zone with white boxes.

They measured MAPE (Mean Absolute Percentage Error) of the statistical, and the hybrid method. For the statistical process the deviation was 5% lower than the measured data, and the hybrid was 25% higher, (respectively 26% and 49%).

CityBES

The City Building Energy Saver (CityBES) web-based platform is created by Hong and his colleagues. (Hong et al., 2016) The main focus of this platform is to help municipalities to assess possible city-scale energy saving programs.

City BES was based on the CBES (Commercial Building Energy Saver) Toolkit, but it was extended with other commercial and also residential building types.

This tool is able to model more than 10000 buildings, and also to identify deep energy savings up to 50%, with the heaps of ECM-s (Energy Conversion Measures) implemented in this framework. Shown on Fig.14. As it can be seen, the model operates at three different layers.

To compute this extraordinary amount of data, they implemented parallel computing architecture to utilize high performance-computing clusters. One of the main attributes

of this model is that it can compute a big amount of data relatively fast in a cloud-based process. CityGML was used for 3D visualization.

CityBES calculates city energy use from annual, monthly, and hourly energy usage data. With the help of the energy end uses data it can identify energy savings for different building systems.

EnergyPlus was used to calculate the ECM-s, then it was applied to CityBES for retrofit analysis. CityBES also provides sensitivity analysis for the electricity consumption as a function for outdoor air temperature. The energy modelling was also carried out by the EnergyPlus software, using OpenStudio interface and an Automated Model Calibration was adopted as well. There were no test cases published, so the percentage of error of this model is yet to be made.

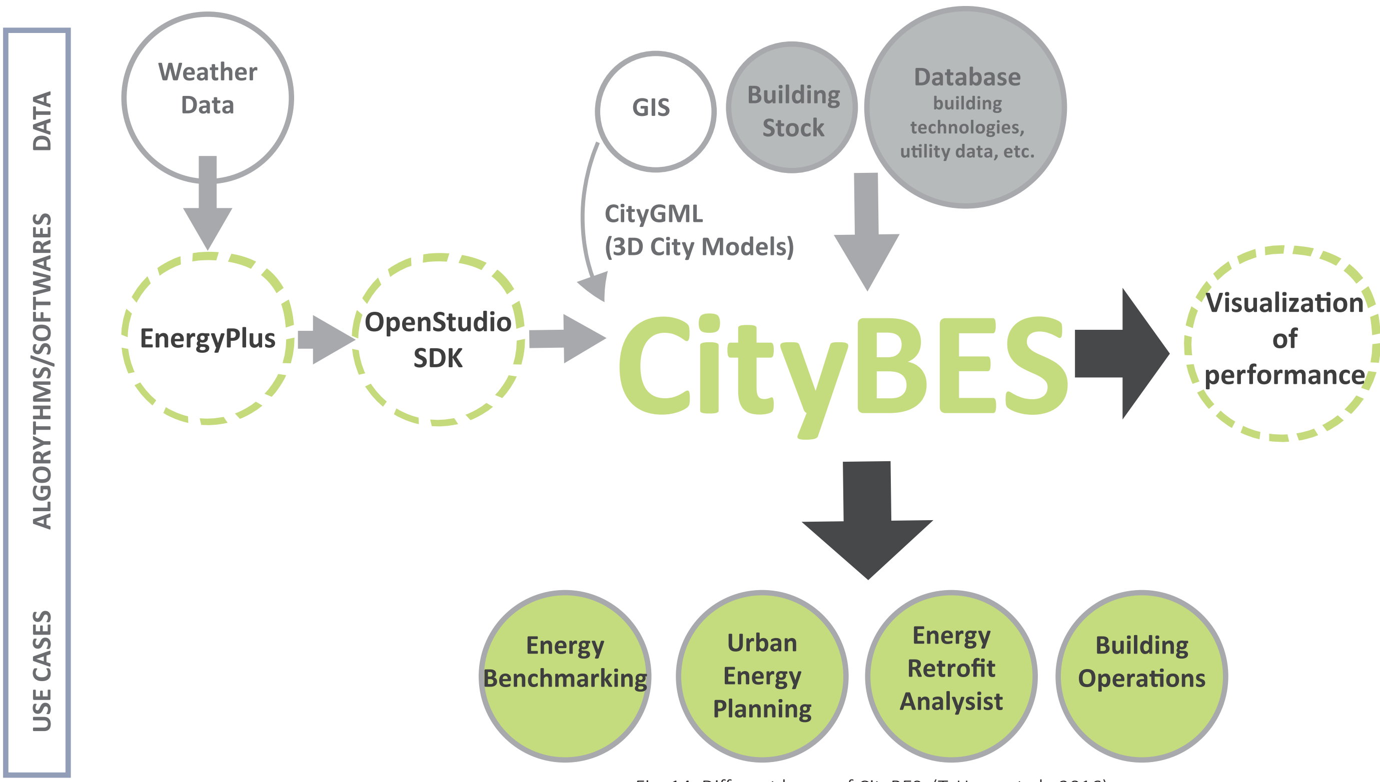

Fig. 14. Different layers of CityBES (T. Hong et al., 2016)

Umi

Urban modelling interface (Umi) (C.F. Reinhart et al., 2013) has been developed by the Sustainable Design Lab at the Massachusetts Institute of Technology.

The goal of this urban modelling design tool is to improve the efficiency of new and existing neighbourhoods in terms of sustainability, in conjunction with operational energy use, daylighting, outdoor comfort and walkability.

This is a Rhinoceros-based system, which comprises the following four modules: the settings of the location and building information, simulations, result visualization. The urban context is set first -such as building volumes with glassed areas, streets, important elements of natural environment and most of the shading objects- in this Windows-based nurbs modeler, then each building is defined by an editable template of constructional data and usage schedules.

Thermal properties are evaluated building by building with

EnergyPlus solver and sent back to the platform of Rhinoceros to make the results visible in order to foster design interventions.

Daylighting and sustainable transportation workflows are integrated in additional expert toolsets of Grasshopper. Evaluations for daylighting runs in a solver called Daysim, which is a Radiance-based extension. Walkability calculations are relying on the density of amenities, number of intersections and block lengths. Python script is used in Umi to evaluate these values. On November 7th 2014 a second version was published containing embodied energy calculation module.

Boston's UBEM

Nowadays the main focus of this field is on finding the adequate connection between modelling tools and the currently available datasets of the examined city, according to the paper of Reinhart et al. (Davila et al., 2016) There are several other hybrid models with the similar framework, we choose this one as the last model elaborated according to our researches.

The urban energy model of Boston is based on three sub-stages: model characterization, model generation and model simulation. The workflow uses a Rhino based CAD environment applying GIS datasets actively maintained by the municipality for creating geometrical properties, ground elevation and urban context.

The model is automatically generated in 2.5D from this input, for further details Rhino plugin Grasshopper interface can be used. For the energy simulation, similarly to the process of Umi, EnergyPlus is handled. The calculation is based on the same method as mentioned previously by Umi's workflow. The model is able to calculate yearly and hourly energy demand on building scale for the entire city as its input is supported by Boston's datasets.

The workflow of this city-wide model also contains a part dealing with scenario analysis strongly with the scope of energy demand and supply on the building and specific systems scale for supporting decision makers and designers (see Fig.15.)

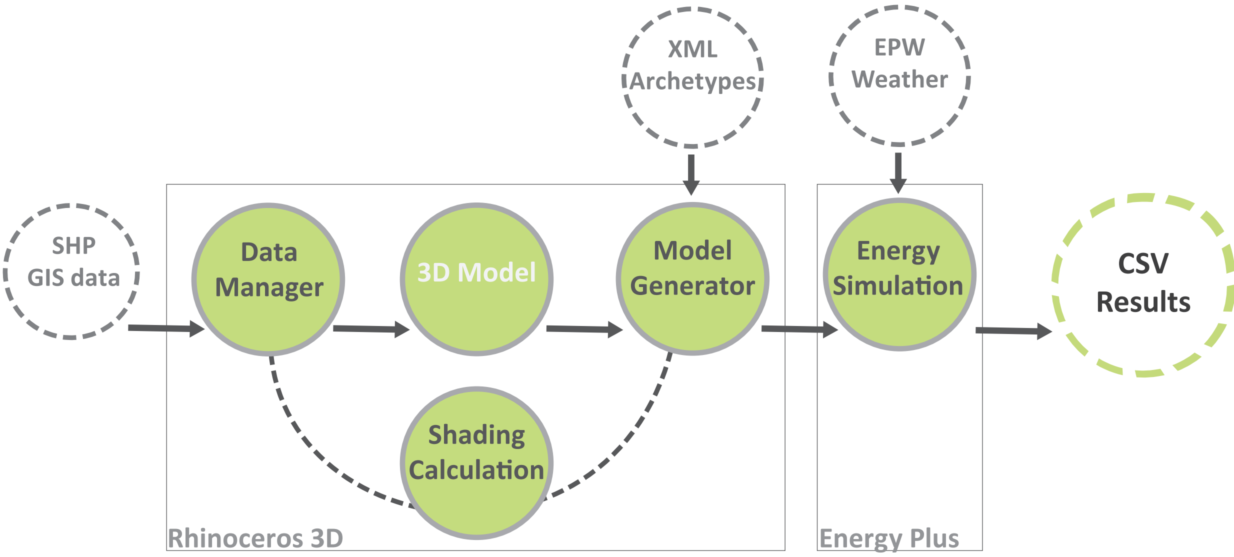

Fig. 15. Boston's UBEM

CEA

City Energy Analyst (CEA) is based on the previous model of the authors. (Fonseca & Schlueter, 2015) They developed a model, with the scope of determining spatiotemporal variability of the energy services in the future. This model was constructed by three main parts, which functioned separately Fig 15. Then it was aggregated, clustered, and visualized by a GIS framework. This itself was a hybrid method, which contains the following four main phases; statistical model (1), analytical model (2), aggregation (3) as well as clustering and visualization (4).The model was validated with a peer model and empirical data. The percentage of errors for the whole zone was 1% and 19% for the neighbourhood and the city district.

The black box method, was used to determine data from local building archetypes, then with the help of the determined data, distribution database, and spatial clustering algorithms, a calculation was carried out with white-box method. Based on this, Fonseca et. al. created a new model called CEA (J. A. Fonseca, T. Nguyen, 2016)

This framework was created to analyse different urban scenarios by the energy, carbon emission, and financial point of view.

This framework was created to analyse different urban scenarios by the energy, carbon emission, and financial point of view.

This model was programmed in Python v2.7 and built as an extension of the Geographic Information System ArcGIS v10.3. This model was built upon the previous one. This framework contains detailed models for forecasting the building demand, assessment of the availability of resources, simulation of conversion, storage and distribution technologies, bi-level optimization, multi-criteria assessment and four-dimensional visualization.

It has a more detailed model structure. CEA framework Fig. 16. (J. A. Fonseca, T. Nguyen, 2016), consists of a demand module (1), a resource potential module (2), a systems technology module (3), a system optimization module (4), a decision module (5) and a spatiotemporal analysis module (6). The detailed features of each module are further discussed in the paper of Fonseca and Nguyen. (J. A. Fonseca, T. Nguyen, 2016) The sensitivity analysis was conducted only by the decision module.

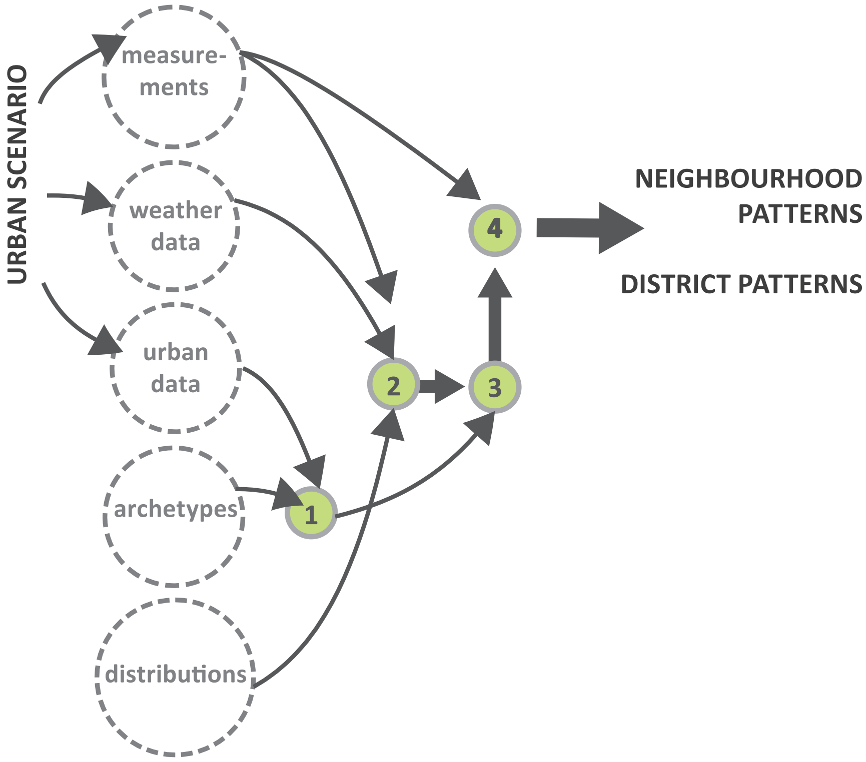

Fig. 15. Model framework (Fonseca & Schlueter, 2015)

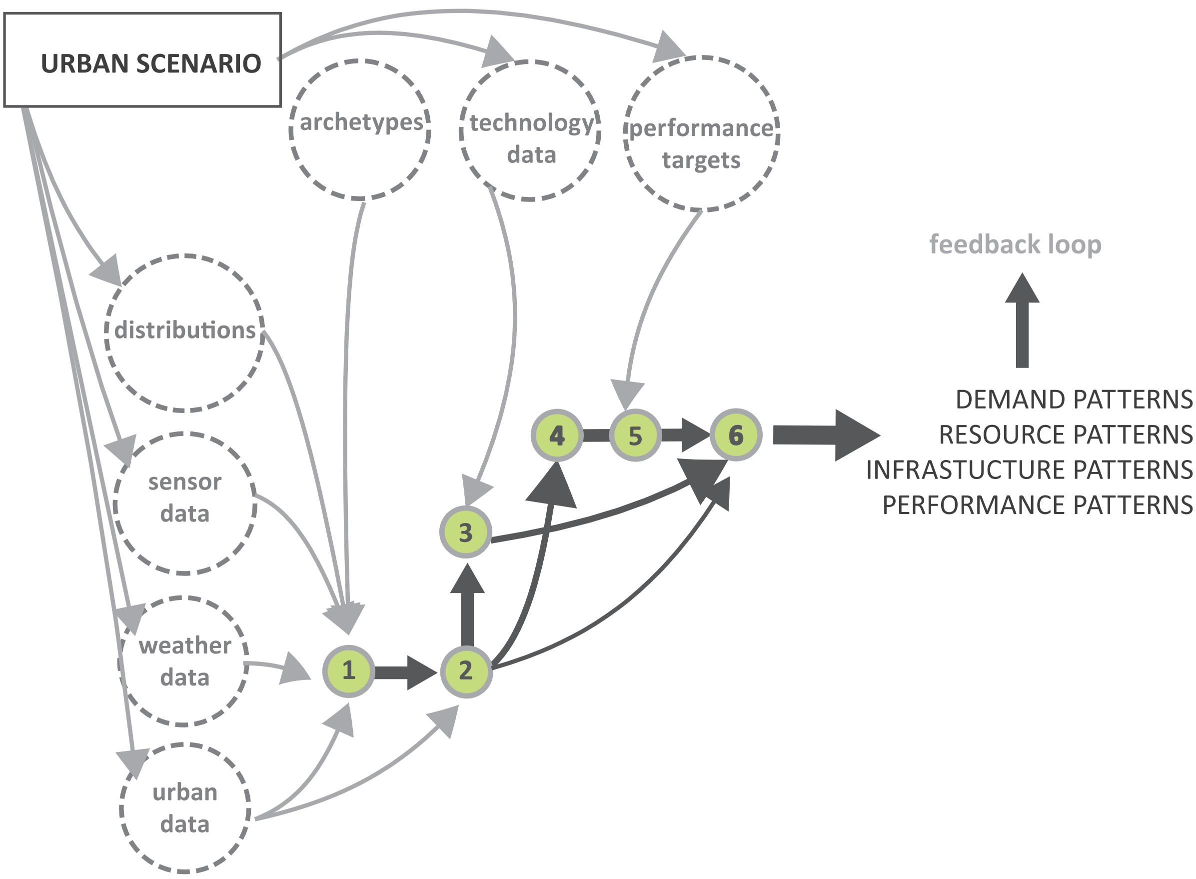

Fig. 16. Operating method of CEA framework (J. A. Fonseca, T. Nguyen, 2016)

Here the prices of the different fuels were examined in relation with the Pareto optimal configuration. They also implemented here a Multi-criteria decision analysis approach (Hirschberg et al., 2004).

The test case was executed, where they examined the Swiss city of Zug.

Four different scenarios were stated by the year of 2035. The percentage of error, the rME (relative mean error), and the RMSE (root mean square error) was between 2%- 5% (except radiation RMSE=14% and the demand model rME=32%) the latter is a common problem by the white-box demand modelling.

These seven urban energy modelling platforms, described below, have been compared in a table, which contains aspect related to energy flow in an urban environment. The aspects has been partly collected from the relevant abilities of each models containing the analysis of energy flow, future scenarios such as retrofit scenarios, climate change and renewable potential calculations and urban-scale synergies. See the comparion tables below. (Table 3. and 4.)

modeling approach	platform	author	energy flow	retrofit scenarios	climate change	renewable potential calculation	financial aspects	synergies-building related energy changes	non-building related energy changes	conversion and storage technologies simulation
bottom-up engineering/analytical	SUNtool	Robinson et al., (2007)	thermal, waste, water flow	x		not included yet		only solar penetration	streetlighting	
bottom-up analytical + statistical, so called hybrid	CitySIM	Kämpf, J., & Robinson, D. (2009).	x	x	not included yet	x		x		
bottom-up analytical + statistical, so called hybrid	Simstadt	Nouvel et al., (2015)	x	x		x				
bottom-up statistical	CityBES	Hong et al., (2016)	x energy benchmarking	x energy saving potential calc.	x	x		x		
bottom-up analytical	umi	Reinhart et al., (2013)	x		x embodied energy calculation in Version 2.0.	x		daylighting via Radiance based Daysim		
bottom-up analytical + statistical, so called hybrid	UBEM	Davila et al., (2016)	x	x	x	x				
bottom-up analytical + statistical, so called hybrid	CEA	Fonseca, J. A., & Schlueter, A. (2015).	x		x carbon emission	x	x	x	x	x

Table 3. Comparison of the selected seven models

work source	scale			building type						method				geometrical data											
	City	District	Neighbourhood	Single family (SF)	Multi family(MF)	Commercial and public (c&p)	mixed use(mu)	Industrial(i)	other(o)	bottom-up			top-down	existing						self-built					
										Statisctial	Analytical	Statistical +Analitycal		2,5D LoD*	LoD1	LoD2	LoD3	Built environment	Topography	2,5D LoD*	LoD1	LoD2	LoD3	Built environment	Topography
(Fonseca et al., 2016)	x			x	x	x	x	x				x											x	x	x
(Hong et al., 2016)	x			x	x	x						x		x	x	x	x	x	x						
(Davila et al., 2016)	x						x				x			x				×							
(Robinson et al., 2007)	x	x										x						x	x						
(Nouvel et al., 2015)		x		x	x		x					x			x	x									
(Reinhart et al., 2013)			x	x	x	x	x	x			x													x	x

work source	meteorological data									building physics		building control			simulation platform	simulation type		validation		sensitivity analysis	
	Model-based		Historical			Microclimatic phenomenons						No	Yes			steady-state	dynamic	Yes	No	Yes	No
	GCM***	RCM***	TMY	WYEC	Other	UHI effect	Local Wind Patterns	Green surface effect	No	**Sets of inputs representing a group of buildings with similar properties(Archetypes)	Individual sets of inputs for every building		BMS	OB							
(Fonseca et al., 2016)	x					x	N/A	N/A		x				x	Python v2.7 (open-source programming language)			x		x	
(Hong et al., 2016)			x						x		x			x	EnergyPlus & Openstudio					x	
(Davila et al., 2016)			x						x	x		x		x	EnergyPlus		x	x			
(Robinson et al., 2007)							x	x						x	a JAVA based GUI, EA and CitySim		x				
(Nouvel et al., 2015)															Simstadt						
(Reinhart et al., 2013)					x	UWG	N/A	x			x		x		EnergyPlus			x			N/A

Table 4. Comparison of the selected seven models

3. Results

3.1. Results of the investigated top-down models

In Table 1 five out of eight model was carried out at country scale: (Balaras et al., 2007; Coffey et al., 2009; Labandeira et al., 2005; Siller et al., 2007; Young, 2008), and the remaining 3 at city scale:(De Santoli et al., 2014; Howard et al., 2012; Tornberg and Thuvander, 2005).

By the building type point of view it occurred, that residential buildings were the focus in three out of eight models (Labandeira et al., 2005; Siller et al., 2007; Young, 2008) the whole building stock at three out of eight, (Balaras et al., 2007; Howard et al., 2012; Tornberg & Thuvander, 2005), heritage buildings by one (De Santoli et al., 2014), and commercial and public buildings by another one (Coffey et al., 2009).

Only one out of eight model (Young, 2008), was technological, and the other seven were econometric model.

There occurred a wide variety of inputs in

Table 1. The main clusters are however: microeconomic inputs, climatic conditions, housing construction/ demolition/ renovation rates, and the technological features of appliances.

Only two models (Howard et al., 2012; Labandeira et al., 2005) implemented meteorological data, the other six model assumed, that aggregated statistical data already contains the meteorological effects.

Each and every model collected data from already existing databases, surveys, and one even used the data from EPCs (Energy Performance Certificate) (De Santoli et al., 2014).

Half of the models did not contained any validation, (De Santoli et al., 2014; Labandeira et al., 2005; Tornberg & Thuvander, 2005; Young, 2008), however the other half of the models were validated (Balaras et al., 2007; Coffey et al., 2009; Howard et al., 2012; Siller et al., 2007)

3.2. Results of the investigated bottom-up models

In Table 2 a total of 13 models were compared. In scale aspect, six of them dealt with city scale, four with district scale, but none of them directly with a neighbourhood scale.

In „building type" seven of them had the scope on residential buildings, two on mixed use buildings, two of them only on single family houses, and the remaining two on all the above mentioned building types.

Under the point „method", seven of them are hybrid (both analytical and statistical) models, further four were statistical models, while the remaining two analytical models.

The next point is the „geometrical data" in the comparison, where is only one self-built model can be read, one is defined with archetypes, and about one is no data available. All the remaining are created using existing databases, like GIS, or CityGML.

At the point „meteorological data" two of the models used data from Circulation Models, two of them use TMY (Crawley et al., 1997; Jentsch et al., 2013), one model applies some form of WYEC (Crawley et al., 1997), and four models used other datasets. There are four models which did not use weather files at all. From microclimatic phenomena only one of them deal with urban heat island effect (UHI) and another one with the impact of green surfaces and local wind patterns.

Under „building physics" can be read that all but one models used archetypes for defining the thermal properties of the building envelope. The one define parameters for every building individually.

Under the next point, „building control", nine of the models consider occupant behaviour, with either stochastic models, or statistical data, and four did not.

The following aspect in the line is „simulation platform”. From the applied energy modelling software three are Energy Plus, although ESP-r, CitySim, Simstadt solvers are also used. The remaining seven are working with self-built software or calculations.

By the column „simulation type” seven are dynamic, and the remaining items are steady-state methods.

The „validation” and the „sensitivity analysis” are also vital parts of modelling, all, but one models are validated, while sensitivity analysis are carried out by four models.

3.3. Results of the investigation of the selected seven UBEM tools

As it is summarized in both tables Table 3 and 4, four (J. Kämpf & Robinson, 2009) (Planung et al., 2012) (Davila et al., 2016)(J. A. Fonseca, T. Nguyen, 2016) from the seven platforms base on the hybrid approach. There are two elements of the comparison (Reinhart et al., 2013) (D. Robinson et al., 2007) using strictly analytical methodology and one is founded on bottom-up statistical method (T. Hong et al., 2016).

Suntool solver is based on building physics related equations. It applies iDefaults datasets as input, which are editable by the user. CitySim builds upon the calculation method of Suntool that has been further improved with a hybrid algorithm. Both platform uses self-built solver. Simstadt is also a hybrid tool based on the combination of bottom-up analytical and statistical methodologies. CityBES uses EnergyPlus for thermal building-by-building simulations, such as UBEM of Boston and Umi's platform do. They rely on this continuously developing software. Umi and Boston's UBEM are working in a Rhino based CAD environment. City Energy Analyst (CEA) also uses its own solver which is created with Python v2.7 open-source script.

Related to input parameters, this seven platforms have been already included in the bottom-up models' comparison previously, nevertheless it is necessary to underline some properties. The following results can be stated. There are four of the underlined modelling platforms which take occupant presence into account (Davila et al., 2016; T. Hong et al., 2016; J. A. Fonseca, T. Nguyen, 2016; D. Robinson et al., 2007). While all of them build the model of urban context in geometrical level, or use existing datasets for this reason, only four of them deal with topography (T. Hong et al., 2016; J. A. Fonseca, T. Nguyen, 2016; C.F. Reinhart et al., 2013; D. Robinson et al., 2007) and two of them predict results regarding to urban heat islands (J. A. Fonseca, T. Nguyen, 2016; C.F. Reinhart et al., 2013). As it is concluded, only one model is able to consider local wind patterns.(D. Robinson et al., 2007)

Regarding table 4. which indicates the capabilities of each models, it can be concluded that all tools satisfy their base target with providing results for diverse aspects of presenting the urban energy flow such as heating or cooling supply and demand of each building of the entire city.

Secondly, the most obvious lacking capabilities are also visible. They are connected to financial calculation and simulation of energy storage technologies, which are implicated in only one model of the seven (J. A. Fonseca, T. Nguyen, 2016). From aspect of future scenarios, under retrofit evaluations five, while under climate change four models can be mentioned, however all but one provide opportunity to calculate renewable potential. Five (T. Hong et al., 2016; J. A. Fonseca, T. Nguyen, 2016; D. Robinson et al., 2007) of the seven platforms deals with building related energy changes, two of them are counting also for non-building related energy changes such as streetlighting for instance.

(J. A. Fonseca, T. Nguyen, 2016; D. Robinson et al., 2007) Each aspect also can be subdivided into diverse properties, however in the examined publications do not contain enough information to infer more detailed results.

4. Discussion

4.1. Existing methods

As it is presented, micro scale modelling approaches included white, grey and black box methods. Each approach contains diverse calculation techniques, described in Section 1.3. Through a literature review the following statements can be concluded. EnergyPlus solver which has been applied in 3 UBEM tools, is based on nodal method, which is a white-box technique. Its application field according to Foucquier and his co-workers (Foucquier et al., 2013) is the determination of total energy consumption, indoor average temperature and cooling or heating load. The nodal method is characterised by its reasonable computation time and easy implementation.

To sum up the statistical technique (also called as black box method), it can be concluded, that each sub-methods (CDA, GA, ANN, SVM) is able to forecast energy consumption. Genetic algorithm (GA) is also able to optimize equipment or load demand, however it needs a large amount of training data.

The literatures separate meso-scale building energy modelling into two groups. Firstly, top-down method manages the sample as a big black-box (Swan and Ugursal, 2009) and uses aggregated data on the level of the sample. This method calculates energy consumption, with some kind of regression.

The second approach is the bottom-up process, where disaggregated data is provided. According to the existing data, this method can further split into 3 methods: statistical, analytical, and hybrid.

The statistical bottom-up method handles every building in the sample as a black-box, and uses some form of regression to calculated the energy consumption.

The analytical method handles the buildings as a white box, and calculates energy consumption with heat-mass balance equations with a software.

The hybrid method can handle some of the buildings as white boxes, some as grey boxes, and some as black boxes. It is used to calculate building energy consumption, where some data is missing, or it can be also used to address shortcomings, of both statistical, and analytical methods.

See relations between these methods is in Fig.17

According to Section 2.2.3. top-down and bottom-up can also be combined. To do so, either a top-down model could implement bottom-up features, or the other way around.

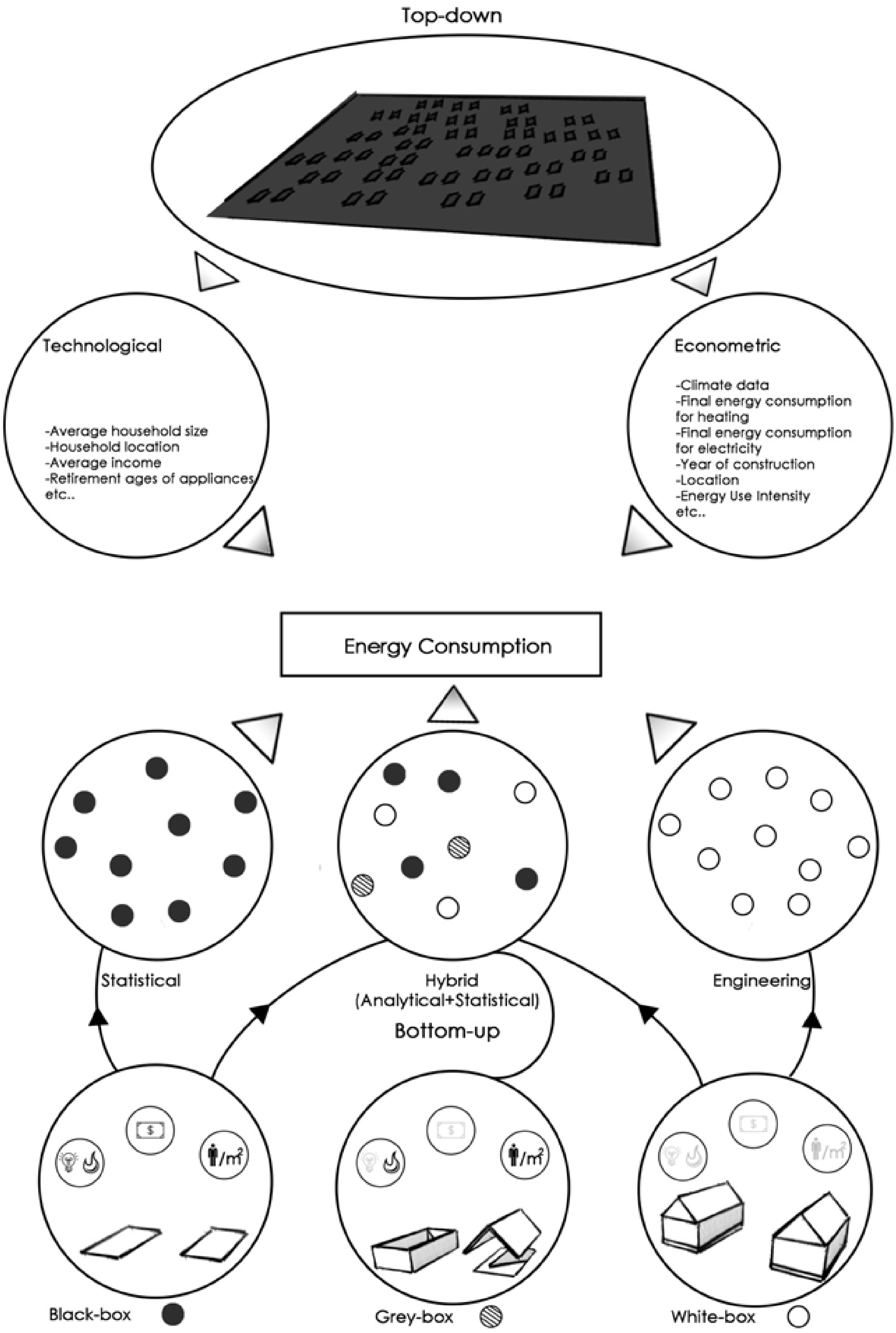

Fig. 17. Relations of the approaches

4.2. The seven assessed models

In the research presented here, urban energy models were revisioned from neighbourhood scale to the scope of an entire city. Neighbourhoods are the blocks of cities, where complex energy flows and synergies can be noticed controlled or in the best case scenario planned, in a bigger scale, than single building, in coherence with the surrounding environment and urban context. In order to better understand sustainable urban design and support decision-making, we need to pay more attention to make energy related changes and flows transparent and comprehensible.

Building modelling is linked to macroeconomic parameters such as population trends and economic activity by traditional top-down building stock models and mainly with the aim of predicting near future energy use foreseeing from the current state. (Howard et al., 2012) Thus they are limited when developing new technologies and they are not adequate for analysing interventions where demands need to be characterized at the scale of the building. The highlighted above introduced methodologies also demonstrates that current philosophies are converging from bottom-up approaches as building scale understanding of the energy flows is the aim at the state of the art.

It is visible by the results in Section 3.3. that not all of the hybrid-based (which contains both statistical and analytical) bottom-up models have an extended power for foreseeing values of most of the energy related issues.

From this statement, it can be drawn as inference that the determination of valuable proportion of the modelling subtasks is yet to be made, because there is no existing platform which would cover all the aspects.

Since these tools has been made to support municipalities and urban planners to understand spatiotemporal energy supply-demand patterns due to buildings and help them in decision-making process, the main focus is on predicting interventions' impacts on future scenarios. Some of the aspects connected to scenarios (retrofit scenarios, renewable potential calculation) are incorporated into the capabilities of most platforms, although the lack of financial calculation is a big problem.(Christoph F. Reinhart & Cerezo Davila, 2016) There is only one model which calculates financial background of retrofitting scenarios, however the methodology of it, is not clearly understandable.

For spatiotemporal analysis of demand patterns and potential infrastructure solutions the capability of modelling synergies between building user and the building itself, among examined buildings and their energy grid, as well as between each building and its urban and natural environment is indispensable. (Fonseca and. Nguyen, 2016)

For modelling these phenomena , the following viewpoints have to be measured, calculated, estimated or predicted (Davila et al., 2016; Fonseca and Schlueter, 2015): the impact of building management system (BMS), occupant behaviour (OB), geometrical dataset such as built environment and topography, local wind patterns (LWP) and urban heat island effect (UHI effect) We can read from Table 4, that there is no model, which could perfectly model all of these aspects. It can be concluded from the table, that CEA (J. A. Fonseca, T. Nguyen, 2016) is the best at modelling synergies and local systems because it deals with infrastructure and performance patterns for selected configuration of scenarios. It is visible, that the set of viewpoints for synergies related to the comparison are not covered by current models.

Nevertheless, in our perspective it is one of the most important stages in case of urban modelling, because aspects considered under this phenomena mean the effect of urban context on each or groups of buildings or the other way round.

Another big shortage is the lack of conversion and storage technologies simulation, even if the calculation of renewable potential is covered in the future scenarios. There are only a few unclear mention of installing new micro grids into an existing urban context in the publications. Thus for reaching the aim of reliably supporting sustainable urban design in energy related issues, great efforts have to be made to bridge the current gaps.

5. Conclusion

Hybrid models are working well in numerous viewpoint. They can support analysing future scenarios including renewable potentials and interventions with new technologies with results including user behaviour -as it is based on statistical dataset. (Davila et al., 2016) For more details of the impact of hourly load profiles on different energy supply systems, these approaches can be further combined with special embedded modules. Because of the lack of data input, calculation difficulties or unrealistically time-consuming simulation processes, there are several gaps, which are not covered in any platform, however, the results, linked to them, would be essential for a comprehensive picture of city-wide energy flows.

The biggest remaining input-uncertainty is correlated with the definition and detailed description of archetypes which used by bottom-up statistical and hybrid models to represent technical characteristics of a building stock such as construction year and U values by structure elements

The main shortage by most of the tools is the lack of financial calculations. Since decision-making is strongly influenced by financial aspects, especially if we talk about building sector and energy related issues, even in case of retrofitting processes or new building's deployment. The problem affects LCC analysis, return on investment by implementing renewable sources in existing neighbourhood and financial benefit prediction by retrofitting for instance.

Another lacking element of the results of urban models' is the evaluation of the climate change rate in future scenarios, although, this aspect is the scope of current policies only four tools are able integrate climate change into future scenarios and among these four platform only one is considering embodied energy, which aspect is strongly connected to inferences of climate change.

With interlinking buildings into wider district systems synergetic connections will be created. So as to accomplish energy- conscious urban design, this process has to be planned. Understanding synergies energy modelling systems is another consequence of the need for urban-level analysis such as non-building related energy changes such as transportation or street lighting and ability to deal with conversion and storage technologies of energy. These elements are important to be modelled and simulated, especially in case of retrofitting, and more related if we talk about integrating renewable and/ or hybrid power supply technologies into existing neighbourhood. There are still many important challenges to be overcome in this field. However, it can be stated that key factors of development are further improving hybrid methods and reduction of data points, which could be interpreted as opening and maintaining statistical datasets instead of measuring data or calculations. Improvement of data collection even those maintained by municipalities is a good method to have reliable and accurate input.

All in all, towards the development of simulation workflows to estimate not only overall operational building energy use, but to deal with all kinds of the urban-scale related energy transitions, it is necessary to define the objectives of the calculations in advance. These objectives must be extended to the entire city to be able to examine synergies in all levels, and to understand and consider microclimatic properties as well. Regarding to future scenarios, climate change and financial issues are not negligible, these items must be covered in the near future development.

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