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Energy planning and forecasting approaches for supporting physical improvement strategies in the building sector: A review

Moulay Larbi Chalal[a,*], Benachir Medjdoub[a], Michael White[a], Raid Shrahily[a]

[a] *The school of architecture, design, and built environment, Nottingham Trent University, Nottingham, UK*

Abstract

The strict CO2 emission targets set to tackle the global climate change associated with greenhouse gas emission exerts so much pressure on our cities which contribute up to 75 % of the global carbon dioxide emission level, with buildings being the largest contributor (UNEP, 2015). Premised on this fact, urban planners are required to implement proactive energy planning strategies not only to meet these targets but also ensure that future cities development is performed in a way that promotes energy-efficiency. This article gives an overview of the state-of-art of energy planning and forecasting approaches for aiding physical improvement strategies in the building sector. Unlike previous reviews, which have only addressed the strengths as well as weaknesses of some of the approaches while referring to some relevant examples from the literature, this article focuses on critically analysing more approaches namely; 2D GIS and 3DGIS (CityGML) based energy prediction approaches, based on their frequent intervention scale, applicability in the building life cycle, and conventional prediction process. This will be followed by unravelling the gaps and issues pertaining to the reviewed approaches. Finally, based on the identified problems, future research prospects are recommended.

Keywords: Urban energy planning, Smart cities, Future cities, Energy forecasting, Building sector.

1. Introduction

Statistics have shown that the building sector consumes approximately 40% of the world’s energy resources and emits around 1/3 of greenhouse gas emissions (UNEP, 2015). From this premise, implementing effective and proactive strategies at this sector is indispensable for achieving the imposed CO2 emission reduction targets (Foucquier et al., 2013). However, since buildings’ energy consumption depends on many interwoven factors including weather conditions, users’ behaviour, and buildings’ characteristics, urban energy planners require useful tools that assist their urban energy planning decision-making with regards;

- Identifying potential areas that necessitate improvement.
- Choosing the right and most effective strategy (retrofit, technology upgrade, reconstruction, demolition, raise users’ awareness, etc…) based on each scenario.
- Determining the degree of change in energy consumption after certain measures have been applied.

For these reasons, a lot of effort has been made in recent years to develop energy prediction approaches to support physical improvement strategies in the building sector. Each approach does not only address specific problem(s) but also has its frequent intervention scale (micro or macro)

*Corresponding author at: Creative virtual technology lab, school of architecture, design, and built environment, Nottingham Trent University, Nottingham, UK NG1 4BU
Tel.:+44 75 42 33 80 09
E-mail address: Moulay.Chalal2014@my.ntu.ac.uk

and a particular applicability in the building lifecycle (Swan and Ugursal, 2009). This has been a subject of great interest to many scholars from various backgrounds who made invaluable effort reviewing and comparing these approaches. For example, Swan and Ugursal (2009) discussed energy prediction models used in the residential sector within two distinct categories namely; top-down (techno-socioeconomic) and bottom-up (physical). This classification was hugely influenced by the type of envisaged measures (techno-socioeconomic or physical), the level of detail and hierarchical position of data inputs in reference to the whole residential sector. On the other hand, Foucquier et al. (2013) classified different energy prediction models into three main categories namely; physical, statistical, and hybrid. Furthermore, addressed them based on their characteristics, strengths, and limitations while providing some examples on each model. Zhao and Magoulès (2012) proposed three categories to energy prediction approaches supporting physical improvements in the building sector namely; engineering, statistical, artificial intelligence (neural networks, support vector machine), and grey models. Besides evaluating the strengths and weaknesses of each category, their level of complexity, user friendliness, inputs' level of detail, computation speed, and accuracy were also addressed. Fumo (2014), however, reviewed and compare in detail previous classifications of these approaches, as shown in (Table.1), while focusing particularly on calibrated engineering methods. However, despite the vital contribution of the above authors, there is no review that has explicitly addressed these methods based on their frequent intervention scale, nor investigated certain prominent approaches which are utilised at the urban scale such as, 2D GIS and 3D GIS (CityGML) based energy planning forecasting methods.

Table 1. Classification of different energy predictions approaches in previous reviews

Authors	**Classification**

(Swan, Ugursal 2009)	• Top Down models
	• Bottom up models:
	  • Statistical (regression, Conditional demand analysis, neural networks)
	  • Engineering methods

(Zhao, Magoulès 2012)	• Engineering methods
	• Statistical methods
	• Artificial intelligence
	  • Support vector machine
	  • Artificial neural network
	• Grey models (hybrid models)

(Foucquier, Robert et al. 2013)	• Physical models • Statistical methods (regression, artificial neural networks, support vector machine) • Hybrid models
(Pedersen, 2007)	• Statistical approaches/regression analyses • Energy simulation programs • Intelligent computer systems (Artificial intelligence)

(Fumo 2014)	• Engineering methods
	  • Calibrated
	  • Forward(non-calibrated)
	• Statistical approaches
	  • Artificial neural networks
	  • Support vector machine
	  • Regression
	• Hybrid approaches

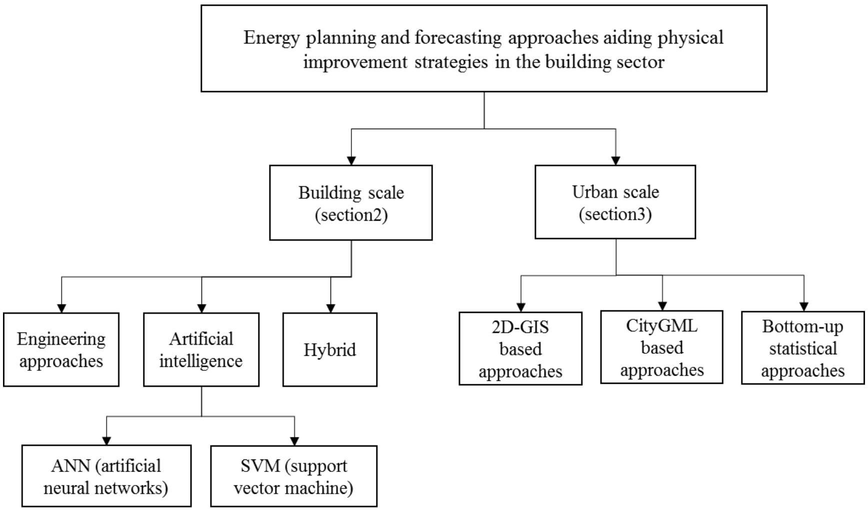

Figure 1.The structure of the article which is influenced by our suggested classification.

This paper aims to provide a comprehensive review of the current state-of- the- art of energy planning and forecasting approaches for aiding physical improvements strategies in the building sector. Please note that top-down approaches for supporting techno-socioeconomic improvements are outside the scope of this paper; please refer to the work of Swan and Ugursal, (2009).

We suggest to classify the reviewed approaches based on their intervention scale into building and urban scale approaches as shown in (Fig.1), although sometimes there are no clear boundaries as some approaches can be applied at both levels. Influenced by the proposed classification, the content of this review has been organised into 4 sections.

First, Section 2 addresses approaches utilised at the building scale namely; engineering, artificial intelligence, and hybrid but with less details since previous reviews exhaustively examined them. We have chosen this categorisation, which we have partially adopted from (Zhao and Magoulès, 2012) and adapted to match the building intervention scale, over other classifications shown in (Table.1) because it takes into account the nature of the involved mathematical model(s) (e.g. thermodynamic model). Furthermore, it acknowledges artificial neural networks (ANN) and support vector machine approaches (SVM) as artificial intelligence methods instead of statistical ones. Section 3, on the other hand, analyses in depth urban scale approaches namely; 2D GIS and 3D GIS (CityGML) based energy forecasting approaches, and statistical methods. The analysis of all approaches either in section 2 or 3 is based on their structure, workflow, advantages and limitations while providing some examples on their applicability in the building lifecycle. Next, section 4 discusses issues and gaps pertaining to both categories. Moreover, recommends directions for future research.

2. Building scale approaches

2.1. Engineering approaches and their tools

Engineering methods use physical principles and thermodynamic relationships to predict the energy performance of the whole building or some of its components. They can be further categorised into sub-groups based on the type and complexity of the used physical equations or thermodynamic formulas, although no clear classification is found in the literature. For example, Zhao and Magoulès (2012) classify them based on the complexity of the employed physical/thermodynamic equations and accuracy into; detailed and simplified engineering models. Others like Maile et al. (2007) categorise them based on the type of heat transfer problem and its corresponding prediction accuracy into; one dimensional, two dimensional, and three dimensional models, as shown in (Table.2).

Due to the potential capabilities of information technologies, a large number of computer simulation tools, which rely on the 3D geometry of the building, are employed to evaluate building energy performance through solving different physical/ thermodynamic problems (Clarke, 2001).

Owing to the prominence of building energy simulation tools in supporting engineering approaches, their structure, prediction pipeline, and applicability in the building life-cycle will discussed in the following sections.

2.1.1. Structure and prediction process

The architecture of the majority of building energy simulation tools, regardless of the type of engineering approach they support (e.g. one dimensional), is composed of two major components namely; Engine and graphical user interface, as illustrated in (Fig.2). The simulation engine component requires an input file, usually simple text based, to perform and write its output into one or several files. There are five different types of input data namely; 3D building geometry (including the layout of thermal zones, material physical properties, and window areas), internal loads, HVAC system components and controls, weather data, occupancy schedule and simulation related parameters (Ham and Golparvar-Fard, 2015).

Table 2 examples of engineering approaches classification

Review	**Classification**	**Main criteria of categorisation**
(Zhao and Magoulès, 2012)	• Simplified • Elaborate	• Complexity of physical/ thermodynamic functions • Accuracy of prediction
(Foucquier et al., 2013)	• CFD tools • Single zone tools • Multi-zones tools	• Type of heat transfer problem • Availability and nature of collected data inside the building. • Accuracy of prediction
(Maile et al., 2007)	• One dimensional • Two dimensional • Three dimensional	• Accuracy of prediction • Type of heat transfer problem

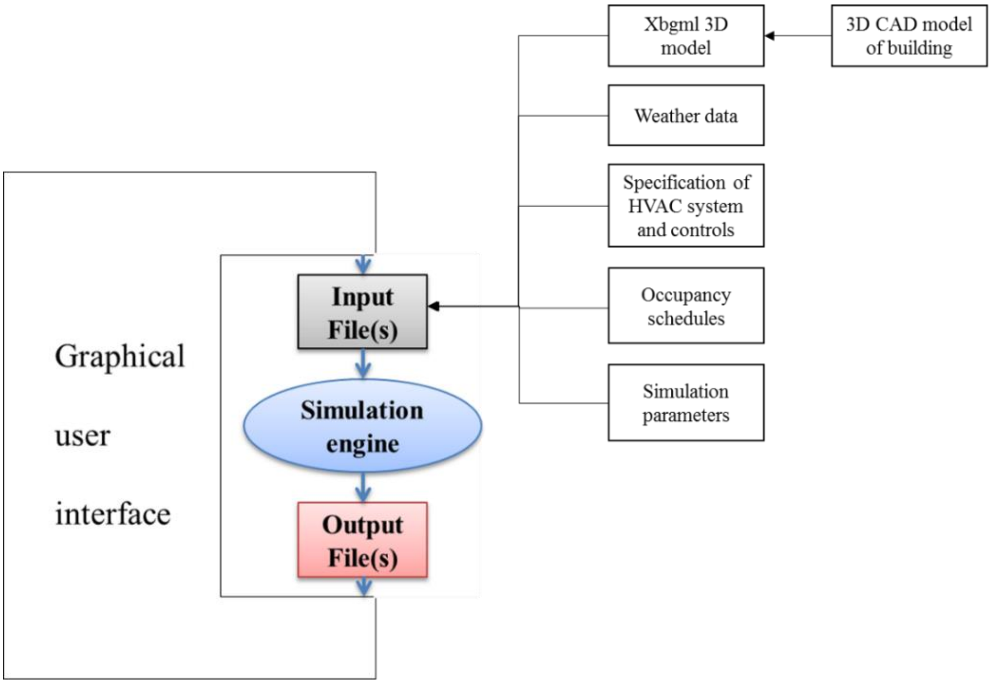

Figure 2. Generic Architecture of energy simulation tools adapted from (Maile et al., 2007)

2.1.2. Applicability in the building life-cycle

Table.3 below represents the life cycle usage of some widely adopted energy simulation tools and puts them into context by providing examples of previous studies. Traditionally, building energy simulation tools were developed to support the design phases through evaluating the energy performance of design alternatives. However, over the last few years their capabilities have been expanded to cover the commissioning, operation, and maintenance of building (Coakley et al., 2014). The difference between both categories is that the tools aiding operational and maintenance stages require a higher level of detail to validate the performance of HVAC systems and their controls during commissioning (Maile et al., 2007).

Table 3. The applicability of some well adopted energy simulation tools in the building lifecycle

Simulation tools	Life cycle usage	Example of relevant studies	Purpose of use in the study
EnergyPlus	Multiple phases but powerful for operational phases	(Attia et al., 2012)	To simulate the energy performance of different design proposals.
eQUEST	Design stages (maily schematic/ detailed design phases)	(Yu et al., 2008)	To estimate the annual energy consumption of a typical residential building in hot summer zones in china
Design builder	Multiple stages but weak in operational phase	(Ortiz et al., 2009)	To estimate the environmental impact of certain physical measures on a typical dwelling in Barcelona during the design and operational stages
IES-VE	Multiple stages (design, operation, maintenance)	(Al-Tamimi and Fadzil, 2011)	To investigate the effect of different shading devices on the thermal comfort of high rise buildings in hot-climate weather
BSim	Design stages	(Marszal et al., 2012)	To calculate the hourly load demand of a reference residential multi-storey zero emission building in Denmark.
ECOTECT	Preliminary design stages	(Sadafi et al., 2011)	To investigate the impact of courtyards on the thermal performance of a tropical terraced house.

2.1.3. Strengths of engineering tools and approaches

- They do not rely on historical data, albeit the latter can be used to increase their accuracy (Swan and Ugursal, 2009).
- They have the ability to model different onsite energy renewable sources such as solar panels.
- Flexible, explicit, user-friendly, well integrated and highly interoperable with CAD/BIM systems which make their adoption widely accepted by urban planners.

2.1.4. Weaknesses of engineering tools and approaches

- May require more input than other methods like statistical one.
- If certain data is unavailable, the performance of very accurate simulation results can be tedious and require experts' assistance (Zhao and Magoulès, 2012).
- The modelling of occupants' behaviour is poor and inaccurate due to the "standardisations" as well as assumptions.

2.2. **Artificial intelligence tools and approaches**

Although the artificial intelligence umbrella groups a wide range of approaches, SVM (*support vector machine*) and *artificial neural networks* models (ANN) are the most used for energy prediction in the building sector (Zhao and Magoulès, 2012).

2.2.1. Conventional prediction process

The process of energy prediction using artificial intelligence approaches usually comprises four steps namely; data collection, data pre-processing, model training, and model testing as depicted in (Fig.3). The process begins with acquiring historical data containing correlated inputs and outputs. The temporal granularity of the collected data ranges from hourly to yearly depending on the project requirement, time, and resources. Once data is collected, the pre-processing phase, which comprises applying some techniques (e.g. transformation and data normalisation) to the data to improve its quality, occurs. This will be followed by a training phase which encompasses the selection of the appropriate parameters determined by the user based on the training data size and selection of input variables. Finally, the performance of the developed artificial intelligence algorithm is tested using existing data (Yilmaz et al., 2015).

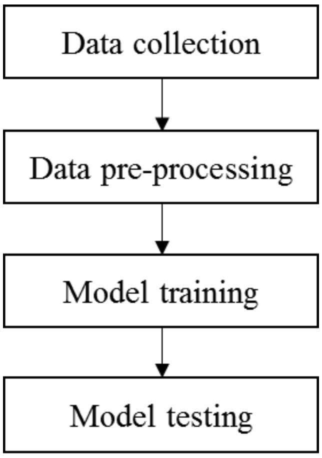

Figure 3. Conventional prediction process of Artificial intelligence tools

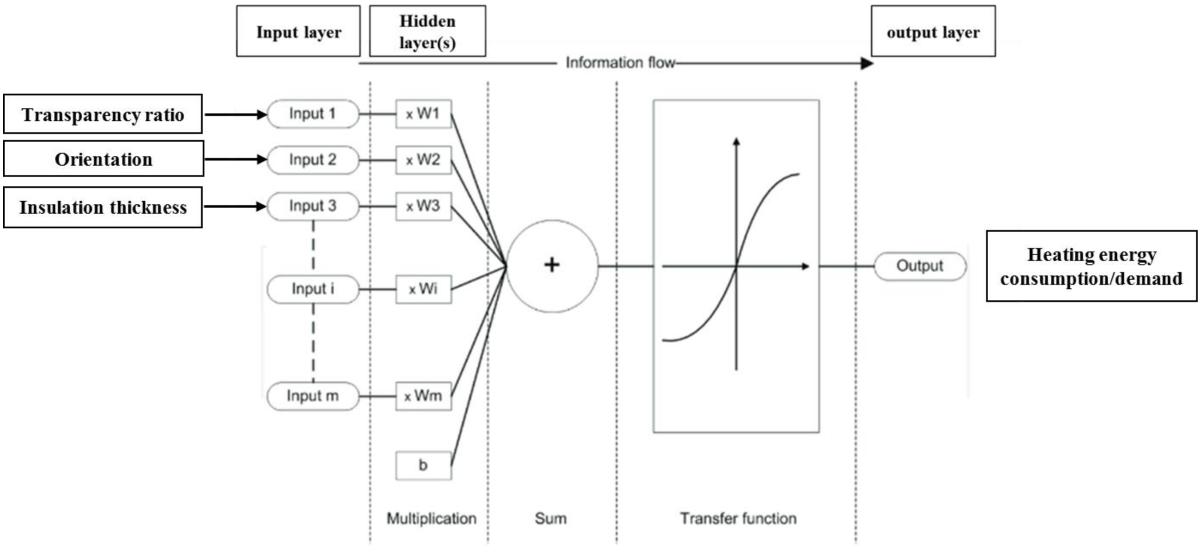

Figure 4. Working principle and information flow of neural network models adopted from (Krenker et al., 2011)

2.2.2. Artificial neural networks (ANN) tools and approaches

2.2.2.1. Structure and workflow

ANN's are mathematical models that mimic biological neural network (Aydinalp-Koksal and Ugursal, 2008). They are not programmed in the conventional way but instead trained using historical data representing the performance of a system. As illustrated in (Fig.4), their generic structure encompasses three main components namely; input layer, one or several hidden layers, and output layer. Every single layer encompasses several neurons in which each one is linked to other ones in the adjacent layer with various weights. Overall, information flows into the input layer, through the hidden layer(s), to the output layer. Each entering signal, which comprises a given parameter value such as, insulation thickness (cm), or glazing ratio (%), is then multiplied by its corresponding neuron weight and summed up with the bias contribution to determine the total input of hidden layer neuron (netj). An activation function will be applied to the latter to define the neurons output, heating energy consumption, for instance.

2.2.2.2. Training of ANN

The purpose of the training process is to apply learning algorithms to obtain a set of neuron weight matrices which enable the artificial neural network to map correctly outputs with inputs. There exist two types of training namely; supervised and unsupervised.

- Supervised: simply mean that data outputs are provided with their corresponding inputs while training the ANN model. So that it possible to calculate discrepancies between the predicted outputs and actual ones. Based on these divergences, the user can make adjustments to the ANN model by updating its neurons' weights. This type is the most common in the building energy prediction literature (Kalogirou, 2006).
- Unsupervised: occur when the user only provides a set of inputs to the ANN model which will in turn find or predict patterns in the inputs without external aid.

2.2.2.3.*Applicability in the building life-cycle*

Due to their ability to represent non-linear processes, the use of ANN models since originated in the 1990's has been devoted to utility load forecasting in the operational phases of the building lifecycle. However, there have been few attempts to utilise them in the early design stages. In general, the scale of those studies ranges from a single building up to few buildings except the work of Aydinalp et al. (2002).

For example, Kalogirou and Bojic (2000), in an effort to assist designers in the assessment of passive solar design, employed 4 layers recurrent ANN model to predict the hourly energy consumption of a passive solar holiday home in Cyprus during summer and winter. This was achieved in function of the level of insulation, masonry thickness, nature of heat transfer coefficient, and time of the day. The author concluded that model's prediction was satisfactory and quicker than dynamic simulation tools. Similarly, Mihalakakou et al. (2002) developed feed forward back propagation ANN model for estimating the hourly electricity consumption of a residential building in Athens based on several climatic parameters such as, air temperature and solar radiation. The model was trained with hourly energy consumption data of the building collected over 5 years.

As for the use of ANN models in early design stages, Ekici and Aksoy (2009) developed a back propagation ANN model to predict the heating demand of three building designs in relation to orientation, insulation, walls thickness, and transparency ratio. Energy consumption data, which were calculated using the finite difference method of transient state one-dimensional heat conduction, were employed to train the model inside MATLAB ANN toolbox. Following the same process, Dombaycı (2010) predicted the hourly energy usage of a house during the design stage but the employed ANN model was trained with energy consumption data calculated by degree hour method covering the period from 2004-2007.

Apart from load prediction, ANN models have been also utilised in optimising the performance of energy management systems. For example, to save the electricity used for water heating, Wezenberg and Dewe (1995) adopted some ANN models in generating an operation schedule for a residential water heating system based the cheapest tariffs and without compromising the thermal comfort. This was performed by training the models with historical tariff rates, ambient temperature, humidity rates, and time data (hour, day, etc...).

2.2.2.4. Advantages of ANN tools and approaches

- Unlike statistical approaches, the ANN ones have a higher accuracy due to their ability to implicitly identify all non-linear relationships between inputs and outputs.
- In a widely cited work by Aydinalp et al. (2002) , the developed ANN models showed their ability in evaluating the impact of socio-economic factors on end-energy use.

2.2.2.5. Disadvantages of ANN tools and approaches

- ANN models have a limited ability to explicit relationships between variables and cannot directly deal with uncertainties (Aydinalp-Koksal and Ugursal, 2008); (Papadopoulos et al., 2001).
- ANN modelling is not cost effective since enormous historical data and computational resources are required.
- ANN models are exposed to overfitting issues in the data training process, which means that the trained ANN model might consider noise as part of the data pattern. As a result, predictions made are outside the range of the training dataset (Tu, 1996).
- In contrast to engineering approaches, ANN models cannot be generalised to different buildings under different conditions (weather, occupancy, etc…). This requires a new ANN model for each building/ situation (Foucquier et al., 2013).
- Therefore, they are not flexible in assessing the effect of energy conservation measures.

2.2.3. Support vector machine (SVM) approaches

Support vector machine (SVM) is a supervised machine learning algorithm that is well-known for its robustness and accuracy. Like ANN, SVM models have to be trained with historical data representing the behaviour of a system. Due to its ability to solve non-linear regression and classification problems, SVM is increasingly being employed both in research and industry since first implemented by Cortes and Vapnik (1995). The principle of SVM in solving a classification problem is based on the division of a dataset into sub categories, whose properties are specified by the user. On the other hand, it is premised on describing a given dataset by a particular equation whose complexity is defined by the user, if the main concern is to tackle a regression problem to forecast future trends in the data, which is the case for energy prediction. The prediction principle using SVM will be addressed in detail in the next section.

2.2.3.1. Prediction principle using SVM regression

The aim of using SVM for regression is to seek the optimal model generalisation to promote sparsity. Let us consider a given training dataset$[(x_0, y_0), \dots, (x_n, y_n)]$. x_i, y_i represent the input and output space, respectively. For example,x_i denote household income values, whereas y_i are energy consumption values. To solve a non-linear problem such as, energy consumption, the non-linearity between variables, x and y in this case, has to be transformed using linear mapping (or transformation) through two steps. The first step consists of projecting the non-linear problem into a high dimensional space known as the feature space. After that, $f(x)$ the function fitting best the behaviour of the problem has to be determined in the feature space. The uniqueness of SVM is that it does allow an uncertainty ϵ in the regression model. This means that any error less than ϵ in the SVM model is tolerated. The function f(x) is defined as follows (Eq.1) (Cortes and Vapnik, 1995);

$$f(x) =< \omega, \varphi(x) > +b \tag{1}$$

Where φ is a variable in the feature space (high-dimensional space) and <, > is a scalar product. b and ω are defined in function of an optimisation problem known as the primal objective function (Eq.2) and (Eq.3) (Cortes and Vapnik, 1995).

$$min_{\omega,b,\xi_i\xi_i^*} \quad \frac{1}{2}||\omega||2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*\rangle \tag{2}$$

Subject to
$$\begin{cases} y_i - \langle\omega, \Phi(X_i)\rangle - b \leq \epsilon + \xi_i \\ \langle(\omega, \Phi(x_i)\rangle + b - y_i \leq \epsilon + \xi_i^* \\ \xi_{i|}\xi_i^* \geq 0 \end{cases} \tag{3}$$

C (known as regularisation parameter), represents the trad off between the flatness of f and the first larger value than ϵ defined by the user . ξ_i and ξ_i^* are the slack variables enabling the constraints flexibility (Fig.5). Finally, the second step to make the complex non-linear map a linear problem is to apply a kernel function without the need to evaluate$\Phi(X)$ as follows (Eq.4) (Cortes and Vapnik, 1995);

$$k(x, \acute{x}) =< \varphi(x), \varphi(\acute{x}) > \tag{4}$$

There are three types of Kernel functions namely; linear, polynomial, and radial. Choosing the right kernel is very important since it has a huge impact on the learning ability and generalizability of SVM algorithm which in turn affect its prediction accuracy.

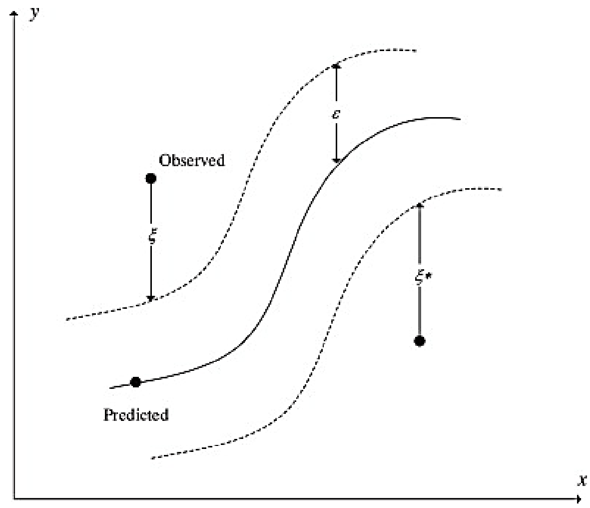

Figure 5. SVM regression function with slack variables, observed and predicted data points (tripod, 2015)

2.2.3.2. Applicability in the building life-cycle

Since first adopted by Dong et al. (2005) for energy forecasting until now, the use of SVM models has been mainly confined to predicting energy consumption and temperature of individual buildings (mostly commercial or administrative) during their operational stages (Ahmad et al., 2014). However, recent work done by Son et al. (2015) used SVM regression models to predict the electricity consumption of government owened buildings in the early design stages. This was achieved by first retrieving the relevant parameters through applying a variable selection algorithm called RreliefF. Afterwards, the SVM model was trained with an existing dataset for 175 government owned buildings. The trained SVM could predict the energy consumption of government owned-buildings during the design stages but with Mean Absolute Percent Error (MAPE) of 35% which means that the SVM prediction accuracy is reasonable according to Lewis (1982) scale.

On the other hand, a lot of publications have addressed the prediction of electricity consumption in non-residential buildings during the operational stages using SVM regression models. For example, Lai et al. (2008) forecasted the electricity consumption of a building for a period of three months after the SVM model had been trained with electricity consumption data measured over one year period. The authors obtained a satisfactory match between measured and predicted data. Similarly, Li et al. (2009) compared the prediction accuracy of a back propagation neural network with an SVM model while forecasting the cooling load of an office building in Guangzhou in function of outdoor dry-bulb temperature, humidity, and solar radiation. The results have shown that the SVM model had a better prediction accuracy than the ANN model. Similar findings were reported one year later by Li et al. (2010) after the following models namely; SVM, back propoagation neural network, radial function neural network, and general regression neural network, have been employed to predict the annual electricity consumption of 9 office buildings.

In an attempt to address the lack of studies applying SVM to residential buildings, Jain et al. (2014) questioned the applicability of SVM regression models for forecatsing the energy consumption of multi-family buildings. This was achieved by investigating the accuracy of the employed SVM regression models in function of different temporal (hourly, daily, etc...) and spatial (whole building, by floor, etc...) granularity of the measured electricity consumption data. Their findings suggested that SVM can be extend to cover energy forecasting of multi-family buildings as long as the measurements used to train the SVM model are perfomed at least at every floor and with a minimum of 1 hour interval.

2.2.3.3. Advantages of support vector machine approaches

- Comparatively to existing artificial intelligence approaches, SVM for regression have shown better results in terms of accuracy.
- In contrast to aritificial neural networks, SVM for regression are less prone for over-fitting issues due to their regularisation parameter C.

2.2.3.4. Disadvantages of SVM tools and approaches

- One of the limitations of SVM for regression is the lack of universal method for selecting the appropriate Kernel function (Yilmaz et al., 2015).
- Since requiring enormous historical data and computational resources, SVM is not cost-effective
- SVM for regression do not rely on 3D models, hence they are not flexible in assessing energy conservation measures and their adoption by urban planners is complex.

2.3. Hybrid approaches

Hybrid models were first introduced in the 1990s for the purpose of improving HVAC control systems efficiency. They are based on the idea of combining physical, statistical, and artificial intelligence models where data samples are reasonably small, incomplete, or subject to uncertainties (Foucquier et al., 2013).

2.3.1. Hybrid approaches' structures and prediction processes

There exist three possible structures of hybrid approaches as shown in (Table.4). The first one involves the estimation of **optimal** physical parameters with the help of machine learning algorithms through the combination of one dimensional heat transfer models with optimisation models (Genetic Algorithms usually). The second approach consists of describing the dwelling behaviour by implementing a learning model through the use of statistics. Finally, the third approach, which is not referenced in building energy prediction literature according to Foucquier et al. (2013), comprises the employment of statistical models in areas where physical/thermodynamic models are inadequate or inaccurate. For example, when thermal properties of a given room are unknown or when the aim is to consider the variation in users' behaviour.

Table 4. Possible strategies of hybrid approaches

Possible hybrid approach	Approaches involved	Common purpose of use
1	• Engineering • Artificial intelligence	Estimation of optimal physical parameters
2	• Artificial intelligence • Statistical	Describing the building thermal behaviour
3	• Statistics • Engineering	Estimation of optimal physical / techno-socioeconomic parameters which could have been missing or inaccurate.

2.3.2. *Applicability in the building life-cycle*

Hybrid models are mainly used for the estimation of optimal physical parameters and energy consumption prediction to a lesser extent. However, despite not directly linked to energy prediction modelling, the determination and optimisation of such parameters to achieve low-energy consumption certainly assist urban planners in their planning strategies. This does not only apply to the design stages but also the operational ones.

To assist energy planning in the design stages Znouda et al. (2007) coupled an energy simulation engine, which was specifically developed for Mediterranean weather, with a genetic algorithm to retrieve the optimum architectural and physical parameters; consequently, improve energy efficiency in summer and winter. The strength of this approach lies in its simplicity as only few parameters are involved. Similarly, Tuhus-Dubrow and Krarti (2010) followed almost the same process using a different energy simulation engine (DOE-2) to determine the most efficient dwelling form(s) for amongst U shape, L shape, T shape, H shape, trapezoidal, and rectangular across 5 different US climatic zones. The findings suggested that the two latter shapes were the most efficient.

Hygh et al. (2012) merged statistical regression methods with building simulation tools to predict the energy consumption of medium size rectangular shape buildings in 4 major climatic zones in the US. It was achieved by first, investigating the range of parameters that are frequently changed at the early design stages and likely to affect energy consumption through analysing the literature. These parameters include, building area, number of stories, aspect ratio, orientation, roof colour, glazing ratio, and U-values of walls and windows. Secondly, based on the possible min-max values of each parameter, Monte Carlo method was adopted to incorporate all possible inputs probabilities and replace default values in the referential thermal model. Thirdly, all the resulting iterations were embedded in energy plus simulation engine using Perl script before computing the annual energy consumption of each scenario. Afterwards, the rich database, which contains the latter and the randomly selected values of each parameter, is generated. This was then used to develop multivariate linear regression model. This approach has been also adopted by Asadi et al. (2014).

2.3.3. Strengths of hybrid approaches

- Hybrid models are a good alternative to ANN and statistical regression models when there is a limited number of parameters or data samples are reasonably small.
- Unlike engineering methods, the hybrid ones do not require a detailed description of the building geometry and thermal properties of the building envelop.
- Their outcomes can be interpreted from a physical point of view.

2.3.4. Limitations of hybrid approaches

- Hybrid models require a considerable amount of computation time and resources.
- May require some support and training due to the fact that they combine two distinct approaches.

3. Urban scale tools and approaches

Urban energy forecasting models for aiding physical improvements are mostly bottom-up models (Heiple and Sailor, 2008). This implies that the energy demand or CO2 emission of the building stock of an urban area are forecasted in function of a representative sample usually via extrapolation.

3.1. 2D GIS based urban energy prediction models

3.1.1. Structure

GIS (geographical information system) is a complex information system that integrates, stores, manages, analyses, interprets and visualises data, which are geo-spatially referenced, in different ways in order to understand trends, patterns, and relationships. This section will focus solely on the structure of urban energy forecasting approaches that utilise 2D GIS tools. In general, the majority of these approaches, despite their diversity, are composed of the following components;

- **Inputs:** comprise variables which describe the physical and thermal characteristics of the dwellings in addition to standard occupational schedules data. (Table.5) represents a list of the most common variables for this approach based on some important examples from the literature and highlights possible sources from which these inputs are derived.
- **Assumptions:** usually apply for some variables related to occupants' behaviour as well as thermal characteristics of the buildings such as, household size, patterns of heating, and level of insulation.
- **Baseline models**: The estimation of energy consumption at the urban scale (in a bottom up fashion) is produced with the help of baseline models which are usually physically based ones, such as BREDEM (the Building research establishment domestic energy model). The inputs requirements and complexity of energy prediction varies from one baseline model to another (Kavgic et al., 2010).
- **Calculation engine**: is the software in which baseline models or algorithms are incorporated to perform energy consumption calculations such as, SBEM (simplified building energy model).
- **Data exchange module:** allows the exchange of data between the GIS platform and calculation engine such as, dynamic data exchange (DDE).
- **GIS platform:** Although it provides certain geometric inputs, a GIS platform is mainly dedicated to visualising the energy consumption or CO2 emission of buildings using thematic mapping techniques (Jones et al., 2001); (Jones et al., 2007); (Batty, 2007).

3.1.2. Conventional prediction process

Generally speaking, the process begins with determining the type of the baseline model and its calculation engine based on the aim of prediction, availability of data inputs, envisaged accuracy, time, and availability of resources as shown in (Fig.6) . Once determined, although not necessary if it is available, data will be collected using various methods ranging from quick inspection surveys to detailed energy audits depending on the decisions made in the previous stage. After that, the geometric variables extracted from GIS (e.g. building area) along with the collected data will be inserted to perform the calculation. This will be followed by a validation process that will compare the outcomes with existing databases such as regional statistical data (top-down consumption data). If there is not a good agreement between both datasets, inputs will be adjusted accordingly. Finally, with the help of data exchange module, GIS platform will automatically geolocate and visualise the outputs on the 2D map of the studied urban area.

3.1.3. Applicability in the building life-cycle

2D GIS based tools are mainly employed in the operational phases of the building lifecycle to estimate and compare the energy consumption or CO2 emission of building areas before and after physical improvement measures (e.g. renewable resources, retrofit, etc…) have been applied. Furthermore, to determine building areas with potential energy savings. For example, Jones et al. (2001) estimated the annual energy consumption of Neath Port Talbot residential sector, UK, in function of a representative sample composed of 100 archetypes of dwellings. After that, certain physical measures included in the UK home energy conservation act (HECA) such as, water tank insulation, were applied to the archetypes whose energy consumption values were re-estimated accordingly. Finally, the archetypes were extrapolated in GIS to thematically visualise the energy consumption and CO2 emission of the whole residential sector before and after physical improvements. Similarly, Heiple and Sailor (2008) estimated the energy consumption of the building stock in Houston, USA in function of 30 archetypes composed of 8 dwellings and 22 commercial buildings. Secondary databases, more precisely residential energy consumption survey (RECS) and GIS lot tax database, were used to retrieve geometric parameters, thermal characteristics, and age of buildings. After the total energy consumption had been calculated using a building simulation tool eQUEST based on the retrieved parameters, the outcomes were mapped into a GIS platform to visualise the hourly energy consumption at 100 m grid resolution.

2D GIS based approaches have been also highly associated with renewable energy planning in the literature. For instance, Aydin et al. (2013); Janke, (2010); Connolly et al. (2010) adopted 2D GIS to identify suitable areas for solar and wind farms, as well as pumped storage hydro plants. Kucuksari et al. (2014) has recently suggested a framework integrating 2D GIS, optimisation algorithms, with simulation engines to assist the placement and dimensioning of solar panels in dense urban areas. In addition to that, 2D GIS approaches played a major role in evaluating the benefit of expanding district heat systems in certain studies (Nielsen and Möller, 2013).

3.1.4. Advantages of 2D GIS based approaches

- Have a potential of being integrated into urban planners' everyday life, since GIS tools are increasingly being adopted in urban planning.
- They are good for analysing and communicating potential renewable energy areas.

3.1.5. Disadvantages of 2D GIS based approaches

- There is a lack of universal guidelines on the processes, nature, and granularity of parameters involved in this approach.
- Energy forecasting using 2D GIS based approaches require a considerable amount of computation time of resources since they reply on building simulation tools.

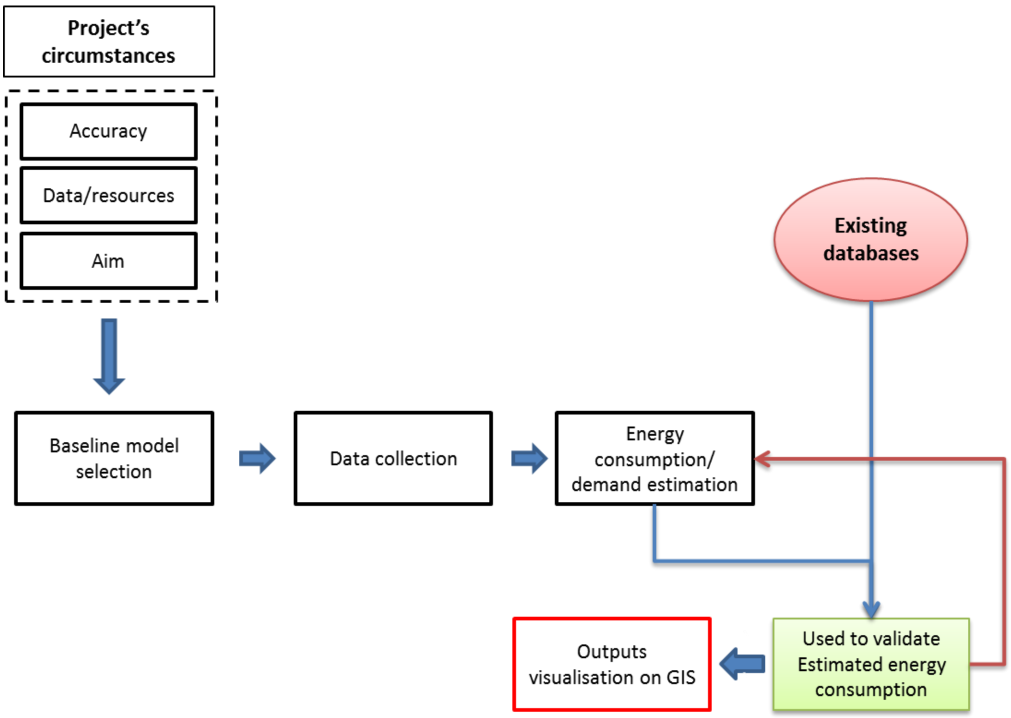

Figure 6.Conventional prediction process of 2D GIS based urban energy planning and prediction models

Table 5. Common inputs for 2D GIS-based energy forecasting approaches and their corresponding derivation sources.

Authors	Inputs	Category of inputs	Source
(Rylatt et al., 2003);	Wind speed	Weather data	-Data from metrological stations or; -Onsite measurements
(Kavgic et al., 2010); (Heiple and Sailor, 2008); (Rylatt et al., 2003);	Heating/cooling degree day		
(Kavgic et al., 2010); (Heiple and Sailor, 2008); (Rylatt et al., 2003); (Jones et al., 2001); (Jones et al., 2007)	Building-age	Building-age	-Official surveys (e.g. English house condition survey) -Existing maps / site inspection
	Building typology (e.g. detached, semi-detached, etc...)	Typology	-Site inspection, existing maps
	exposed perimeters	Building geometry	-GIS tools or; -Building footprints from existing maps and ; -Building typology and ages
	roof and wall areas		
	Building volumes		
	Façade orientation		
	U-values for roof, external walls,	Thermal characteristics	-Assumptions -Official surveys based on Building age and typology or; -Energy audits
	Type and thickness of insulation		
	Window area and glazing ratio		
	Thermal zones and their U-Values		
(Kavgic et al., 2010); (Heiple and Sailor, 2008); (Rylatt et al., 2003);(Jones et al., 2001); (Jones et al., 2007)	Type of boiler, number of pumps and fans, size and insulation of hot water tank, insulation of pipes, type of controls, solar panel area (if available).	HVAC system specification	-From building regulations based on age and typology of the building -Energy audits -Assumptions
(Kavgic et al., 2010); (Heiple and Sailor, 2008); (Rylatt et al., 2003);(Jones et al., 2001);(Jones et al., 2007)	Number of occupants, temperature of each building zone, heating hours, etc…	Internal gain and occupancy schedules	-Assumption -Official surveys

3.2. CityGML (3D GIS) based urban energy prediction models

Recently, there has been a shift in focus from conventional 2D GIS urban energy planning models towards CityGML (3D GIS) based ones. This is owing to the growing interest in 3D CityGML models and their applications (Krüger and Kolbe, 2012); (Gröger and Plümer, 2012).CityGML is an XML object-oriented information modelling approach for representing, storing and sharing 3D city model data. It provides the standard mechanisms that govern the description of different 3D objects in relation to their geometry, semantics, and topology. It is equipped with 10 core thematic modules including building, vegetation, relief, and others as illustrated in (Fig.7). However, other features such as, the ones related to energy forecasting can be added through application domain extensions (ADE).

The building module, which is the backbone of CityGML, permits the geometric as well as semantic representation of buildings and their elements (Kolbe et al., 2005). Each Building in CityGML possess the following attributes namely; *class, address, usage, function, roof type, building height, number of floors, year of construction, year of demolition, and cross-reference number*, in which the three later attributes are shared between all types of buildings and their components. The cross-reference number facilitates the update of objects' features and also the extraction of additional information from other databases. Apart from sematic properties, the geometric description of the building module is built upon the GML 3.1.1 Model (ISO 19107) developed by Cox et al. (2002). Therefore, buildings can be represented as solid or multisurface geometry. However, the former is more preferable for energy related applications since the calculation of volumes is a straightforward task (Gröger and Plümer, 2012).

One advantage of CityGML over other city 3D modelling approaches is its flexible discrete level of detail (LOD) which is not only confined to geometric but also sematic characteristics (Chalal and Balbo, 2014). However, since the granularity of geometric as well as semantic information varies from one LOD to another, the chosen level detail(s) influence the energy prediction accuracy. For instance, a building with a gabled roof in LOD1 is represented as a block resulted from the extrusion of its footprint with a flat roof surface, whereas in LOD2, it processes a rough gabbled roof structure, which certainly has an impact on the building heated volume calculation.

The wide adoption of BIM 3D models in the architecture, engineering, and construction industry in addition to the widespread of 3D GIS systems over last few years, have led a lot of researchers to investigate the interoperability between IFC (industry foundation class) and CityGML (Hijazi et al., 2009); (Mignard and Nicolle, 2014). This will be subsequently discussed in more detail in the 3.2.1.

3.2.1. Interoperability between CityGML and IFC

There exist three distinct approaches to interoperability between CityGML and IFC namely; unidirectional conversion, unifying approaches (Bi-directional conversion), and approaches based on extending the CityGML models (Table.6).

The first one consists of exchanging information between both standards in a unidirectional fashion, meaning from IFC to CityGML or vice-versa. Please note that unidirectional conversion from CityGML to IFC is beyond the scope of this article, please refer to the work of Nagel et al. (2009). Unidirectional conversion from IFC to CityGML is the most addressed in the literature and widely supported by some commercial software packages such as FME (feature manipulation software) or GeoKettle. However, none of them has the ability to generate 3D building models which comply geometrically and/or semantically with CityGML standards (Donkers et al., 2015). This is owing to the structural differences between IFC and CityGML which cause a lot of loss of information during the conversion process. Another drawback of this approach is that the geometric conversion to high CityGML level of detail (mainly LOD3, LOD4) is still challenging and require extensive post-processing as well as users' judgement (Delgado et al., 2013) ; (Boyes et al., 2015). For example, in (Fig.8), which depicts the conversion of a roof and slabs from IFC to CityGML, it is clear that a slab in IFC is represented as a solid object and defined by an IFC class (*ifcSlab*), whereas in CityGML, it is composed of two surfaces classified under *CeillingSurface* and *FloorSurface*, or *GroundSurface*. The upper surface is considered as floor surface for the upper building level, whereas the lower one, represents a ceiling surface or ground surface for the lower building level.

As for CityGML Roof, the upper surface is a roof surface, whereas the lower one is a ceiling surface for the below storey (El-Mekawy et al., 2011).

On the other hand, some researchers like El-Mekawy et al. (2011); Xu et al. (2014) tried to bridge the interoperability gap of unidirectional conversion approaches by integrating BIM with CityGML. This approach is often referred to as unifying information model or Bi-directional conversion in the literature. However, it is still fairly at the conceptual stages and has not been implemented yet (Amirebrahimi et al., 2015).

The third approach, which relies on extending CityGML model, can be performed in two distinct ways namely; 1) generic objects and attributes 2) application domain extension (ADE) mechanism. The first method consists of using generic objects to model and exchange features which are not predefined by existing CityGML thematic classes (e.g. walls). However, this method is limited due to the objects nomenclature conflicts it can create between CityGML users. Furthermore, the difficulty of validating the occurrences and layout of generic objects/ attributes by XML parsers (El-Mekawy et al., 2011). Conversely, the second method relies on application domain extension (ADE) in either introducing new properties to existing CityGML classes (e.g. household size) or defining new object types. For example, the GeoBIM extension developed by Van Berlo (2009) does not only add new classes to CityGML (e.g. Stair class) but also new IFC properties such as, width and height, to existing CityGML classes including windows, room, building, and door. The advantage of ADE over generic objects is that the former overcome the nomenclature limitation of generic objects as it is defined within an additional XML schema definition file with its own namespace (Gröger et al., 2012). However, despite this benefit, embedding information from IFC through ADE CityGML extension can result in large file formats as claimed by (El-Mekawy et al., 2011). Nevertheless, ADE is the first choice strategies for certain applications such as urban energy planning.

Table 6. Strengths and limitations of different interoperability approaches between IFC and CityGML

Approach	Approach Principle	Relevant Example	Strengths	Weaknesses
Approach 1	- Unidirectional conversion from IFC to CityGML	(Nagel and Kolbe, 2007) (Isikdag and Zlatanova, 2009) (Nagel et al., 2009)	-Widely Supported by commercial software packages. -Benefit urban planning applications.	-Loss of information. -Conversion to lower LOD (LOD1, LOD2). -Focused on geometric transformation issues. -Extensive post-processing is needed.
Approach 2	unifying approaches (Bi-directional conversion)	(El-Mekawy et al., 2011) (Xu et al., 2014)	-Intends to bridge the interoperability gap between IFC and CityGML.	-Remains fairly at the conceptual stages.
Approach 3	Extending the CityGML model by either;			
	A. Introduction of generic city objects.	(Gröger et al., 2012)	-Ability to model and exchange new features in CityGML.	- Nomenclature issues. -The validation of generic objects and attributes represent an issue for XML parsers.
	B. Using Application extension domain (ADE)	(Van Berlo, 2009)	-Defined with an additional XML schema to avoid nomenclature conflicts. -Widely adopted for urban energy planning applications.	-Massive file size -The combination of different ADE modules is not possible

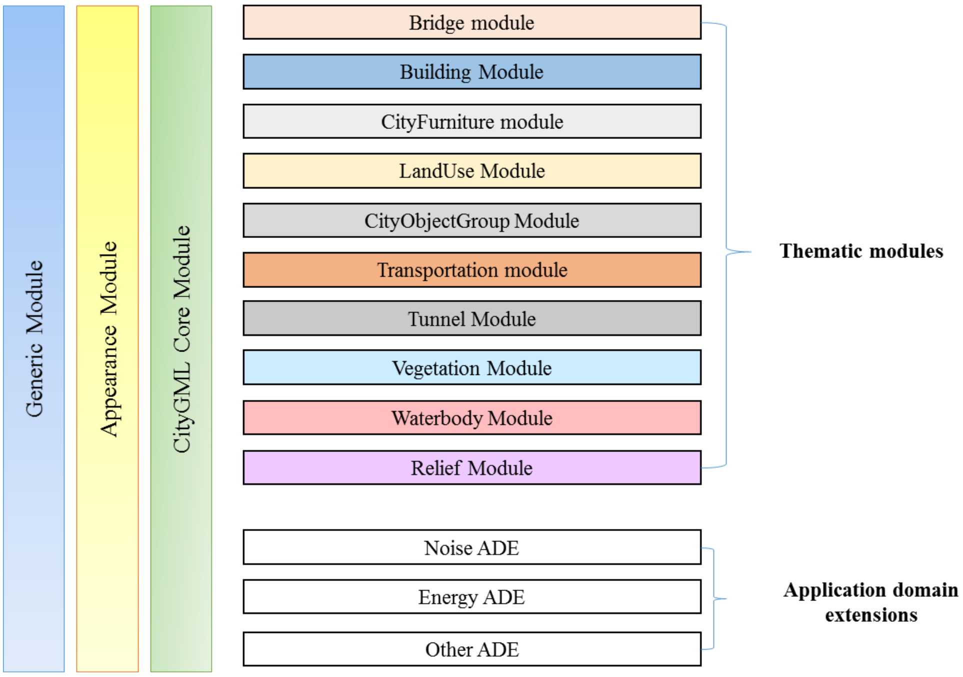

Figure 7.CityGML modules

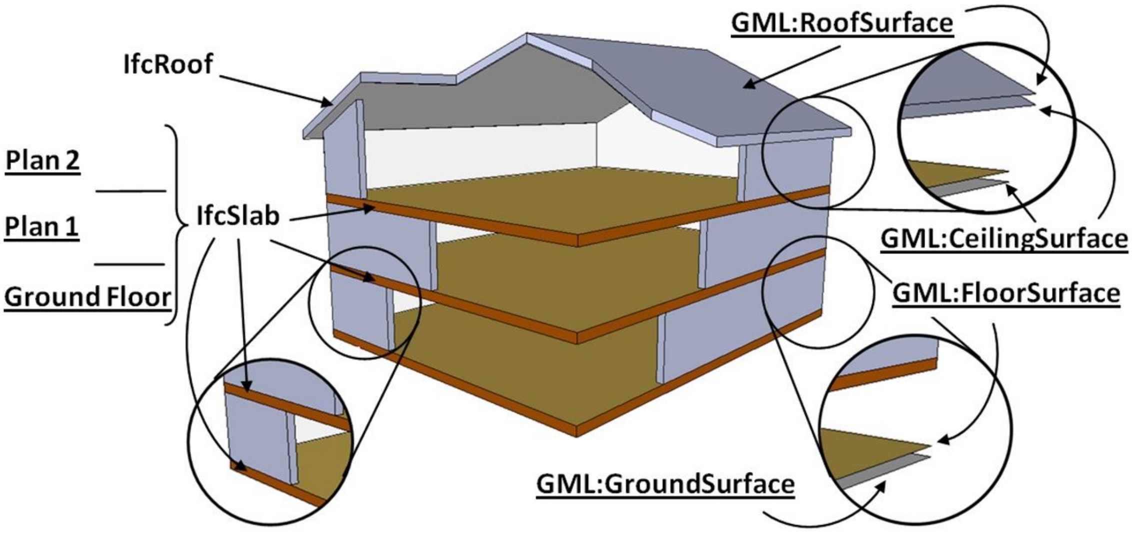

Figure 8. Unidirectional conversion of roof and slabs from IFC to CityGML (El-Mekawy et al., 2011)

3.2.2. Structure of 3D GIS (CityGML) models

Apart from the 3D thematic visualisation, energy ADE, the employed baseline models (described below), most 3D CityGML urban prediction models consist of a similar structure to the 2D GIS ones.

- **Energy prediction models:** are the algorithms used in the calculation of energy consumption of dwellings (mainly for space heating). Beside recent studies that utilised building energy simulation tools such as IESVE, researchers in this field tend to frequently employ steady –state energy balance prediction models such as; quasi-state model (ISO/FDIS 13790) (Corrado et al., 2007); (Nouvel et al., 2013); or DIN V 18599 (Strzalka et al., 2011).
- **Calculation engine:** unlike 2DGIS models and very recent studies in this area, Excel-based simulation tools incorporating steady-state energy balance algorithms such as, Fraunhofer-IBP or EnerCalC, are used calculate the energy consumption of dwellings.

- **Energy ADE:** it facilitates the integration of energy indicator and indexes into CityGML models. In the well-known energy ADE developed by Krüger and Kolbe (2012) for instance, this integration is performed in two distinct ways. First, elementary indicators variables such as, number of accommodation units, are directly retrieved from buildings' semantic properties. Secondly, complex indicators values (e.g. heated volume) are defined using complex functions. Further indicators such as, assignable area, can also be obtained from elementary indicators and other complex indicators. Recently, the international consortium of urban energy simulation has recently called for the development of a universal energy ADE (SIG3D, 2015).

3.2.3. Conventional prediction process

In contrast to studies on 2D GIS prediction models, it has been noticed that the choice of prediction models and data collections procedures has not been explicitly addressed. This is believed to be due to the influence of two studies that endeavoured to define standard or universal inputs for this type of models. These are the energy atlas of Berlin study conducted by Krüger and Kolbe (2012) and the model developed by Carrión et al. (2010). For these reasons and other related to the familiarity with data collection methods pertaining to these standard parameters, it is believed that a conventional prediction pipeline begins with ***acquiring data*** as demonstrated in (Fig.8). Dwellings heights, footprints, and type are usually obtained from GIS or digital cadastral databases, whereas energy consumption values are provided by utility companies. Year of construction, on the other hand is usually obtained from historical sources (e.g. raster maps). If 3D CityGML models covering the pilot area are not available, the next step consists of ***generating a sematic CityGML model*** following two possible strategies. First, different formats of 3D city models can be exported to CityGML format. However, due to the lack or loss of sematic information after the format conversion process occurred, the exported model is subject to a ***pre-processing phase*** embedding all the collected data and fixing issues related to geometry. The second strategy is to create a CityGML sematic model from scratch using one or a combination of different modelling techniques such as laser scanning and LIDAR, depending on the envisaged LOD and prediction's accuracy (Nouvel et al., 2013). This can be time consuming and challenging for models with LOD2 or above. After creating a CityGML model, with the help of ADE energy, further inputs such as, *assignable area*, are first obtained from the buildings geometry and exiting inputs, then integrated into the model. Once these parameters are embedded, dwellings with similar age and size are ***grouped into archetypes.*** After assumptions covering thermal parameters (e.g. U-values) are made based on the age and size, the ***calculation of energy consumption***, in most cases the space heating demand, of these archetypes is performed. This is achieved with excel-base software supporting steady-state energy balance models. Afterwards, the outputs are validated against existing energy consumption values and if necessary certain adjustments to the inputs until a good match is achieved. Finally, the outputs are transferred to the 3Dcitygml model with the help of a data exchange module to be thematically visualised.

3.2.4. Applicability in the building life-cycle

CityGML based approaches have been mainly used in the operational phases of the building life-cycle. More precisely, to target building areas with retrofits potentials through diagnosing their heating demand (Nouvel et al., 2014). However, recently their applicability has been extended to cover the identification as well as assessment of renewable energy potentials across building areas (Saran et al., 2015).

For example, Carrión et al. (2010) suggested an approach to easily assess potential refurbishment in building areas. This was first achieved by deriving parameters such as, *storey heights* and *building age* from the German cadastral information system as well as scanned raster maps, respectively. Other parameters such as, *building volume, building height, assignable area, the surface- to-volume ratio,* were extracted from the atlas of Berlin CityGML model either directly or indirectly using functions. Once these parameters were obtained, the heating energy consumption of the building area has been statistically calculated in excel based simulation tool using a degree day model. Finally, the results were then compared to consumption values from existing building libraries based on the building age and typology. Similar methodology and process have been applied to areas in cities like Stuttgart, Hamburg, Ludwigsburg, and Lyon in the work of Krüger and Kolbe (2012); Nouvel et al. (2013); Bahu et al. (2013); Strzalka et al. (2011) with the exception of the study of Kaden and Kolbe (2013) who extend the capabilities of this approach to cover electricity and hot water consumption in residential areas. The estimation of electricity power demand was achieved by assigning the mean electricity values published by Vattenfall utility company to each household in the building based on their size while presuming that all of them possess similar appliances.

On the other hand, few studies have focused on exploring the potential(s) of CityGML in assisting renewable energy planning. For instance, Alam et al. (2012) proposed a method to assess the performance of PV systems through simulating roof shading analysis for direct radiation inside a CityGML 3D model. This method, which is similar to ray tracing in CAD rendering engines, comprises first triangulating all roofs' surfaces and drawing straight lines from their centroids towards the sun direction. The second step consists of checking intersections between the sun ray vector and other roof surfaces. Any triangle containing an intersection means that is shaded. After that, shaded triangles were combined to represent the overall shaded roof area. Conversely, Saran et al. (2015) addressed the evaluation of PV systems from a completely different perspective by proposing a new approach built upon incorporating building energy simulation tools outputs into CityGML, (Fig.9). This was accomplished by first, generating a 3D CAD model using conventional CAD tools, in function of collected geometric parameters (e.g. Footprints) using total station surveys as well as satellite maps. Secondly, the CAD model was converted into a CityGML model with the help of feature Manipulation Engine (FME) converter. Similarly, a thermal model containing thermal zones, external/ internal walls, windows etc… was created from the CAD model using gModeller-Energy Analysis Sketchup Plug-in and then exported as a gbxml file. Thirdly, the solar gain of different building parts (roofs and walls), was simulated using Suncast module in IESVE while considering shading surfaces, orientation, and seasonal changes. The outputs were then stored in a PostGIS database to perform semantic queries such as, where should PV systems be installed to generate 5 MW of power per annum? With the help of query filter expression in java, CityGML displays only the building components with matching values.

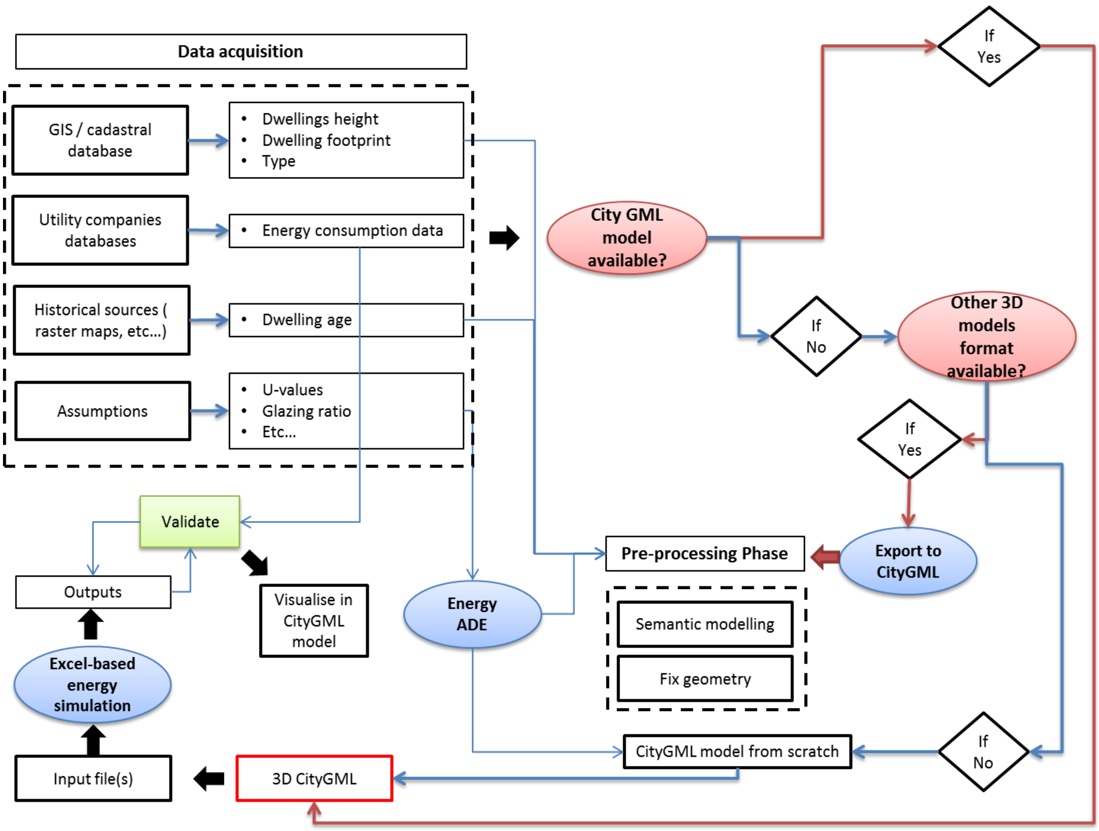

Figure 9.Conventional prediction process of 3D CityGML approaches

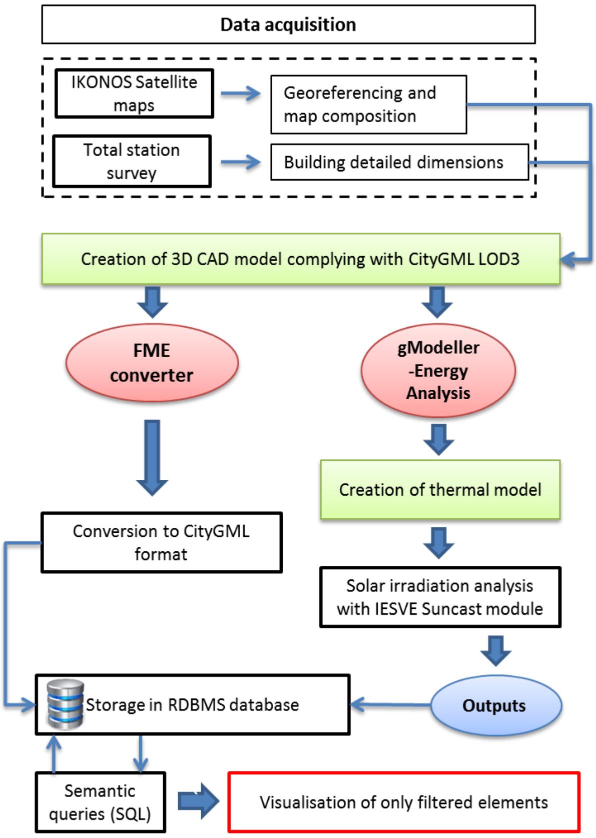

Figure 10. The prediction process adopted by Saran et al. (2015)

3.2.5. Advantages of CityGML based planning and forecasting approaches

- Unlike other city 3D model formats, CityGML has the ability to model and represent objects in different level of detail(s) LOD geometrically and semantically.
- CityGML approaches have shown lot potentials for the estimation of heating energy consumption.

3.2.6. Disadvantages of CityGML based approaches

- Their prediction accuracy relies heavily on the availability and quality of data obtained from municipalities as well as onsite measurements (Nouvel et al., 2014).
- 3D CityGML models for a particular city/region are not applicable to another since their development is mostly achieved using non-standardised data structure specified locally.
- The interoperability between CityGML LOD3/ LOD4 and other standards like IFC is still challenging and require extensive post-processing (Zhu and Mao, 2015).
- The potential of 3D CityGML models is not fully utilised for energy prediction applications. Indeed, they are mainly dedicated for visualisation purposes except providing certain geometric inputs.

3.3. Bottom-up statistical methods

Statistical bottom-up methods are based on correlating energy consumption/indexes with influencing factors, mostly weather parameters. This is usually achieved by applying different regression analyses, either linear or multivariate, to sufficient historical performance data (usually energy bills data), although Bayesian and Monte Carlo based approaches could be also employed

(Fumo and Rafe Biswas, 2015a). However, historical performance data must have a high level of statistical significance to meet the accuracy requirements of energy planning (Pedersen, 2007). Indeed, this is evident in the work of Cho et al. (2004) in which the developed regression models on the basis of 1day, 1 week, 3 months measurements resulted in errors in the prediction of annual energy consumption of 100%, 30%, and 6%, respectively. For this reason in addition to their ability to handle big data sets, statistical approaches are mostly employed at the urban scale. However, their applicability can be extended to cover the building scale as well.

3.3.1. Applicability in the building life-cycle

After being trained with large samples of hundreds or thousands of dwellings, statistical methods can be employed to estimate the energy consumption of entire dwellings or the thermal characteristics of their components in function of influencing parameters (Foucquier et al., 2013). Such factors are not only prominent for the evaluation of buildings energy performance but also the assessment of energy management strategies or saving potentials during commissioning (Ghiaus, 2006). For example, energy signature, which is best fit straight line correlating energy consumption with climatic variables, was adopted by Belussi and Danza (2012) for two main purposes. The first one is to check the conformity of certain buildings energy performance at the operational phases against the one estimated at the design phase as shown in (Fig.10). On the other hand, the second aim consists of determining potential savings through the comparison of their energy signature models in the operational phase with the one in accordance with building regulations.

As for determining thermal characteristics, Jiménez and Heras (2005) for instance, compared the accuracy of two regression models namely; single output and a multi-output auto regression with extra inputs, in predicting the *U*- as well as *G* values of few buildings' components. The results of latter model had a better agreement with the measured values in comparison to the former. Furthermore, the predicted values of windows in both models were more accurate than the ones of the walls. Fumo and Rafe Biswas (2015) assessed as well as compared the quality of simple linear and multiple regression models corresponding to the energy consumption of an unoccupied demonstration house in function of weather parameters. The authors concluded that the more time interval is allowed between observed data, the better regression model quality is obtained, regardless of the nature of the employed regression model. Similarly, Richalet et al. (2001) presented an assessment methodology for single family dwellings which consists of deriving the thermal characteristics through the development of building energy signatures using continuous onsite measurements. Those thermal parameters are then used to determine a normalised heating annual consumption based on standards occupant schedule and weather conditions. However, despite the authors' intention to distinguish the impact of occupants' behaviour from climatic influences by evaluating occupied and unoccupied dwellings, the potential of onsite measurement was not utilised for this purpose. Instead, standard EU internal gains values and occupants schedules were employed for all dwellings. Therefore, errors in the estimation of normalised annual energy consumption were superior to 20% for some occupied dwellings.

3.3.2. Advantages of bottom-up statistical methods

- Unlike engineering approach, the statistical one do not depend on the 3D geometry of the building since it is not based on thermodynamic models (Foucquier et al., 2013).
- In comparison to other prediction methods, statistical models are the easiest to develop (Zhao and Magoulès, 2012).
- Statistical methods have a great ability to recognise and model the variation in households' energy behaviour (Swan and Ugursal, 2009).

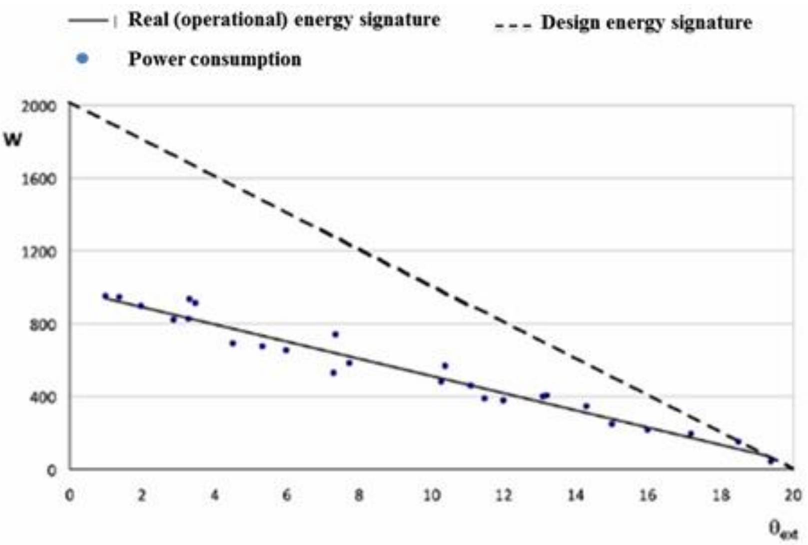

Figure 11 depicts a comparison between the design and real (operational) signature models by Belussi and Danza (2012). It is clear that behaviour of building during the operational stage is different from the design one since both curves are not overlapping.

3.3.3. Disadvantages of bottom-up statistical methods

- Since statistical approaches rely primarily on historical data, their adoption is impractical when data is unavailable or cannot be measured.
- Statistical methods are less accurate than other approaches. Furthermore, their ability to evaluate the impact of physical improvements is limited (Swan and Ugursal, 2009).

4. Discussion

This article has extensively reviewed different energy planning and forecasting approaches supporting physical improvement strategies in the building sector. This analysis was performed in accordance with their structure, conventional prediction pipeline, advantages and limitations, while providing some relevant examples on their applicability in the building life cycle (Table.7).

At the building scale, Engineering methods, which rely heavily on buildings 3D models and energy simulations tools, are characterised by their flexibility, user-friendliness, high integration with the majority of CAD/BIM tools, and comprehensive outputs. However, the large number of inputs requirement and involvement of calibration procedures to generate accurate results in certain projects, represents their major drawbacks. Nevertheless, they are still first choice methods for physical interventions at this scale. On the other hand, artificial intelligence energy prediction models in general, ANN and SVM particularly, do not rely on 3D models to proceed and can generate accurate estimations due to their great ability to handle non-linear and complex processes. However, since trained with large amount of historical data, they are impractical when these datasets are unavailable or their size is small. Furthermore, unlike engineering models, their main disadvantage is the lack of generalizability of their algorithms to represent the wider sample of dwellings at the urban scale. In other words, even if certain changes have been applied to the same building envelop, its HVAC system, or even occupancy, the employed artificial intelligence model has to be re-trained from scratch. Therefore, they are not time and cost effective approaches to adopt in urban energy planning given the imposed strict CO_2 emission targets. Conversely, Grey box (Hybrid) models, which combine the strengths and eliminate the weaknesses of the above approaches in addition to statistical ones, are well known for their great ability to handle problems related to small samples and missing data. Thus, it could be possible to utilise them in urban energy planning when certain parameters, especially the thermal ones (e.g. U-values, glazing ratio, etc…), are unattainable.

Table 7 Summary of the reviewed approaches

Frequent Intervention scale	Approaches	Require 3D models?	Require historical data?	Easy to employ?	Prediction accuracy	Applicability in the building life-cycle
Building scale	Engineering	Yes	No	Easy to moderate depending on the complexity of the simulation tool.	Fair to High	Multi stages including Design, operational, and maintenance stages
	ANN	No	Yes	No	high	Mostly operational stages Very limited for design phases
	SVM	No	Yes	No	Fairly high	Mainly operational stages Very limited for design phases
	Hybrid	Yes, if engineering methods are involved	Yes, partially	No	Fairly high	Design and operational stages
Urban scale	2D GIS	Yes but not necessarily	No	Moderate	Fair	Operational stages
	3D CityGML	Yes	No	Moderate	Fair to High	Operational stages
	Bottom-up statistical	No	Yes	Yes	Fair	Operational and maintenance stages

As for the urban scale, the analysis of the 2D GIS and 3D CityGML based energy prediction approaches have shown a great integration potential in the everyday's life of urban planners since GIS tools are increasing being adopted in urban planning. Furthermore, it has outlined the similarities between both approaches' processes and visualisation patterns, except the 3D environment, energy application domain extensions (ADE), and discrete level of detail for 3D CityGML. This clearly indicates that there is a major problem in the shift from 2DGIS to 3D GIS approaches. Indeed, what is the point of investing more time or maybe resources in using 3D CityGML for energy prediction if the 2DGIS ones can perform exactly the same task? It is believed that answer to this question is related to the fact that the great potentials of 3D CityGML models are not fully utilised yet for energy prediction applications at the urban scale. This evident in the majority of work on 3D CityGML heating demand analysis models which exist only in LOD1 or LOD2 at most, although the minimum level of detail requirement for this particular purpose should be LOD3. This is simply because LOD1 and LOD2 do not contain openings and protruding building elements such as, shading devices, which certainly affects their prediction accuracy. Another problem is the independence of 3DCityGML and 2GIS models from energy calculation engines. In fact, both GIS and 3D CityGML models are only employed as visualisation platforms despite providing few geometric inputs. Finally, although bottom-up statistical approaches do rely on historical data to solve linear problems and have fair prediction accuracy, they are adequate tools for quick buildings energy performance inspection at the urban scale. Furthermore, they have a great ability to discern impact of occupancy on building energy consumption. Therefore, their adoption is indispensable in urban energy planning.

This article has undoubtedly highlighted a lot of gaps and issues with regards energy planning and forecasting tools that are used both at the micro as well as macro level. Among them, it is very interesting to mention that despite the wide adoption of CityGML urban planning applications including energy planning, most of the energy simulations are performed outside a CityGML environment in an excel based software or building energy simulation tools (e.g. IESVE). This is a major problem because the forecasted energy performance of buildings at the urban scale using this approach does not consider the effect of buildings on each other (including shading effect, wind effect, etc…). Therefore, we strongly recommend the development of an energy simulation plugin embedded in CityGML environment. So that the full potential of 3D models in exploited and accurate predictions are obtained.

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