GIS-Based Residential Building Energy Modeling at District Scale

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Abstract
Urban planners often develop strategic sustainable energy planning processes that aim to minimize the overall energy consumption and CO₂ emissions of buildings. Planning at such scales could be informed by the use of building energy modeling approaches. However, due to inconsistencies in available urban energy data and a lack of scalable building modeling approaches, a gap persists between building energy modeling and traditional planning practices. This paper develops a methodology based on bottom-up approach for GIS-based residential building energy modeling at a district scale. The methodology is applied to districts in Dublin and modeling results indicate where and what type of buildings have the greatest potential for energy savings throughout the city.

Introduction
The world has witnessed a major population shift to urban areas over the past few decades. At present, approximately half of the world’s population (54%) reside in urban areas compared to a mere 30% in 1950, and the number is projected to rise to 66% by 2050 (UN [2014]). With higher levels of technology and services compared to rural areas, urban areas account for about two-thirds of the world’s total energy consumption, this relates to approximately 70% of global greenhouse gas emissions (OECD/IEA [2016]). Furthermore, around 39% and 36% of the CO₂ emissions are associated with buildings in the US and Europe respectively (EU-Energy [2018]; EESI [2018]). The most significant factor contributing to CO₂ emissions is buildings. In Europe, buildings are responsible for 40% of the overall energy consumption (EU-Energy [2018]). Buildings play a significant role in urban demand and supply of energy. Therefore energy management and sustainable energy planning in urban areas as active important research topic because of climate change concerns.

At the urban scale, individual building analysis is often difficult due to lack of data availability and users’ privacy issues. Hence, archetypes development is a common approach for individual building analysis at district or neighborhood scale (Davila et al. [2016]; Reinhart and Davila [2016]). Moreover, energy planning is often implemented at the national level and thus, is not effectively addressed within local or regional level planning structures. Therefore, local authorities are not wholly informed when making energy efficient decisions are strategic level in their locality. One of the most promising solutions is to improve the energy efficiency in buildings with limited information, which can be accomplished by using energy modeling (Reinhart and Davila [2016]). In this approach, energy models help us to virtually analyze and compare different design scenarios and optimize energy performance of the buildings. Furthermore, these models aid in identifying the the impact of different energy efficiency policies. The European Commission uses the energy modeling approach to formulate different energy policy decisions (EU [2016]).

Table 1: Description of different geographical scales for archetypes development and GIS mapping

<table>
<thead>
<tr>
<th>Scale</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>City</td>
<td>Group of regions/ local authorities</td>
</tr>
<tr>
<td>Regions/ Local authorities</td>
<td>Geographical division of a city into different areas and each local authority constitutes a number of districts.</td>
</tr>
<tr>
<td>District</td>
<td>The district constitutes a group of small areas</td>
</tr>
<tr>
<td>Small Areas</td>
<td>Groups of buildings in a district</td>
</tr>
</tbody>
</table>

This paper proposes a generalized methodology, based on bottom-up approach, for GIS-based building energy modeling at district scale. The entire district is divided into smaller areas to include more levels of detail. As such, instead of using national building archetypes, new levelized archetypes are developed at the district level and energy demand from monthly to yearly levels is examined. The main goal of this research is to develop an energy model for the residential sector that helps the local authorities to analyze the energy consumption and CO₂ emissions at the district level. Different geographical scales used in
Energy modeling is usually performed at two different scales such as Building Energy Modeling (BEM) and District or Urban Building Energy Modeling (DBEM/UBEM). The BEM approach is suitable for implementation at the individual building level while the DBEM approach covers the entire district level. BEM approaches are divided into three main categories: white box (physics based), black box (empirical or statistical based), and gray box approaches (both physics and statistical based) [Magyari et al., 2016]. Similarly, district or urban energy modeling approaches are further divided into two main categories, namely, top-down and bottom-up approaches [Kavgic et al., 2010]. The top-down approach uses macro-economic variables (e.g. energy prices, geographic, social) and statistical data to make future energy predictions. On the other hand, the bottom-up approach models groups of buildings with similar technical and geometrical characteristics. DBEM can help to enable intelligent supplier decisions and enhanced integration in planning, management and control [Sivakumar, 2013]. However, due to inconsistencies in available urban energy data and a lack of scalable building modeling approaches, a gap persists between building energy modeling and traditional planning practices. Typical energy modelling studies usually on commercial buildings and limited work has been done in the residential sector due to the scarcity of publicly available data [Hong et al., 2016; Patti et al., 2015].

Energy modeling requires building geometric and non-geometric data. Over the past decades, geometric data have been retrieved from 3D data models. The 3D city modeling is the most widely used approach for DBEM. The 3D data modeling also admits spatial data analysis, interpretation and visualization. The most common data models used were Building Information Model (BIM) and Geographic Information Systems (GIS). The BIM data models such as IFC and gbXML are used for individual building simulations. The GIS database is more popular choice for DBEM due to the increased accessibility to the general public. However, with the increasing maturity of GIS and 3D dataset availability, 3D based GIS has emerged as an essential tool to enhance the dynamic energy modelling capabilities [Balu et al., 2013]. Similarly, non-geometric data can be retrieved in two ways. Data can be collected as real-time data from various sensors such as smart meters, smart plugs and environmental sensors that provide actual information about building usage and thermal characteristics. When real-time data is not available or limited information is available, the building archetypes approach is often the preferred choice [Reinhart and Davila, 2016].

The building archetypes concept is most commonly used in energy modeling at the urban scale. There are three different methodological approaches for archetypes development, namely, synthetical average, real example and real average [Sousa Monteiro et al., 2015]. In the synthetical average building approach, the archetype selection is performed by using information about the most commonly used materials and systems. Several projects at the European and international levels are being developed to define the building stocks at national level, for instance, TABULA (Loga et al., 2012), BPIE (European Union, 2018) and DOE (US Department of Energy, 2018).

In the real example building approach, the selection of the building type is done by means of experience; the building type is selected on the basis of the experience of panel experts and other sources of information within an actual climatic context. The other information sources normally include the most commonly used materials, specific size and construction period classes. In the real average building approach, the selection of building type is performed through the statistical analysis of a large building sample data [Famuyibo et al., 2012].

Although all the aforementioned databases and projects provide a valuable overview of the building stock, the available data could not be used directly for an archetype-based energy modeling. The main issues associated are lack of buildings’ physical description and the information is mostly outdated. Projects such as TABULA and BPIE Data Hub are now updated on a regular basis and significant improvements have been done in past few years. However, these databases cover only the national top-level archetypes and lack the crucial information related to district level or small area building stock. For instance, a study by Famuyibo et al developed archetypes for Irish national building stock based on dwelling types. These archetypes considered only 13 relevant variables and neglected important variables such as year of construction and floor level details etc. Detailed archetype modelling at micro level is required for efficient implementation of deep retrofits at an urban scale. Development of archetypes at the micro level provides opportunities for detailed energy modelling even at the district scale. Detailed urban energy modelling would ensure an efficient implementation of energy retrofits at a deeper scale [DAgostino et al., 2017].

Energy modeling for buildings in DBEM is a complicated and time-consuming process. Generally, sim-
Figure 1: Methodology for GIS-based residential building energy modeling at district scale.

Data Collection

Weather Data

Geometric Data

Non-Geometric Data

Energy Simulation

Building Archetypes Development

Mapping Energy to Small Areas

Validation Results

GIS Visualization & Analysis

Simulation engines and languages such as EnergyPlus \cite{Crawley2001}, Modelica \cite{Fritzon1998} and TRNSYS \cite{Klein1988}, are used to predict heating and cooling loads for individual building in DBEM. These simulation engines are computationally efficient for dynamic simulation models. One of the powerful choice for performing simulations is EnergyPlus, which has been implemented in multiple DBEM projects including CityBES \cite{Hong2016}, UMI \cite{Reinhart2013} and Boston-DBEM \cite{Davila2016}. However, district scale modeling can be complex and time-consuming as the high-level information is required for dynamic simulation. There is a trade-off between effort and accuracy, especially regarding modelling and the data collection of the building stock \cite{Remmen2017}.

Methodology

The proposed methodology for GIS-based residential building energy modeling at the district scale requires a number of steps, as shown in Figure 1. The methodology consists of data collection, followed by archetypes development at the district scale, energy simulations and GIS based energy consumption mapping with results validation.

Data Collection

A DBEM requires the combination of several data inputs including meteorological data, building geometry and non-geometry information \cite{Wate2015}. These are follows:

Meteorological Data

Weather data sets are required for building thermal simulations. The most common hourly climate datasets have been available for a number of years, and describe the local climate known as Typical Meteorological Year data (TMY). All existing data sets are based on historical data and possess limitations such as how to deal with climate change, uncertainties involved, incorporating urban heat island effects and extreme events. Therefore both Typical Meteorological Year 3 (TMY3) and Weather Year for Energy Calculations 2 (WYEC2) are used to obtain long-term updated weather patterns. For example, weather data in EnergyPlus Weather format (EPW) files are available online for more than 2100 locations derived from 20 sources under funding from the US Department of Energy (EPW Weather Data\footnote{https://energyplus.net/weather}).

Building Geometry Data

The geometry input data required by the DBEM approach consists of building envelopes, shapes, number of floors, walls, and window opening ratios etc. Typically, geometric building data is gathered through as building stock and energy performance certificates data. Building footprint is collected from the GIS data model; the most appropriate standard format model is geospatial vector data format, also known as shapefile that contains the geometry data such as points, lines, and polygons.

Non-Geometric Building Data

In addition, non-geometric building properties are also required for DBEM, including user occupancy, usage pattern and HVAC systems, etc. In DBEM, the primary challenge is the availability of all above information for modeling. Typically, non-geometric building data is gathered through as national census databases or statistical survey.

Building Archetypes Development

In this paper, the real average building archetypes development approach is used for energy modeling. Detailed building data can be obtained using national level building stocks data. The archetypes are developed using data mining algorithms rather than traditional qualitative techniques, these algorithm generate an accurate representation of the overall building stock. The methodology of archetypes development includes the following sequential steps: data preprocessing, feature selection, outlier detection and aggregation, as shown in Figure 2.

The building data obtained through measurement systems or through extensive surveys is often incomplete and lacks certain important variables. Data preprocessing is a data mining technique that involves transforming raw or real-world data into an understandable format. During preprocessing, the data goes through a series of steps such as data cleaning, data integration, data transformation, data reduction and data discretization. Feature selection, is
the process of selecting a subset of most relevant variable or attributes for the model. The feature selection method aims to remove irrelevant and redundant attributes to get accurate results. Outlier detection is the process of identification of observations in the data that deviates by a significant amount from a given set of data. The most common outlier detection techniques are distance-based, density-based and Local Outlier Factor (LOF). In this paper, the LOF algorithm is used for detecting the outliers. The aggregation process involves categorizing the data into groups and then applying arithmetic or geometric mathematical operations. The obtained aggregated value represents the characteristics of one building archetype.

**Energy Simulation**

Simulations are performed using the climate data and other inputs available for each developed building archetype. At the urban scale, energy modeling is highly complex and differs according to the desired output such appropriate for the purpose of study. In this paper, EnergyPlus is used as simulation engine for modeling dynamic energy and environmental performance of buildings. The EnergyPlus models are calibrated against static energy performance certificate model outputs using industry standard analytical and comparative tests, i.e. ANSI/ASHRAE Standard 140-2011. All the energy simulation results for the building archetypes are stored and used for further GIS mapping.

**Mapping Energy to Small Areas**

The quantification step determines the number of buildings in the country represented by each archetype building. To aggregate the result, a parameter called "weighting coefficient" is assigned to each archetype building. Generally, buildings’ national statistics are used to quantify the number of buildings. For example, Arababadi [2012] used Building Research Establishment (BREs) domestic and non-domestic fact files data for UK energy studies. To achieve an enhanced overview of the energy consumption, a small areas concept is used in this paper. The small areas concept allows detailed mapping of energy consumption. Archetypes are then developed for those regions to calculate the energy consumption. The small area energy mapping concept has been implemented by Codema (Dublin’s Energy Agency) for Dublin city’s spatial energy demand analysis. However, the energy consumption results were obtained using static survey data ignoring the dynamic aspects such as buildings external environmental conditions [Gartland 2015].

**Validation of Results**

The final step includes the validation of the energy modeling results. The energy demand of each archetype is computed and further compared with the corresponding values of energy use found in national and international statistics for a particular reference year. For instance, Mata et al. used the Energy, Carbon and Cost Assessment of Building Stocks (EC-CABS) model for energy consumption calculation of archetype buildings [Mata et al. 2014]. To compare the results, the authors used the statistics data. The results show the deviation from statistics ranges from -6% to +2%, depending on the country. At the aggregate level previous validation works have reported acceptable errors of 5 to 20% compared to real energy use [Cerezo et al. 2015].

**GIS Visualization and Analysis**

To gain better insights in to the results, GIS is used to map the energy consumption of the small areas. GIS aids the public administrators in visualization of energy consumption along with static characteristics such as construction period, cooling/heating system, etc for each archetype. GIS also helps in the visualization of energy consumption with socio-economic, demographic, and correlated data. This feature helps the building owners and designers to visualize energy load profiles and better understand the energy usage under different scenarios including lighting, cooling and heating demand.

**Case Study**

The main objective of this paper is to develop a GIS-based building energy model for an entire district.
Table 2: List of Dublin city dwelling types u-values obtained from building archetypes development

<table>
<thead>
<tr>
<th>Apartment</th>
<th>...1918</th>
<th>1919-45</th>
<th>1946-60</th>
<th>1961-70</th>
<th>1971-80</th>
<th>1981-90</th>
<th>1991-00</th>
<th>2001-05</th>
<th>2006...</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wall</td>
<td>1.39</td>
<td>1.18</td>
<td>1.28</td>
<td>1.24</td>
<td>0.81</td>
<td>0.55</td>
<td>0.62</td>
<td>0.57</td>
<td>0.43</td>
</tr>
<tr>
<td>Roof</td>
<td>0.69</td>
<td>0.51</td>
<td>0.62</td>
<td>0.75</td>
<td>0.27</td>
<td>0.13</td>
<td>0.11</td>
<td>0.10</td>
<td>0.07</td>
</tr>
<tr>
<td>Floor</td>
<td>0.34</td>
<td>0.30</td>
<td>0.44</td>
<td>0.55</td>
<td>0.36</td>
<td>0.26</td>
<td>0.14</td>
<td>0.12</td>
<td>0.09</td>
</tr>
<tr>
<td>Window</td>
<td>3.49</td>
<td>3.18</td>
<td>3.10</td>
<td>2.89</td>
<td>2.93</td>
<td>2.90</td>
<td>2.96</td>
<td>2.57</td>
<td>2.04</td>
</tr>
<tr>
<td>Door</td>
<td>1.76</td>
<td>2.60</td>
<td>2.46</td>
<td>2.62</td>
<td>1.96</td>
<td>1.97</td>
<td>1.86</td>
<td>1.76</td>
<td>1.91</td>
</tr>
<tr>
<td>Houses</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wall</td>
<td>1.52</td>
<td>1.47</td>
<td>1.56</td>
<td>1.37</td>
<td>0.98</td>
<td>0.46</td>
<td>0.48</td>
<td>0.47</td>
<td>0.28</td>
</tr>
<tr>
<td>Roof</td>
<td>1.05</td>
<td>0.83</td>
<td>0.82</td>
<td>0.63</td>
<td>0.39</td>
<td>0.25</td>
<td>0.30</td>
<td>0.28</td>
<td>0.20</td>
</tr>
<tr>
<td>Floor</td>
<td>0.56</td>
<td>0.61</td>
<td>0.62</td>
<td>0.64</td>
<td>0.60</td>
<td>0.53</td>
<td>0.43</td>
<td>0.39</td>
<td>0.25</td>
</tr>
<tr>
<td>Window</td>
<td>3.43</td>
<td>3.30</td>
<td>3.33</td>
<td>3.15</td>
<td>3.10</td>
<td>3.11</td>
<td>2.91</td>
<td>2.64</td>
<td>1.74</td>
</tr>
<tr>
<td>Door</td>
<td>2.81</td>
<td>2.60</td>
<td>2.39</td>
<td>2.11</td>
<td>2.26</td>
<td>2.35</td>
<td>2.63</td>
<td>2.52</td>
<td>2.08</td>
</tr>
</tbody>
</table>

Table 3: Grouping EPC dwelling types to small areas for mapping in GIS

<table>
<thead>
<tr>
<th>EPC</th>
<th>CSO City</th>
<th>CSO Small Areas</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mid-floor apartment</td>
<td>Apartment</td>
<td>Apartment</td>
</tr>
<tr>
<td>Top-floor apartment</td>
<td>Apartment</td>
<td>Apartment</td>
</tr>
<tr>
<td>Apartment</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maisonette</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ground-floor apartment</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Basement</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dwelling</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Semi-detached house</td>
<td>Semi-detached</td>
<td>Semi-detached house</td>
</tr>
<tr>
<td>Detached house</td>
<td>Detached</td>
<td>Detached</td>
</tr>
<tr>
<td>Mid-terrace house</td>
<td></td>
<td>Terraced house</td>
</tr>
<tr>
<td>House</td>
<td></td>
<td></td>
</tr>
<tr>
<td>End of terrace house</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The whole district is analyzed as small areas through archetype development for each of the individual regions. Decomposition into smaller regions provides analysis of energy consumption across different regions. This methodology is applied to the publicly available Irish Building Energy Performance Certificate (EPC) data by Sustainable Energy Authority of Ireland (SEAI). The EPC data contains the building’s energy performance or certificate rates in terms of primary energy consumption (kWh/m\(^2\)/year) and varies on a scale of A-G. An A-rated building has the highest energy efficiency and will tend to have the lowest energy consumption and CO\(_2\) emissions. On the other hand, a G-rated is the least energy efficient. The EPC is calculated with Dwelling Energy Assessment Procedure (DEAP) software, Ireland’s official method for calculating the building energy rating of new and existing buildings. EPC data contains more than 600,000 Irish buildings’ data with 203 variables including building physics, energy, and CO\(_2\) information. This paper focuses on a energy demand analysis for the Dublin City local authority, this represents 10% of the residential EPC building stock in Ireland. A total of 18 archetypes are identified at local authority scale based on the dwelling types and construction year. For instance, Dublin has been divided into four local authorities: Dublin city, Dn Laoghaire-Rathdown, Fingal and South Dublin. The energy consumption is mapped into small areas using a two step process. The dwelling types from the EPC data are narrowed to city level. The city level archetypes are then decomposed into small areas as specified in Table 3 using the Central Statistics Office (CSO) housing data. The related data is then pre-processed for inconsistencies such as removing missing values, filtering out the irrelevant variables or less frequent values using the standard deviation threshold. A total of 73 relevant variables, out of a list of 203, are selected in the pre-processing and feature selection process. An outlier detection process is also run to
enhance the quality of the filtered data. Outlier detection is an important step in data mining that filters out the noisy or dis-similar information and eliminates all those inconsistencies from the data. The LOF algorithm is used for detecting the outliers by using euclidean distance. This follows the aggregation process where the average values of the relevant variables are considered with respect to building energy rating. The set of average values for any archetype is used to develop the database for the building energy modeling. A detailed description of the u-values with respect to the building dwelling type and construction year is shown in Table 2.

Once the building archetypes are developed, the next step is to simulate the building energy in EnergyPlus with respect to dwelling types and year of construction. Comprehensive EnergyPlus models for Irish building stock have been developed by Nue and Sherlock which are used for base-case archetype model inputs [Sherlock’s 2013, Neu et al. 2016, Egan et al. 2018]. Dynamic energy modeling through simulation engine is very complicated and time-consuming. To solve this problem, a 48 cores server with a specification of 2 x Intel Xeon E5-2697 CPUs with 30 MB cache on each processor (256 GB RAM) was used. This resource greatly reduce the cost of execution. The simulation results are then mapped or quantified into small areas in terms of energy consumption.

Each small area represented a groups of buildings and a collection of small areas makes one district. For small areas mapping, Ireland Census 2011 Small Area Population Statistics (SAPS) datasets were used [CSO 2011]. In this paper, Dublin City local authority is used for small areas mapping. Based on information available from the central Statistics Office of Ireland, Dublin City local authority comprises nine small districts and 2203 small areas with more than 210,000 residential buildings. The small areas concept allows mapping of energy consumption by dividing the entire district into groups of buildings. The EPC database has been developed using 60,000 buildings which represents only 28% of the building stock in Dublin City. The rest 72% of the building stock doesn’t have any associated DEAP calculation results. Therefore, EnergyPlus simulations are used to account for the energy use intensities of the remaining stock.

The primary energy consumption computed using EnergyPlus compared with EPBD and TABULA archetypes to validate and check any ambiguities in the aggregated energy consumption values of developed archetypes against the existing ones. Figure 3 depicts the comparison of primary energy consumption for the two identified archetypes. The results show that there exist slight variations in consumption values between different approaches, mainly, be-

Figure 4: Dublin city small areas buildings’ energy use per unit of residential floor area in kWh/m$^2$/year

Figure 5: Comparison of Dublin city small areas buildings’ energy use per unit of residential floor area for houses and apartments in kWh/m$^2$/year
cause of different calculation methods and underlying assumptions related to the building.

In the final phase, all the energy mapping results are visualized using a GIS map. The annual small areas energy demand intensity (kWh/m²/year) of different dwelling types in Dublin city local authority is shown in Figure 5. The main city area of Dublin has a low energy intensity (kWh/m²/year) per dwelling in comparison to the rest of the city. This is due to the fact that dwellings close to the centre are relatively new or have been recently retrofitted (around 52% buildings were constructed after 1990). Other areas show above average use per dwelling (represented in red and orange) because of older establishments.

The variation in energy demand is significant across the two dwelling types, houses (detached, semi-detached, end of terrace, etc) and apartments (mid-floor, top-floor, maisonette, etc), and is depicted in Figure 6. Houses have a larger variation in the energy demand because around 86% of such dwellings have been built before 1990. However, there is less variation in the energy demand across different apartments in the Dublin city region as the because the majority of these apartments (around 51%) are relatively newer establishments being built after 1990. Also, apartments have been recently constructed in the Dublin city region; this explains the small green energy efficient zones when examining the energy map for apartments. Likewise, apartments are considered as the preferred choice for newer residential areas in order to cope up with the increasing demand of housing in Dublin and are constructed considering the new building regulations.

Conclusion

The research conducted in this paper identifies a generalized methodology for GIS-based district energy modeling using bottom up approach. At the district scale, the system experiences a two fold increase in complexity, particularly, due to a significant increase in the number of buildings and associated entities. This in turn increases the resources, geometric and non-geometric inputs, required for energy modeling. These inputs are often collected through building archetypes development using a data mining approach. The developed building archetypes, with appropriate input parameters are simulated in the EnergyPlus simulation engine using a high performance computing server. All the energy outputs from these simulations are mapped to GIS using census survey data. Instead of mapping results directly to districts, the small areas concept is used for detailed analysis. The modeling results help in the identification of energy efficient areas from the inefficient ones in the district. Furthermore, GIS-based modeling will aid the local authorities or city planners to identify priority areas for implementing energy efficiency measures and further improve sustainable energy policy decisions.

In this paper, detailed building stock characteristics are decomposed into general types due to unavailability of detailed GIS and census surveys data. The results achieved by using the proposed methodology could further be improved by using more detailed building type quantification data. Other major limitation of this methodology is the use of static occupants profiles. The future work might also include the dynamic occupant behavior data to improve the energy modeling results.

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