Computers, Environment and Urban Systems 64 (2017) 68–80

Contents lists available at ScienceDirect

Computers, Environment and Urban Systems

journal homepage: www.elsevier.com/locate/ceus

The influence of data quality on urban heating demand modeling using 3D city models

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ARTICLE INFO

Article history:
Received 14 December 2015
Received in revised form 15 December 2016
Accepted 17 December 2016
Available online xxxx

Keywords:
3D city model
Urban energy analysis
Heating demand
Data quality
CityGML
LoD

ABSTRACT

3D city models are rich data sets for urban energy analyses, providing geometrical and semantic data required to estimate the energy demand of entire districts, cities and even regions. However, given the diverse availability, uncertainty and Level of Details of these data and the resources required to collect them, managing data quality is a common challenge of urban energy modeling. Knowing the influences of the different input data for different configurations and applications enables to control the result accuracy and recommend intelligent and adequate data collecting strategies, by assigning resources on the most important parameters. This paper investigates the influences of geometrical, meteorological, semantic and occupancy related data quality on the heating demand estimated by the urban energy simulation platform SimStadt, applied to the City of Ludwigsburg in Germany. A focus on a district with consumption data available at building block level allows for a critical comparison between estimated and measured energy demands. Although the quantified information presented in this paper is specific to a case study, the main trends and developed methods are transferrable to other urban energy analysis studies based on 3D city models.

1. Introduction

Cities occupy only 2% of the Earth's land, but account for over 70% of both energy consumption and carbon emissions (Sustainable cities' report 2013). An urban energy transition is thus essential to lower greenhouse gases that contribute to climate change (Van der Veken, Saelens, Verbeeck, & Hens, 2004) and the exhaustion of energy resources (Pérez-Lombard, Ortiz, & Pout, 2008).

To evaluate the urban energy performance and predict the impact of energy saving measures, urban city models can play an essential role (Keirstead, Jennings, & Sivakumar, 2012). Two different modeling strategies may be mainly distinguished: top-down and bottom-up approaches (Swan & Ugursal 2009; Heiple & Sailor, 2008). Top-down approaches are not particularly appropriate to plan and model the energy transition, since they model long-term forecasting in absence of any discontinuity, while energy transition involves a rupture of people's habits and mentalities, an acceleration of building retrofitting and renewables implementation, and the introduction of new technologies. In particular for the modeling of building energy at urban scale, bottom-up approaches should be prioritized, based on statistical or on physical models depending on the input data availability: statistic models require disaggregated historical consumption data for a representative group of buildings (Mastrucci, Baume, Stazi, & Leopold, 2014, Project Heat RoadMap Europe, 2016), while basic inputs for physical models are 3D building geometries and attribute data about building physics (Kavgic et al., 2010).

3D city models generated from airborne laser scanner or photogrammetry technologies can provide an excellent dataset for bottom-up physical modeling, storing geometrical and semantic data of entire cities (Strazalka, Monien, Koukofikis, & Eicker, 2015, Biljecki, Stoter, Ledoux, Zlatanova, & Cöltekin, 2015a). Based on such city models, several urban heat demand analyses have been recently carried out in some European cities such as Berlin (Carrión, Lorenz, & Kolbe, 2010, Kaden & Kolbe, 2013), Karlsruhe and Ludwigsburg (Nouvel, Zirak, Dastageeri, Coors, & Eicker, 2014), Trento and Ferrara (Prandi et al., 2015). However, a very disparate input data quality was observed in these projects, leading to an alteration of the result accuracy (too rarely controlled in such urban analyses).

Data are considered high quality if they fit their intended purposes (Hoffer, Ramesh, & Topi, 2011), i.e. heating demand analysis in this study. The norm ISO 19157:2013 defines the different data quality aspects (also called data quality elements) for geographic information: completeness, accuracy (positional and thematic), temporal validity, usability for the intended purpose, and consistency. In the urban modeling field, data completeness is closely linked to the data availability, which depends on the data collection methods as well as data privacy and ownership issues. The Levels of Details (LoDs) of 3D city models

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http://dx.doi.org/10.1016/j.compenvurbsys.2016.12.005
0198-9715/

Nomenclature

3D	three dimension
.a	annual
AB	apartment block
ALKIS	Authoritative Real Estate Cadaster Information System
CityGML	City Geography Markup Language
EnEv	German Energy Saving Ordinance
Energy ref. area	Energy Reference Area
IWU	Institut Wohnen und Umwelt
OGC	open geospatial consortium
LoD	Level of Detail
MAPE	Mean Absolute Percentage Error
MPE	Mean Percentage Error
MFH	multi-family house
PE	Percentage Error
RH	row house
SFH	single-family house
TMY	typical meteorological year

associate both completeness and accuracy aspects. However, a higher LoD is not always synonym of a higher positional accuracy, this depends on the acquisition process resolution. Temporal validity, while modeling urbanities with buildings which are built, refurbished and destroyed following the "pulse" of the city evolution, is a key aspect. Finally, data consistency is a major concern of urban data analysts, while dealing with non-standardized databases of different formats and sources. Introducing a standard for data recording would enable to increase data quality, and consequently to harmonize and facilitate the collection of relevant data for urban energy models. Several European Directives as well as projects dealing with urban data management are already working on this issue; INSPIRE Directive (Official Journal of the European Union 2007) or SUNSHINE project (Dörrzapf, Mušič, Schrenk, & Wasserburger, 2013). Further to this data standardization improvement process, investigating the impact of the different input variables on the result accuracy in different configurations and applications enables the identification of the most influential input data and the supervision of data uncertainty (Keirstead et al., 2012, Biljecki, Gerard, Ledoux, & Stoter, 2015b). This is generally carried out by means of sensitivity analyses based on simulations, like in the study of Strazalka et al. (2015) which analyses the impact of the building LoD (LoD 1–3) and several physical parameters on the annual heat demand of six test buildings. As a result, intelligent and adequate data collecting strategies can be designed, by assigning resources to the most important parameters, while parameters with minor influence can be assessed with coherent benchmarking values.

This paper studies the influence of input data on the estimated building heating demand based on 3D city models, paving the way for standardization of required input data for urban energy modeling. After introducing the urban heating demand model used for this study and the case study of Ludwigsburg (South-West Germany) on which it is applied, the influences of the different input data are deeply investigated. Data quality is studied for various input data categories: geometric data, semantic data, occupancy-related data, and meteorological data. Finally, the inputs with the greatest impact on the heating demand are identified and data collecting strategies and policies are subsequently recommended.

2. Urban heating demand modeling and data requirements

The urban heating demand analysis described and tested in this paper is based on an integrated process using a 3D city model. This integrated process is implemented in the urban simulation platform SimStadt (Nouvel et al., 2015), whose development is ongoing in a German funded research project of the same name (www.simstadt.eu). SimStadt is structured in workflows (e.g. photovoltaic potential analysis, heating demand analysis), which basically consist of chains of modules (so-called workflow steps) that process, enrich and simulate a given city model. The heating demand analysis used in this paper starts with a parsing and quality checking of the 3D city model. Then the data model is processed and enriched through multiple data preprocessing modules for geometry, building physics and building usage. Local weather data, such as temperatures and radiations, are extracted from monthly databases and pre-processed with the software INSEL 8 (www.insel.eu). Finally, the heating demand of each building is estimated based on the monthly energy balance described in the German standard DIN V 18599-2, 2011 (equivalent to the international norm ISO 13790, 2008).

The 3D city model is described by the OGC standard CityGML (Gröger, Kolbe, Nagel, & Häfele, 2012), which is an open data model and stores the city model based on Extensible Markup Language (XML) format. It represents the building model in three dimensions with 4 possible different Levels of Detail (LoD), standardized in the OGC 12-019. In our case study, buildings are modelled with LoD1 and/or LoD2. LoD1 represents a building as a cuboid while LoD2 represents a more detailed building geometry integrating a roof shape. The details about the integration of 3D city model and the SimStadt platform are found in Nouvel, Zirak, Dastageeri, Coors, and Eicker (2014).

The required building parameters for the described workflow may be categorized as:

- geometrical data
- building physics attributes
- building usage attributes and operating parameters.

From the building geometry described in the CityGML file, the SimStadt geometrical preprocessing module extracts the geometrical data required for the heating demand calculation: the building volume, the heights (mean height for the LoD1, eaves and ridge height for the LoD2), the boundary surface type (e.g. exterior walls, shared walls, roof, basement) and the boundary surface orientations (azimuth and inclination). If missing, the number of stories, which is required to estimate the energy reference area, may be retrieved based on the building height and some typical story heights coming from benchmarking data libraries (e.g. IWU, 2003).

Then, the SimStadt building physics preprocessing module assesses the building physical attributes, based minimally on two building attributes available for all of Germany year of construction, and the building function, derived from the standardized building function codes stored in the Authoritative Real Estate Cadaster Information System (ALKIS®). This process used benchmarking values from building typology libraries (IWU, 2003), which categorizes buildings according to their type (Single-Family House (SFH), Multi-Family House (MFH), Row House (RH), and high tower or Apartment Blocks (AB)) and building age class. The building typology of each building is automatically determined based on the analysis of their 3D model (i.e. criteria on building height, ground floor area and proportion of adjacent walls).

By mapping ALKIS building function codes with the reference building usages of building energy norms (DIN V 18599-10, 2011), building usage and operating parameters (occupancy time, air change requirement, set-point temperatures etc.) can be assessed based on standardized and benchmarking values.

On-site surveys and other acquisition methods, which enable to collect additional sets of energy-relevant information data (number of stories, date of full refurbishment, window proportion per façade, (non) heated attic/cellar story etc.), can refine the library benchmarking values and improve the result accuracy.

Beside these building attributes, local weather data are also required to calculate the building heating demand. Either Typical Meteorological data (e.g. DIN V 4108-6, Annex A) or recorded weather data for specific years can be used, as shown in Section 7 of this study.