ENRICHING THE DIGITAL CADASTRE WITH MATERIAL PROPERTIES FOR AN URBAN SIMULATION OF HEAT DEMAND AND LIFE CYCLE ANALYSIS

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ABSTRACT

This paper presents an innovative method to enrich the digital cadastre (base year 2010) with material properties. This enriched database is then used to: (1) perform a thermal simulation on selected buildings, using the material properties to estimate the heat transmission coefficients of the building components; and (2) perform a life cycle assessment (LCA) of two retrofitted options for the selected buildings, using the material properties to estimate the embodied energy of retrofit scenarios.
The results show: (1) the performance of the algorithm to match materials among material databases and the digital cadastre; and (2) a simple computation of energy payback time for two retrofit scenarios.

INTRODUCTION

The application of LCA at a building level has been performed by many authors (Gian Andrea, 2009; Blengini & Di Carlo, 2010; Ramesh, Prakash, & Shukla, 2010) as well as the analysis of individual construction materials (Papadopoulos & Giama, 2007).
The promotion of national databases containing reliable information on the life cycle of construction materials is essential for a holistic view of policies targeting the energy consumption of the building stock (Zabalza Bribián, Valero Capilla, & Aranda Usón, 2011). Not only the access to data is important for this endeavor but the ability to use it. In order to use such rich data sets we need to start developing databases that can be linked to each other. A first approach to link four data sets is here presented here. Only one of these data sets contains information on the life cycle of construction materials.
Aim of this approach is to contribute to the development of integrated urban energy models, previous research aiming to the same endeavor have successfully developed models for the integration of user behaviour at an urban scale (Muñoz H., 2014; Muñoz H. & Peters, 2014).
The presented analysis summarizes the efforts to create a database of the building stock with rich characteristics regarding its construction materials. This kind of databases should make possible to take the embodied energy into account in urban energy simulation models. The explicit consideration of embodied energy of the building stock can help decision makers to efficiently allocate resources of future retrofit incentives.

METHOD

In order to develop an integrated urban model, we need rich data sets describing the building stock. Most of the needed data to perform these computations exist. The challenge ahead is to link this data sets together. For our use case, four data sets have been linked: (1) the first data set is a description of regional building components sorted by construction period (Klauß, Kirchhof, & Gissel, 2009); (2) a data set of material properties, needed for the computation of U-values (Fraunhofer Institut für Bauphysik Holzkirchen Institut für Bauklimatik Technische Universität Dresden Zentrum für Umweltbewusstes Bauen e.V., 2007) (3) a Life Cycle Inventory (LCI) containing information about the embodied energy of construction materials (Bundesinstitut für Bau-, Stadt- und Raumforschung, 2013); and (4) the digital cadastre of the city of Hamburg, needed to retrieve geometrical information of the building stock (AdV, 2008). In a second step the paper defines an use case comparing different retrofit alternatives applied to the building stock and assess these alternatives based on the estimated energy payback time. The energy payback time is computed as the number of years that it will take for the energy savings (achieved trough the retrofits) to pay back the embodied energy in the materials used for the retrofits.

Databases

The analysis is based on the digital cadastre for the city of Hamburg (369,416 buildings) which is enriched using the MASEA[1] data set, describing physical properties of materials, and the Ökobaudat[2] data set, describing ecological properties of construction materials.
The U.S. equivalent material data sets are: (1) Building Component Library NREL (NREL, 2015) for the estimation of U-values; and (2) U.S. Life Cycle Inventory Database NREL (NREL, 2012) for the estimation of embodied energy.
In order to enrich the cadastre with the desired ma-

[1]http://www.masea-ensan.de/
[2]http://oekobaudat.de/

terial properties we first needed to combine the two material data sets. The matching of both databases is performed based only on the material name. In a second step the materials are attributed to layers of different construction elements (roof, wall, floors and slabs) which consequently are attributed to individual buildings of the digital cadastre. The different construction elements are based on regional characteristics and construction epoch (Klauß et al., 2009). Because the digital cadastre contains the construction year of the individual buildings, the developed algorithm is able to attribute the corresponding building components to the building stock.

This model focuses on the city of Hamburg but could easily be expanded to other German cities having a similar digital cadastre and to other countries with a similar data basis.

In order to link the different data sets we first decompose the individual building components into material layers. The data set containing the building components classifies each building component by: (a) construction epoch, (b) region within Germany and (c) construction element (roof, wall, slab, etc.); and describes each building component by: (a) the individual material layers name, thickness $[m]$, its density $[kg/m^3]$ and conductivity $[W/mK]$; and (b) the component U-value $[W/m^2K]$.

These properties are divided between numerical and descriptive properties. For each set of properties a matching probability is computed (see subsection *Linking the data* for a detail description of the matching algorithm)

From the MASEA database we use the following material attributes: (1) name, (2) family, (3) subfamily, (4) density and (5) conductivity to match the individual building component layers. We validate the match by comparing the original U-value from the building component to a new computed U-value using the material attributes of the MASEA database.

The Ökobaudat database does not contain physical attributes of the individual material but only ecological attributes. For the matching we use a single attribute: material name. For the estimation of embodied energy we use the Total Energy Input (TEI) attribute. The database contains rich information regarding other ecological attributes like: water use, use of natural resources or Ozone Depletion Potential (ODP).

Digital cadastre

The enriched building components database is now used to enrich the individual buildings from the digital cadastre. The digital cadastre contain the georeferenced building stock for the city of Hamburg and some attributes for each building on the database. We use the construction year attribute to assign individual building components to each buildings. The digital cadastre also provides information about the building geometry. With this information we compute the heat demand of the individual buildings, the digital cadastre provides information about the building geometry, the building components give us information about the heat transmission coefficients and the Ökobaudat allow us to estimate the embodied energy in construction materials. All other input parameters requires for the computation of heat demand are maintain constant for the rest of the building stock (e.g: glazing share, internal temperature, ventilation rates, etc.).

Because the building of the digital cadastre are georeferenced we are able to analyze the effect of retrofit policies not only to a specific building stock but to a specific urban area.

Linking the data

The linking of these data sets is performed with a ranking algorithm. The linking procedure matches pairs of data sets: (1) the digital cadastre with the regional building components; (2) the layers of the building components with materials from the MASEA data set; and (3) individual materials to the LCI data set.

For each of these links we use different attributes, for: (1) construction year, location (in this case only one location) and building type; (2) material name and material conductivity; and for (3) material name.

The linking is performed with a ranking algorithm. This algorithm computes a rank for each element of the corresponding data set based on the similarity of attributes. In this example we use only the top ranking match, in a further analysis we want to include also secondary connections between materials in order to account for uncertainties (see Section "Integrating Uncertainties" for a further discussion).

The develop matching algorithm computes for each material/layer of the first database $D1$ (divided in numerical properties $D1V$ and descriptive properties $D1T$) a matching "probability" P for each material i in the second database $D2$. This probability is expressed as a ranking. The material with the highest P value is defines as the matching material.

$$P_i = \kappa \times Q_i + R_i \tag{1}$$

Where κ is a weight factor Q_i is the matching probability for all numerical material properties j:

$$Q_i = \sum_j 1 - \frac{|D2V_{i,j} - D1V_j|}{\sum_i D2V_{i,j}} \tag{2}$$

And R_i is the matching probability for all material descriptions k:

$$R_i = \sum_k \frac{ch(D2T_{i,k}, D1T_k)}{\sum_i ch(D2T_{i,k}, D1T_k)} \tag{3}$$

Where ch if a function that counts consecutive matching characters between material name $D1T_k$ and all material names $D2Ti, k$. This function weights the matching characters by the number of consecutive matched characters.

The weight factor κ used in Equation 1 is necessary because the computed probabilities R_i have a higher level of inaccuracy, the weight factor balance this error giving more importance to numerical attributes. In order to achieve better results a more sophisticate algorithm for matching descriptive values is needed.

Table 1: Original U-values and matched U-values with MASEA data $[W/m^2K]$

	(Klauß et al., 2009)	MASEA	**Error**
Wall	1.08	1.0889	8.9e-3
Roof	0.60	0.6091	9.1e-3
Slab	0.52	0.5187	4.5e-3
Floor	0.98	0.9844	4.4e-3
Windows	3.50	—	—
Mean			**6.7e-3**

In order to validate the material match we compute the U-value of the components with the corresponding material properties of the MASEA data set and compare them to the original U-values from the regional material catalog (see Table 1). The estimation of the U-values is automatically computed with the *heat* R library (Muñoz H., 2015), a simplified version of the German DIN 4108–3 and DIN 6946 norms (Deutsches Institut für Normung e. V, 2012, 2008).
Table 1 shows that the error range for the selected components is very low. Nonetheless, a more systematic validation is needed in order to establish a robust model for the prediction of grey energy at an urban scale. The link between these two data sets works well because the algorithm is able to use two attributes to find an appropriate match: (1) conductivity and (2) material name.

USE CASE

In the following section we present an use case of the enriched digital cadastre. We analyze and quantify the effect of two retrofit options for an individual building type. We compare the retrofit options by comparing the net heat savings and the embodied energy of the applied insulation materials.
With the matched materials from: (a) the regional material catalog and (b) the MASEA data set, we compute the U-values for each building component. For the analysis we take four building components, attributed to building type: single family homes of construction period (1958–1968).
In order to demonstrate the function of this enriched database we simulate the heat demand for 100 random selected buildings from the digital cadaster corresponding to the defined building type. In a second step we estimate the heat demand for two hypothetical retrofits. These retrofit scenarios are taken from building typology “EFH_E” from Loga, Diefenbach, and Born (2011).
In order to estimate the energetic payback time of these retrofit scenarios we compare the net energy saving with the embodied energy of the insulation materials used in the retrofits (see Subsection “Embodied Energy”).

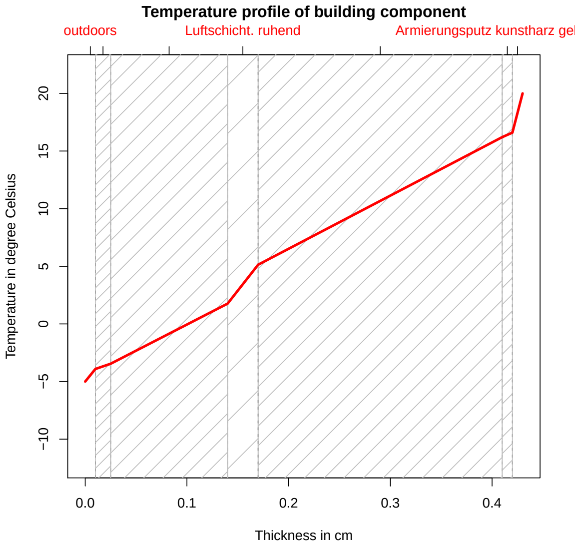

Figure 1: Example of temperature profile for generated wall constuction element

Figure 1 shows the temperature profile of the wall component used in the use case. This temperature profile is generated based only on the information provided by the building component material catalog.

Table 2: Status quo U-values and U-values after the retrofits (r1 & r2) $[W/m^2K]$ *(top) and applied insulation thickness* $[cm]$ *and type (bottom)*

	STATUS QUO	r1	r2
Wall	1.09	0.24	0.14
Roof	0.61	0.40	0.18
Slab	0.52	0.52	0.52
Floor	0.98	0.33	0.25
Windows	3.50	1.30	0.80

	SQ	r1	r2	type[a]
Wall	—	12	24	WDWS (EPS)
Roof	—	12	24	WDWS (EPS)
Slab	—	—	—	—
Floor	—	8	12	EPS PS 15
Windows	—	—	—	—

[a] see Table 3

Retrofit scenarios

Two retrofit alternatives are tested. Both retrofits add insulation to the building components (wall, roof, and slab) of the random selected building from the digital cadastre. The U-values for the windows are manually inputted because the developed framework does not yet take windows into account.

The first retrofit scenario (*r1*) adds: (1) $12cm$ of EPS insulation to all the walls and roof: and (2) $8cm$ of EPS insulation to the building floor. In addition to the insulation, the U-value of all windows is improved from 3.5 W/m^2K to 1.3 W/m^2K. The second retrofit scenario (*r2*) adds: (1) $24cm$ to walls and roof; and (2) $12cm$ to the building floor, windows are improved to a 0.8 W/m^2 U-value. Table 2 gives an overview of these retrofit scenarios and the corresponding values used in the computations.

RESULTS AND ANALYSIS

Operational energy

With these values and the geometry extracted from the digital cadastre (see Muñoz H. (2015 –Under Review–) for further details on the extraction of geometrical parameters from the digital cadastre) we estimate heat demand for the randomly selected buildings. For the computation of heat demand we use the thermal simulation model EnergyPlus (EnergyPlus Development Team, 2012).

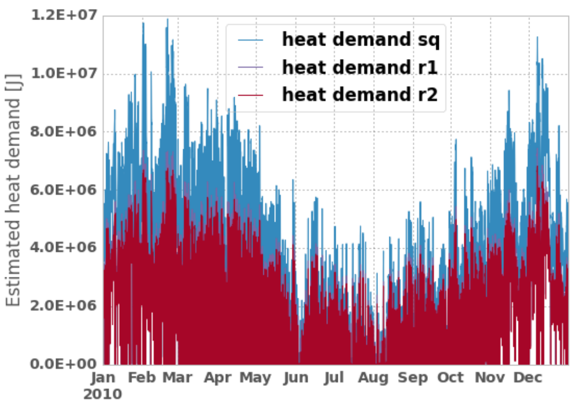

Figure 2: Estimated heat demand for the status quo (sq) and for both retrofit options (r1 & r2) for a single building of the sample

Figure 2 shows the computed heat demand for a single building for all simulation scenarios. The reduction in heat demand is evident. The estimated heat demand for both retrofit options varies depending on building size and geometry. The estimated values for all selected building are plotted on Figure 3. Although the added insulation for retrofit scenario *r2* has twice its thickness, the achieved heat reductions are comparable to retrofit scenario *r1*.

Embodied energy

In order to estimate the embodied energy of the retrofit scenarios we used the attached LCI materials and their attached embodied input energy values. For this analysis we only take the values corresponding to the insulation added to the buildings, the embodied energy of windows is neglected in the analysis.
The selected insulation for the retrofit alternatives is still not optimal. Because the link between the materials from the MASEA data set and the LCI data set is performed based only on the name of the material, the result is suboptimal. The algorithm selects a product exclusive for walls to be applied to the roof component as well. In order to improve this, the algorithm needs to analyze the embedded description of materials rather than just the material name. The architecture development of such an algorithm requires further research.

Table 3: Selected insulation materials and corresponding embodied energy $[MJ]$

ÖKOBAUDAT Code Name	TEI[a] $[MJ]$	Unit
WDVS (EPS)	384.77	m^2
EPS PS 15	1478.56	m^3

[a]Total Energy Input

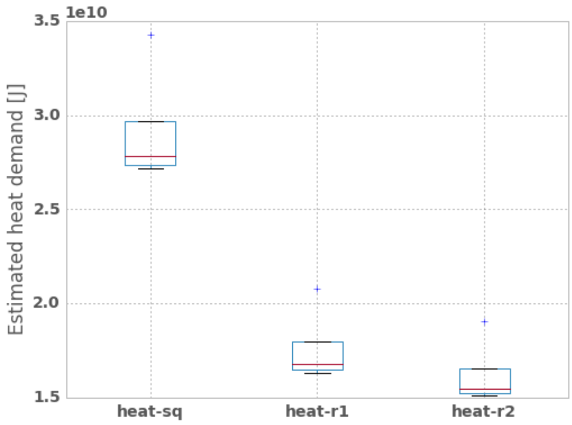

Figure 3: Estimated heat demand for status quo (sq) and both retrofit options (r1 & r2)

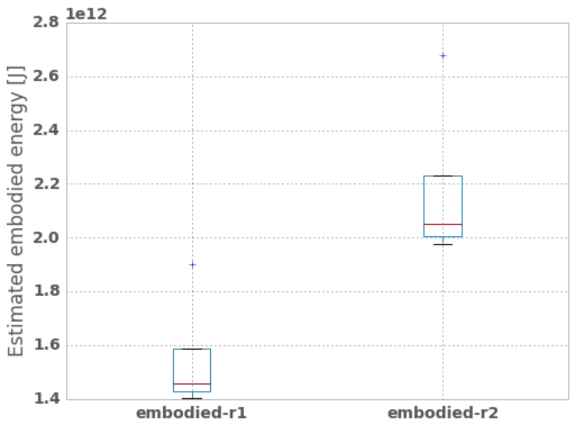

Figure 4: Embodied energy used for the retrofits (r1 and r2) of the buildings

The estimated embodied energy for both retrofit scenarios is depicted on Figure 4. A difference on the computed embodied energy between both scenarios is evident, as expected scenario *r2* accounts for more embodied energy.

Results from this computation show that the algorithm linking material data sets and the estimation of building geometries are working correctly. Because the selected 100 buildings correspond to the same construction period and construction type, there is a relative low variation in building size, making a comparison of absolute values possible.

Energy payback

In order to assess the performance of the retrofit scenarios we compare the estimated embodied energy with the net energy savings for both retrofit scenarios. With this two values (embodied energy EE and operational energy OE) we estimate the payback time Y in years. Equation 4 expresses this relation where s is the retrofit scenario and i the selected building.

$$Y_{i,s} = EE_{i,s} / (OE_i - OE_{i,s}) \tag{4}$$

The energy payback time for this type of insulation material is probably more than the live spam of the material itself. The scope of this paper is not the assessment of payback times but the performance of the algorithm combining the different data sets. The described analysis shows that the linked materials can be used for this type of analysis.

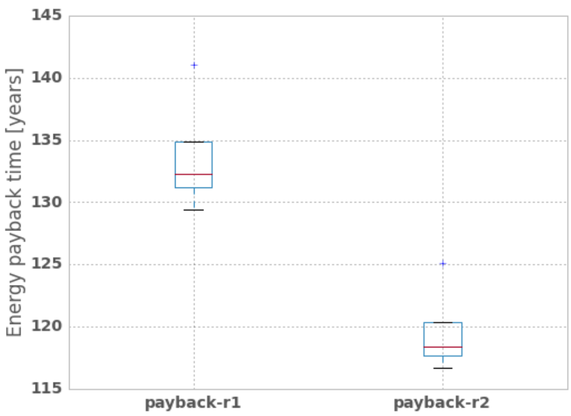

Figure 5: Estimated energy payback time of retrofit alternatives

In this paper the use of a single insulation material has been assessed. The selection of this insulation material was hard coded into the building component from the regional material catalog following the retrofit alternatives proposed by Loga et al. (2011). For future analysis the use of different insulation material is envisioned.

The possibilities to select insulation material can be, as done for this analysis, hard coded into the building components, simulated as function of environmental factors such as location, demographics of the building owner, material price, regional availability, etc., or as function of hypothetical policy scenarios like green labels of construction materials or the introduction of a "green tax" to insulation materials.

CONCLUSIONS AND PERSPECTIVES

This analysis shows that a connection of different data sets is possible. The simulation opportunities and the implications of the simulation results are promising. Nonetheless, the development of this method still needs improvement specially by linking data sets with a single common parameter. The need for better algorithms able to analyze complex description of records is needed. A simple ranking algorithm presents itself as an interesting first step towards an integrated urban energy simulation model taking explicit consideration to construction materials.

In this analysis we have only used the top ranking link to match the data sets, for future analysis we aim to use a set of top ranking matches to estimate uncertainty in the estimation of heat demand and embodied energy. Uncertainty in this type of estimations play an important roll, not only at the selection of materials but also uncertainties embedded on available LCI data sets (Dixit, Fernández-Solís, Lavy, & Culp, 2010).

The use case presented in this paper takes into account a single building type. The variation in heat demand fluctuates considerable depending on the building geometry and size. We expect to use this approach to simulate more realistic retrofit scenarios. The ability to simulate plausible retrofit scenarios of the building stock and the needed input energy for these scenarios is exiting. By allocating residents to the individual buildings in the digital cadastre (Muñoz H. & Peters, 2014) we will be able to compute an individual retrofit probability based on demographic characteristics, building construction year, building geographical location, etc. The enriching of the digital cadastre with LCI data allows us to account for embodied energy of these retrofit scenarios as well.

This analysis aims to make a contribution to the development of integrated urban energy demand models. A big advantage of using the digital cadastre for this type of analysis is the potential to map the results, this mapping makes it possible to prioritize retrofit efforts not only to specific building types but to specific locations of an urban agglomeration. Another interesting approach with the use of spatial referenced databases is the identification of vulnerable or problematic areas within urban agglomerations. The identification of hot spots in urban areas is one of many applications of enriched georeferenced databases.

The path to achieve robust integrated microsimulation models working at an urban scale is certainly not an easy task, nonetheless the potential of such models and the possible policy implications are worth our best effort to achieve this goal.

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