A BUILDING SPECIFIC, ECONOMIC BUILDING STOCK MODEL TO EVALUATE ENERGY EFFICIENCY AND RENEWABLE ENERGY

C. Nägeli[1]; M. Jakob[2]; B. Sunarjo[2]; G. Catenazzi[2];

1: Department of Civil and Environmental Engineering, Chalmers University of Technology, Sven Hultins gata 8, 412 96 Gothenburg, Sweden

2: TEP Energy GmbH, Rotbuchstrasse 68, 8037 Zürich, Switzerland

ABSTRACT

In developed countries, the residential and commercial building stock account for a considerable share of final energy demand and greenhouse gas emissions. Building stock modeling is an established tool to assess different development paths of buildings on city, region or country level. Current building stock models (BSM) as well as previous works of the authors, however, lack a holistic approach that take technological, economic and ecological factors into account on an individual building scale. There are, therefore, limitations in the conclusions that can be drawn. In order to increase their significance, current research shows trends towards spatial differentiation, representation of individual building and owners as well as economic decision modeling. However, no model combines all three aspects in a more holistic approach. This paper describes a novel approach which combines spatial differentiation with building specific heat demand modeling and an economic decision simulation.

The model developed combines a building specific engineering model with a micro-economic discrete choice approach. Using spatial building data, the engineering model calculates space heat and hot water energy demand on a building level. The alteration of the building refurbishment state is modeled using a discrete choice approach to simulate the decision process of building owners of building envelope refurbish and/or to substitute the heating system. Due to the building specific approach, the decision model is able to take into account building specific information such as size, geometry, room temperature, investment, maintenance and energy costs and achievable energy savings as well as other factors such as local potentials and restrictions on the use of renewable energy.

In a case study of the city of Zürich we demonstrate the feasibility and strengths of the new model approach. The results demonstrate that modeling space heating demand on an individual building scale yields specific heat demand distribution across building clusters (and not simply in average values as in other models). The building level approach enables the model to deliver differentiated results of the heat demand development for the whole building stock, building types building periods or spatially distributed as shown in the results.

Keywords: building stock model, energy efficiency, discrete choice model, energy planning, policy evaluation

INTRODUCTION

In developed countries, the residential and commercial building stock account for a considerable share of final energy demand and greenhouse gas emissions. As a consequence, policy makers in both the European Union and Switzerland are implementing stricter and stricter efficiency standards for new as well as existing buildings [1, 2] and have set ambitious reduction targets. However, especially for urban areas making use of the potentials for energy-efficiency and renewable energy poses numerous challenges. Moreover, clear pathways for the transformation of the built environment to reach energy and GHG reduction targets are lacking.

Building stock models (BSM) are used to develop and evaluate different such pathways and improve the understanding of the specific potentials and challenges in the development of the building stock. BSMs include a variety of different modelling techniques which are used to describe both the energy demand of the current as well as possible development scenarios for the future building stock. [3] gives an overview of the different modeling techniques available. More recent development in the field including previous work by the authors show trends towards spatial differentiation [4, 5], as well as including economic factors for optimal use of local potentials [6].

While the level of detail of BSM keeps increasing, the examples mentioned above, however, still rely on representative building archetypes based on average geometries. This reduces the complexity of these models as well as the computational time, however limits the accuracy of the model on a building level [7], which can affect the development of transformation strategies. Therefore, in order to increase the accuracy of BSM to give more meaningful information for the development of transformation pathways the individual building needs to be considered [8]. The representation of individual buildings not simply increases the accuracy of the energy demand model, but also enables a detailed modeling of refurbishment and heating system substitution processes. Instead of relying on average refurbishment rates, a building specific evaluation of the costs and benefits of different energy efficiency and renewable energy measures can be modelled.

This paper describes the further development of the building stock model previously developed by the authors [4, 9, 10] to combine spatial differentiation with a building specific heat demand model and an economic decision simulation to model the development of the building state.

MODEL CONCEPT

The bottom-up simulation methodology previously developed by the authors [4, 9, 10] to model building stock energy demand and carbon emissions was advanced from a building archetype level to building level. However, building stock level information is still used both to calibrate the initial building state as well as influence the alteration during the model period. Figure 1 depicts the interaction between building level and building stock data as well as the building development model concept.

The model adopts an inverse approach from the previous model developed by the authors [4]. Instead of using individual building data to form building cohorts by aggregating it by building type, construction period, etc., the model uses the individual building level data directly. However, building stock level data is used in order to substitute missing building level data and to determine the initial building state. Thus, building level data from building registers as well as from local utilities is combined with generic data that is known or assumed on the building stock level. The building geometries (wall, roof, floor and window areas) are calculated by matching the building register with a city 3D model. Based on the initial building state the model calculates the space heating and hot water demand based on the Swiss norm SIA 380/1 [11].

Instead of using average refurbishment or diffusion rates the model applies a discrete choice approach to model the refurbishment and heating system substitution decisions for each building. Both decisions are modeled in a two-step approach. In a first step the timing of the refurbishment/substitution is modeled based on the age of the building component using the hazard rate function (equation 1). The hazard rate h describes the probability that a technical system is going to fail in the year t given that it has not failed so far. The models applies the hazard rate of the Weibull function, which is commonly used to model the lifetime of

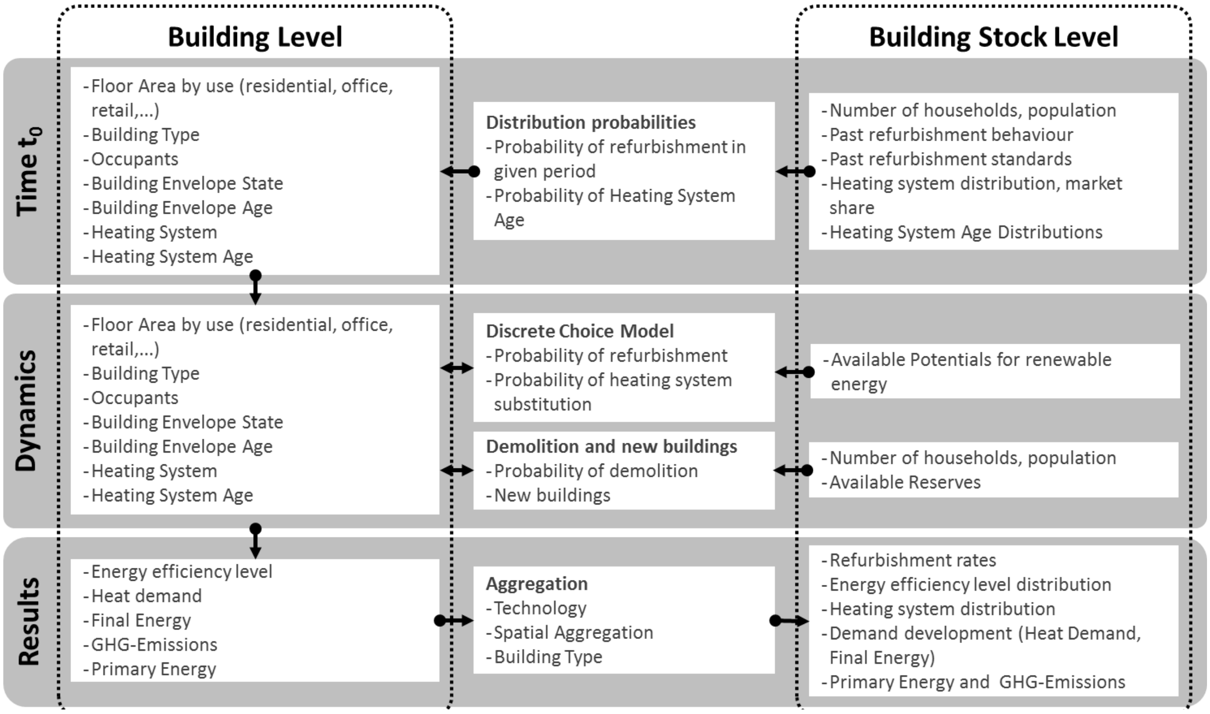

Figure 1: Model concept of interaction between building level and building stock data

technological systems. Based on the hazard rate the year in which a given building component or the heating system has to be refurbished/substituted is determined.

$$h(t,k,\lambda) = \frac{f(t,k,\lambda)}{1-F(t,k,\lambda)} = \frac{k}{\lambda}\left(\frac{t}{\lambda}\right)^{k-1} \tag{1}$$

In a second step the model evaluates different refurbishment or substitution options for each component based on a predefined choice set. In case of the refurbishment the choice is between simply overhauling the building component without efficiency improvement or different levels of predefined refurbishment standards. The resulting U-values are defined based on the current standards [11]. The choice set for the heating systems is defined based on general as well as locally available options (i.e. district heating is only available to buildings close to the district heating distribution network). The choice probability of the different options in the choice set are then calculated based on a discrete choice approach. The discrete choice model calculates the choice probability P_i of a certain option based on the utility U_i of the alternative as well as the utility of the other options in the choice set (equation 2).

$$P_i = \frac{e^{U_i}}{\sum_j^S e^{U_j}} \tag{2}$$

The utility of the different refurbishment options is modeled for each building component individually according to the utility function described in equation 3. It takes into account the annualized investment costs (AC_i), the resulting energy costs (EC_i), the energy savings (dE_i), a factor for comfort improvements (dC_i), the protection status of the building (P_i) as well as the willing ness to pay (WTP_i) of each option in the choice set. The costs of the different options are calculated using cost factors from [12]. The model takes into account results from choice experiments as in [13] and is then calibrated using results from [14].

$$U_{i,BR} = \beta_{AC}AC_i + \beta_{EC}EC_i + \beta_{dE}dE_i + \beta_{dC}dC_i + \beta_{pro}P_i + \beta_{WTP}WTP \tag{3}$$

The utility of the heating system substitution choice is defined similarly to the utility function of the refurbishment choice. However, as can be seen from equation 4, the utility function differs in certain values. The maintenance costs (MC_i) of the different heating systems are included in the function. Furthermore, a factor for the previous system (PS_i) is included to account for the advantages of replacing an existing system with a system of the same type and the reluctance of the building owner to change system. Both investment and maintenance costs of the different systems are calculated using data from [15].

$$U_{i,HS} = \beta_{AC}AC_i + \beta_{EC}EC_i + \beta_{MC}MC_i + \beta_{dE}dE_i + \beta_{ps}PS_i + \beta_{WTP}WTP \quad (4)$$

Similar to the modelling of the refurbishment and heating system also the demolition probability of each building is modelled individually based on the building age. However, instead of using a Weibull distribution the survival function of the loglogistic distribution shown in equation 5 is used to estimate the demolition year of a building. This was found to give a better fit when calibrating the function based on the building register data of the city of Zürich. Next to the building age also the building type, city district and construction period are included in the statistical fit of the survival function yielding differentiated demolition rates across building types and districts.

$$S(t) = \frac{1}{1+(\lambda t)^{\frac{1}{\gamma}}} \quad (5)$$

The modelling of new construction is linked to the demolition model as especially in urban areas buildings are mainly demolished to make way for new buildings. The size and geometry of the new building is defined based on the available reserves according to the zoning restrictions for the parcel it will be built on. Similarly, the model also includes extensions and additions to existing buildings, if the available reserves on the parcel allow it.

In a final step, the model calculates both the heat demand and the final energy demand of every building based on the current state of the building envelope and heating system installed for each year until 2050. Using emission and primary energy factors the model then estimates GHG emissions and primary energy use. These building level results can then be aggregated according to building type, building age or location depending on the research question.

RESULTS

The following section shows the results for the development of the existing building stock in the year 2010 (excluding new construction) of the district Altstetten of the city of Zürich previously studied in [5]. Compared to the previous model used in [5], figure 3 shows that the building level approach not simply results in average energy consumptions, but that the specific heat demand varies greatly in the building stock. The results indicate that the largest share of buildings shift from having a heat demand from 250 - 450 MJ/m^2 in 2010 to 200 - 350 MJ/m^2 for existing buildings.

Figure 4 shows the spatial distribution of the heat demand based on an aggregation on the individual building data in a hectare-raster. While the results show that the heat demand in general will decrease according to the calculated scenario, they also indicate that the energy demand in the centre of the district will remain high do to the high density of buildings. Such local clusters of high heat demand could therefore be cover by a localized district heating network.

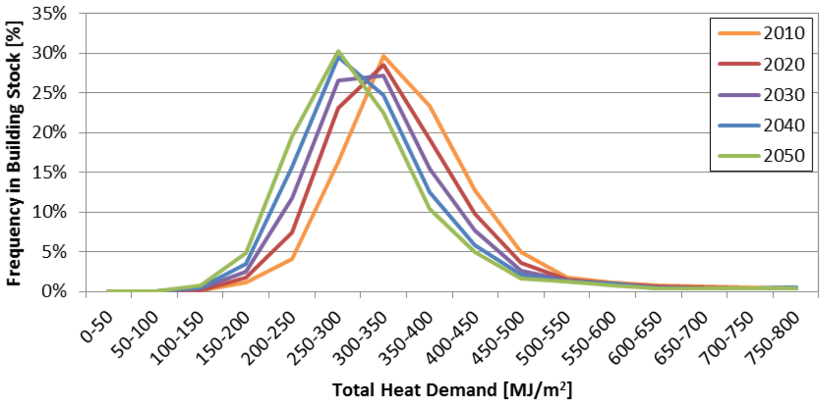

Figure 3: Exemplary results of the development of the distribution of the specific heat demand of the existing building stock from 2010 to 2050 (Reference scenario)

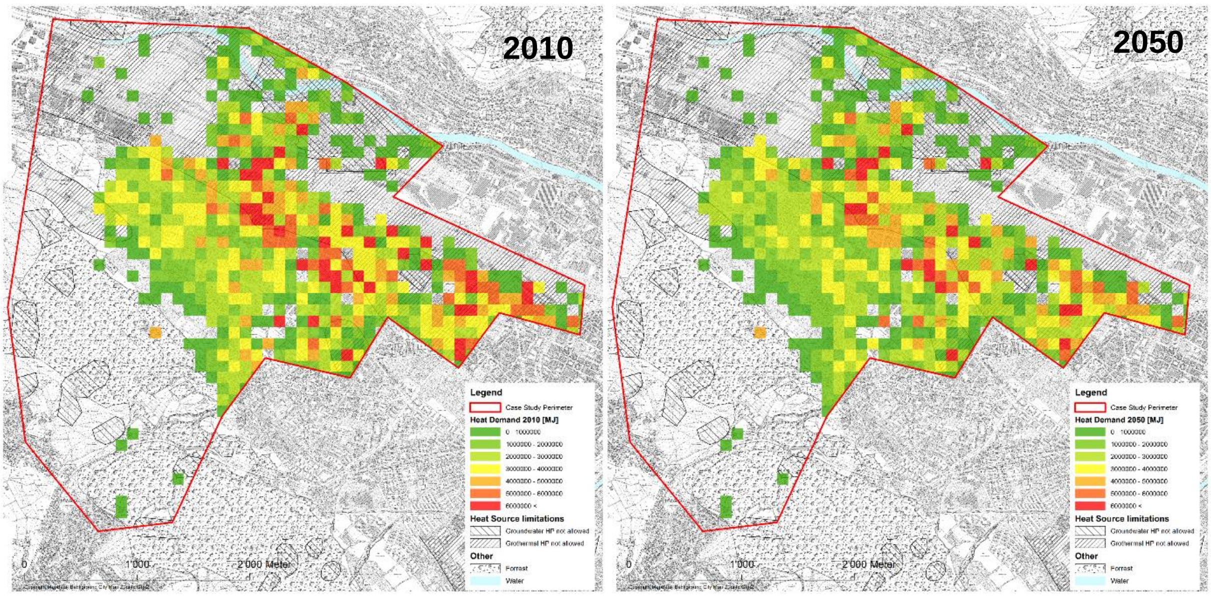

Figure 4: Exemplary results of the spatial distribution of the heat demand of the existing building stock in 2010 and 2050 (Reference scenario)

CONCLUSION

The developed approach of building specific BSM including a discrete choice model make it possible to include building specific information such as the actual building geometry or heating systems. Moreover, the developed discrete choice approach is able to take into account investment, maintenance and energy costs based on that building specific information resulting in individual decision criteria for each building. In addition to this, implemented decision model accounts for locally available energy infrastructure (e.g. district heat) and potentials for the use of renewable energies in the choice set. The developed BSM approach can be used both to evaluate policy measures (e.g. effect of subsidies, taxes and other policy measures) as well as for energy planning on a local scale, enabling a mutually consistent assessment of both. Moreover, if measured energy demand data is available, the building level approach, makes it possible for the model to be calibrated based on actual measurement data, increasing the accuracy even more [16]. Furthermore, the model is currently being extended to include electricity use and the embodied impact of buildings within the project GEPAMOD and therefore include the environmental impact of both construction and use phase of the building.

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