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THE INFLUENCE OF AN AGEING POPULATION AND AN EFFICIENT BUILDING STOCK ON HEAT CONSUMPTION PATTERNS

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ABSTRACT

This paper presents an innovative analysis of a likely scenario in developed countries: an ageing population and an increase in energy efficiency of the building stock. In this paper we present the case of the city of Hamburg, Germany. The aim of this paper is to analyse the changing heat consumption patterns on a city with: (1) an ageing population and (2) a rapid increase in its building energy efficiency. For the analysis in this paper we compared demographic changes of the population and improvements on the building stock to a base scenario in 2010.
The results from this analysis show: (1) the effect on energy reduction of different retrofit scenarios; and (2) Districts most affected by the explicit consideration of user behaviour in urban heat demand models.

INTRODUCTION

In this paper we analyse a plausible scenario for many developed countries, this is: a parallel increase in the energy efficiency of the building stock and an ageing of population. The consequences of this development for a secure heat supply of the residential sector is the focus of this paper.
The influence of users on domestic heat demand has been identified as an important factor to reduce the gap between estimated heat demand and consumed heat demand (D'Oca, Fabi, Corgnati, & Andersen, 2014; Durand-Daubin et al., 2013; Haldi & Robinson, 2011; Guerra Santin, Itard, & Visscher, 2009). In a scenario with a large share of energy efficient buildings and an old population the incorporation of residents influence on energy demand models could be essential for: (a) securing heat supply of the residential sector, and (b) achieving an optimal heat supply in this sector.
In order to assess these consequences we: (1) project demographic benchmarks at a district level fitted to national statistics; and (2) project the characteristics of the building stock at the same aggregation level. We use these benchmarks to reweight the German microcensus survey for each district in the city and each simulation year.
The method presented here makes use of microsimulation techniques developed for the reweighting of surveys to small areas, see (Tanton, 2014) for an overview of these techniques and their applications. Microsimulation is a simulation working at a micro scale (individuals, households, firms, buildings). This would include tax transfer, transport and land use models. In this paper we make use of two methods used by the spatial microsimulation community: (1) a survey reweighting for the creation of synthetic populations allocated to geographical areas, this method is the starting point of many spatial microsimulation models (a reweighing of a population survey is not the only method for the generation of synthetic populations); and (2) the reweighting of the same survey to projected statistics of the same geographical areas. This methods allows us to generate a synthetic population for each simulation year. The use of these methods to estimate energy demand are not very common among the microsimulation community, some examples of this application are (Muñoz H., 2014; Muñoz H. & Peters, 2014b)
Static spatial microsimulation models have also been used to project microdata, benchmarking the survey to projections at a small area level (Vidyattama & Tanton, 2013).
The paper is organized as follows: (1) we present the data used for this analysis; (2) we discuss the used methods; and (3) discuss the results and future improvements of the developed method.

DATA SOURCES

For our analysis we use four datasets, three of them containing demographic information at different aggregation levels and one dataset containing information about the building stock.

1. Historic demographic benchmarks for Hamburg districts[1]. This data set contains historical data, describing the following parameters: (1) total population, (2) gender distribution and (3) foreign national share.
2. Demographic projections for Hamburg until year

[1]Bevlkerungsentwicklung in Hamburg
www.statistik-nord.de/daten/bevoelkerung-und-gebiet/bevoelkerungsstand-und-entwicklung
Years 2011–2013 Update based on Zensus 2011 (Fortschreibung auf Basis des Zensus 2011) Years 2003–92011 Update based on Zensus 1987 (Fortschreibung nach den Ergebnissen der Volkszhlung 1987)
[2]Bevlkerungsvorausberechnung für Hamburg
www.statistik-nord.de/publikationen/publikationen/statistische-berichte/bevoelkerung-und-gebiet/

2030[2]. The available projections for the city of Hamburg are age/gender tables projected from base year 2008 until 2030.

3. The German microcensus[3]. The 2010 German microcensus is only available for scientific use. This dataset is a 1% sample of the German population in 2010 and contains 486,630 records with 529 parameters.
4. The digital cadastre of the city of Hamburg ALKIS[4] for the year 2010. The digital cadastre contains information regarding the building stock of the city. This datasets contains: (1) the geometry of the entire building stock of the city; and (2) some attributes of the individual buildings like: construction year, construction type (single family house, terrace house, etc.), number of stories, etc. We use a pre classified version of the cadastre performed by Muñoz H. and Peters (2014a), describing the buildings as types of a defined building typology.

DATA EXTRAPOLATION

In order to project the population growth at district level we: (1) extrapolate the growth rate based on historical data for the corresponding district; and (2) fit this extrapolation to the national population projections.

For the extrapolation of historical values we use a linear function. We created a sample with eight observations (2003–2010), being all the available records online at this aggregation level.

In a second step we fit these extrapolations to the available national projections.

$$G(y) = P_y \div P_{y-1}^{1/\Delta y} \tag{1}$$

$$E(y, s) = a_s y + b_s \tag{2}$$

Where $G(y)$ is the growth rate as a function of year y, P_y is the projected population in year y, $E(y, s)$ is the extrapolated growth rate as a function of year y and district s and a_s and b_s are the resulting coefficients from the extrapolation function as a function of the historical data for district s.

$$G_y = \sum_{s=1}^{n} E_{s,y} \tag{3}$$

$$D(y) \sim \mathcal{N}(G_y, sd) \tag{4}$$

$$sort(E_y) = sort(D_y); by\ s \tag{5}$$

Where $\mathcal{N}(G_s, sd)$ is a set of random numbers with a normal distribution with mean G_y and standard deviation sd (default set at $1e-3$).

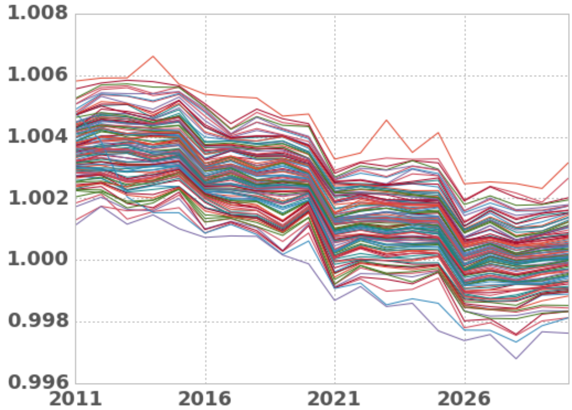

Figure 1: Extrapolated and fitted growth rates for all districts

Figure 1 shows the fitted extrapolated growth rates for all districts in the city of Hamburg. These growth rates are capped in order to meet the aggregated projections of the city.

The available projections for the city contain information about age, gender and foreign national share, but historical data from individual districts contain only information about gender and foreign national share. At this time we do not make any assumptions regarding different changes in age distribution for the individual district, but simply inflate these values to match the city official projections.

SYNTHETIC BUILDING STOCK

Because we use the microcensus to create a synthetic population for each district of the city, constrained by aggregated statistics, we decided to define a synthetic building stock based on the microcensus. We define a synthetic building for each individual in the microcensus. We use the following available parameters to generate the synthetic buildings: (1) household size, (2) construction year, (3) dwelling unit size and (4) number of dwelling units in the building.

With these variables we create a micro building stock that in its aggregation represents the “real” building stock of each district. The advantages of describing the building stock in this fashion are many. This simplification allows us to perform a relatively simple reweighting of the microcensus, making the method transferable to many cities around the world, for German cities we only have to change the aggregated district statistics, a simulation at a national level is also possible.

ESTIMATING HEAT DEMAND

For the estimation of heat demand we use a simple heat demand balance method (Muñoz H., 2015) developed

[3]Mikrozensus Scientific Use File (SUF) 2010
`www.forschungsdatenzentrum.de/bestand/mikrozensus/index.asp`
[4]ALKIS Amtliches Liegenschaftskatasterinformationssystem

in the R language. This library is a simplification of the German DIN V 18599 standard. The library does only compute heat gain and losses. The difference of this values is interpret as the heat demand. Factors like heat recovery systems of mechanical ventilations or the efficiency of the heat supply infrastructure are not consider within the library. We vary the following input parameters for the estimation of heat demand:

- Geometry of the buildings, expressed as: (a) length, (b) width and (c) height. See previous Section "Creating a Synthetic Building Stock"
- Heat transmission coefficients of building components, U-values of: (a) roof, (b) walls and (c) widows. See next subsection "Building typology"
- Ratio of glazing surface. See next subsection "Building typology"
- User influenced parameters: (a) Internal heat gains Q_i, (b) Internal temperature set point T_i and (c) Air exchange rate n. See subsection "Estimation with user influence" and Table 1.

Because the focus of this model is primarily on method we decided to use a heat balance model instead of a thermal simulation model like EnergyPlus or ESP-r because of: (a) the heat balance model requires less input parameters and less complicated input parameters; and (b) the computation time of the heat balance model is less that of the thermal simulation model. The use of a thermal simulation model is possible (see (Muñoz H., 2014)), the advantage of using a thermal simulation model is its ability to take occupational schedules as input.

Building typology

For the estimation of heat demand we make use of the well established building typology from the IWU institute (Loga, Diefenbach, & Born, 2011). We use this typology to define heat transmission coefficients and glazing ratio of the building stock. The same typology is used by Muñoz H. and Peters (2014b) to classify the building by building type. With the heat transmission coefficients and glazing ratio from the building typology we compute two absolute heat demand values for each synthetic building on the survey: (1) only taking into account characteristics of the building stock — building geometry and heat transmission coefficients — variables influenced by the user are maintained constant for all buildings; and (2) including demographic characteristics, by manipulating variables influenced by the user as function of the working hours of each individual in the sample.

Because of the nature of the model the synthetic population is generated for each simulation year, benchmarked to aggregated statistics of both: the population (demographic parameters); and characteristics of the building stock (capture by the distribution of building types). A retrofit rate of the building stock modifies the distribution of building types at an aggregated level, a 2% retrofit rate will pick 2% of the buildings of each geographical area and attribute them to the new energy efficient building types. See section "Benchmarking population" for a more detailed description of this computation step.

Estimation with user influence

Table 1: User influenced variables used in the model as function of working hours (WH)

WH	$n[h^{-1}]$	$T_i[C^\circ]$	$Q_i[W/m^2]$
≤ 1	0.7	22	7
≤ 4	0.6	21	6
≤ 8	0.5	20	5
≤ 9	0.4	19	4
> 9	0.3	18	3

The variables used to simulate the user influence on heat demand are listed in Table 1. These variables are modified as a function of the occupant working hours. The variation in these parameters has not been empirically validated. The aim of this modification is to represent a hypothetical change in heat consumption based on demographic characteristics. We use the variable *Working Hours* as a proxy to induce this influence based on empirical analysis of other authors. A brief literature review by Muñoz H. and Peters (2015) concludes that occupancy rates of users seem to be the determinant of user influence in heat demand in the residential sector.

One of the attributes of the population survey is "working hours". We use this attribute in order to define: (a) ventilation rates; (b) internal temperatures; and (c) internal heat gains. These three parameters are given as input to the heat demand model. There exist approaches to simulate occupancy rates in a stochastic fashion (Page, Robinson, Morel, & Scartezzini, 2008; Hoes, Hensen, Loomans, de Vries, & Bourgeois, 2009). We aim to contribute to these efforts by simulating the influence of a specific group of users on heat demand at a district level.

Figure 2 shows the relative difference between both estimations of heat demand: (1) taking user influence into account; and (2) maintaining variables influenced by the user constant. As expected, the influence of users is higher on more efficient buildings. Building type 18 (large multi family houses of construction period 1958–1968) shows a lower variation and lower mean than the rest of the building typologies, this effect is caused by the low number of individuals from the microcensus attributed to this type.

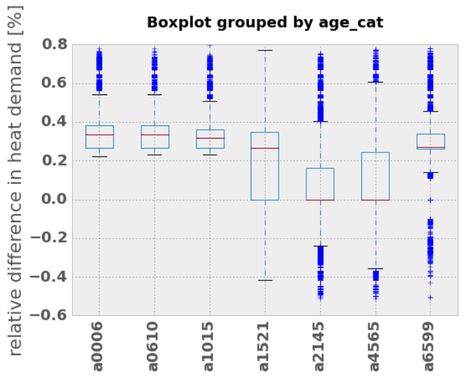

Figure 2: Difference between estimated heat demand with and without demographic parameters, grouped by building type.

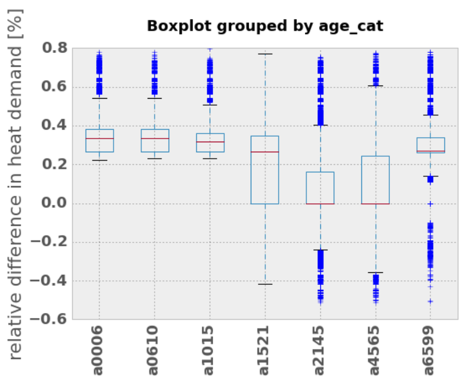

Figure 3: Difference between estimated heat demand with and without demographic parameters, grouped by age class of user.

An analogue comparison of relative heat difference is presented in Figure 3, in this plot the difference is grouped by age class. This plot shows a higher variation in heat demand for ages older than 15. We can see that the mean of both age classes, 21–45 and 46–65 are exactly on the zero line (no difference), these are the values used in the models that do not take user influence into account.

BENCHMARKING POPULATION

In order to assess the impact of: (1) an ageing population; and (2) a rising of efficiency rates of the building stock, we reweight the survey to demographic and building stock benchmarks projected until 2030 in a five year step at a district level.

For the reweighting of the survey, containing heat demand values for each individual in the sample, we use an implementation of the GREGWT algorithm in the R language (Muñoz H., Tanton, & Vidyattama, 2015). This method is used in the spatial microsimulation community to generate synthetic populations of small areas, Tanton, Vidyattama, Nepal, and McNamara (2011) deliver a detail description of the algorithm and its application. The GREGWT algorithm is based on "method 5" from Singh and Mohl (1996). For a technical description of the algorithm see (Bell, 2000) and for applications of it see (Tanton & Vidyattama, 2010; Tanton, Harding, & McNamara, 2013).

SIMULATION SCENARIOS

For the development of simulation scenarios we define six different scenarios divided into two groups: (1) base scenarios, and (2) [EM]retrofit scenariosDifferent retrofit rates.

1. Base scenarios

   Scenario 1 Base scenario.
   The building stock benchmarks are constant through the simulation. The distribution of building types is constant.

   Scenario 2 New buildings scenario.
   New buildings added to the building stock (driven by population growth) are attributed to the newest building type.

2. [EM]Different retrofit rates

   - Average user.
     User parameters (n, T_i and Q_i) are constant for all buildings and all simulation years.

     Scenario 3 0.5% retrofit rate
     Scenario 4 1.0% retrofit rate
     Scenario 5 1.5% retrofit rate
     Scenario 6 2.0% retrofit rate

   - User influence.
     User parameters (n, T_i and Q_i) are define based on the working hours of the building residents.

     Scenario 3-User 0.5% retrofit rate
     Scenario 4-User 1.0% retrofit rate
     Scenario 5-User 1.5% retrofit rate
     Scenario 6-User 2.0% retrofit rate

Base scenarios

For this analysis we define six different scenarios. The first "base" scenario only considers changes in the population, maintaining the state of the building stock constant. This "base" scenario is not very realistic as all new families introduced into the district will be attributed a building with the characteristics of the district. A more realistic "base" scenario is therefore introduced, we call this scenario "new buildings". In this scenario each new family introduced to the district is attributed a new building with energy efficiency standards corresponding to the last four types of the building typology.

Different retrofit rates

The following scenarios define different retrofit rates for the entire city. In these scenarios we take a weighted sample of the entire building stock and "retrofit" these buildings to new construction standards defined by taking one of the last four building types of the building typology.

In order to pick the buildings to be retrofitted we take a sample with a given probability based on the building

construction year, which is embedded in the building typology.
This probability is expressed with help of an exponential function in Equation 6 where $p(b)$ is the sampling probability as a function of building type. This function is used to assign probabilities to the survey, V contains these probabilities (Equation7). We select m number of buildings from the sample with the estimated probability (Equation 8). Set S contains the m buildings that will get retrofit in the specific simulation step.

$$p(b) = e^{1/b} \tag{6}$$

$$V = p(B_i); for\ i = 1\ to\ l \tag{7}$$

$$S_k = v_i \quad ; \in V - S \\ ; while\ k < m \\ ; if\ \mathrm{v}_i \geq rand\left(e^{1/\max(b)}, e^{1/\min(b)}\right) \tag{8}$$

$$m(r, y) = B \times (1 + r)^{y-2010} - B \tag{9}$$

We define four annual retrofit rates, which define our scenarios: (1) 0.5%, (2) 1.0%, (3) 1.5%, and (4) 2.0%. For each one of these scenarios we run two simulations: (1) taking the occupant influence into account ("user") and (2) using the same "average" occupant for all buildings. The number of buildings selected for retrofitting at a specific at a specific simulation year is defined by Equation 9.

RESULTS

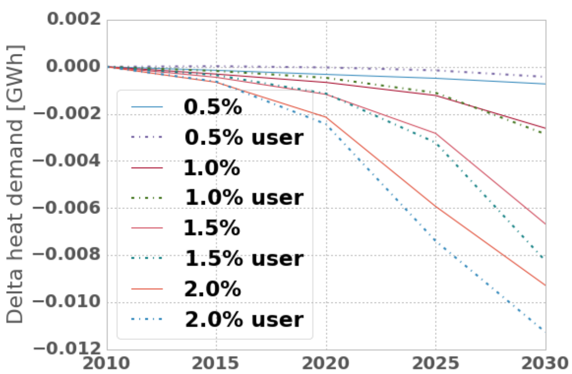

Figure 4: Estimated development for all four retrofit scenarios in heat demand for the city of Hamburg expressed as difference from base scenario, simulations including user influence are depicted with dashed lines

The simulation results show: (1) the impact of the different retrofit scenarios on total heat demand for the city of Hamburg, see normal lines on Figure 4; and (2) the difference between the model that takes user influence into account and the one that maintains this variation constant, see dotted line in Figure 4. A map showing this difference for simulation year 2030 is depicted on Figure 5 for all districts in Hamburg. The map shows the simulated difference between the "user" scenario (taking occupant influence into account) and the "average user" scenario. The difference is expressed as heat density for simulation year 2030 with a 2% retrofit rate. We see a concentration in the city center where most of the old buildings are located.

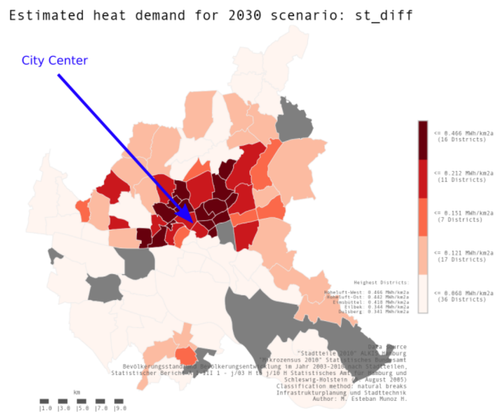

Figure 5: Difference in heat density $[MWh/km^2a]$ between model including and not including user influence in the computation for all districts.

An interesting observation in the results is that the difference in heat demand (absolute difference from base scenario)[EM], contrary to what we expected, is bigger (more net savings) when we include user behaviour in the model. This observation does not occur on all scenarios. On scenario "0.5% retrofits" we observe the expected behaviour, this is a higher heat demand under explicit consideration of user behaviour. On Scenario "1.0% retrofits" we see a breakpoint on simulation year 2025. For all the other scenarios this breakpoint occur in 2020 and 2015 for scenario "1.5% and 2.0% retrofits" respectively.

We observe this effect because the absolute influence of user behaviour is higher (more kWh) on older buildings while the relative user influence (higher %) is higher on energy efficient buildings. Figure 4 shows the net energy savings for the different scenarios. For scenarios including user behaviour (dotted lines), the line represents the simulated heat demand of corresponding scenario minus the simulated heat demand of the "base" scenario (no retrofits) also taking user influence into account. For the base scenario, the absolute user influence on heat demand is higher than the influence on simulation scenarios with more energy efficient buildings. This result on higher net savings for scenarios with user behaviour. It must be noted that the relative influence of user behaviour increases as does the energy efficiency of the building. This is important for the dimensioning of heat supply systems. This effect is also represented in the map plotted in Figure 5, we see a concentration of the highest difference in the city center where most of the old buildings are located.

CONCLUSIONS

This paper shows the application of a microsimulation model used for the estimation of heat consumption with an explicit consideration of user influence. We project this estimation into the future considering: (a) the aging population of the city of Hamburg, Germany and (b) ambitious scenarios to retrofit a substantial share of the buildings stock. The estimate indicates that the biggest changes could be concentrated in the city center where most of the old buildings are located. Nevertheless, this estimation can still be improved by integrating further characteristics of both the population and the building stock into the model. For future analysis we want to take other demographic parameters to sample the building stock and include new building typologies in order to simulate retrofit cycles. Further applications of this method may integrate more elaborated user behaviour models developed by the building simulation community. The developed model architecture also can accommodate the use of weather files projected under different climate change scenarios. A dataset describing the building stock and the individuals living on it can be used for many analysis. The impact of fluctuating temperatures has a health consequence, specially on the elderly population (Shi, Kloog, Zanobetti, Liu, & Schwartz, 2015). Models projecting this type of effects on the population need to take the build environment and possible developments of the build environment into account. The presented method shows a model to project the building stock and the population living on it. The developed scenarios can growth in complexity as the model matures. We aim to include more parameters (and the corresponding algorithms) driving: (a) the selection of buildings to be retrofitted and (b) the interaction between buildings and residents.

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