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Spatial aggregation and visualisation of urban heat demand using graph theory. An example from Hamburg, Germany

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ABSTRACT

Because of the physical properties of heat energy, information about the spatial pattern of building heat demand is important for designing climate protection measures in the heating sector (efficiency improvements and renewable energy integration). Many cities in Germany currently prepare ‘heat demand cadastres’ – thematic maps, depicting building heat demand. The growing trend towards open data points into the direction of making these cadastres public, so that different actors can make use of them. However, making such data public may violate the legal requirement of protecting private data. We present a way of tackling this problem with an approach for the aggregation of spatially represented heat demand. Using an algorithm based on graph theory, we group buildings such that the tracing of energetic characteristics and behaviour to individuals is rendered unfeasible. Our method also allows additional constraints to be introduced, for example, aggregating with respect to plot boundaries. We discuss how the building groups can be visualised in a map by presenting a method of generating customised geometries for each group. Finally, we present a visualisation of both specific heat demand (in kWh/(m²*a)) and total heat demand (in kWh/a) in one and the same map. This aids the analysis of more complex questions involving energy efficiency and heat supply.

Keywords:

Urban heat demand;
Data protection;
Aggregation;
Graph theory;
Visualisation;

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1. Introduction

The building sector is a large contributor to CO₂ emissions (in the higher latitudes mainly through space heating). Reducing these emissions through energetic refurbishing of buildings and integration of renewable energy sources has become a major focus of climate protection policy. So-called “Urban Building Energy Models” (UBEMs) [1] are being developed to support these measures. With the use of GIS, these models become spatial models, allowing the visualisation of the spatial pattern of heat demand in thematic maps, or “heat demand cadastres”. Space is of the essence in heat planning as heat transport (distribution grids) is traditionally associated with losses and costs. Renewable energy sources, on the other hand, are in many cases

local and their utilisation also requires understanding the spatial patterns of demand and supply.

At the same time the need for more cooperation and coordination between public and private actors in urban planning as defined for example in the Copenhagen Charter [2] has caused spatial data to be made increasingly public. There are currently many examples of municipal and regional authorities that operate geoportals allowing open access to numerous spatial datasets - natural environment, built environment, technical and transport infrastructure and many more. This trend has also reached the energy sector with the introduction of publicly accessible energy-relevant datasets on both the supply and the demand side – e.g., solar or geothermal energy potentials but also building energy demand maps.

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Acknowledgement of value

Solving the data protection issue when developing the Hamburg Heat Demand Cadastre proved to be much less trivial and more practically difficult than we expected. The presented aggregation method is what we currently use, without it, we would not have been able to publish the cadastre in its current form.

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However, energy consumption and demand reflect personal behaviour as well as the condition of property such as buildings (which to a large extent are privately owned). Therefore, a potential conflict arises between the need for open data and the need for personal data protection. Different countries and authorities go about this issue in different ways. We concentrate on the case of Germany, where data protection requirements in this context are relatively strict.

The context in which this paper originated was our work on the GEWISS Project Hamburg [3] and our cooperation with the Hamburg Ministry of Environment and Energy (*Behörde für Umwelt und Energie - BUE*) in developing the Hamburg “Heat Demand Cadastre” (*Wärmekataster*), which was published in 2017. The cadastre is a thematic map depicting demand for space heating and hot water. It is based on consumption-corrected heat demand values from the IWU Typology [4] and the German VDI standard [5]. See [6] for methodological details

Since many buildings are privately owned, however, the cadastre had to adhere to data protection requirements. Even though the heat demand at the building level was only *estimated* based on the type and age of the building (no measured consumption), it could not be released as it was, but had to undergo aggregation. The aggregation requirement defined by the BUE states that aggregated building groups had to include a minimum of five units. A unit in a residential building is the dwelling unit, while each non-residential itself comprises a single unit.

This definition raises some questions, in particular who is to be protected: Individuals in their function of building users or real estate property owners? While this is still to be explored, we developed a method for performing the required aggregation, which provides the flexibility to be adjusted for alternative formulations of the aggregation criterion that might be developed in the future (e.g., a change in the minimum required count for each group).

We also added some further requirements to increase the usability of the cadastre. The purpose of heat demand

mapping is to support planning. For strategic energy planning at the city level, the size of the aggregation units may be less important. However, for the concrete planning of individual projects, a finely grained heat demand map is very useful, even necessary, as the location of energy sources in relation to energy sinks is a major criterion for project viability. Additionally, data at a coarser spatial level run into averaging-out effects that mask spatial variability. To avoid this, we set a requirement to aggregate only until the minimum data protection requirement was achieved.

In addition, heat demand maps greatly facilitate the analysis of potential for district heating, which is considered a key technology for a sustainable heat supply in urban contexts with a high share of a relatively inefficient building stock. Since district heating infrastructure tends to follow the street network of a city, the method presented here respects the street layout of a city. It goes without saying that the aggregation should partition the urban space, i.e. form groups that do not spatially overlap, as this would counteract the consideration of the intrinsically local nature of heat energy.

Finally, aggregation in thematic maps can be split into two distinct tasks – defining the aggregated groups and defining the geometry to represent them, the latter being a non-trivial issue. The requirements for the algorithm were then: (i) grouping buildings to satisfy a minimum unit count, (ii) optimising unit count to make it as close to the required minimum as possible, (iii) producing spatially non-overlapping groups that respect the street layout, and (iv) generating a geometry for each individual group.

2. State of the art

The easiest way of approaching the aggregation task is to use existing spatial units like census tracts, postal code areas or similar. However, all of these units are predefined which lowers the flexibility of the aggregation and does not satisfy (ii). The “urban block” unit (the areas in-between the street network) comes close to satisfying all requirements for aggregation. Urban blocks

per definition follow the street layout (iii) and have a known geometry already made available by the public authorities of Hamburg (iv). A further argument for their use is that some official data, mainly about demography, is available at this level. Having energetic data at an aggregation level which corresponds to an official unit of governmental statistics allows for multi-sectoral analysis (for example analysing connections between heat demand and socio-demographic data). Although the urban block only partially satisfies requirements (i) and (ii), we use it as a starting point of our aggregation.

An alternative to existing spatial units is the use of a raster grid. The first problem with this approach is that the resulting groups depend on the raster grid position. Shifting the grid around in the Cartesian plane would change the content of each cell. In other words, the allocation of a building to a cell is arbitrary and depends upon the initial position of the raster. A further problem is that it does not satisfy the requirements for having as few units as possible (ii) and following the street layout condition (iii).

Note that we do not consider our task to be a “clustering” task in the normal sense. Cluster algorithms, although a broad group of algorithms, are generally designed to optimize for within-group homogeneity and between-group heterogeneity and have an exploratory character. Our task was not exploratory. We had to first group in such a way that each group has a minimum size, while having homogeneous groups (“clustering”) was a secondary objective. The difference is subtle. An example is the standard “k-means” method. It requires a desired number of clusters as input, while we needed a desired minimum count within the clusters.

3. Literature review

In the area of energy planning, the focus is increasingly on the spatial dimension of consumption and generation and numerous tools are being developed for simulation and optimization at local levels [7–11]. Simultaneously, as decentralized generation leads to the emergence of “prosumers”, ICT allows for new forms of public participation [12–14].

In cartography, the problem of building aggregation is part of the broader map generalisation problems. Weibel and Jones [15] summarise that there are two forms of generalisation – one is cartographic, where the goal is high quality map symbology at different scales and database generalisation, with the goal of deriving reduced databases for storage or computational efficiency, and

two, as a pre-step to cartographic generalisation. Data protection could fall into the second category, but we could not locate examples for this in the context of urban energy mapping.

There is however a body of literature on spatial grouping and generalisation of objects. Yan et al [16] propose using Delaunay Triangulation to describe adjacency relations, filter the connecting triangles and then calculate building parameters (size, orientation, shape) to arrive at building groups. Wang and Eick [17] use a contour-line based density algorithm to derive polygons from point objects and then a Poly-SNN algorithm to cluster the polygons into new polygons. Beilschmidt et al [18] use a quadtree for the description and fast query of adjacent points. In a similar context to Beilschmidt but using Delaunay triangulation is the work by Jänicke et al. [19].

Most of these works were designed in the different, broader, context of point aggregation. The closest to our work is the work by Yan et al, but the specifics of our context – finding a balance between map usability for energy planning and data protection – led to differences in the method.

4. Methodology

4.1. Number of units per building

Adhering to the “five plus” rule is not a straightforward task, since the digital cadastre of Hamburg (ALKIS) does not contain number of dwelling units per building. Therefore, we need to estimate this value. We intentionally underestimate the unit counts, to err on the side of caution, avoiding the cases where our estimation is too high and a building group is presented as having more than five units, when in reality it has less. We use the number of stories of the building as a proxy for the number of dwellings - assuming that there is at least one dwelling per floor. These assumptions are summarised in Table 1. It is obvious that this leads to an underestimation for most of the buildings, but it is a precaution that serves to make our algorithm safer.

Table 1: Rules for estimating the number of units per building

| Building use | Floors | Estimated units |
|--|--------|--------------------------------|
| Residential and mixed-use with residential | 1 to 3 | 1 |
| | 3 to 5 | 3 |
| | >5 | number of floors |
| Non-residential | any | 1 |
| Any building use without heat demand | any | not considered for aggregation |

4.2. Defining the building groups

Since the urban block satisfies many of the defined requirements, we start at this spatial unit. Although most urban blocks contain more than five units, there are a few exceptions. We deal with these by manually merging these few urban blocks with neighbouring ones. Urban blocks with less than five units and very small heat demand are filtered out. We could tackle this in an automated way, but since these exceptions are few and far between, we leave this as a manual step prior to running the algorithm.

The idea is to partition the urban block into building groups with a unit count as close as possible to the minimum required. Firstly, all buildings receive an ID corresponding to the ID of the urban block (for example “710005”). Then we group within the urban block by appending an additional integer to the urban block ID – “710005_1”, “710005_2” etc. The problem then lies in generating the additional IDs in a meaningful way that respects the requirements. There are two obvious possibilities – to group spatially or based on building function. For energy planning, a grouping based on function makes sense, since buildings with different functions have different typical demands and load curves etc. and summary statistics for a group of homogenous buildings are more meaningful. However, this will impede the use of the map, since it is visually difficult to represent spatially intertwining groups of buildings (this is why we have requirement of spatial non-overlap (iii)). For this reason, we group spatially. However, we respect plot boundaries, which tend to encompass buildings of similar use in many cases (see below).

In order to produce spatially clustered groups, we need to describe the spatial relationships between

buildings. We present the method by means of an example urban block (Figure 1). In a first step, we compute all the distances between all pairs of buildings in the urban block. Let this be represented by a complete graph G , where each node is a building and each edge is the straight line between all pairs of two buildings. From graph G , using the Scipy Python library implementation [20] of Kruskal’s algorithm [21], we compute a minimum spanning tree (MST). A MST is such a subtree of G , that spans all the nodes of G and has a total edge length that is minimal compared to all other subtrees of G that span all the nodes of G . The MST is represented with red lines (edges) in Figure 1 (left). Describing the buildings with their MST is advantageous because now we can group by removing edges from the MST (Figure 1 centre). We remove the edges based on their length, starting from the longest. If removing an edge leads to a connected component (group) that is below the minimum dwelling count, we restore the edge and proceed to the next edge. After we have iterated over all the edges we give a unique identification number (ID) to each connected component. Since there are five groups in the example (the small building in the West is an exception, see below) the IDs are from zero to four (due to Python’s zero indexing, see Figure 2).

We then append the ID to the urban block identifier of each building within the same component. Which group receives which ID is irrelevant as long as the IDs are unique and the groups are defined.

In this way, we define the building groups. Although this is the basic logic of the grouping, we introduce two additional rules. Firstly, for the purpose of neighbourhood energy planning, well-defined building complexes

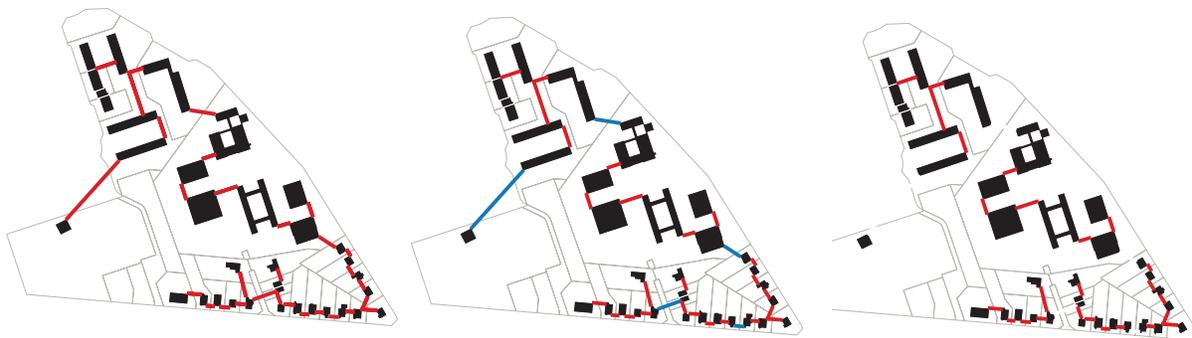


Figure 1: Splitting the minimum spanning tree of the urban block into spatially well-distinguishable groups. Red lines depict the edges of the MST, blue lines the edges that were removed during the aggregation process



Figure 2: Building groups represented with building geometries

of similar use (e.g. large prefabricated apartment blocks, hospital complexes or school campuses) are of great importance, since they are large consumers and can play a role as “anchors” for district heating. Therefore, it would be advantageous to attempt to group the individual buildings in these complexes into the same building groups. Attempting to cluster only spatially will not take this into account in many cases. We use the plot boundaries as a proxy for finding such complexes. For this, we apply an initial re-weighting to the complete graph G . We multiply the distance between two buildings in the same plot with a factor of 0.05. In this way, the MST algorithm considers such edges as being shorter than they truly are and are more often part of the MST. When we then sort the edges based on length, these edges are further down in the list and are less often split. Since building functions generally follow plot boundaries (school or hospital buildings, but also industrial buildings of similar use are usually within the same plot), the algorithm will tend to put them in the same group, although the purely spatial logic might dictate something else.

The second adjustment to the splitting logic is the introduction of a maximum distance between the buildings in a group. There are situations in urban space, where a single building is in a highly isolated location even within an urban block - a small hut within a park complex, or a small workshop in agricultural land on the outskirts of a city. Since such buildings often are irrelevant to the purpose of the mapping (heat demand), the algorithm may split them from a group and note them as

“anonymised”. The behaviour of the algorithm is dependent upon a parameter, which controls how small and how far away does a building have to be to be excluded. Consult the Github repository for more details [22].

4.3. Creating Geometry Representation

After all buildings in the urban block receive a group ID (or are anonymised) the question remains how to present their heat demand. For specific heat demand (i.e. per m^2) at the group level we use the area-weighted average of the specific heat demand [$kWh/(m^2 \cdot a)$]. One way of spatially representing this value is to use the existing building geometries and symbolise each with the colour that reflects the specific heat demand of the building group (Figure 2). The problem is that from the viewpoint of the map user it is difficult to understand that the colours refer to values for the groups and not for the individual buildings. This can be written in the legend, however it is not directly visible. Moreover, when groups have similar values one cannot distinguish which buildings are in which group (for example between 710005_4 and 710005_2). Labelling each group (Figure 3. left) does not help to overcome this. Labelling each building (Figure 3. right) does, but it overloads the map with annotations. An alternative to the building geometry is to use the plot geometry, but plots come in various shapes and sizes and using them as basis fails in areas where there is a single building in a large plot. Therefore, we generate a custom-made group geometry.

We use an approximation of a concave hull using a combination of two polygon buffers. This approach is

referred to as “Aggregate Polygons” available as SQL code at Github [23]. Although we do not use the code itself, we adopt its approach. In essence the method buffers each building geometry outwards at a given distance and dissolves the overlapping polygons to produce a single buffer (Figure 3). Then a second buffer is generated, but with negative distance, which means it buffers inwards from the previous buffer. In the process the areas in-between buildings become parts of the buffer area. The orthogonality of the geometry representation stems from the buffer options. We use a “metre limit” of 2.5 meters, as in [23]. The options for the buffer generation are part of the buffer class of the GEOS library [24].

4.3. Visualisation

There are generally two numeric heat demand characteristics that are used in our context – specific heat demand in kWh/(m²·a) (which can be interpreted as a measure of

energy efficiency) and total heat demand in kWh/a (or MWh/a). While heat loads, heating system types, heating system temperatures or building refurbishment state can also be of interest, we concentrate on the specific and total heat demands, as the most widely depicted in heat demand maps.

If we use the typical coloured filling for symbolising the groups (Figure 4 left), we run into the same issue as the plot representation – if buildings are far away from each other, the polygon will be big and noticeable, but its size is actually irrelevant. The purpose of the polygon representation of the building group is to represent the buildings’ characteristics and designate which buildings are in which group. The size of the polygon however is not in any way a function of any heat demand related characteristics. Buildings with very large footprint areas will have a large polygon representation, but so will small buildings with large distances in-between. In order

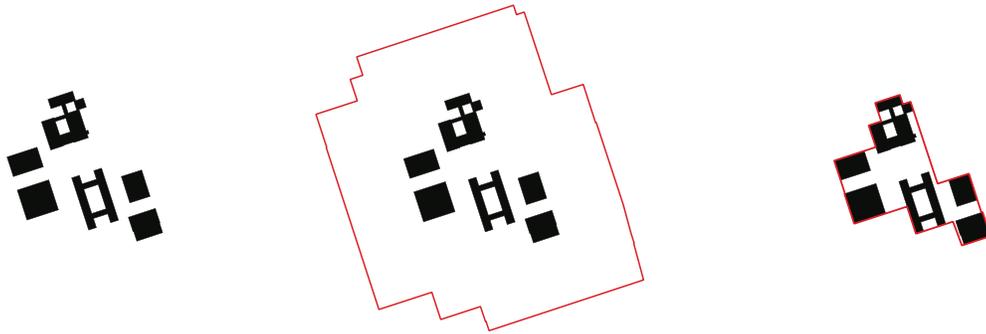


Figure 3: Geometry representation with two buffers. See [23]

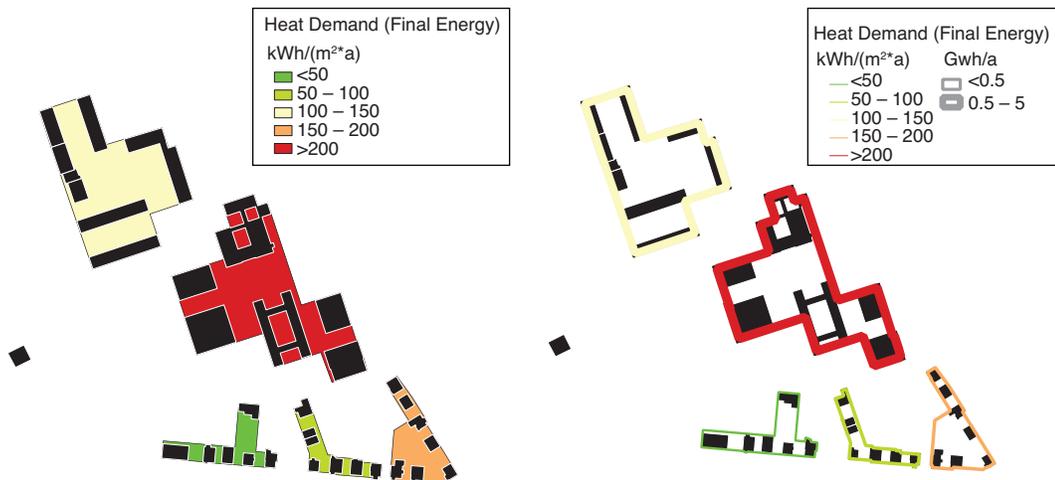


Figure 4: Visualising aggregated final energy

to avoid giving visual significance to the size of the polygon, we use only its outline (Figure 4 right).

We colour the outline based on specific heat demand and additionally adjust its thickness as function of the total heat demand. This has the advantage that it allows a more integrated analysis of heat demand. For example, it allows the quick visual localisation of large ‘heat sinks’ with low or high energy efficiency. This is advantageous for planning since it points towards appropriate measures. For example, a large heat sink with low specific heat demand is likely a target for renewable heat supply, while a large heat sink with high specific heat demand is likely first a target for an increase of efficiency through energetic refurbishment.

For the colour scheme, we use an already relatively known colour scheme in Germany – the green-yellow-red colour gradient of the energy certificates according to the Energy Efficiency Ordinance in Germany (*EnEV*) [25]. We adjust the tone, depending upon the background map and reclassify the scale into 50 kWh/(m²*a) bins, to make the classes more

distinguishable. An important point is to adjust for colour blindness, but this would require changing the basic green-yellow-red palette. This adjustment is beyond the scope of this paper.

4.5. Software used

The presented algorithm was written in Python using the Numpy [26], SciPy [20] and Shapely [27] libraries and the PyQGIS library of the open-source GIS software QGIS [28]. We used QGIS also for the visualisations. The code is available on Github[22].

5. Results

We applied the described methods to a dataset of 300 000 buildings (residential and non-residential) in the city of Hamburg. The algorithm produced 40 000 building groups. The size of the groups was between five and nine units. We use the geometry representation and the visualisation approach to produce Figure 5. We use a digital orthophoto [29] as background map.



Figure 5: Proposed visualisation of the aggregated heat demand (building groups). Background map: [29]

6. Conclusion and Outlook

With the increase in available geodata, protecting privacy in public maps and datasets is gaining importance. Despite rising concerns about the potential violations of data protection requirements, energy policy should be based on quantitative analysis. The difficult, but important task is to find the balance between protecting privacy and retaining usability. This paper is an effort in this direction. There is, of course, room for improvement. The defined rules for the number of units per building are simplified and generalised. They can be adjusted if different strategies for different building types are formulated. For example, data on publicly owned buildings may be considered as not requiring the same extent of data protection as privately owned buildings. The municipality or another public and semi-public entity being the building owner, can agree to make this data public. This can easily be implemented into the algorithm if the function for assigning the number of units is changed so that it assigns a value of five units to publicly owned buildings. Then each public building will have enough units to constitute a building group and the algorithm will attempt to define such a building as a group by itself.

On the visualisation side, large amount of spatial data nowadays include the third dimension. Representing the heat demand of building groups in a 3D visualisation is a further area to be explored.

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