# COMPUTATIONAL APPROACH FOR SPATIOTEMPORAL MODELLING OF HEATING LOADS USING AMR AND OTHER EXTERNAL DATA

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## *ABSTRACT*

*Different registries of the society are constantly opening for free usage and can be utilized to enhance spatial load modelling needed in strategic planning of electricity distribution networks. The main innovation of this paper is that of demonstrating possibilities of public geographic data, namely socio-economic, building and meteorological data, in spatiotemporal modelling of controllable heating loads. In the paper, the computational approach based on fixed spatial computation/planning units forming a grid is proposed. The benefit of the approach is on enhanced computational performance and integrity to public sector region level data, related scenarios, analyses and models. In the next stage, the approach can be linked with small-scale generation and local energy storage models in order to obtain overall power demands.*

## INTRODUCTION

Demand response (DR) is envisioned to be an essential mechanism in balancing between power consumption and supply, especially in the context of Smart Grids. In Finland, control of residential heating loads has showed significant potential compared with other domestic appliances, and can be shifted in time without disturbing the comfort of customers [1]. Implementation of demand response in a large scale requires reliable and accurate models, which are capable of predicting controllable loads in varying behavioural and environmental conditions.

At present, a range of sound modelling approaches already exist [2]. Methods are needed both from network planning and operational perspective. For strategic planning of distribution system operators (DSOs), it is beneficial to be able to forecast future loads in the network. For instance, the extent to which new network investments could be avoided in areas by using demand response (DR) instead is one interesting question.

However, the challenge is often the lack of sufficient information. For instance there are no extensively available up-to-date and reliable building specific data, which could be used to generate accurate models. The situation is however appearing to change as different registries of the society produced by public funding are increasingly opening for free usage and can be utilized to improve models. This is mainly due to such information content's significant value in stimulating research and commerce [3]. In EU level, there are INSPIRE and PSI Directives (2003/98/EC) which mainly define common legislative frameworks for release and use of public sector data. However, until now, the directives have not provoked large scale opening of the data for free usage. A significant obstacle has been that the public sector is allowed to use information disposition pricing to cover their short-term costs. The situation is however about to change as the European Commission is preparing considerable changes to the PSI Directive until 2013. Furthermore, there are notable national-level initiatives and decisions under work.

The aim of this paper is to demonstrate the possibilities of opening public register data in the spatiotemporal modelling of loads. In the paper, the modelling approach based on fixed spatial computation is presented with initial experimental results achieved in the selected target area. The main benefit of such approach is enhanced integrity to heterogeneous geographic data produced by public sector. The main data sets employed in this study include the automatic meter reading (AMR) data, socioeconomic grid data, building data and meteorological data.

## TARGET AREA AND DATASETS

Hourly energy of 1204 small customers was measured during the year 2008 using smart meters in the distribution network of Savon Voima Oyj, Finland. In addition to the recorded AMR data, available geographic data were gathered from public sector information sources, including the following data sets:

- Socioeconomic grid data (Statistics Finland)
- Building information (Population Register Centre), supplemented with a query data concerning primary and secondary heating systems
- Meteorological data, temperature measurements (Finnish Meteorological Institute)

### Socioeconomic grid data

Statistics Finland's grid data include various annually updated socioeconomical variables for areas with resolutions of 1x1 km and 250m x 250m. The variables describe population's structure, education, type of activity and income, household's stage, as well as building and workplaces. For privacy reasons some information are hidden, e.g. in cases where the amount of cases per the grid unit is not above a certain limit. The variables provided by the database have good potential to model loads in different variable dependent scenarios.

## Building data

Building data used in this study are available from Population Register Centre, Finland. It is maintained by municipal building supervision authorities and updates are typically applied when a modification requiring permission is made. Consequently, there is no guarantee that the information are up to date in every case. For instance, from the point of energy system modelling and analysis view some relevant data are commonly missing such as information about secondary heating system installations (e.g. air-to-air heat pumps, solar panels, etc.). On the other hand, building information has the benefit of having high spatial accuracy if compared to the grid database.

In this study, the building data was supplemented with a query data concerning primary and secondary heating systems of the target customers. According to the building information, proportion of heating systems in the target customer group was as follows:

- Oil heating 7%
- Wood heating 12%, Pellet 2%
- Direct electric heating, DE 22%
- Direct electric+air-to-air heat pump, DE+AA 6%
- Ground source heat pump, GS 8%
- Electric storage heating, ES 3%
- District heating 40%

## Temperature data

Temperature data used were based on the 10 min temperature measurements of representative 15 meteorological stations during the year 2008 in the target region. In order to achieve sufficient spatial coverage, the hourly outdoor temperatures were estimated in each computation location using the distance weighted average of station-specific hourly temperature measurements.

# COMPUTATIONAL APPROACH

In this paper, the computational approach based on the use the AMR data and the public sector data is proposed for spatiotemporal modelling of heating loads. The main computational stages of the approach include:

- Recognising type of consumption and heating system segments
- Building heating segment specific load curves
- Spatial grid based modelling of loads

Next, these stages are briefly described and discussed.

## Recognising type of consumption and heating system segments

In the first stage, temperature dependence $T_c$ (%/˚C) and specific energy consumption E (kWh/m$^2$) were computed for each customer based on the AMR data and the estimated hourly outdoor temperatures (Figure 1). Temperature dependence was calculated using simple linear regression using daily energy consumption as regressand and daily average temperature as regressor. Following Mutanen et al. [4], the effects of daily and monthly fluctuations in electricity demand were eliminated by calculating regressand as percent error between the daily energy consumption and the average daily energy consumption on a similar day, and regressor as difference between the daily average temperature and the average temperature on a similar day.

Next heating segment specific $T_c$ and E values were defined as average $T_c$ and E of the customers having similar heating system (Figure 2). In this study, the available building information was used to determine subsets of customers. However, if that information is missing customer classification and load profiling methods, based on daily load profiles, load-shape factors or load patterns, can be adopted to recognise type of heating [e.g. 4, 5].

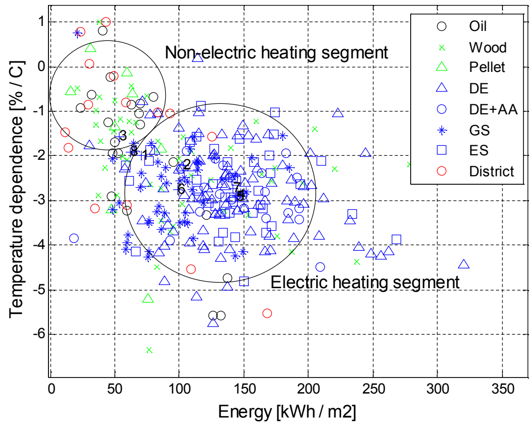


**Figure 1: Specific energy consumption and temperature dependence of the target customers.**

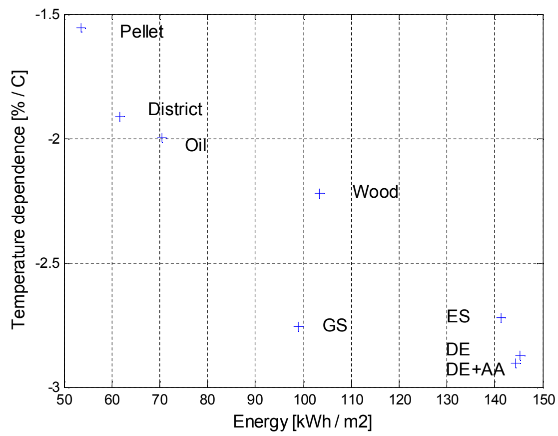


**Figure 2: Specific energy consumption and temperature dependence of the heating segments.**

## Heating segment specific models for hourly loads

Load profiles were constructed based on the AMR data of each heating system segment using Self-Organizing Map (SOM) and *k*-means based approach [5]. Load profiles were based on 26 two-week profiles summarizing hourly electricity use separately for weekdays, Saturdays and Sundays (Figure 3). Load profiles were normalized in respect to outdoor temperature and annual energy.

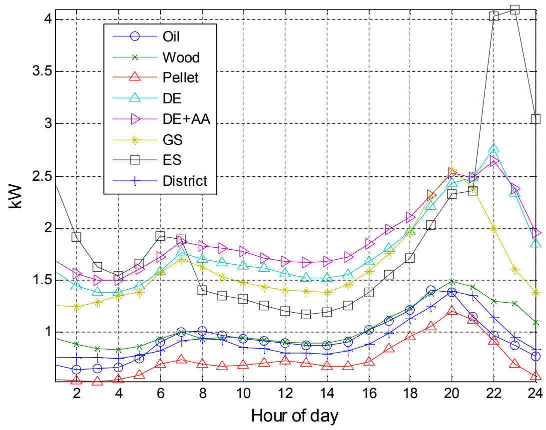


**Figure 3: Hourly load profiles of the heating segments.**

## Spatial grid based modelling of loads

Based on afore mentioned issues and experiments spatial load modelling approach based on the socioeconomic grids is proposed (Figure 5). The computational stages behind the overall approach are next briefly described.

In the first stage, for each spatial grid, temperature dependency $T_c$ and specific energy consumption E are calculated based on the total annual energy of the grid (calculated from the grid-specific AMR data) and the total area of heated floor in the grid (Figure 5). Based on that information, the group membership of each spatial grid in respect to different heating segments $u_i$ is described using the Euclidean distance: $d_i = \lVert x - c_i \rVert$, where x is the vector which contain E and $T_c$ of the grid, and $c_i$ is the vector which contain E and $T_c$ of the heating segment.

The membership is scaled so that the total sum of heating segment specific membership values is 1. The maximum Euclidean distance $d_{max}$ between the target grid and the heating segments is used as the scaling factor. For instance, in Figure 5, the maximum distance $d_{max}$ is determined based on the Euclidean distance of the target grid and the pellet segment.

In the final stage, hourly load estimates of the spatial grid are simulated using heating segment specific load profiles, scaled with the grid-specific outdoor temperature estimate and the annual total energy of the grid. Lastly, the final hourly load estimate is constructed as the membership weighted sum of heating segment specific load estimates.

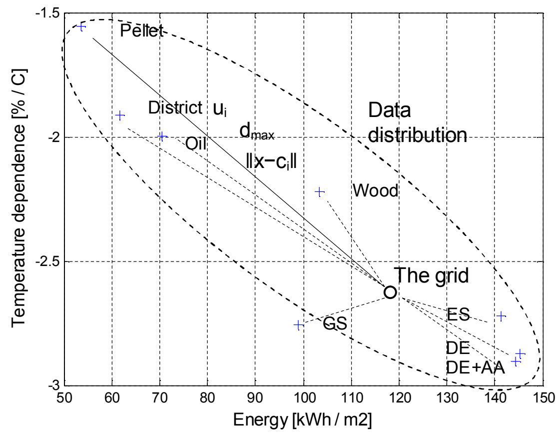


**Figure 5: Computation of the membership between the spatial grid and the heating system segments.**

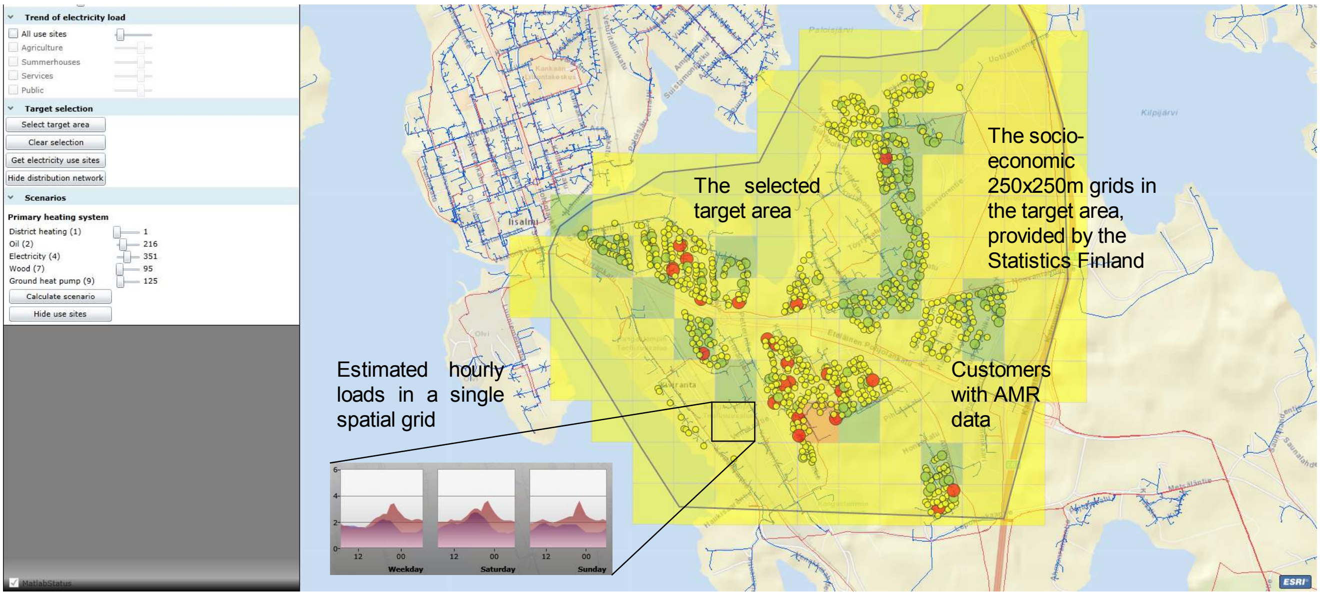


**Figure 4: The grid based spatial load modelling approach.**

## CONCLUSIONS

In this paper, computational approach based on the fixed spatial grids (e.g. 250m x 250m, 1km x 1km) is proposed for spatiotemporal modelling of heating loads. The benefit of the approach is especially on the enhanced integrity to regularly updated public, geographic information (population, education, buildings, type of activity and income, work places etc.) and related models, scenarios and decision making [6]. In addition, the approach enables rapid modelling of loads using large amount of geographic input data. Computational performance can be further increased by merging the spatial grids to larger spatial entities using spatial clustering methods. This was however out of the scope in this study. Further development and evaluation of the approach with more extensive AMR data is required. In addition, as a recommendation for future work the approach can be linked with small-scale generation and local energy storage models in order to obtain overall power demands.

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