ELECTRICITY CONSUMPTION ANALYSIS OF SERVICE SECTOR USING AMR MEASUREMENTS

Report SGEM WP 6.11 Spatial Load Analysis

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Abstract

Current and expected customer mix, land use and prior electricity consumption are vital inputs for spatiotemporal load forecasts. The aim of this report was to study characteristics of electricity consumption in service sector in the Helsinki city area. Furthermore, the report examined deployment of automated meter reading data in spatial load analysis. The report provides also an insight into the research conducted in WP 6.11: Spatial Load Analysis.

Contents

1 Introduction

A long-term spatial load forecasting involves the projection of magnitude and location of electric load in the future (10-20-30 years). Spatial load forecasting uses a geographical model to merge together distribution system data with land use and community development data. Long-term load forecasts are an essential part of strategic network planning, because forecasts help utilities to identify where and when to construct new network infrastructure. This improves also the communication between network planners and city authorities. In addition, spatio-temporal analyses enable engineers to explore changing end-use patterns in existing areas. The starting point of spatial load forecasting is the present and past loading in the network. Spatial analyses deploy small area approach where the utility service territory is divided into many small areas and forecasts are done for each separately. These small areas can be for example city districts or service areas of the feeders.

The small area approach allows utilities to calculate specific consumptions (kWh/m^2, a) spatially for each customer class. Customer classification allows representation of land uses according to their typical load profile and also allows changing end-use analysis. Therefore, customer classification suitable for network analysis should distinguish customers based on their load behavior and usage patterns. The aim of customer classification is to identify load groups that use electricity consistently. These groups are used in forecasting as a basis of load modeling. Therefore, customer classification together with land use data are a vital input for long-term load forecasts.

In Finland, utilities are currently implementing large scale meter upgrades to automated meter reading (AMR). By the end of 2013, AMR meters should be installed practically to every measuring point. Previously, meters were read by a meter reader or by the customers themselves. The AMR meters are read remotely and they provide hourly measured consumption data. The AMR deployment increases significantly the data available for network analysis. However, new applications and analyzing methods are required in order to utilize the hourly measured data efficiently.

The goal of this task is to develop a computerized tool for spatial long-term load forecasting. In long-term planning, the key challenge is the estimation of peak power. The task involves four sections. Firstly, the task examines mechanisms to manage the current land use and vacant land data in the forecasting process. Secondly, the task includes the analysis of present electricity consumption and develops methods to model changing and new load types. Thirdly, the task studies tools for load classification and load profiling. Finally, the task develops a process to convert the results of load analyses and land use data into the spatial scenarios of electric load. Figure 1 depicts the outline of spatio-temporal forecasting process.

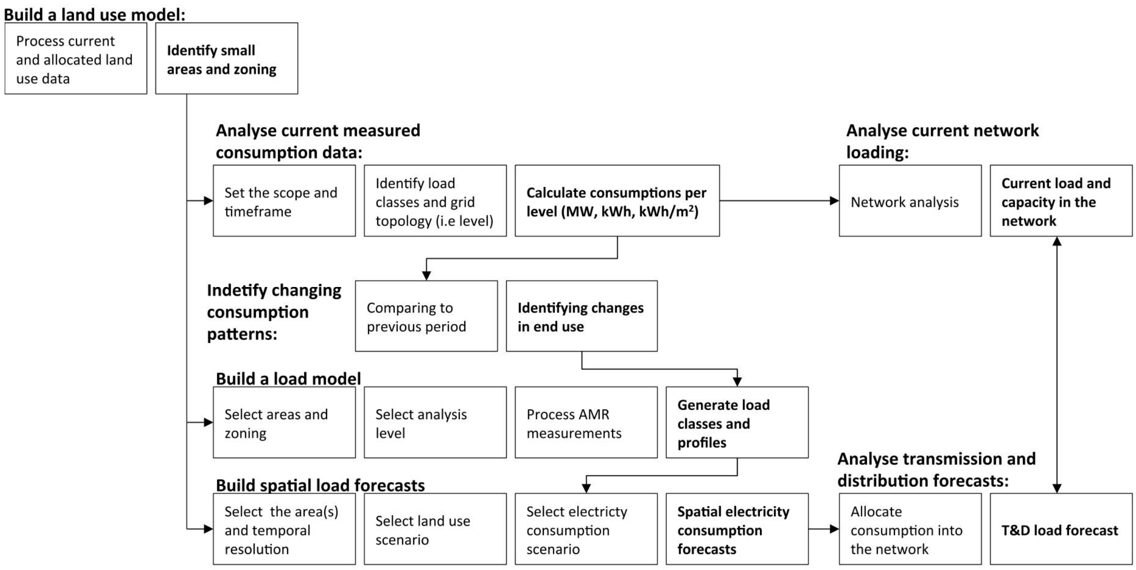

Figure 1: The information flow in the forecasting process divided into sub processes and sub tasks.

This report discusses the characteristics of electricity consumption in service sector in the Helsinki city area. In addition, the report examines the deployment of automated meter reading data in spatial load analysis. The report is a part of national Smart Grids and Energy Markets (SGEM) research program as work package 6 Task 6.11: Spatial load analysis. The partners in the Task 6.11 are Aalto University School of Electrical

Engineering, Helen Electricity Network, Elenia Verkko, Tekla and Vantaa Energy Electricity Networks. Previous research in WP 6.11 has discussed following topics (see References):

- Development of spatial electric load forecasting process (Kaartio, 2010)
- Functional description of the forecasting tool (WP 6.11, 2012)
- Definition of the required properties in forecasting tool and methods for data collecting and linking (Rimali, 2011)
- Load modeling and classification in distribution systems (Koivisto, 2012)
- Electricity consumption analysis of service sector utilizing AMR measurements (Larinkari, 2012)
- Modeling of photovoltaic power generation (Hellman, 2011)
- Load disaggregation and consumption pattern analysis (Degefa, 2012)

Next, the research focuses on analyzing changing load types. In addition, the research in load modeling and load classification will continue. Furthermore, the demonstration of computerized forecasting will be covered in coming deliverables. The goal of computerized demonstration is to present the feasibility of forecasting process (i.e. inputs and outputs) in practice (Figure 1: The information flow in the forecasting process divided into sub processes and sub tasks.

2 Land use and electricity consumption

The present electricity use is the starting point of load modeling and forecasting. Therefore, it is essential to understand the current loading in the network. Spatial city district level analysis are performed utilizing annual electricity consumption data, land use information and present customer classification used in customer information system. Figure 2 illustrates the load densities in 200 m x 200 m squares in the Helsinki city area. The figure is received from the network information system. Spatial difference in power densities can be explained with the structural differences between areas. There is a high load density in and around the central city area featuring many commercial buildings and public services. Lower load densities are located in the outlying suburban areas, where households are the dominating load type.

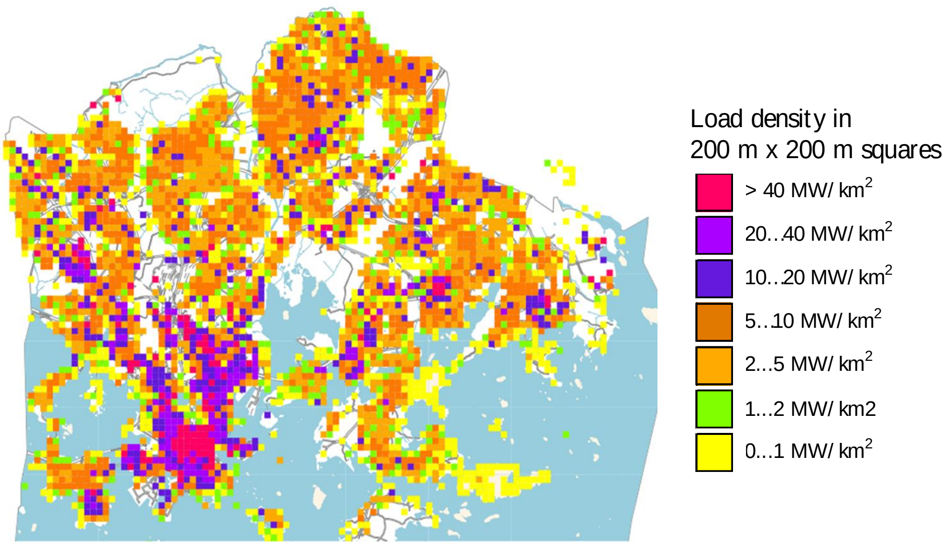

Figure 2: Load density distribution in Helsinki city

Figure 3 presents the shares of electricity consumption in Helsinki in 2011. It is worth noting that the service sector consumed more than a half of the total electricity consumption. The service sector consists of private and public services including commercial buildings, offices, schools, hospitals etc. The largest load group was services for business life (i.e. offices and shops).

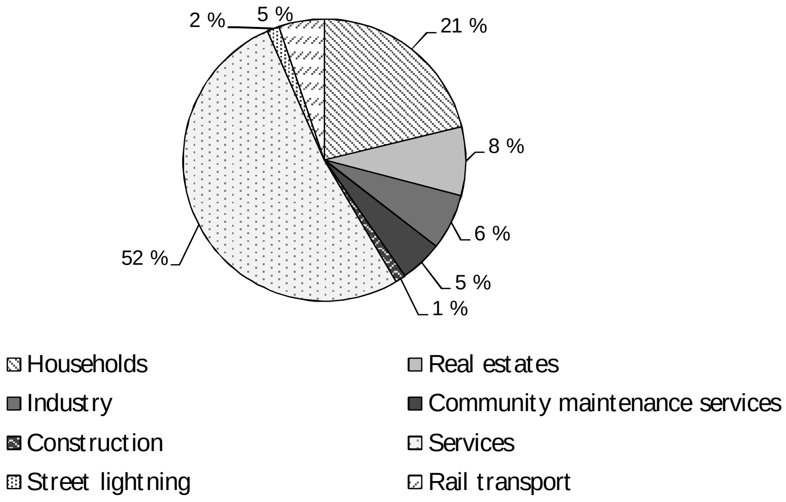

Figure 3:Share of electricity consumption by sector in 2011

Many commercial and office buildings are located in the central city and its surroundings (Figure 4). In addition, there are a few service facility clusters in the other districts such as Pitäjänmäki and Vartiokylä. High load density areas correspond fairly well with areas where offices and shops are located. Vacant areas for nonresidential buildings are located in the same areas as the current office buildings.

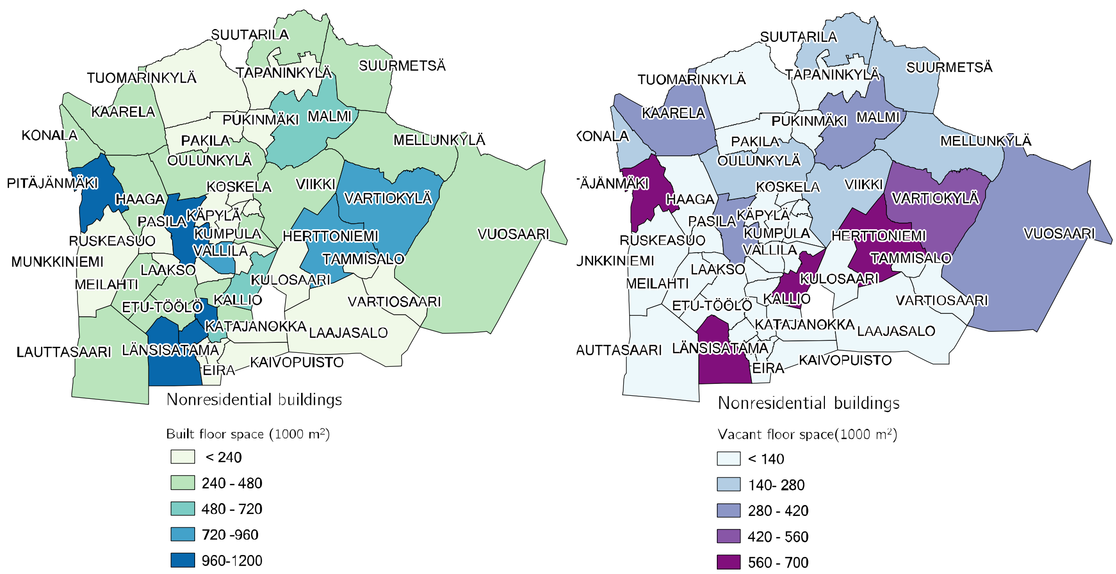

Figure 4: Distribution of built floor space (left) and vacant floor space (right) in nonresidential buildings in Helsinki

Figure 5 presents specific consumptions for nonresidential and residential buildings by city district. Specific consumptions are calculated using the annual electricity consumption information and district level land use data. The specific consumption for nonresidential buildings were approximately 127 kWh/m2, a and for residential buildings 24,2 kWh/m2, a.

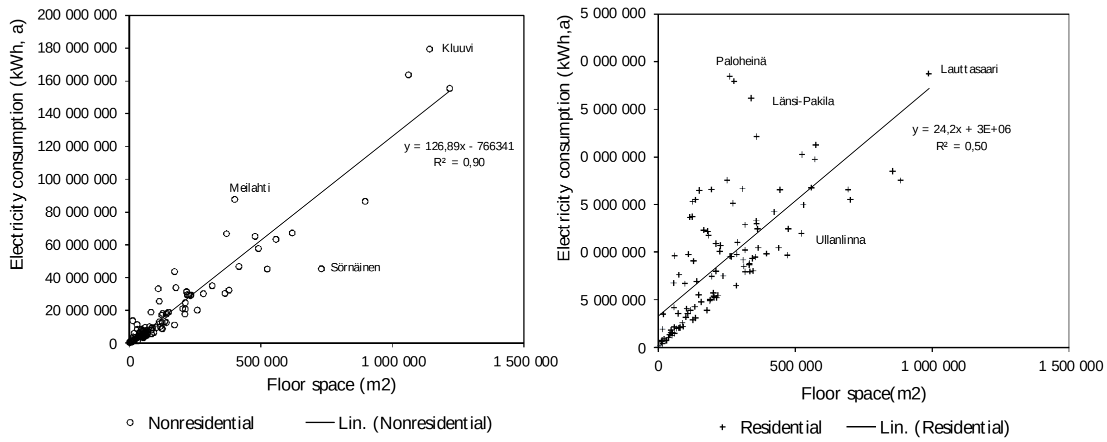

Figure 5: Specific consumptions (kWh/m2, a) for nonresidential and residential buildings by city district

3 Clustering service sector

Figure 6 presents the examples of hourly profiles for highly air-conditioned offices and medium sized super markets. Profiles were obtained by manually averaging consumers that belong to group at issue. Summer profiles include measurements from May to July and winter profiles measurements from December to February. This method differs fundamentally from mathematical customer classification because grouping must be known in advance. As seen in Figure 6 (up), the profile from offices has a clear weekly structure where offices are employed Monday to Friday during normal office hours. In addition, it can be seen that offices use more electricity during summer than winter due to the air conditioning. Figure 6 (down) presents weekly profile for medium sized super markets. The weekly structure in super markets differs from offices especially on weekends. Although super markets have longer opening hours than offices, they are open as well on Saturdays and Sundays. Super markets have many refrigerators and freezers, which consume more electricity summer. In both profiles, the summer consumption is approximately 10-15 % higher than winter consumption.

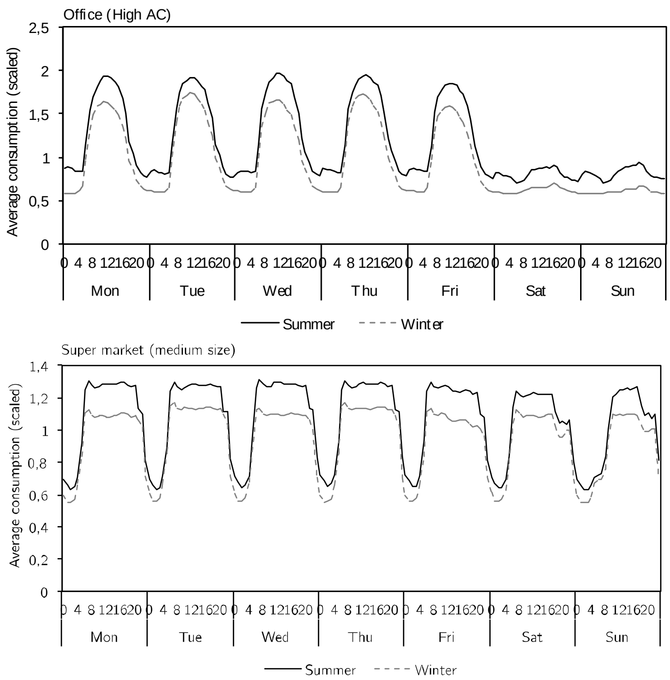

Figure 6: Examples of hourly profiles for offices (up) and super markets (down) in winter and summer months

The automated meter reading data was deployed for customer classification. The analyzed AMR data was collected from the central city area and form a residential district with a predominance of detached houses. In total, the analyzed data matrix contained the hourly measurements of 2728 connection points from 1.1.2010 to 31.12.2010. The objective of the method was to classify connection points according to consumption structures using principal component analysis (PCA) and mathematical clustering. Before the analysis, the data were pre-processed and prepared. The applied classification method is described in detail in the reference (Koivisto, 2012).

Figure 7 presents the results from the PCA after size and variable scaling and SOBI-rotation. The cumulative plot in Appendix A shows that the PC 1 and PC 2 retain one third of total variation of the original variables. PC 1 was clearly interpreted as office-like behavior (i.e. separates night-time/day-time usage). PC 2 separated the connection points according to heating. Mathematical customer classification produced three electric heated groups, a district heated and a service consumption groups.

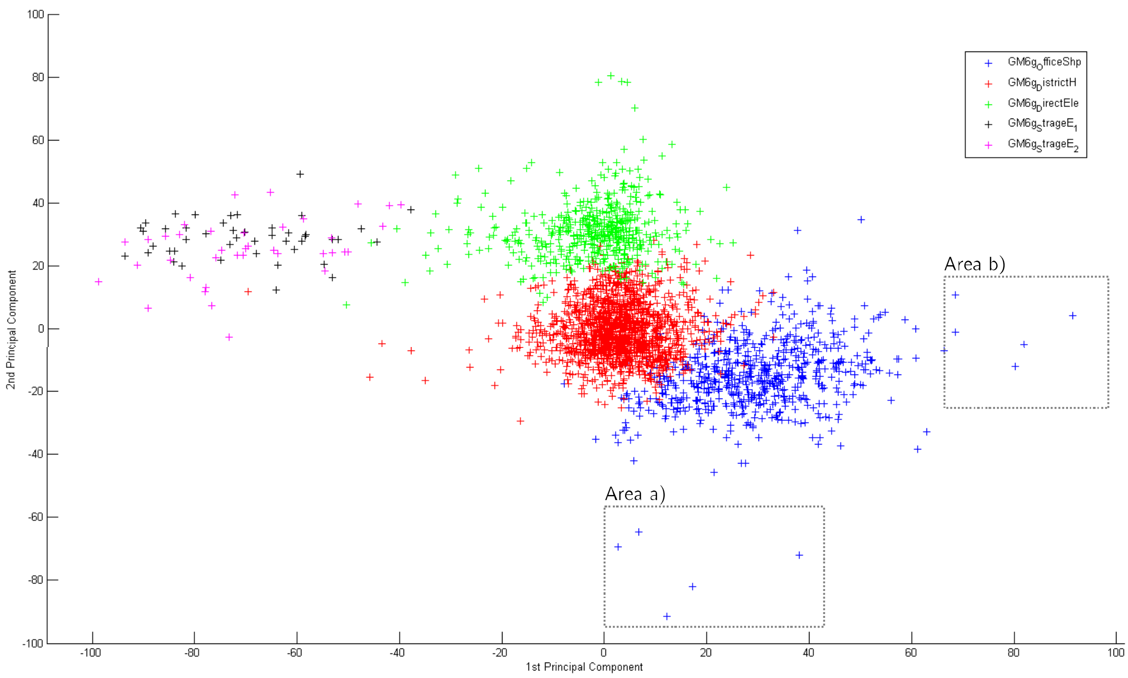

Figure 7: Analysed connection points plotted using the first and second SOBI-rotated PC scores. Coloring is from Gaussian mixture models based clustering using eight first PC scores (excluding PC 5) as an input. Squared areas illustrates the differences inside the office/shop group (blue dots).

Mathematically formed load profiles were meaningful and represented each group coherently (see Appendix B). In addition, the mathematical customer classification results were mainly consistent with present customer classification. District heating group was the largest cluster if measured in number of consumers. However, the service sector cluster composed 86% of total energy consumption (Table 1). It is worth noting that offices and shops can be considerably large connection points in energy.

Table 1: Summary of clustering results

Group	Numb of connection points	Numb of Consumer points	Year consumption (MWh)
Office/shop	647 (24%)	2 424 (13%)	956 671 (86 %)
District heating	1 497 (55%)	15 554 (81%)	115 061 (10%)
Direct electric heating	501 (18%)	1 135 (6%)	31 951 (3%)
Storage electric heating A	45 (2%)	55 (0%)	1 894 (0%)
Storage electric heating B	38 (1%)	49 (0%)	1 475 (0%)
In total	2 728	19 127	1 107 052

More detailed classification of service sector was challenging due to the diversity of service consumption. Service consumption cluster, including offices and shops, did not divide meaningfully into subgroups. As can be seen in Figure 7, blue dots (office/shop cluster) are spread around quite a large area. This does not mean that all the connection points have a similar consumption profile. In truth, the cluster contains consumption points with quite different profiles. For example, Figure 8 presents profiles created from squared areas a) and b) shown in Figure 7. The electricity consumption differs between these two areas although the consumption points were mathematically clustered into same group. Area a) includes consumption points, which have high consumption when the temperature is high. On the other hand, consumption points inside area b) use electricity mainly during typical office hours.

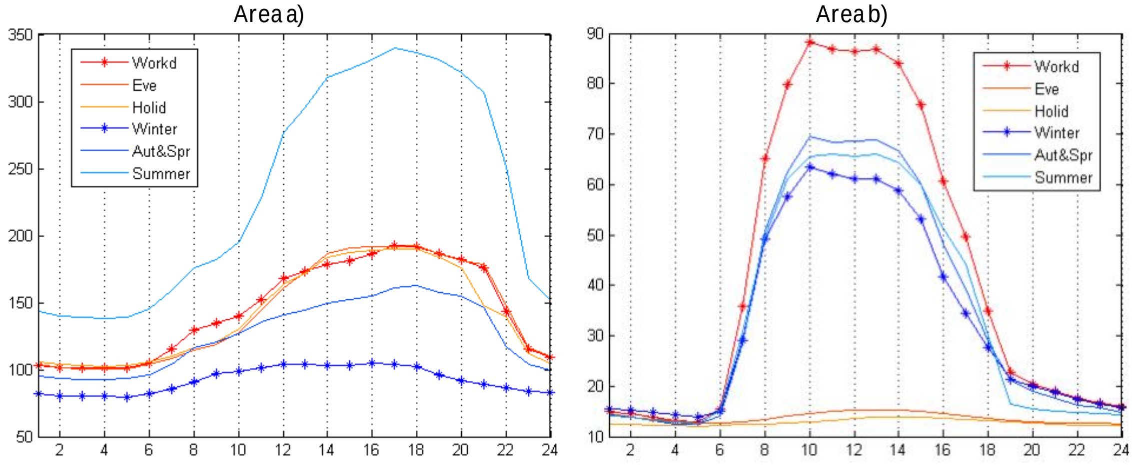

Figure 8: Two manually created sub-groups inside the office/shop cluster. Area a (left) contains highly air-conditioned connection points and area b (right) has very office-like behavior.

The specific consumptions of present buildings (kWh/m2, a) are crucial input for spatial load analysis. However, this requires linking between electricity consumptions and real estate data. The applied linking method is described in the reference (Rimali, 2011). The annual specific consumption was 151,8 kWh/m2 in electrically heated buildings and 47,9 kWh/m2 in district-heated buildings. The annual specific consumption for service facilities was 128 kWh/m2. The results obtained were meaningful and supported the current understanding.

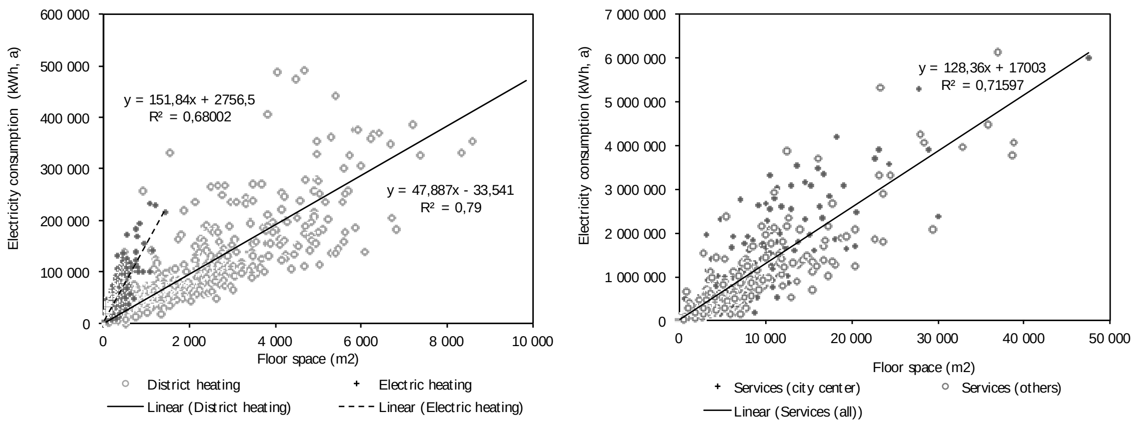

Figure 9: Calculated specific consumption for mathematically formed electric and district heating groups (mainly households) and office/shop group (Services)

4 Conclusions

The increasing amount of AMR data yields a high potential for developing data-driven approaches in load modeling and forecasting. Spatial load forecasting helps to identify future load centers and provides tools to model changing end-use patterns. The aim of spatial load modeling is to determine specific consumptions and load profiles spatially for each load class using electricity consumption data. In practice, load forecast is compiled by using different scenarios, because of uncertainty related to land use and future electricity development.

The goal of customer classification is to identify load groups that use electricity consistently. These groups are used in forecasting as a basis of load modeling. The principal component analysis and mathematical clustering found only one service consumption group, which had a meaningful interpretation. In Helsinki, this is problematic, because more than a half of electricity consumption would be modeled with one load profile. Service sector includes various activities, and this diversity causes challenges for the load modeling. In the future, clustering methods have be developed further to meet the characteristics of the service sector.

The Task 6.11, Spatial Load Analysis, will continue until the end of 2014. In the coming studies, load modeling will focus on changing end-use patterns and address to the difficulties of service sector clustering. In addition, long-term trends will be studied using GDP and other econometric parameters. The final goal of the task is to demonstrate the forecasting tool.

References

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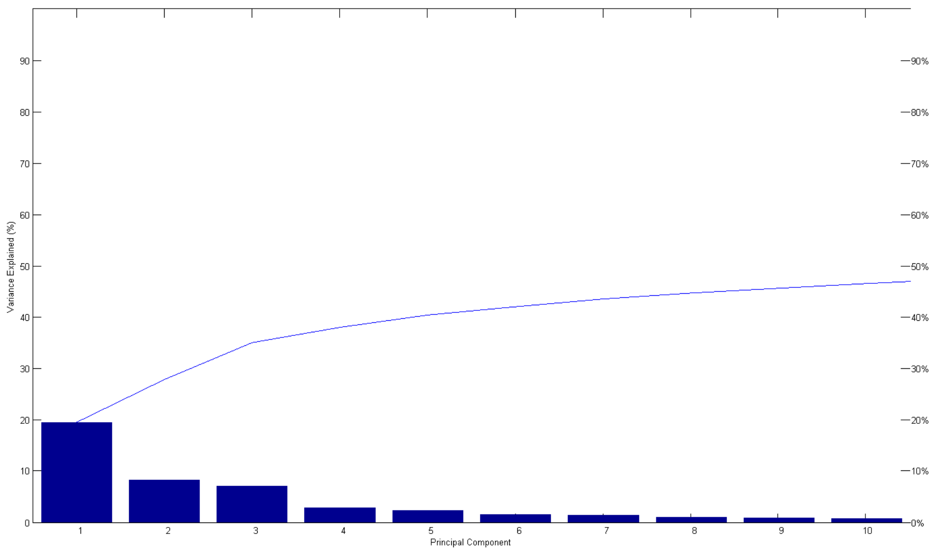
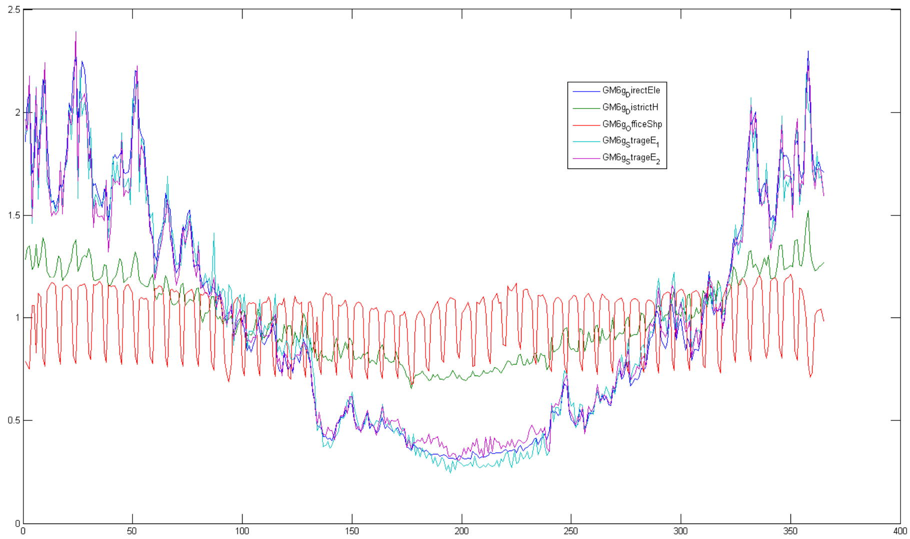
Appendix A:

Variance explained by the ten first principal components compared to the variance of the original variables before SOBI-rotation



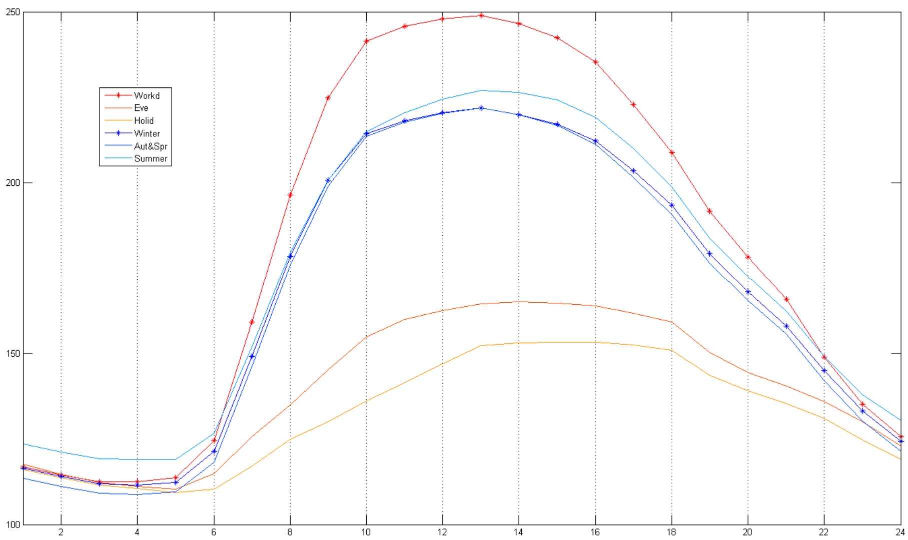
Appendix B:

Scaled day energies of the year

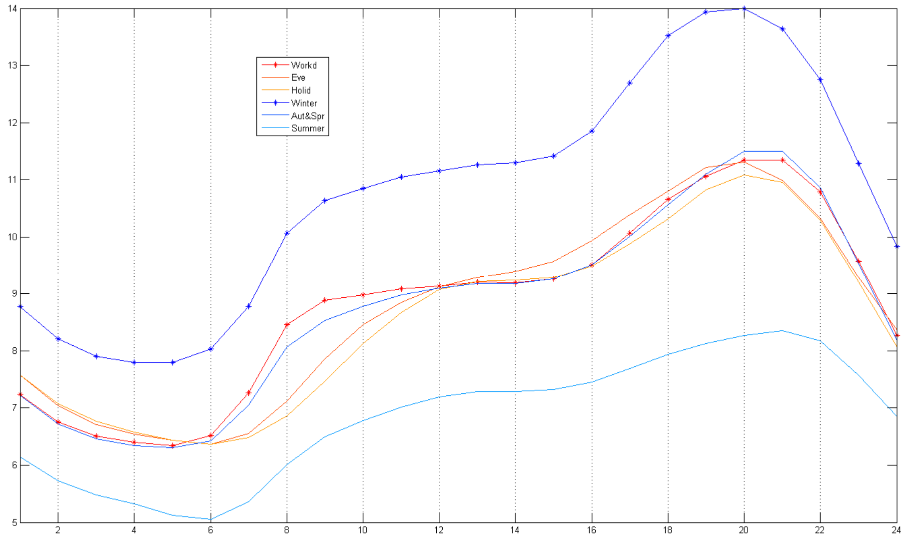


Scaled day profiles of the average connection points from the clusters

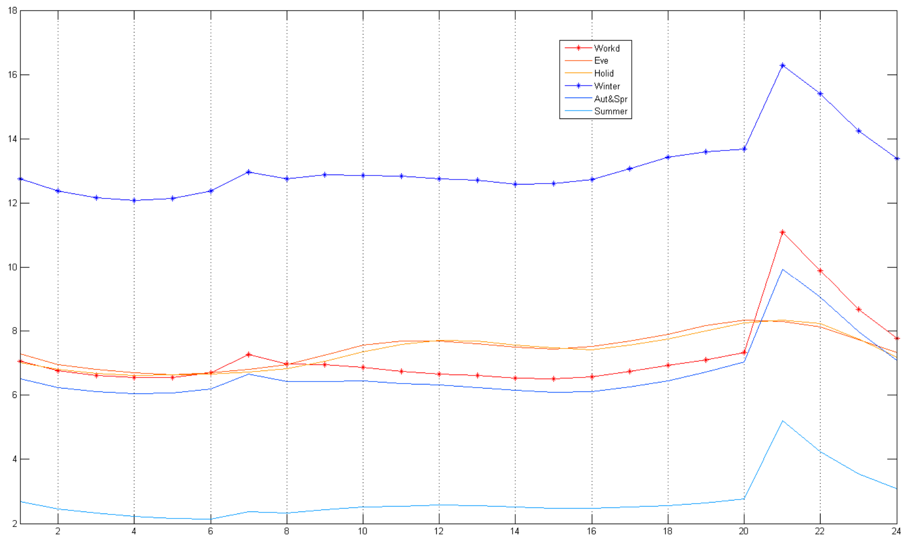
GMM office/Shop:



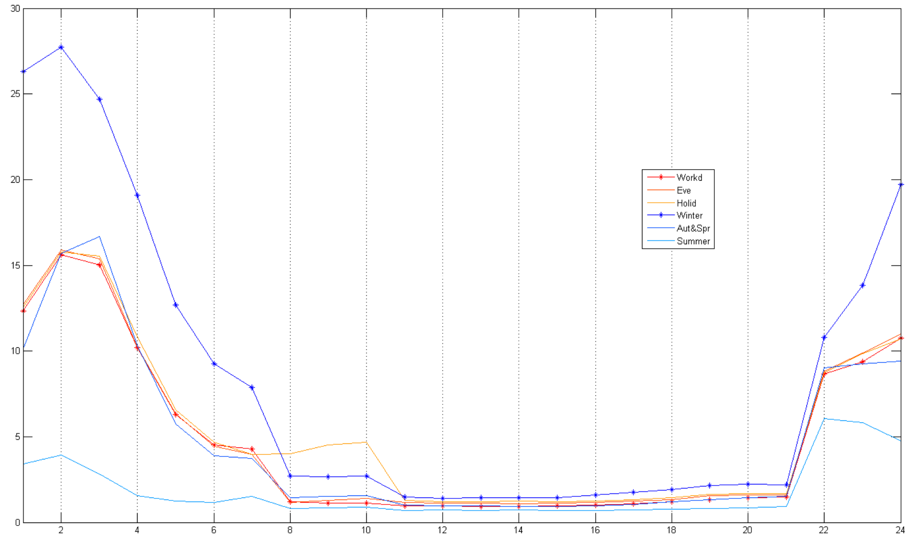
GMM district heating:



GMM direct electric heating:



GMM storage electric heating A:



GMM storage electric heating B: