SGEM Research Report D4.2.5

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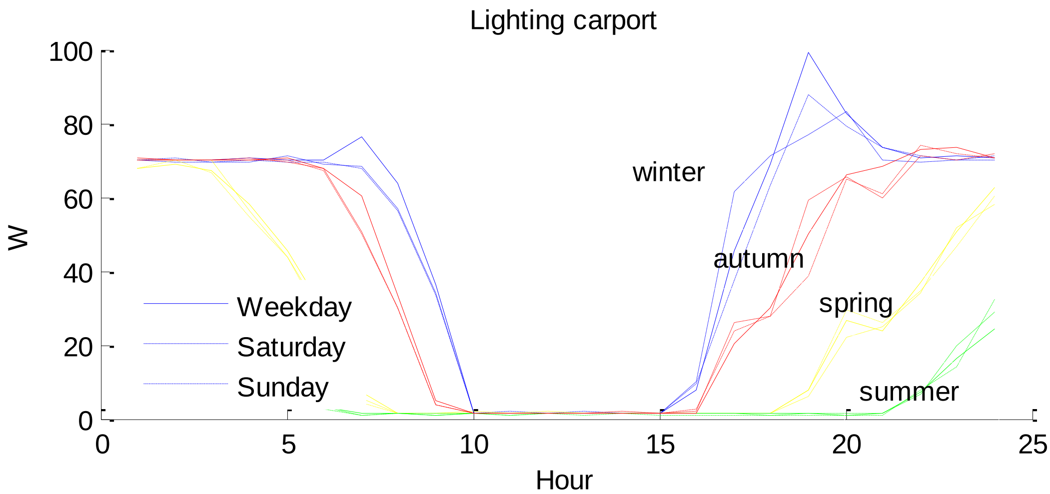
CI/DDM approaches for analyzing and modelling loads using metering data from pilot houses and other data

Report 1/2



Abstract

In this report, the research activities related to SGEM FP2-3 WP4.2.1 “Novel load modelling methods” are reported. The main objective is on the investigation and testing of new type of load modelling (e.g. hybrid) approaches, which combine the metering data from pilot houses and AMR data, with external information sources.

The report is comprised of two separate reports which are: “Description of experimental data and set-up” (Report 1/2) and “Modelling experiments and results” (Report 2/2).

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Preface

The work presented in this report is part of the project Smart Grids and Energy Marketing (SGEM). The SGEM project belongs to Cluster of Energy and Environment (CLEEN), financed by Finnish Funding Agency for Technology and Innovation, TEKES industrial partners, universities, and research institutes.

We wish to thank the funding organizations and the steering group of SGEM programme for making this work possible to carry out.

The authors

Abbreviations

AMR	Automated metering data
ANN	Artificial Neural Network
CI	Computational Intelligence
DDM	Data Driven Modelling
DSO	Distribution System Operator
GIS	Geographic Information System

1 Background

Methods for load modelling and prediction have an essential role in management and planning of electricity distribution in Smart Grid vision.

Reliable and computational powerful load models are required as a solid part of load control and its automation and optimization systems, to forecast loads in different consumer behaviour and environmental conditions. In addition, from the perspective of the planning of the grids, the load modelling is required to assess loads and their long-term development in different regions and scenarios.

Different approaches have been developed varying from simple statistical regression and clustering methods to dynamic physical-based models. Many examples can be found in the literature (e.g. Willis et al 2002, Hahn et al. 2009, Räsänen et al 2010, Mutanen et al 2011). However, the possibilities of opening databases (e.g. public sector data) and other metering data have not been extensively investigated so far.

Thus more attention should be placed on ideating new types of modelling approaches based on both AMR and external data sources, and their combination.

2 Experimental data

2.1 Metering data from pilot houses

UEF has been developing energy and indoor air quality monitoring system in order to research energy efficiency and indoor air quality in several national TEKES/ERDF (e.g. Asteka, Asko, Insulavo) research projects. The system was first presented in the Kuopio housing fair 2010. The developed monitoring system is composed of sensors, data transfer unit (ZigBee), database and user-interface (see Appendices 1-2). The more detailed information of the system can be found in Skön et al. (2011).

Metering data collected for the pilot houses (currently covers approx. 8 apartment houses, 10 schools, 5 detached houses) and include the following variables:

- Energy (electricity and district heating)
- Water
- Indoor and outdoor temperature
- Differential air pressure (some target(s))

- Move detector (some target(s))
- Indoor air quality (CO2, CO RH, VOC)

The data enables the developing and testing the models with customer specific high-resolution data. It is possible to analyze e.g.:

- The dynamics between temperature and loads, and building information
- The relationships between loads and indoor air quality (from control perspective)

2.2 AMR data

Automated metering data (AMR) are increasingly available and forms the basis dataset for the load modelling. However, there are some challenges with AMR, among them:

- AMR represents the total load of user-site i.e. does not represent the loads caused by separate appliances or shiftable load components
- Integration of AMR data with other datasets is complicated due to the lack of common key / ID / spatial reference (see Figure 1)

Figure 1: Spatial locations of user sites (red-points) and RHR/VTJ buildings.

2.3 Other datasets

In addition, there exist various external information sources that can be useful in load modelling. Combined with AMR and other house-specific metering data new more accurate and reliable models could be achieved. Most of the external information sources include geographic data hosted by the public sector, the most promising datasets in Finland includes:

- Building information (VTJ/RHR/KTJ)
- Socio-economic grid data (Statistics Finland)
- Weather data (FMI)
- Land use data, CORINE (MML/SYKE)

Some of the public sector data are opening for free use for research and commercial purposes (see e.g EU's PSI and INSPIRE Directives), enabling thus the development of new type of modeling approaches based on that data.

3 Load models and related methodology

3.1 DDM/CI models

When dealing with large amount of data, it is often difficult for human to notice the patterns and interrelationships within. However, in "data-rich" conditions data-driven modeling (DDM) methods provide new possibilities for the analysis and modelling. More sophisticated DDM methods rely often on novel data mining / computational techniques contributed by the field of Computational Intelligence (CI), including:

- Artificial neural networks (e.g. support vector machines, multi-layer perceptron networks, self-organizing maps, radial basis networks, elman networks)
- Evolutionary and genetic algorithm
- Fuzzy logic
- Clustering methods (e.g. k-means, isodata, fuzzy-c-means)

The DDM methods combined with conventional statistical methods and geocomputing techniques could result substantial enhancements in solving modelling problems related to planning and management of smart grids.

Advantages of DDM/CI methods are that they are capable of (Niska and Saarenpää 2011):

- Searching complex spatiotemporal patterns, load curves, in different data presentation levels
- Modelling non-linearity and temporal dynamics of loads, including time-delays and interaction with external variables
- Forecasting future behaviour of load series
- Handling measurement errors, noise and missing data

Recently clustering based approaches have been developed to calibrate and update group-specific load curves using AMR data (e.g. Räsänen et al. 2010; Mutanen et al. 2011).

Furthermore, regression and artificial neural network (ANN) models have presented for load modelling and forecasting (e.g Aldo et al. 2010; Hong 2009; Beccali et al. 2004).

3.2 Physical models vs DDM models

DDM methods, which rely solely on the data, are often shown to outperform physical/mechanistic based models in several problem domains. However, a drawback of DDM methods is that they are restricted solely on the domain of training data. If new situations outside the data range are under modelling and prediction, some physical reality is required to be incorporated to the models.

The benefit of the physical models over data-based models is that, if well-formulated, they can cover also the situations, which are out of the training data. This is particularly important from the perspective of load control and management.

A challenge is however often that loads are caused by complex interactions/dynamics between customer behaviour (use of appliances etc), physical characteristics of building and environmental conditions (particularly temperature). The description of such system at sufficient level of representation is often complicated.

However, the use of simple physical models could catch major behaviour at a level sufficient for load and response management (Koponen 2011).

3.3 Hybrid models

Developing hybrid approaches, which combine the benefits of data-based models and physical models can yield significant enhancements in the load modeling. Interesting question is how to construct/update site/region-specific models efficiently using the collected AMR data and other supporting background information (e.g. temperature data, building information etc).

4 Conclusions and further SGEM activities

In the next stage, during SGEM 3FP, the objective is to develop and demonstrate new type of load modelling approaches based on the previously described data, collected both from the pilot houses (Asteka, Asko and Insulavo projects) and other supporting information sources (e.g. VTJ/RHR and FMI). Furthermore the objective is to investigate the possibilities of hybrid modelling based on the physical modelling (Koponen 2011) and DDM/CI based black-box modelling methods.

5 References

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Skön J-P., Kauhanen O. and Kolehmainen M. 2011. Energy Consumption and Air Quality Monitoring System. In: Proceedings of the 7th International Conference on Intelligent Sensors, Sensor Networks and Information Processing '11, Adelaide, Australia, pp. 163-167.

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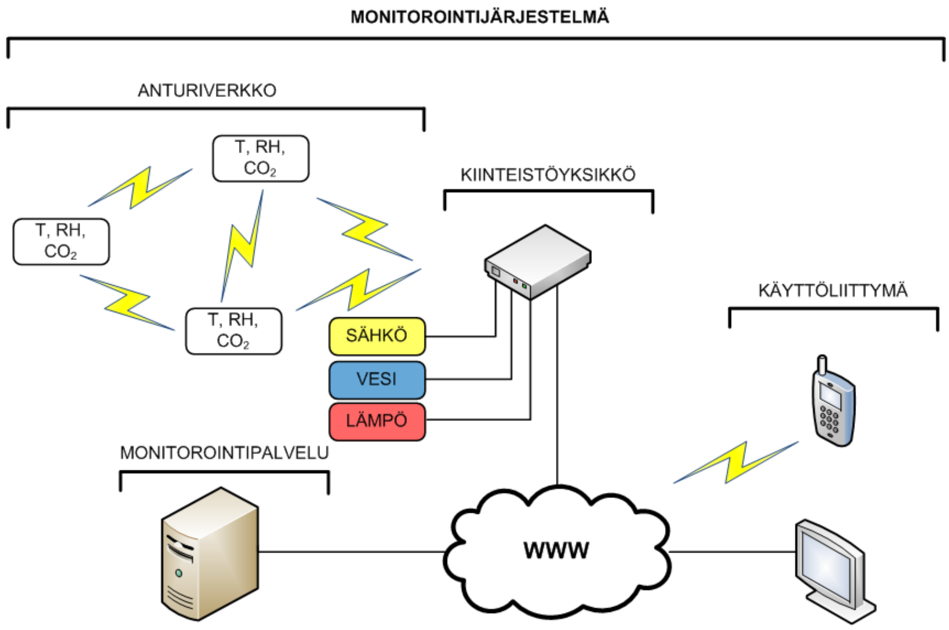
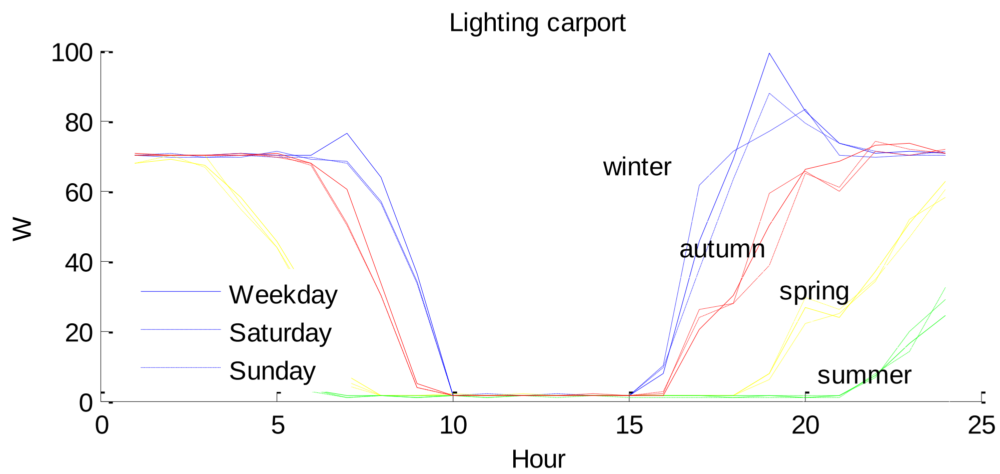
6 Appendices

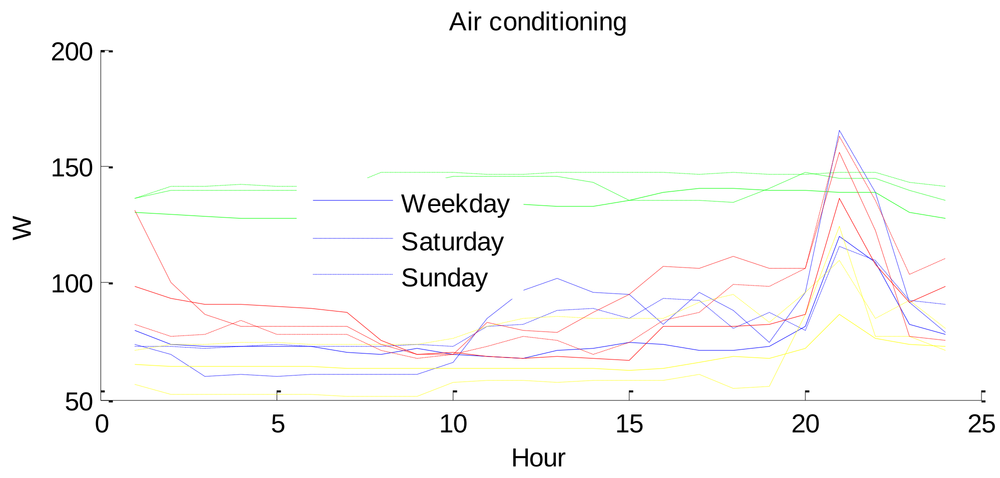
Appendix I: Overview of monitoring system



Appendix II: User-interface of the monitoring system

Appendix III: Appliance specific metering data form one target house

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Sunday
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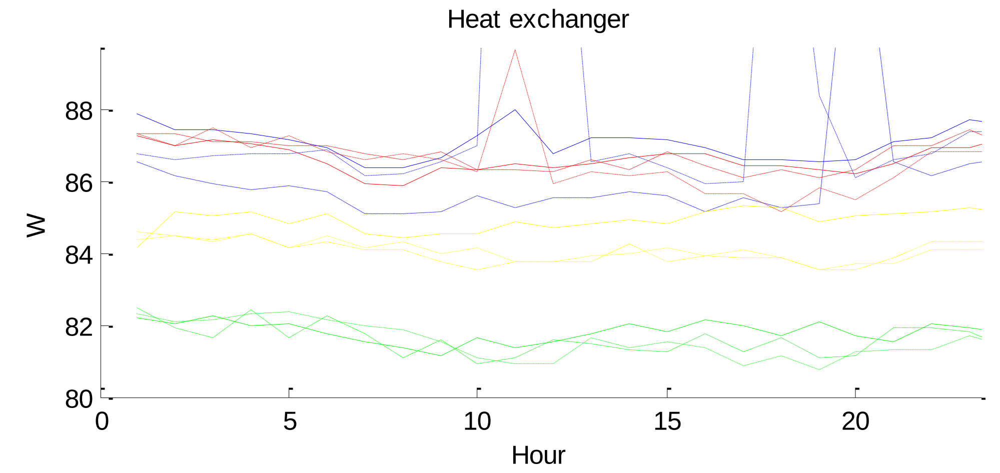
Hour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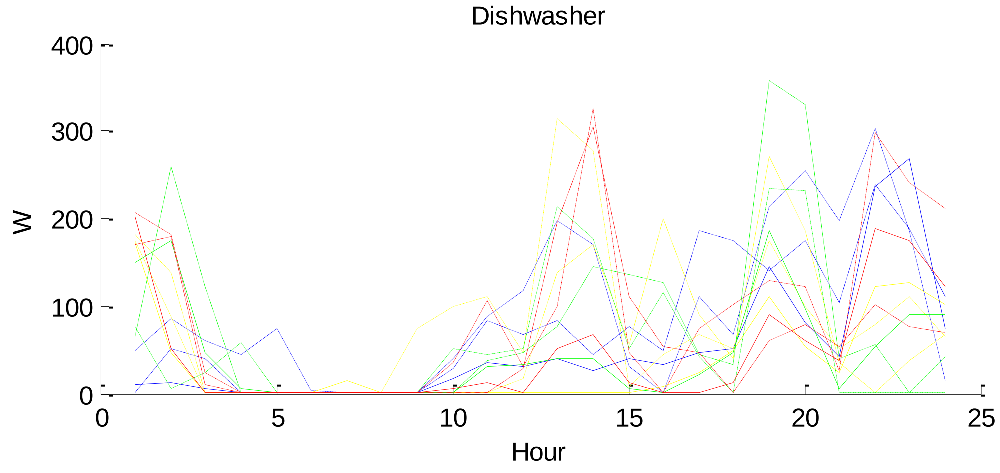
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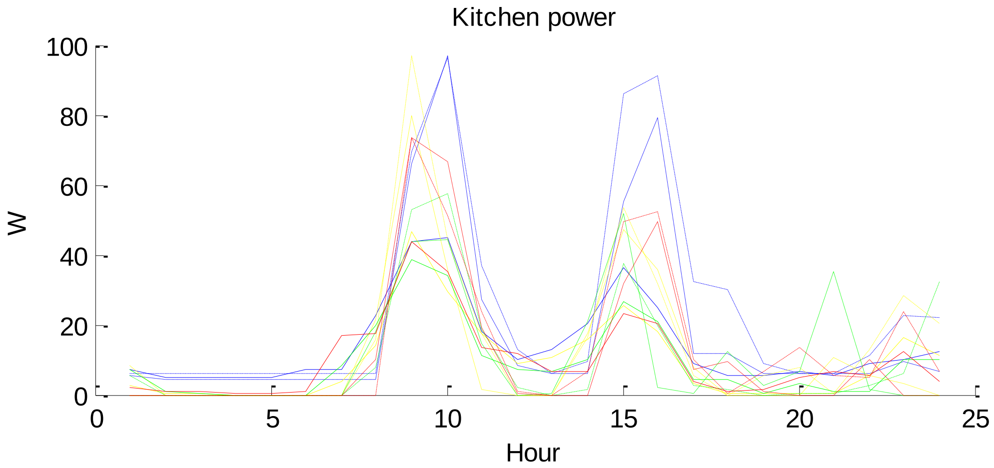
Kitchen power
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