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Load and response modelling workshop in project SGEM

10 November 2011, Kuopio

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tel. växel 020 722 111, fax 020 722 4374

VTT Technical Research Centre of Finland, Vuorimiehentie 5, P.O. Box 1000, FI-02044 VTT, Finland
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Pekka Koponen & Jukka Saarenpää (Eds.)

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Abstract

Finnish national project Smart Grids and Energy Markets (SGEM) organised a workshop on modelling loads and demand responses for smart grids and energy markets. This report gives summaries of the presentations and results of the workshop. Presentations were given by experts working in project SGEM but also by the Spanish experts who developed load and response modelling in the European smart grids projects EU-DEEP, FENIX, and ADDRESS.

The presentations by experts from Distribution Network Operators discussed 1) utilizing smart metering in network business and 2) analyzing and applying smart metering data for long term scenarios related to distribution network development. Presentations by research organizations covered 3) using smart metering measurement data in load profiling and network calculation, 4) DDM/CI approaches for analyzing and modelling loads using smart metering measurements and environmental data, 5) novel structuring of load profiles as building blocks, 6,7,8) physically based load response models for price response and direct load control, 9) bottom-up approach to response modelling, and 10) using building energy simulation for optimizing direct load control for a Virtual Power Plant.

Load and response models are needed, when aggregating demand response for energy markets and balance management, and for electricity network operation, management, and planning. The value of demand response depends on how accurately the responses can be estimated, predicted and optimized.

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Foreword

We included the initiative and commitment to organise a workshop on load and response modelling to our related task plan in the Demand Response related working package in the second funding period of the project Smart Grids and Energy Markets (SGEM). When developing the plan for the task we realised that different partners had excellent expertise that when put together nicely covers the key areas of the field and a common expert workshop is an excellent way to improve our collaboration mutually and internationally. Already then we had received a positive answer regarding participation from our foreign friends who are the experts who developed load and response modelling in the three large EU projects EU-DEEP, FENIX, and ADDRESS. In the project SGEM we also had experts from Distribution Network Operators working with these and closely related questions and we invited them to the workshop. The participants comprised of experts from research institutes in Finland and Spain, and from Finnish Distribution Network Operators. The SGEM team in the University of Eastern Finland took care of the practical arrangements excellently.

Organising the workshop was relatively easy and smooth. We knew whom to ask for the presentations and those asked were eager to come and give a presentation, because they also saw the value of this workshop to all the participants. All the presentations and summaries are of adequate quality and content, and they were prepared in time. The presentations are valuable, but even more valuable was the lively discussion initiated by the presentations. It was comfortable, efficient and fruitful to work together with these competent professionals. The feedback was positive and we look forward to continuing and further strengthening the collaboration with our Spanish friends. The experience was so good that we initially plan to have a new workshop focused on some other, but closely related aspects of demand response.

The organising committee of the workshop comprised:

Jukka Saarenpää and Harri Niska, UEF (University of Eastern Finland)

Pekka Koponen and Göran Koreneff, VTT (Technical Research Centre of Finland)
Antti Mutanen, TUT (Tampere University of Technology).

16th December 2011, on behalf of the organising committee,

Pekka Koponen and Jukka Saarenpää

Contents

Appendix E: A new approach to load profiles: the use of building blocks

Appendix F: Physically based load modeling for distributed energy resources applications: EU-DEEP project

Appendix G: Models for customer flexibility evaluation for price demand response

Appendix H: Load response models based on simple physical models of the response dynamics

Appendix I: A bottom-up approach to forecast residential load demand response to incentive signals

Appendix J: A direct load control model for virtual power plant management

Introduction

The electricity infrastructure is facing new challenges. The necessity of drastically reducing CO_2 emissions has been understood, and shortage and increasing prices are expected for some important fuels, such as natural gas. In order to cope with the situation electricity generation from renewable and distributed energy resources is planned to increase. Power generation from wind and sun is intermittent. In addition new very big nuclear power plants increase the challenges for maintaining and managing the power balance in the electricity network. Competitive electricity markets with unbundled actors further complicate the picture but provide also an essential part of the solution. In this context new technologies such as improvement in automation and distributed intelligence, and horizontal connections between systems are needed to avoid excessive expensive investments in the electricity networks and in reserve and peak power generation, and to enable reducing operational margins to save costs. This can be made possible by intelligence and automation enabled by modern information and communication technologies also called smart grids.

Accurate management of the power flows and balances is a necessary key functionality for smart grids and energy markets. Management comprises state estimation, monitoring, predicting, and controlling. All these functionalities are strongly based on load and response models. This workshop focused on a necessary corner stone of smart grids and smart energy markets. Important smart grid applications such as balance management in electricity market and network management and control rely on these models. The value of demand response is much bigger if the load and its responses can be predicted and optimised. The operational margins of the electricity networks and generation assets can be smaller, if also the loads and responses can be controlled accurately.

The main purpose of this workshop was to bring together and review the electricity load modelling expertise within the SGEM project and thus help planning and coordination of the work and collaboration. This included also strengthening and sharing the international contacts with those Spanish experts in this field that were responsible for developing load and response modelling in the big European Smart Grid projects EU-DEEP, FENIX, and ADDRESS, and have worked in this field in many other projects as well and written many good scientific papers on the subject. The workshop comprised presentations on utilizing and analysing smart metering data and environmental data for load modelling and long term scenarios, physically based load response models, and approaches for developing and structuring load models and load profiles. This provided adequate coverage of the field for meeting the objectives of the workshop.

Opening words

Dear Reader,

On behalf of the University of Eastern Finland, hosting the “Load and response modeling workshop” in Kuopio on November 10th, 2011, I would like to express my gratitude to the organizing committee for excellent work, as well as to the presenters for their contribution to this successful workshop. It was a real pleasure to have you all here; the Finnish Cleen/SGEM partners as well as the Spanish collaborators. I hope this occasion will guide and focus the work on this important area to contribute to the creation of a new level of smart electricity distribution networks which are reliable and cost effective to both customers and energy corporations.

Mikko Kolehmainen, professor

Environmental Informatics
University of Eastern Finland

Utilizing AMR in network business

Markku Kauppinen
Vattenfall Verkko Oy

Background

This is summary of a presentation how AMR can be utilized in a distribution company. Following are examples about applications based on AMR system implemented in a Finnish Distribution Company Vattenfall Verkko Oy.

What AMR enables

A view of the intended functionalities is needed for the specification of a smart metering system or an AMR (Automated Meter Reading) system. AMR enables opportunities to versatile development of the business of the distribution network operator. Figure 1 shows which business processes can utilise smart metering. Thus almost all business processes of the DNO can benefit from smart metering. But developing and replacing only the meters is not enough to achieve this. Even bigger investments are needed in the various Information Technology (IT) systems of the DNO so that the information provided by the meters can be utilised in them.

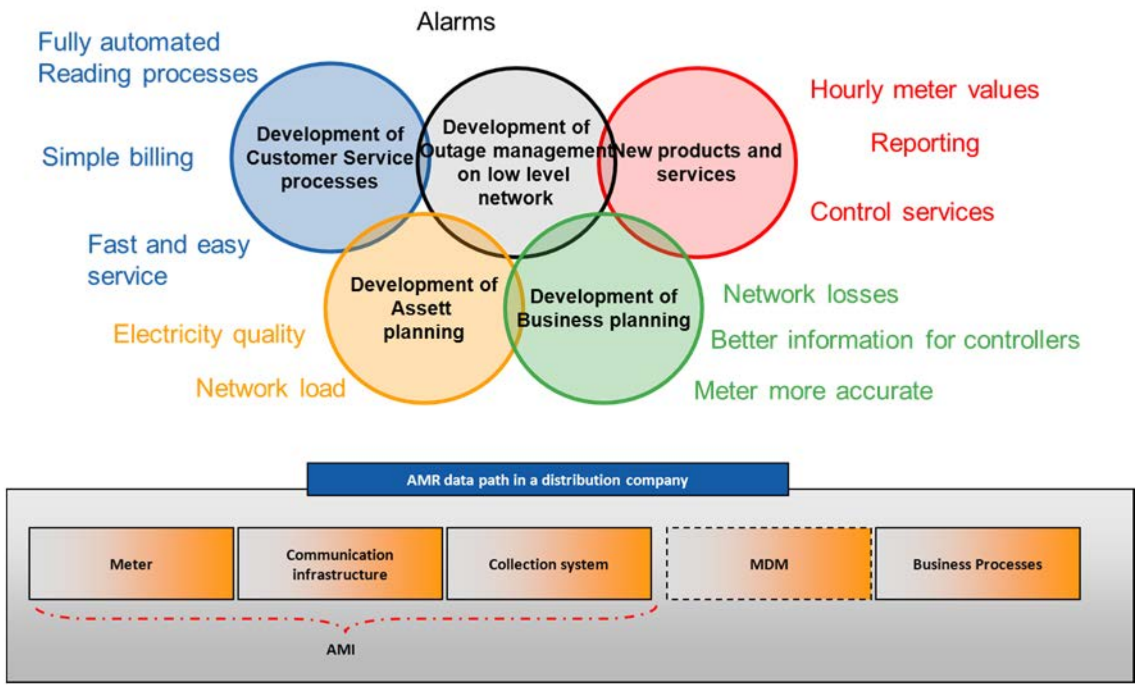

Figure 1. What AMR enables.

MDMS Main Functionality

In this context Meter Data Management System is a central IT system. Its most important functionalities include

- Supervision of received data
- Control of validation and estimation
- Control of progress of billing and settlement readiness
- Control of fuse size and connection demands
- Network loss calculation and reporting
- Control of distribution business periodization
- Power quality reports
- Service requests
- Self control
- Data quality monitoring.

Of these receiving, validating, and distributing metered data to the other systems can be especially mentioned. Monitoring and managing the quality of data is an important functionality of the MDMS. It is not limited to metered data but covers all information and data that is exchanged through the interfaces of the MDMS.

AMR and low voltage network monitoring

Traditionally only substations and MV (medium voltage) network could be monitored in real time so that alarms and measurements were received automatically. Similar automation can be extended to cover also the LV (low voltage) network by using the AMR-meters and a smart metering system. This will multiply the amount of distribution network that is automatically monitored. The most important functionalities include in addition to automatic alarms also queries to individual meters or meter groups initiated from the control room. Such queries are mainly used for getting fast real time situational awareness regarding those parts of distribution network that seem to be most critical at that time. As a result the following benefits are achieved:

- Number of customer trouble calls reduced
- Faster fault repairing and shorter interruptions
- Reduced amount of trouble shooting and unnecessary customer visits
- Security: real-time information of zero conductor faults and voltage level
- Accurate and extended reporting and statistics.

On-line web presentation

Benefits from AMR to end customers such as consumers are often mentioned. One such benefit is provision of metered data to the use of end customers. Hourly metered data can be shown over the Internet as soon as it is in the data base of the MDMS. In Finland the new electricity market legislation requires that the customers have access to hourly metered data in the beginning of 2014 at the very latest. The customers benefit from this data in monitoring their energy consumption and identifying targets for energy saving measures. Reporting the hourly metered data has big impact in increasing the awareness of their own energy usage. Figure 2 shows the on-line web report. The customers have quickly and widely adopted this service.

la 23.10.2010	Sähkön käyttö (kWh)
00:00 - 01:00	4,92
01:00 - 02:00	3,59
02:00 - 03:00	1,52
03:00 - 04:00	1,18
04:00 - 05:00	1,63
05:00 - 06:00	1,51
06:00 - 07:00	1,53
07:00 - 08:00	2,7
08:00 - 09:00	0,55
09:00 - 10:00	0,38
10:00 - 11:00	0,39
11:00 - 12:00	0,39
12:00 - 13:00	0,45
13:00 - 14:00	0,47
14:00 - 15:00	0,59
15:00 - 16:00	0,55
16:00 - 17:00	0,53
17:00 - 18:00	0,44
18:00 - 19:00	0,38
19:00 - 20:00	0,38
20:00 - 21:00	0,45
21:00 - 22:00	0,4
22:00 - 23:00	1,99
23:00 - 00:00	4,3

Figure 2. On-line web presentation for a family house equipped with accumulated electric heating (electric heating with a heat storage tank).

Analyzing AMR measurements to be applied for long term scenarios

Ville Rimali, Pirjo Heine & Markku Hyvärinen
Helen Electricity Network Ltd., Finland

Matti Koivisto & Matti Lehtonen
Aalto University, School of Electrical Engineering, Finland

Foreword

The presentation "Analysing AMR measurements to be applied for long term scenarios" reports a work that has been carried out in the Smart Grids and Energy Markets (SGEM) research program coordinated by CLEEN Ltd. The project is a part of the CLEEN SGEM project representing during the first funding period the work package WP 1.4 as Task 1.4.1: First Generation Smart Metering and Spatial Load Analysis. The work continued in the second funding period as WP 6 and Task 6.11: Spatial load analysis. The partners of the work have been Helen Electricity Network Ltd., Aalto University School of Electrical Engineering, TEKLA, and Vantaa Energia Sähköverkot. Vattenfall joined the task during the second funding period.

This presentation mainly focuses on the research work done by Ville Rimali from Helen Electricity Network Ltd. and Matti Koivisto from Aalto University.

The spatial forecasting of the electrical energy and power is a vital task for distribution system operators (DSO). Spatial load scenarios provide information how much power must be delivered (magnitude), where (space) and when (time) it will be needed. The time scales for forecasting are long. While realization of investments in high voltage transmission routes and primary substations in city urban areas may take from several years to over a decade the scenarios should cover e.g. 30–50 years. The total time scale is several decades. However, some intermediate views should be taken e.g. by having time steps of 10 years. The more remote future the forecasting covers, the more alternative scenarios should be considered.

The starting point of the future spatial forecasting is the present loading. The development of the whole society is the general guide line for the future. The socio-economic factors of the area in question, like the growth of population and workplaces, the purpose of use of the land (residential, industry, municipal, etc.), the costs of energy, political incentives and penalties especially in the energy field, affect the future energy use. In addition, the present load profiles are developing. In spatial forecasts, some basic factors are taken into account. The future will bring changes for this present situation and the main developments arise from

- changes in present consumptions
- future growth and redevelopment of areas.

At the moment, AMR meter deployment is going on in Finland. By the end of 2013 practically all the customers will have new meters. In the future, a considerable amount of hourly metered load data will be available and new applications based on this data is being developed.

In this SGEM project utilizing AMR data to be installed for long term spatial load forecasts, the measured load data acts as a starting point of the scenarios. In addition, by analyzing the measurements understanding and knowledge of the characteristics of the present use of electricity can be achieved. Only by understanding the characteristics of the present electricity use, changes and modifications modeling the future can be included in the forecasts.

In this SGEM project, the main performed analyses are:

1. Background data from various sources, like the network information system, the customer data base, municipality registers, interviews, the temperature data, was linked to the measured AMR data. One major question is the common data between various data bases. Between the data bases within DSO, the common data was straightforward to determine. However, the combining of AMR data to the data of city registers may be challenging. In this project, this linking was made with coordinates and succeeded well. When having done this, a major amount of background data was available. In this part, e.g. specific consumptions were determined for the demo areas for various customer groups. This data was further applied in the scenarios when modeling the effect of future construction of the city on spatial electricity use.

2. Present spatial load curves can be modeled utilizing linear regression where outside temperature, day length, and day type are used as explanatory variables. Based on hourly measurements of an individual customer, different customer types can be recognized mathematically exploiting key figure method. Customer groups can then be obtained using clustering or limiting value method.

3. Based on hourly measurements of an individual customer, different customer types can be recognized mathematically exploiting principal component analysis (PCA) and clustering.

A spatial simulation method is applied to create the load forecasts. In this part, the spatial future construction of the area is critical input data. In addition, the future changes of the use of electricity and totally new loads can be added to the present, temperature normalized load curve. Thus, it is possible to model the changes arising in the coming decades.

In the project, spatial load forecasts were created for two different districts of Helsinki. Only future construction plans of the city were modeled. The other city district has mainly apartment houses with households and offices, the other mainly small and row houses. The expectations of the coming construction activity are considerably different and are clearly seen in the results. The scenarios covered the years 2010–2030. For the time being, the first scenarios and demos have been created manually. During the coming months, the analyses are deepened, new demo areas are handled and the actual demo tool is further developed. Main efforts are addressed also to the modeling of the future development of electricity use.

Reference

SGEM report: Development of spatial load forecasting utilizing AMR measurements, 2/2011Master thesis: Ville Rimali, Etäluettavan energiamittaustiedon hyödyntäminen alueellisissa kuormitusennusteissa, Aalto yliopisto, 11/2011.

Using AMR measurements in load profiling and network calculation

Antti Mutanen
Tampere University of Technology (TUT), Finland

Background and motivation

Finland has a long history in load profiling and network calculation with load profiles. Finnish electric utilities started to co-operate in load research in the 1980's. As a result of this co-operation, load profiles were born. In 1992, Finnish Electricity Association (Sener) published customer class load profiles for 46 different customer classes. Since then, these load profiles have been used extensively in distribution network calculation. Load profiles are used for example in load flow calculation, planning calculation, state estimation, pricing and tariff planning. Pretty much any function in a distribution management system that contains either load flow calculation or load estimation relies on load profiles.

However, there are several defects in the current load profiles. The biggest problem is that the load profiles are old. The original Sener load profiles, which are still used in many utilities, are based on measurements that were done over 20 years ago. This is not acceptable, since electricity consumption habits change over years. For example, during the past 20 years the amount of heat pumps and air-conditioners has multiplied, the use of entertainment electronics has increased and electricity consumption in recreational dwellings has changed. Furthermore, in the future, the changes will be even bigger if plug-in hybrids and customer-specific distributed generation become popular. The load profiles have also several other error sources. Such as, sampling errors, errors caused by geographical generalization and errors related to customer classification.

While load profiles have grown old, the requirements for network calculation accuracy have become tighter than before. Modern smart grid functions, such as co-ordinated voltage control, require accurate information on the network state. When automation and intelligent control are used to increase the network utilization rate, the requirements for planning calculation and state monitoring become tighter. Therefore, smart grids need also better load models.

TUT goals in load profiling

In Tampere University of Technology (TUT), our goal is to improve load profiling accuracy by utilizing the measurement data provided by AMR systems. AMR data can be used for creating new load profiles and updating customer classifications. Since AMR data is collected continuously, adding dynamic and adaptive properties to the load profiles is also possible. In our vision, dynamism and adaptivity are achieved through constant load profile updating. More accurate load profiles will ultimately lead to more accurate network calculation.

For easy and fast practical implementation, the new load profiles should be compatible with existing network calculation software. That is why the load profile format is kept unchanged. The full potential of existing load profile format is harnessed by updating the load profile content. Currently, load profiles are expressed either as *topographies* or as *index series*. Topographies can contain more information and that is the format we are going to work with. Topographies contain expectation values and standard deviations for each hour of the year. They can also include monthly temperature dependencies [%/°C] and power factors.

Temperature dependency parameters

Outdoor temperature has a clear effect on electricity consumption. This should be taken into account when making load forecasts and planning calculations. AMR measurements and regional temperature measurements make the calculation of temperature dependency parameters possible. The temperature dependency parameters can be calculated with simple linear regression. In our calculation method, the effects of daily and monthly fluctuations in electricity demand are eliminated by choosing the dependent and determining variables as follows:

- Dependent variable (regressand): the percent error between the daily energy consumption and the average daily energy consumption on a similar day (same day of the week and month).
- Determining variable (regressor): difference between the daily average temperature and the average temperature on a similar day.

Linear regression from this data set gives results directly in the form %/°C.

Clustering

There are several ways to use AMR data to improve load profiling accuracy. AMR measurements can be used to reclassify customers to the nearest existing customer class load profile or they can be used to update existing customer class load profiles. Naturally, the best result is achieved if these two methods are combined. Combining customer reclassification and load profile updating requires an iterative process where reclassification and profile updating are repeated until the customer classification does not change anymore. Basically, this is a clustering problem and can be solved with clustering algorithms such us K-means or ISODATA. Figure 1 shows how the above-mentioned methods affect load profiling accuracy.

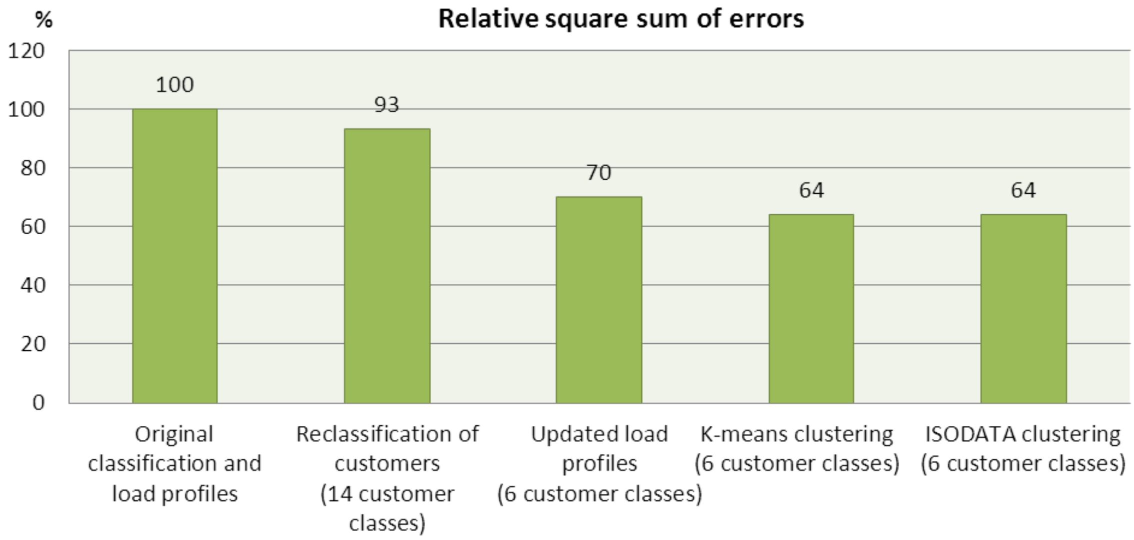

Figure 1. Comparison on the impact of different load profiling methods.

The clustering method we have developed utilizes weighted K-means clustering with pattern vectors. Each AMR measurement series is converted into a pattern vector witch consist of 864 hourly values. The hourly values are calculated as monthly averages for three day types (workday, Saturday and Sunday). Pattern vectors help us to reduce the dimension of the clustering problem and since they are formed from temperature normalized measurements, they can contain information from several different years.

The flow chart in Figure 2 describes the clustering method developed. After the formation of pattern vectors, the initial cluster centres are calculated using the original customer classification. After first K-means clustering, outliers which do not fit any cluster are filtered and customer-specific load profiles are calculated for them. Then the K-means clustering is repeated and finally customer class load profiles are calculated for each cluster.

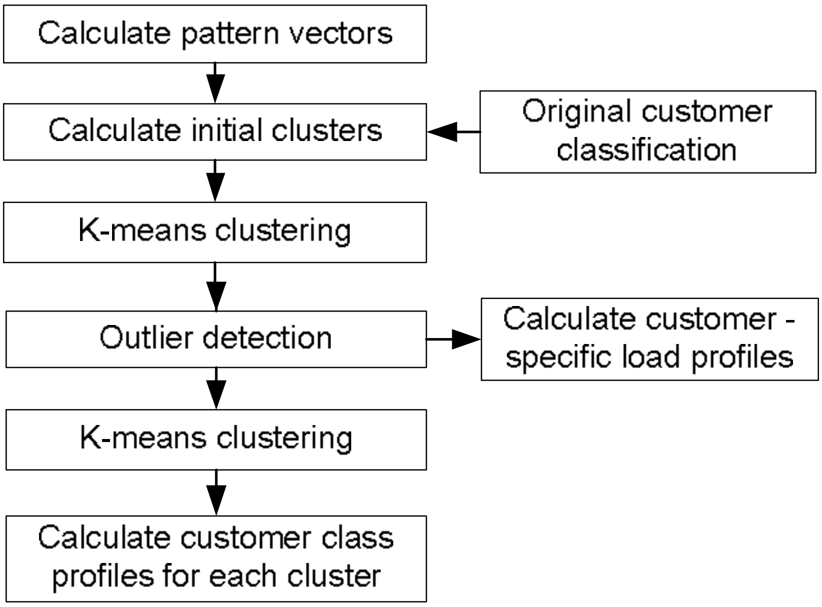

Figure 2. Flow chart of the clustering method developed.

Customer-specific load profiles

Since all customers cannot be modelled accurately with customer class load profiles, customer-specific load profiles are also needed. Load profiling accuracy can be enhanced by increasing the number of customer-specific load profiles but the amount of load profiles that can be handled in current network calculation software is limited. Therefore, we must select the customer-specific profiles with care. In the previous clustering method, outlier filtering was done so that only those customers who would have the largest absolute profiling errors when using customer class load profiles are selected for individual profiling.

When forming customer-specific load profiles, we should remember that last year's measurement does not directly forecast next year's electricity consumption. The customer-specific load profiles, as the other load profiles, should be normalized to long term monthly average temperature. When used, the load profiles are corrected to the forecasted or expected temperature by using the temperature dependency parameters.

A single customer usually has high stochasticity. The stochasticity can be filtered by using type days (workday, Saturday, Sunday) and calculating hourly mean values for each month. Type days also enable the calculation of standard deviations which would otherwise be impossible from one year's measurement data. The final customer-specific load profiles are formed from the type days. Special days, such as Easter, Christmas and New Year's Day, should of course be taken into account when forming the final load profiles.

Ongoing and future work

During the SGEM project, we will use the aforementioned load profiling methods in a demonstrative Matlab program that uses AMR data to reclassify customers and updates load profiles. As Figure 3 shows, the Matlab program will read AMR measurements from a database, performs clustering and exports updated customer classifications and load profiles in to the network information system (NIS).

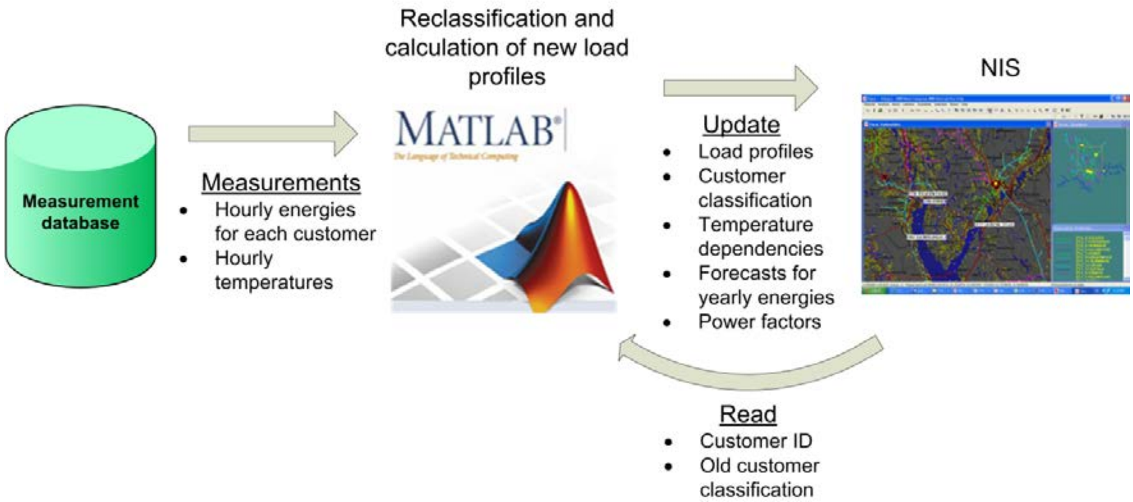

Figure 3. Load profiling demonstration.

Once the load profiling is done, we will use NIS to make calculations and comparisons on how the new load profiles affect network calculation and state estimation accuracy.

DDM/CI methods and experiments in load modelling using AMR and other environmental data

Harri Niska & Jukka Saarenpää
University of Eastern Finland (UEF)

Introduction

Load modelling is an important part of planning and management of smart grids. The AMR meters, which are soon to be found from every home, provide a large amount of electricity measurement data. In addition, huge amount of external environmental data, which has been collected over the years to the various registers of the society, are constantly more open and available to public use.

Some of the registers currently available and possibly opened for free use in the future include:

- Building information (VTJ/RHR/KTJ)
- Socio-ecomonomic data (Statistics Finland)
- Weather (FMI)
- Land use (MML/CORINE/SLICES).

The better availability of large amounts of data provides interesting opportunities in load modelling and possibly enables creation of a new type of models that are more accurate. For privacy and technical reasons the data is often restricted to regional/spatial level, which suggests developing regional modelling (or spatial analysis) approaches.

DDM/CI techniques

When dealing with large amount of environmental data, it is often difficult for human to notice the patterns and interrelationships within. However, in “data-rich” conditions data-driven modelling (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:

- Neurocomputing
- Evolutionary and genetic algorithms
- Fuzzy logic
- Clustering methods (k-means/fuzzy c-means/Isodata).

The DDM methods combined with conventional statistical methods and geocomputing techniques could result in 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 (i) searching complex spatiotemporal patterns, load curves, in different data presentation levels, (ii) modelling non-linearity and temporal dynamics of loads, including time-delays and interaction with external variables, (iii) forecasting future behaviour of load series and (iv) handling measurement errors, noise and missing data.

Main load modelling experiments using DDM/CI methods so far

Redefinition of load curves

Methods for redefinition of load curves (Figure 1) using AMR data were developed using the data from 4454 small scale customers (Savon Voima). The basic principles of the method are described in Räsänen and Kolehmainen (2009) and Räsänen et al. (2010). At general level, i.e. not paying attention to the details of implementation, the main stages of the load curve redefinition were as follows:

- Temperature corrections
- Feature extraction from AMR data
- Clustering AMR data using the features extracted (SOM+k-means)
- Extracting new load curves basis of cluster centers
- Evaluating the new load curves.

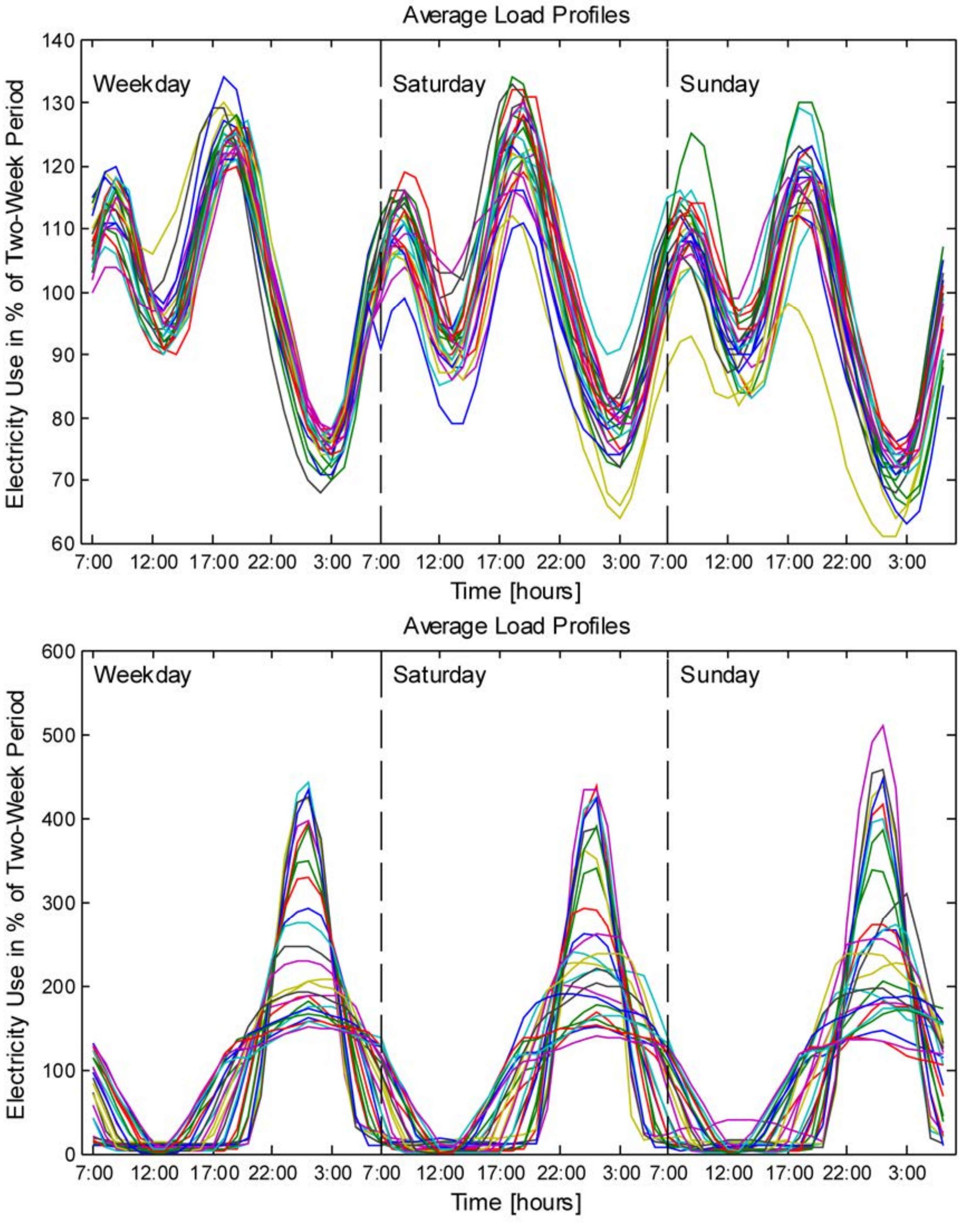

Figure 1. Load curves redefined from the AMR data.

Regional modelling

Spatial load forecasting is required in long-term distribution network planning. As there is high uncertainty involved in the long-term planning, it is recommendable to prepare for several possible scenarios. To facilitate this process regional modelling experiments were done. The research so far has been mainly focused on:

- Assessing regional loads in scenarios involving changes in residential heating systems using data from Population Register Centre's Building and Dwelling Register
- Modelling the regional potential for PHEV adoption based on socio-economic characteristics using data from Statistics Finland's Grid Database and Finnish Transport Safety Agency's Vehicular and driver data register.

In both cases the common approach has been to first simulate the phenomena leading to changes in loads (i.e. changing heating type or obtaining electric vehicle). The question is then: How to predict which consumers change their electricity consumption behaviour by obtaining new technology? Consequently, new or updated load models must be adapted to the scenario, the problem being: How to select or modify the load model when consumers change their behaviour?

The basic hypothesis is that similar customers have similar behaviour, which leads to the question of how to measure the similarity.

A methodology for predicting regional electricity loads in scenarios where consumers change their residential heating system has been proposed by Saarenpää (2011) and Niska et al. (2011). The modelling has been demonstrated using rich internet application based on Silverlight, Matlab and ArcGIS Server (Figure 2).

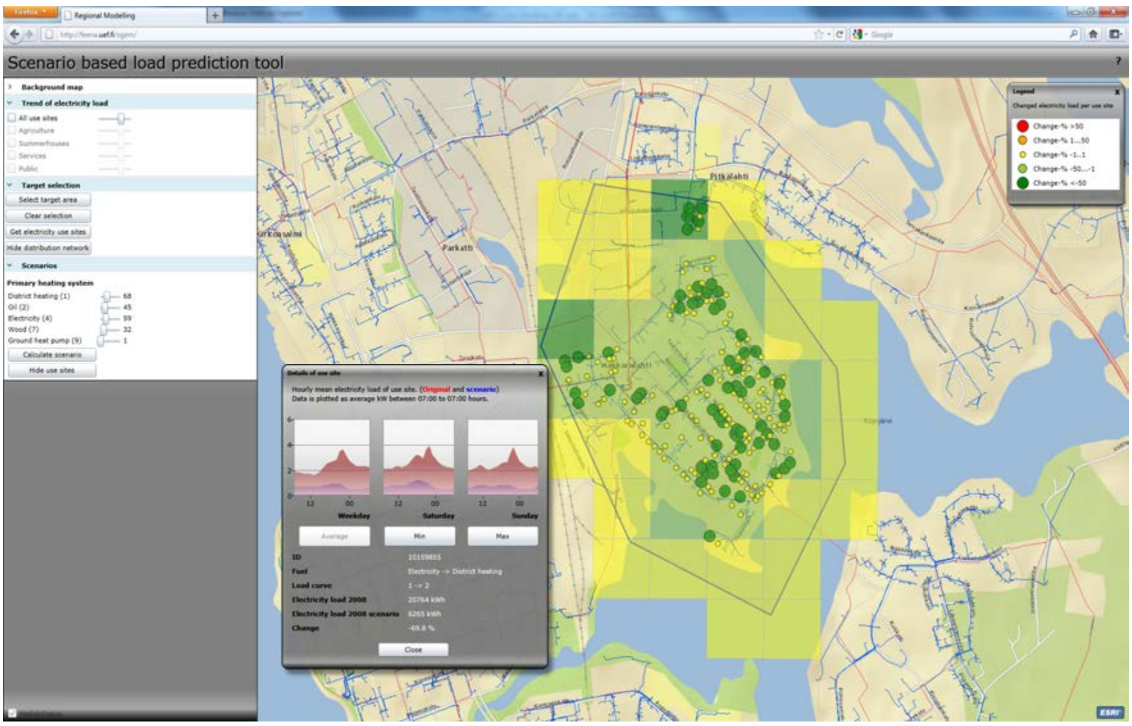

Figure 2. Regional modelling tool for assessing loads in heating system scenarios.

The idea is to reduce the uncertainty involved by enabling easy creation and inspection of multiple scenarios. In each scenario, the consumers who are most probable to change their heating system according to given scenario are first identified. This could be modelled using historical data of heating system changes, but since such data is not easily available, utilizing expert knowledge is necessary. In the second phase, new load models are allocated using non-linear regression based on the Self-organizing map. In the regression model, building characteristics are used as independent variables while load curve type or yearly electricity consumption are used as the dependent variable.

Conclusions

AMR data combined with external data will open new possibilities in the field of load modelling, both from the perspective of network management (load-response) and network strategic planning. Data-driven and computationally intelligent methods excel in finding patterns and previously unknown interrelationships in new data.

Further work is required in developing and applying DDM/CI approaches for constructing physical-based load/response models using AMR and external environmental data (such as temperature measurements, building information, socio-economic data).

Additionally, in respect to the strategic planning of the electric grid, new type of spatial load modelling methods are needed for assessing loads in future scenarios. In this context, particular issues include the encapsulation of DG/DER scenarios into load models (e.g. EV, solar panels) and the prediction of behaviour on different regions.

In parallel with developing new load modelling methods and approaches, technical issues related to data interfaces and model integration should be investigated. Moreover, modelling approaches developed should be demonstrated to the potential end-users.

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A new approach to load profiles: the use of building blocks

Göran Koreneff
VTT, Finland

Introduction

There are 46 load profiles in use in Finland (SLY 1992, Seppälä 1996) and they stem from sparse and infrequent measurements in the 1980's and early 90's. The number of customer end recordings behind each profile varies. For single family house profiles, the number of recordings behind them is between 4 and 56, but it is good to remember that each recording might be just a few months long. They are also from different seasons and years. The profiles have nevertheless proven their usefulness for the network utilities. VTT updated these models partially in 2002, but access to the updated models is restricted to the project partners of that time.

With AMR being on the march into every household, the availability of measurements will be on a very different scale. Thus, updating the national profiles or even creating new local network dependent profiles will be possible, even updating or automating the profile classifications (see e.g. Mutanen 2010, 2011a, and 2011b). However, especially for network long-term planning purposes, national easy-to-use and clearly defined profiles will be advantageous.

The main obstacles to continuing touse the existing classification of 46 load profiles are the overwhelming changes that take place at the end-users' consumptions. A lot of new significant part loads have been or are to be introduced in households. The new additional part loads in the households do not only change the annual energy consumption, but they also change the profile and in very decisive ways. In addition, parts of the loads are temperature dependent, other parts not. Scalability of load curves is another problem, as even if the right class is used, the internal share of the part loads might be wrong for a single customer. The question is, shall we nevertheless try to introduce new profile classes for all the main combinations, use the old classification, or is there another solution?

The building block research here is based on the research recommendations (Koreneff 2010) from the Inca-project.

The problem

There are 12 load profiles for single family houses:

110 direct electric heat, water boiler < 300 liter
120 direct electric heat, water boiler = 300 liter
130 direct electric heat, floor heating > 2 kW
210 partial storage electric heat, short disconnect periods
220 partial storage electric heat, long disconnect periods (7–22)
300 full storage electric heat, (7–22)
400 heat pump
510 dual heat, flat tariff
520 dual heat, night tariff
530 dual heat, seasonal tariff
601 no electric heat, no electric sauna
602 no electric heat, electric sauna.

In the future, we would need a tremendous amount of profiles (NB! the calculations have been updated from the workshop presentation):

- 4 types of basic one family houses heating modes (no electric heating, direct heating, partial storage heating, full storage heating)
- 4 types of basic electric heating sources with different behaviour (direct electric, ground source heat pump (GSHP), air-water heat pump (AWHP), and exhaust air heat pump (EAHP))
- 6 additional heat source possibilities with different behaviours (no additional, air-air heat pump (AAHP), AWHP, solar heat, micro-CHP, and a manual source such as a stove/fire place)
- 11 different electric vehicle (EV) constellations (0…2 pieces, full EV(FEV) or plug-in hybrid EV (PHEV), smart or dumb charging)
- 4 types of micro generation possibilities (none, photovoltaics (PV), wind power, micro-CHP)
- electric sauna or not.

This would result in (1 + 3*4)*6*11*4*2 = **6864** new distinctive load curves for one family houses, which is not manageable. Even with AMR, it would be very difficult to get enough measurements for all the classes, as some combinations are rarer than other.

Approach

One solution to the exploding amount of profiles needed is to divide the load into feasible and more easily managed part loads (building blocks), see Figure 1. A similar approach has been studied and tested in different connections for household electricity, that is, household appliances and lighting, but we are not convinced that is the right way for load profiles. Here we plan to do the opposite: model the household electricity (appliances and lighting) as a whole. Instead, model large distinctive parts of the load (e.g. heating, EV) separately. There is, for example, no benefit in modelling a coffee maker, as it is such a small part of the whole, there is no CIS information on it, and the usage is in short and quite irregular spells. As there are several small, independent and stochastic loads in a single household, it is easier and more useful to manage their sum load. On the other hand, modelling of the direct electric heating separately is very useful: it is large, it has a distinctive temperature dependent profile which can be influenced by other likewise distinctive profiles (additional heat sources such as AAHP or solar heat).

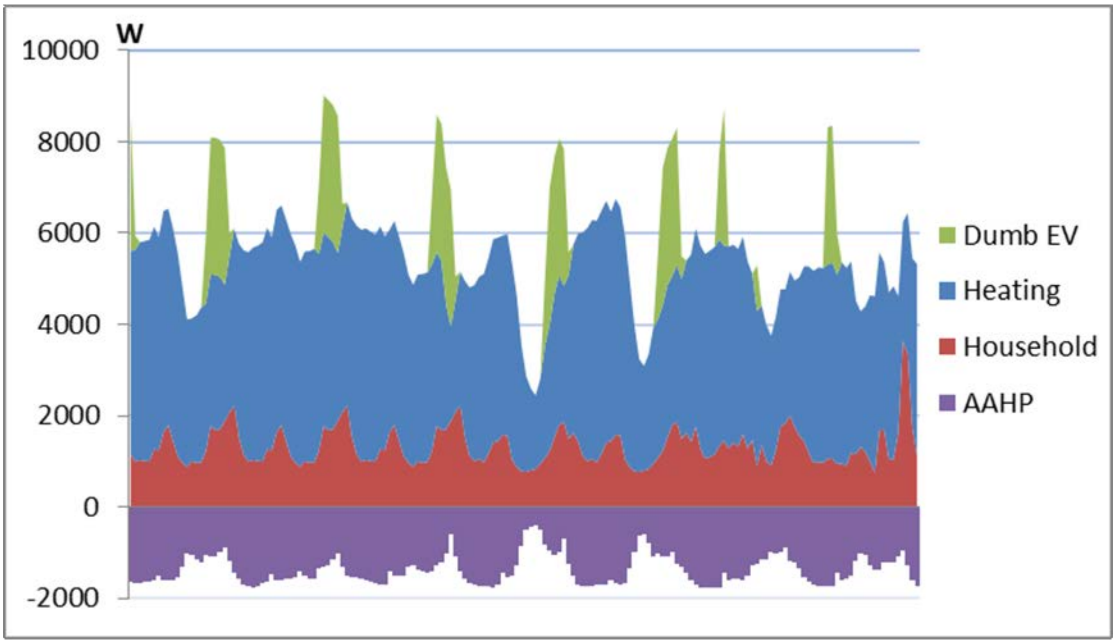

Figure 1. The end-user load can consist of several very distinctive part loads, even negative ones (i.e. savings). The sum of the part loads form the total end-user load.

The building block approach suggests that we construct a user’s load using part load profiles, which can be added or subtracted. For example, the customer’s load can be calculated as:

+ household electricity
+ DHW
- solar heat panel for DHW (= savings)
+ direct electric heating
- AAHP in electric heated house (= savings)
+ AAHP during the summer
+ one PHEV without smart charging
+ sauna.

The number of building block (bb) load profiles can now be restricted to (NB! calculations have been updated from the workshop presentation):

- Household: 1 bb; electricity used for appliances, lighting etc.,
- Domestic hot water: DHW: 1 bb
- Basic heating need: 1 bb; basic heating need is also the same as direct el heating
- Additional main electric heating curves or models: 3 bb; GSHP, AWHP or AAHP, EAHP, etc.)
- Heat storage: 1–3 bb (zero, 3 load curves, or a model dependent of storage size and heat demand)
- Heating saving (negative) building blocks: 5 bb; AAHP, AWHP, stove, solar, micro-CHP
- Electricity saving building blocks: 1–3 bb; PV, wind, micro-CHP
- Extra consumption blocks: 5 bb; EVs, directly heated sauna.

All in all, approximately 1 + 1 + (4 *(1…3) + (0…3)) + 5 + 3 + 5 ≈ 20…27 building blocks are enough to construct any single family house constellation.

Discussion

One of the benefits of building blocks is that part of the loads can be calculated instead of relying on measurement. Traditional load profiles have also been partly modelled through their temperature dependency, so it is not a new idea, but here the benefits of modelling are becoming clearer, as we can use separate models tailored for each sub-load. When one uses one profile for the whole load, it is not easy to adjust it to take into account condition changes that affect only part of the load, but using tailored sub-load models makes it easier to take into account that, for example:

- temperature dependency concerns only the heating and the regression coefficient can itself be temperature dependent,
- demand response is not easily measured, per se,
- sub-loads may depend on variable inputs such as the spot price or varying tariffs,
- heating electricity may depend on the usage of auxiliary electric or non-electric heaters, and
- usage of heat storage is not only a amplitude issue, it is also a time duration issue.

Some parts of the loads, especially the household electricity, are best based on measurements. Household electricity is too complicated to be modelled using sub-loads; a better and a more usable load profile can probably be achieved using measurements of household electricity.

The building block approach is modular and as such also easy to expand. Amending single building block doesn't affect other building blocks. Overall, maintenance of the system shows promises of being very straight-forward.

Results

The aim of this project is to test the feasibility of this approach by designing the setup and constructing logical rules for the usage of building blocks. As a part of the feasibility study, a number of part load profiles and models will be constructed based on, for example, SGEM funding period 1, 2, and 3 results (among others Laitinen 2011), Inca-project results (Koreneff 2010, Mutanen 2010), SEKKI-project results (Koreneff 2009).

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Physically based load modeling for distributed energy resources applications: EU-DEEP project

Carlos Alvarez
University of Valencia, Spain

This presentation is devoted to reinforce the need to detailed physical modeling of customer processes to allow credible customer response to energy prices in electricity markets.

The first part of the presentation is oriented to connect Customer Demand response and SmartGrids initiatives. Customer issues are centric in SmartGrids, and a massive response of the customers is a basic objective of this initiative as rational and intelligent energy consumption is basic in the framework of Distributed Energy resources implementations and solutions.

Most of Demand Side Management initiatives have been Supply oriented, and now is the time for fully integrated Supply and Demand solutions.

A large 5 years European Project (EU-DEEP, The birth of a EUropean Distributed EnErgy Partnership that will help the large-scale implementation of distributed energy resources in Europe) was completed in 2009, whose objective was to investigate opportunities to enhance the integration of Distributed Generation, Storage and Demand in Europe.

The Institute for Energy Engineering of the Universidad Politecnica de Valencia was in charge of the Demand Research and Modeling tasks in this project, and some relevant results are shown in this presentation.

The energy consumers were first segmented all over Europe according energy consumption issues, resulting in: 93 segments for residential consumers, 154 in the commercial and 378 in the industrial segment.

All these segments where documented (mainly with utility data) and ranked according to their suitability to implement Distributed Generation, Distributed Storage and Demand Response.

The highest ranked segments were analyzed and modeled in detail, in order to produce real figures and information that allowed the selection of real customers for three pilot experiences that were implemented in EU-DEEP.

The main objective of these experiences was to show the ability of Distributed Energy Resources (DER) in providing Balancing Mechanisms. More specifically:

– Case 1: Aggregating Demand response and DER contracts to compensate imbalances caused by Renewable Energy Generation.

– Case 2: ESCO/Aggregator using customer flexibility and micro-CHP for selling Balancing Services.

– Case 3: ESCO internal balancing to cope with long term contracts.

The developed modeling tools were Physically Based process oriented, according to Figure 1.

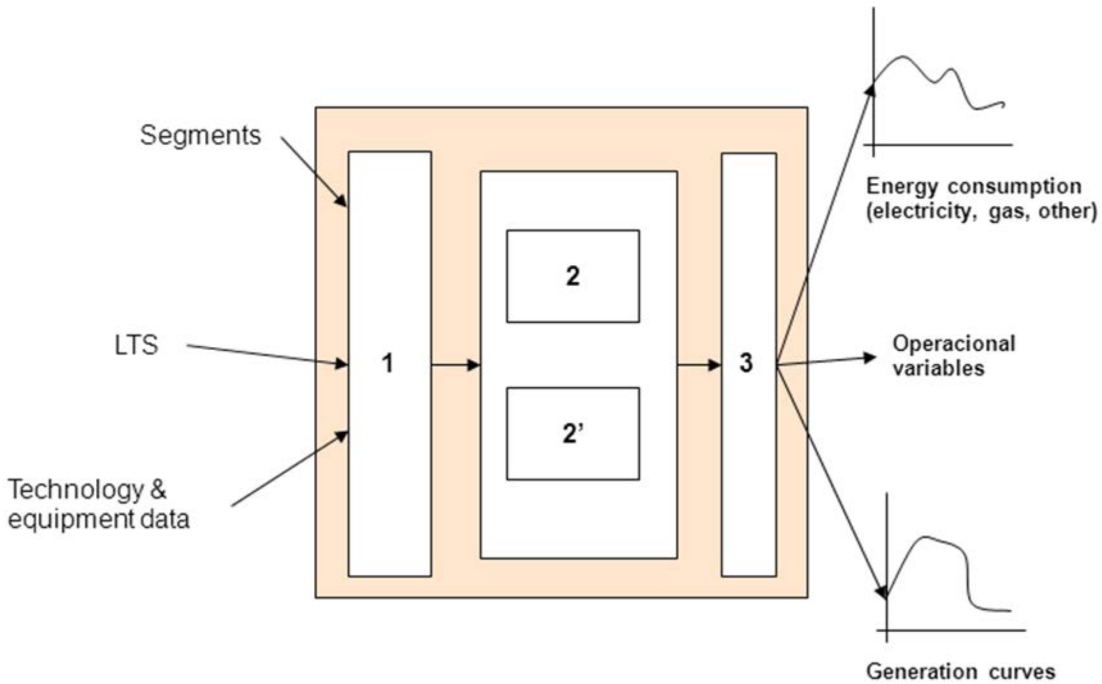

Figure 1. Main steps of the modeling process.

Where three modeling steps can be identified:

- Demand Module, where the use of each single process is identified.
- Physically Based Module, where each process is modeled according to physical mathematical description laws.
- Aggregation module, where all customer consumption processes are aggregated to find the customer total energy consumption.

The presentation is completed with a demonstration about the use of some models: Hotels, Apartments and one industrial example.

Editor's explanations of abbreviations:

ESCO Energy Service Company

LTS Local Trading Strategies that connect DER with the electricity market. (See Figure 1.)

Models for Customer Flexibility evaluation for Price Demand response

Carlos Alvarez
University of Valencia, Spain

This presentation is devoted to show a methodology for customer energy demand analysis and organization for participation in electricity markets.

The organization of the customer energy needs into Demand Bids is first discussed, where each "piece" of demand required by the customer is assigned a price that corresponds to the benefit the customer will obtain by consuming this energy.

The result of this demand organization is the hourly energy need for this customer, as shown in the next figure (Results from EU-DEEP project):

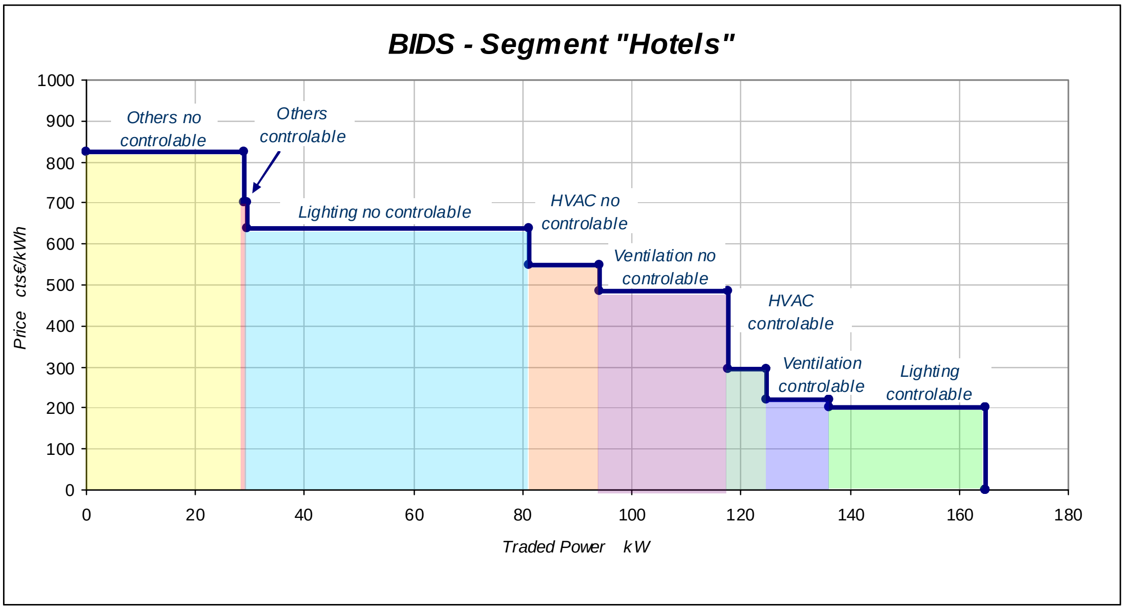

Figure 1. Demand Bids, an example.

One of the most relevant issues in building this “demand Curve” is the price determination, that is usually determined by means of some other indirect costs/benefits (Substitution costs, Stand by generation, Contracted insurances, Long term planning costs, etc.).

More important for customer demand participation in ancillary services markets is the short term ability to modify its consumption. This can be found in the processes where some short term flexibility in the energy consumption can be found. This flexibility can be organized also in Demand Packages (DP) characterized by:

- Trigger price: to account costs incurred by the reduction/increase of the energy consumption
    - direct costs
    - costs of the control equipment
    - cost of Storage.
- Size and shape of the package.
- The notice time required for the change in the demand
    - other limitations such as reliability of the package (possible penalties once committed), number of occasions/season, year, etc.

Once identified this process flexibility and associated price, it can be organized as shown in the Figure 2:

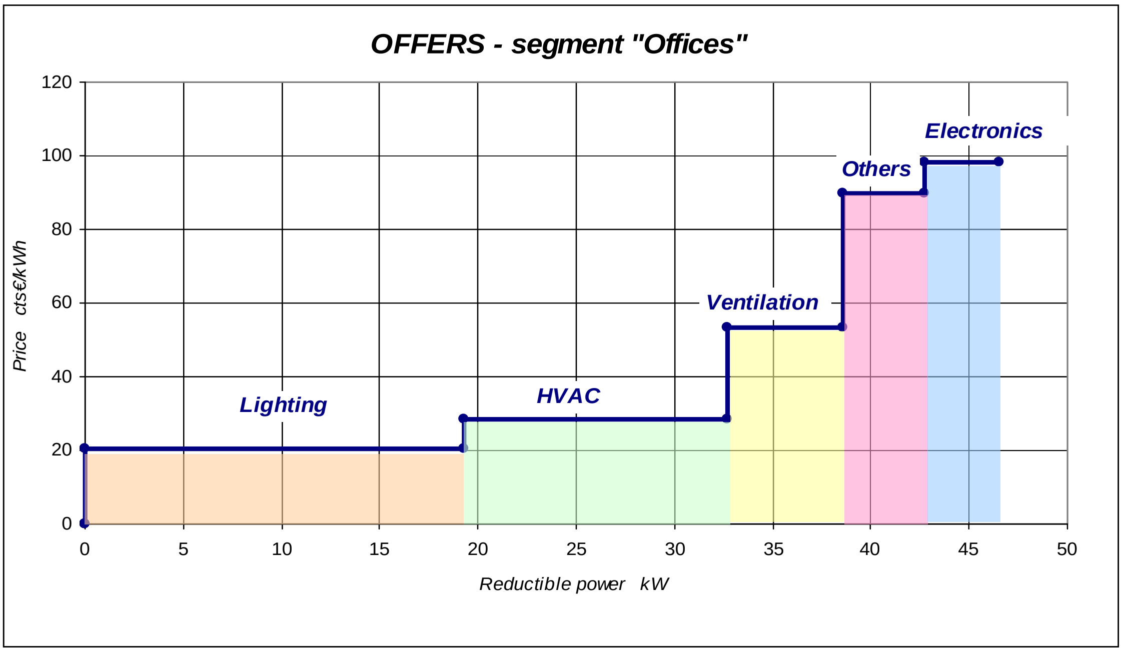

Figure 2. Offers to reduce power in operational markets, an example.

Figure 2 represents the power that can be traded in operation markets, for one specific hour and customer facility (Results from EU-DEEP project).

Extensive physically based models have been used for different customers to evaluate their flexibility.

As conclusion, a methodology for the evaluation of the Demand response capacity of customers based on customer interaction to perform the evaluation of the impact (economic) of the energy in the customer processes.

This methodology could also be used by ESCO companies to evaluate the aggregated response of its customer portfolio.

Identification of simple physically based models of the response dynamics of electrical heating loads

Pekka Koponen
VTT

Introduction

In the smart grids demand response will be extensively applied. Predictability of loads will be increasingly important as operational margins are reduced with the help of automation. Thus it becomes necessary to predict the responses of load control actions. The traditional load control models described and developed by Seppälä (1996) have been so far successfully applied in Finland, but those models cannot predict control responses. A solution is to use simple physically based models of the building heat dynamics with parameters identified from measured data and building properties. In addition the physically based dynamic models can predict the responses to outdoor temperature variations better than the models by Seppälä (1996) and do not require quite as much and as complete measurement data time series for updating.

Already Haase (1971) and Martikainen et al. (1987) applied simple physical models of building heat dynamics in simulations of load control responses of electrical heating. Koponen (1997) applied them for predicting the responses of direct control of electrical heating and Koponen et al. (2006 and 2007) in optimisation of load control responses.

Approach

The suggested modelling approach is the following. The controllable houses are classified to some segments based on the type of the heating system and the building properties. Measurement data and a priori information are used for this. For each segment some simple dynamic model structures are defined based on the heat dynamics of a typical house. Also feasible range of the model parameters is defined. Then the model parameters are fitted so that the response agrees with measured control responses, the load of a non-controlled reference group, and long term measurement data.

The models are made to predict the load of groups of houses using as inputs

- measured and predicted environmental conditions such as outdoor temperature in the region
- load control actions
- available information on usage of the houses.

Figure 1 illustrates the modelling approach. In addition to measurement from smart meters also other available measurements can be used such as power measurements from distribution substations. Especially when modelling individual houses also measurements of indoor temperatures in the houses have been used taking into account that the state variables of the model represent lumped temperatures of the house.

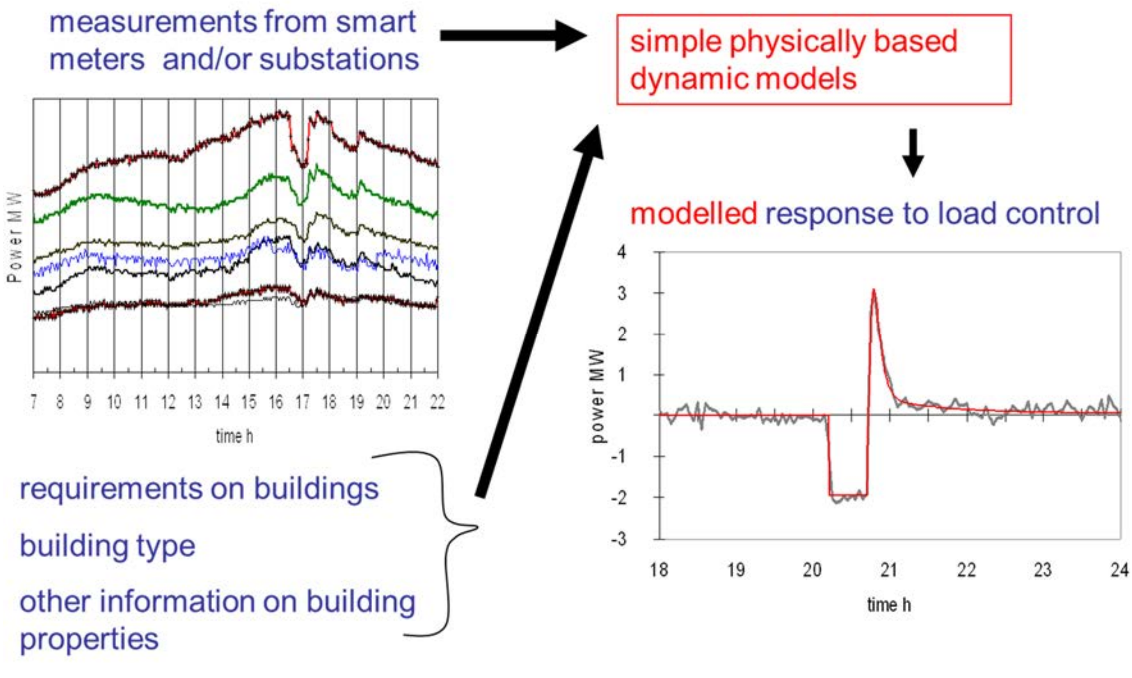

Figure 1. Response models are built combining measurements with information on building heat dynamics.

Model

Typically the simple physical model comprises 3 to 8 state variables. As an example such a model taken from Koponen (1997) is shown next followed by results with it.

$$C_1 \frac{dx_1}{dt} = -k_{12}(x_1 - x_2) + P$$

$$\begin{aligned} C_2 \frac{dx_2}{dt} = \; & k_{12}(x_1 - x_2) \\ & + k_{23}(x_3 - x_2) \\ & + k_{24}(x_4 - x_2) \\ & + k_{2o}(T_{out} - x_2) \end{aligned}$$

$$\begin{aligned} C_3 \frac{dx_3}{dt} = \; & k_{23}(x_2 - x_3) \\ & + k_{3o}(T_{out} - x_3) \end{aligned}$$

$$C_4 \frac{dx_4}{dt} = k_{24}(x_2 - x_4)$$

The variables and parameters in the example model are described next. The state variables were the following lumped temperatures:

x1(t)	temperature of the heating element e.g. in case of floor heating
x2(t)	temperature of the indoor air
x3(t)	temperature of the outside walls
x4(t)	temperature of the other heat storing masses of the building.

The constant parameters were

C1, C2, C3 and C4	the heat storage capacities related to each state variable
k12, k23, k24, k2o, k3o	the thermal conductivities between the state variables (temperatures in the model).

The time variable input variables were

Tout(t)	outdoor temperature
P(t)	the electrical power heating the house.

After adding the control loop, P(t) becomes the main output variable.

Results

Figure 2 shows a comparison of the model response (simulation) with response estimated from measurements at substation for load control of 463 vacation house metering points in a resort. Outdoor temperature was -19 °C. The control actions were applied separately to four groups of houses and each group was controlled at a different time to shut down their controlled loads for half an hour.

Regularly repeating load variations and impact of temperature variations are filtered out. The responses were identified from measurements at substations. The normal load profile was eliminated using both simultaneous measurements at non controlled reference substations and identified temperature dependency model. Normally the 4 groups were operated in a way that roughly cancelled the payback peaks, but in the test the timing is different to make the payback peaks visible and better identifiable. For more information, see Koponen (1997).

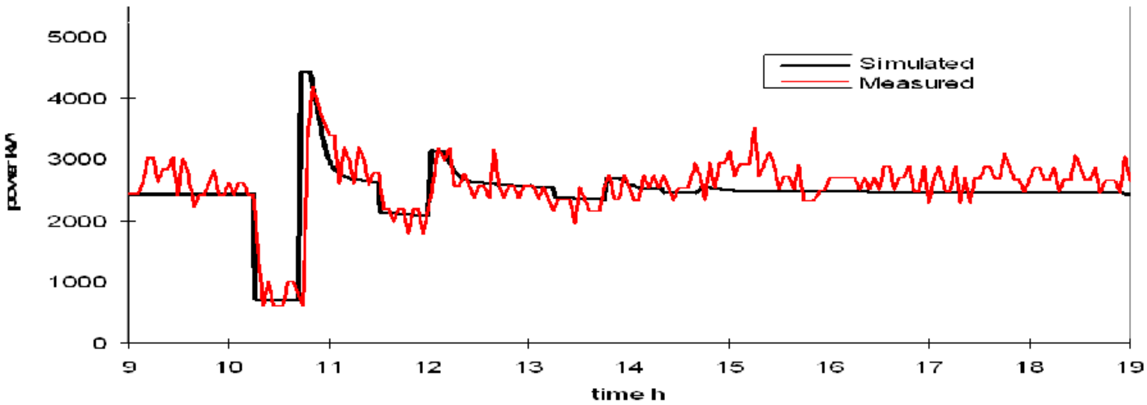

Figure 2. An example of a response identified in the direct load control field tests of electrically heated houses in winter 1996–1997 (Koponen 1997).

Discussion

It can be expected that the simple dynamic response models can be identified from smart metering measurements that have time resolution of some minutes during the load control tests and time resolution of one hour otherwise. The above example shows that simple dynamic models can sometimes be identified even from data measured from the substations. They have also been applied for predicting and optimising responses of individual houses.

Data from well-designed load control field tests is needed for updating and improving the models based on the old tests. A new field test is reported by Jäppinen et al. 2006, but the usefulness of its results is limited by the fact that neither long term measurements nor reference group measurements are available from it.

Increasing availability of smart metering data and improved simulation models enable the development of the simple dynamic load response models. Research collaboration within SGEM and internationally is needed for making it possible to utilise these models as one important building block in a comprehensive load modelling framework. To enable that also a methodology and tools for developing and maintaining the models need to be developed.

Conclusions

A promising solution is suggested to the increasing need of load response models.

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A bottom-up approach to forecast residential load demand response to incentive signals

Nerea Ruiz
Tecnalia, Spain

This work has been carried out within the ADDRESS project (Active Distribution network with full integration of Demand and distributed energy RESourceS) which is a 4-year large scale R&D project launched in June 2008 and is funded by the European Commission within the 7th Framework Program, FP7. The project coordinator is ENEL Distribuzione and the Technical Manager is EDF. The consortium consists of 25 partners from 11 European countries including research centres and universities, utilities and manufacturers. Major participants in the ADDRESS consortium are ENEL, EdF, Iberdrola and ABB together with e.g. KEMA, VITO, Ericsson, Landis & Gyr, Philips, Alcatel, Electrolux and universities of Manchester, Cassino, Comillas and Siena.

The ADDRESS project aims to deliver a comprehensive commercial and technical framework for the development of "Active Demand" in the smart grids of the future. Specifically, ADDRESS investigates how to effectively activate participation of domestic and small commercial consumers in the power system markets and in the provision of services to the different power system participants.

In the proposed ADDRESS architecture, the Aggregator is the key mediator between the consumers on one side and the markets and the other power system participants on the other side. The aggregator: gathers ("aggregates") the flexibilities of consumers to "build" Active Demand (AD) services, offers the AD services to the power system participants via the markets, manages the risks associated with uncertainties in the markets and responsiveness of the consumer base, maximizes the value of consumers' flexibility and interacts with consumers through price and volume signals and assesses their response and behaviour

At the consumer level, the Energy Box is the interface between the consumer and an aggregator. It receives the price and volume signals from the aggregator as well as local information about some individual load consumption and displays them to the consumers. In addition, it carries out the optimisation and the control of the loads and local distributed energy resources at the consumer's premises.

The objective of the developed residential load demand model is to forecast the aggregated load demand curve of a group of customers (cluster or prototype) under the effect of a specific price/volume signal. The deviation of the obtained curve from the one corresponding to the base case, that is, without price/volume signals, represents the demand flexibility of the aggregator. This algorithm is intended to be run by the aggregator for different price/volume signals in order to assess how the demand flexibility offered by the customers changes according to the different incentive patterns.This information is essential for the Aggregator in order to estimate the load demand flexibility of the consumers in its portfolio, and therefore to define the strategies for market participation and consumers' portfolio optimization.

Input data to the model can be classified into two main groups:

1. Prototype information: it comprises data related to the consumers in the prototype that is going to be simulated such as, contractual power and tariff, characteristics of the building, controllable equipment ownership, technical characteristics and usage of controllable equipment and flexibility characteristics.
2. Simulation information: it includes specific information for the simulation that is going to be carried out. It includes the price/volume signal that the Aggregator wants to simulate, the simulation period, the sample size and forecasts of outdoor temperature and load demand curve in the base case.

The tool employs a "bottom-up" approach based on physical end-use load models where first a sample of consumers of the prototype is randomly generated according to their statistical reference patterns and afterwards the responses of their individual loads to the considered price/volume signal are simulated. Finally, the load demand curves of all simulated consumers are aggregated in order to build the aggregated response of the prototype.

Simulation of the response of each individual consumer is performed employing a household load model based on an optimization algorithm. The controllable loads included in the model are shiftable loads characterised by having a fixed power consumption profile (washing machine, dish-washer, dryer) and thermal load (air-conditioning and space heating system)

The optimization algorithm optimizes the overall power consumption of the household for the next 24 hours. The approach is based on reproducing the rescheduling that the EnergyBox would perform over the operation set-points of the controllable appliances in the household if it received the considered price/volume signal. This calculation is based on the assumption that the algorithms implemented in the EnergyBox search the objective of minimizing the electricity bill while user comfort preferences are maintained. The possible control actions consist of delays on the starting-times of the shiftable appliances to time-periods with lower electricity prices (higher incentives) and changes on the temperature set-points of the thermal loads by performing pre-cooling or pre-heating actions during off-peak periods and switching off the devices or reducing their consumption during peak price hours.

Comfort preferences are modelled with price-sensitivity factors that define the willingness of the consumer to lose living comfort, that is, to perform control actions over his controllable appliances, as a function of electricity prices. This parameter quantifies the demand flexibility offered by the consumer as a function of the electricity prices which in case of shiftable loads defines the maximum time that it allows to delay the starting time of the appliances according to electricity prices and in case of thermal loads the maximum number of degrees that it allows to increase/decrease the temperature set-point accordingly.

The optimization algorithm includes physical models for simulating the power consumption of the loads. Shiftable loads are characterised by their power consumption profiles. Thermal loads are simulated with a thermal model describing the dynamics of the house as a function of the outside temperature and building thermal characteristics.

The objective function can be written as follows:

$$\text{Minimize} \quad \sum_{i=1}^{N} (Cost_i - Incentive_i) + \sum_{k=1}^{K} \lambda_s \cdot \left|\Delta Time\right|_k + \sum_{i=1}^{N} \lambda_t \cdot \left|\Delta Temp\right|_i$$

where:

N	Number of time-steps in the scheduling period
K	Number of shiftable appliances
$\lvert\Delta \text{time}\rvert_k$	Delay applied to the starting time of the shiftable appliance k (h).
$\lvert\Delta \text{Temp}\rvert_i$	Deviation between the initial temperature set-point and the final one
(ºC).λ_s	Price-sensitivity of the consumer for shiftable loads (€/h)
λ_t	Price-sensitivity of the consumer for thermal loads (€/ºC)

The first summation in the previous equation represents the final cost of the electricity for the end-user. It is calculated as the difference between the electricity cost paid to the retailer and the incentive received from the Aggregator which will depend on the power consumption performed by the consumer during the time-step i.

The second summation introduces a penalty for each shiftable appliance over the difference between the initially scheduled starting-time by the end-user and the finally scheduled one by the Energy Box.

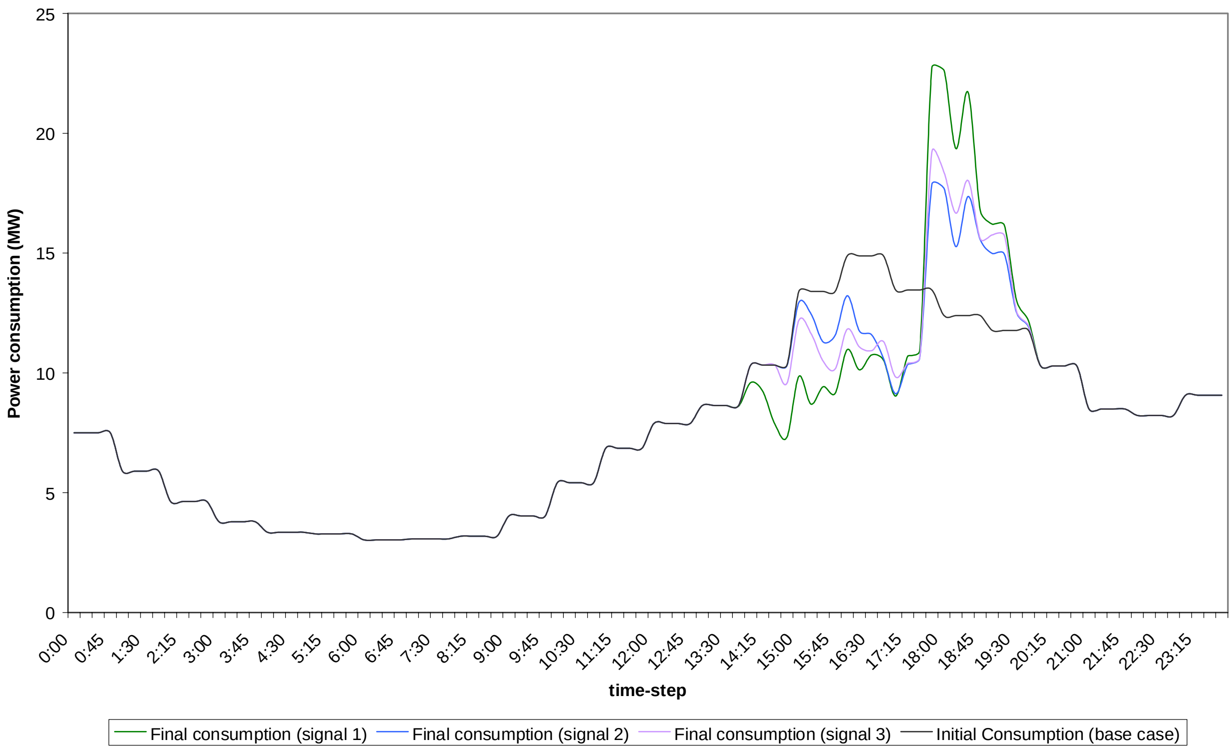
Similarly, the third summation is a term that models the price-sensitivity of the consumer regarding thermal loads by penalising deviations between the actual temperature and the ideal one (temperature set-point) for each time-step of the scheduling period.

As a result, one obtains the optimal starting time of shiftable appliances and the optimal temperature set-point of the air-conditioner/space-heating system for all time-steps of the scheduling period that minimise the electricity bill while price-sensitivity of the consumer is fulfilled. With this information, the load demand curve of the considered end-user during the simulation period under the effect of the considered price/volume signal is obtained.

The Residential Load demand model estimates the forecasted demand curve of all the consumers within the prototype under the effect of the considered price/volume signal. This information will be employed together with the demand curve corresponding to the base case, to estimate the flexibility offered by the consumers in the prototype in case such an incentive scheme was delivered by the Aggregator.

The following graph shows a comparison of the results obtained for load reduction with three different control signals:

1. Two price steps and high incentives; from 15:00 to 17:45 consumer receives 5 cent€ per time-step, if power consumption is lower than 1 kW.
2. Two price steps and low incentives; from 15:00 to 17:45 consumer receives 1 cent€ per time-step, if power consumption is lower than 1 kW.
3. Three price steps; consumer whose power consumption is less than or equal to 1 kW is rewarded with 2 cent€, and each consumer whose power consumption is between 1 and 2.5 kW is rewarded with 1cent€.



It can be seen that the higher the incentive, the higher the load reductions that can be achieved because the consumers offer more flexibility and therefore they are more willing to control their loads. Consequently, they allow higher delays on the starting times of shiftable appliances and higher modifications on the temperature set-points of the air-conditioning system. Similar comparison was also made for the load increase requests.

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A direct load control model for virtual power plant management

Nerea Ruiz
Tecnaliaz, Spain

This work was carried out within the FENIX project. The main concept of this project is the Virtual Power Plant (VPP) which is based on the idea of aggregating the capacity of many distributed energy resources (DER) – generation, storage or demand- in order to create a single operating profile. In this way, individual DERs gain visibility and manageability to system operators, optimizing their position and maximizing their revenue opportunities. A VPP is comparable to a conventional power plant with its own operating characteristics such as schedule of generation, generation limits and operating costs. It can be used to make contracts in the wholesale market and to offer services to the System Operator.

The objective of the developed model is to manage a VPP composed of a large number of end-users with controllable appliances. The model, which is based on a direct load control (DLC), is valid for the aggregation of domestic and commercial customers with appliances that have thermal storage capabilities (Air-conditioning or Space-heating systems). The possible control actions are established by contract between the end-users and the aggregator and can consist of a modification of the thermostat reference temperature setting or a disconnection of the devices for a predetermined period. As a result, the load reduction capability of the VPP is obtained so as to define the corresponding load reduction bid to be presented in the electricity market.

The first step in the DLC algorithm is to calculate the load consumption curves of the controllable loads in the base case as well as under the effect of all control actions. In this way, the reduction in demand that can be achieved through the application of each control strategy can be determined. It has to be taken into consideration that the consumption of these devices is influenced by many variables: building characteristics (dimensions, construction materials, etc.), local climate conditions (temperature, humidity, etc.), comfort settings, equipment characteristics,... In order to model it more accurately, a building energy simulation tool was employed (EnergyPlus software). The methodology consists of defining a model building that represents the average behaviour of each customer type and simulating their thermal behaviour with the mentioned software. Taking the model building for the base case as a reference and modifying the schedule of the controllable load according the control strategy considered, a new consumption curve that represents the influence of such a control action is obtained. This process is repeated for all control possibilities.

Figure 1 shows an example of the application of this methodology to a domestic air-conditioner. The model building is considered to be a 90 m^2 flat sited in a block of apartments. It is west oriented and the construction materials fulfil the current Spanish regulation in relation to edification. Regarding the mode of operation of the air-conditioning system it is assumed to be connected during the whole day being the temperature setting of the thermostat 23ºC.

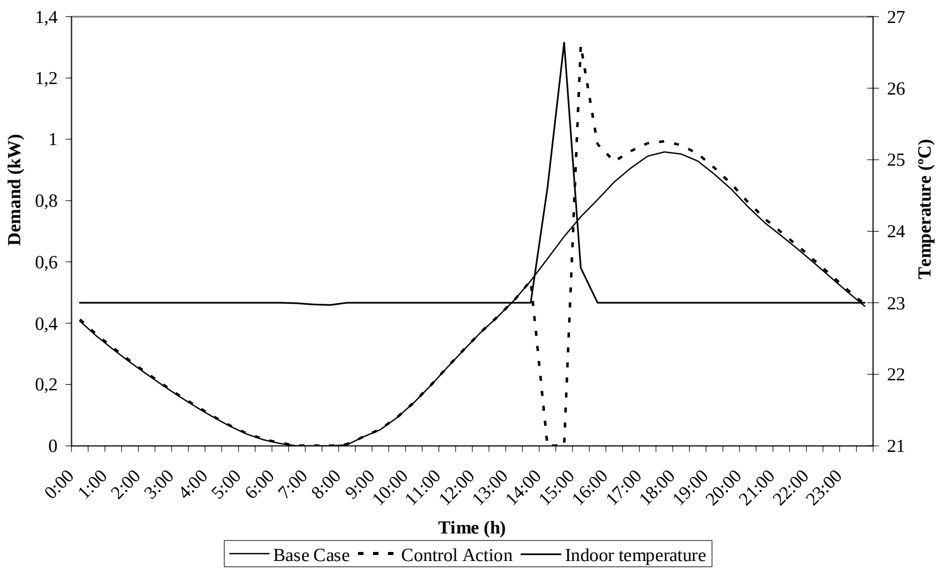


Figure 1.Simulated impact of a 60 min long interruption of air-conditioning.

The solid line represents the consumption curve for the base case and the dashed line the consumption when it is switched off during 60 minutes starting at 14:00. It can be observed the impact of such control action on the temperature inside the building that reaches almost 27ºC and the demand peak occurred just after the control period (which represents the payback).

Input parameters to the model include the forecast load demand of the aggregator portfolio, existing customer types that have controllable devices and the number of controllable devices within each customer type, the available control actions for each customer type and finally the load consumption curves in the base case and under the effect of the different control actions. These curves are simulated in advance with the EnergyPlus software as it was explained previously.

The decision variables are:

- number of devices of the type K customer which are controlled after the optimization with the strategy s starting at time-step t
- number of devices of the type k customer no controlled after the optimization.

The objective of the optimization problem, which is based on Integer Load Programming, is to maximize load reduction over the control interval or, which is the same, to minimize final demand over that period. The values of the final demand for each time-step can be obtained as the addition of the forecasted demand at that time-step plus the variation in load that occurs in that time-step when the control actions are applied. This variation can be divided into two parts: 1) load variation at time-step z due to the control actions starting at z and 2) load variation at time-step z due to control actions starting before z:

$$\text{Min} \sum_{z=1}^{n} load_z = \sum_{z=1}^{n} (forecLoad_z + \Delta Load_z)$$

$$\text{Min} \sum_{z=1}^{n} [forecLoad_z + \sum_{k=1}^{m} \sum_{s=1}^{p_{kz}} Y_{ksz} e_{ksz}(z) + \sum_{k=1}^{m} \sum_{t=1}^{z-1} \sum_{s=1}^{p_{kt}} Y_{kst} e_{kst}(z)]$$

The optimization algorithm includes a constraint that limits the final demand after the control period in order to ensure that the generated payback is within acceptable limits.

The solution to the algorithm provides the optimal combination of control strategies and the number of devices that should be controlled with each of them in order to maximize system load reduction during the control period. The resulting daily load demand curve can be also calculated.

The following case study aims to demonstrate the applicability of the proposed model for managing the participation of the VPP in the Spanish Deviation Management Market. This market is called by the TSO when deviations between generation and demand over 300 MW are expected between two intraday markets. When this occurs, market agents have 30 min. to send their offers. Currently, only generators and pumped storage power stations can participate in this it.

Simulations have been carried out with information from an actual power system in northern Spain. The analysis considers a particular power system area characterized as having a significant number of domestic and commercial buildings connected. It is assumed that an aggregator operates in the region, offering DLC contracts to end-users with controllable devices in order to obtain a significant load reduction capacity that can be offered in the market. It is considered that the TSO calls the deviation management market for a period running from 14:00 to 16:00. Consequently, the aggregator runs the algorithm to generate the load reduction bid corresponding to that control interval. The study is performed in a summer scenario where air-conditioning system control is considered. The same methodology could be employed for the control of space-heaters in a winter scenario.

Table 1 shows the results provided by the optimization algorithm. It includes the optimal control actions and their durations, the initial time and the number of devices that must be controlled with each action so as to obtain the maximum load reductions over the control interval, which runs from 14:00 to 16:00.

Table 1. Results provided by the optimisation algorithm.

Type	Action	Duration	Start time	Number of customers
Domestic customers	OFF	60 min.	14:00	1544
	+ 2ºC	120 min.	14:00	1830
	+ 3ºC	90 min.	14:30	2917
	+ 4ºC	30 min.	15:30	3
Supermarkets	+ 3ºC	90 min.	14:30	12
Offices	+ 3ºC	90 min.	14:00	197

By applying the above control actions, the aggregator can attain the load reductions presented in Table 2.

Table 2. Load reductions attained with the control actions provided by the optimisation algorithm.

Time-step	Load reduction (kW)	Reduction (%)
14:00 – 14:30	2128	2.46
14:30 – 15:00	1864	2.00
15:00 – 15:30	1940	2.06
15:30 – 16:00	2123	2.24

Table 2 also includes the percentage of forecast demand represented by those variations.

The load reductions achieved are practically constant for all time-steps in the control period, and average 2 MW. This represents a drop of 2.2% in relation to the expected demand and a potential energy reduction of 4 MWh for the whole control period.

The following figure shows a graphic representation of the load reduction achieved:

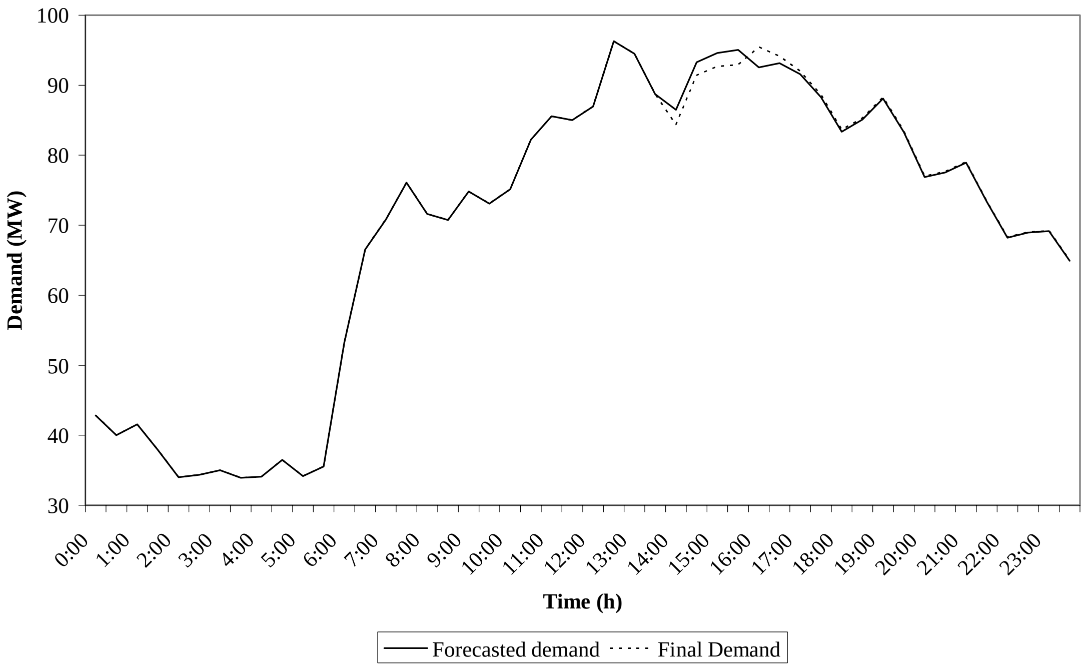


Figure 2. Forecasted load reduction achieved with the control actions provided by the optimization algorithm.

It can be observed that consumption drops for the two hours of the control period, but rises in the subsequent time-steps. This is the payback effect that represents the extra amount of energy that the air-conditioning systems demand in order to restore their temperature settings.

Finally, Table 3 shows the load reduction bid that the aggregator would send to the TSO (constrained scenario). The planning periods considered are 1 hour long, coinciding with the current characteristics of the Spanish market. The bid formulated is upward because consumption reduction is similar to generation increase. The bid includes the energy offered for each planning period and the corresponding price. These prices should be set by the aggregator taking into consideration financial compensation for customers and its own costs and profit. In addition, the complex condition that establishes the indivisibility of the bid is defined.

Table 3. Load reduction bid based on the load reduction forecasted.

	14:00-15:00	15:00-16:00
Energy (MWh)	1.996	2.032
Price (€/MWh)	P1	P2

Reference

Ruiz, N. Cobelo, I. & Oyarzabal, J. 2009. A direct load control model for virtual power plant management. IEEE Transactions on Power Systems, Vol. 24, No. 2, pp. 959–966.

Feedback from workshop participants

Questionnaire

After the workshop, a short questionnaire was produced for the participants to answer. The participating experts were enquired for their opinions on the future needs of load modeling and similar workshops. Even though the response rate was only 25 percent, many good ideas were laid out for the future research and organization of events of similar type. The answers of the questionnaire are summed up below.

Question 1. What do you see as the most important things to develop in load modeling on short (less than 5 years) and long (over 5 years) term?

Short term

One quite popular opinion among all the respondents is to make good use of the available AMR-data. Especially the old load curves utilized in the DSOs could be made more accurate by using AMR-measurements. Ideally the updating would be an ongoing process, handled as automatically as possible, and enabled by easy-to-use software and adequate interfaces. Moreover, to get more benefits out of the AMR-data, it could be used for better energy efficiency information and analysis.

As for the other short-term developments, the use of AMR-data is also suggested in making models for accurately forecasting the load at MV/LV substation level. Such models are needed for state estimation applications and for the active management of distribution networks.

On short term, also more dynamic load models compared to the current static ones would generally be more desirable. However it should be done by taking care of their usability in the current information systems and processes.

Long term

Many of the respondents think that, on the long term, modeling of new load types should be sought after. More specifically, many new types of load behavior and functionality related to smart grids should be somehow considered in the load modeling. Such things include for instance demand response, electric vehicles, dynamic pricing scenarios, and the distributed energy resources in general.

Additionally, it was proposed that several aspects of electricity consumer behavior should be further analyzed. Suggested were the analysis of the specific consumption and trends, better inclusion of spatial and temporal information in the load analysis and in the analysis of the behavioral changes in the consumption (e.g. residential heating type changes, electric vehicles, and consumption habits).

Question 2. What kind of a new perspective or ideas would you like to see in load modeling?

Three clear themes can be seen in the issues the respondents would want to see addressed in load modeling. New methods are wanted for modeling non-existing load types. Additionally, geographical area and grid component level load curves are of interest.

Another perspective the respondents would like to see is a more practical one. For instance different load modeling approaches could be compared in real test cases.

The third theme mentioned by the respondents, is the refining and better utilization of customer data. This can be seen in different ways, i.e. how to get more relevant information about the customer and his electricity consumption as well as how to utilize the data (e.g. in providing the customers with information about their consumption).

Question 3. What would you like to see changed or done better in a similar type of seminar/workshop in the future?

The respondents were mostly satisfied with how the workshop was arranged. However, there is clear demand for more time and opportunities for open discussion. More concrete results are also wanted, which could be in the form of a new idea or a new method. One interesting idea brought up for producing such results would be to have more regular "virtual workshops" among load modeling experts by using the Internet as means of communication (i.e. Skype, wikis, Moodle). Overall, more tight cooperation and exchange of ideas among the participants are things that should be kept in mind for a similar event in the future.

Question 4. Do you think there is a need for a topic specific seminar/workshop of a similar type also in the future? Fromwhat topic?

The respondents expressed that there is a need for similar load modeling workshops also in the future. Moreover, it was suggested that a workshop could be arranged on the application of load and demand response modeling in some specific target area such as electricity supply & trading or distribution planning/management.

Other topics suggested to be covered in a specific workshop were distribution network management with smart metering, distributed generation, demand response, end user tariffs, distributed energy resources, and activation of the smart customer.

Question 5. Additional comments

Not many additional comments were given. However, a pressing issue in load and response modeling seems to be the availability and sharing of raw data for research. Due to privacy, competitive and technical reasons, the availability of AMR-metering and other data from the DSOs for research purposes is often extremely restricted. Better possibilities to share the data would go a long way toward supporting the load and response modeling research.

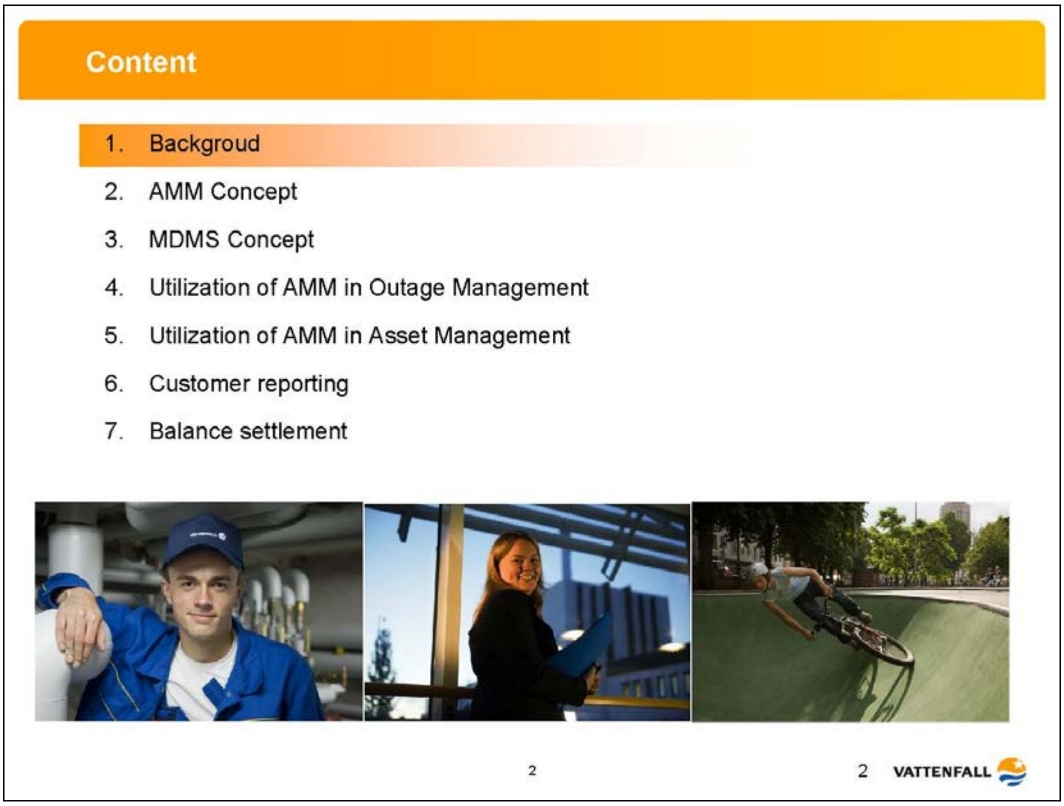
Conclusions

The workshop is considered a success by the participants. It strengthened contacts and collaboration between load and response modelling experts. This progress covered both internal and external international networking of project SGEM. The participants got an overview of research being conducted in SGEM as well as the results of earlier Finnish and European smart grids projects. Much useful exchange of information and ideas took place during the lively discussions following each presentation. Research collaboration continues and initial planning of a new workshop is starting.

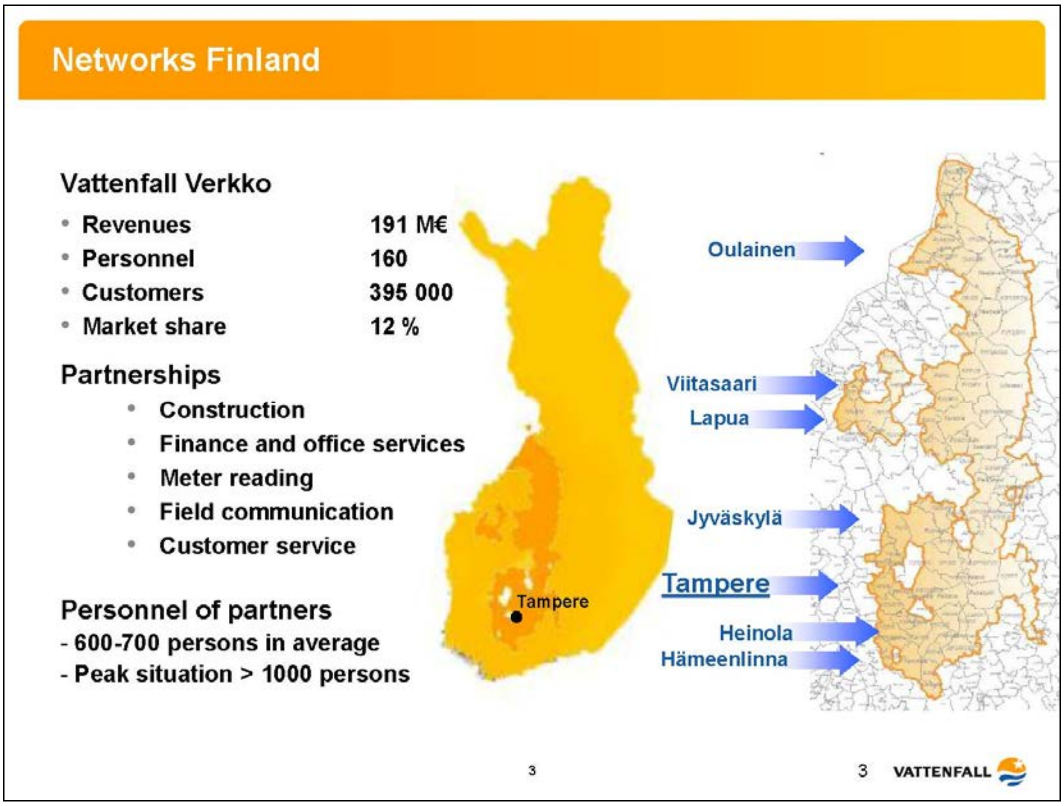
Acknowledgements

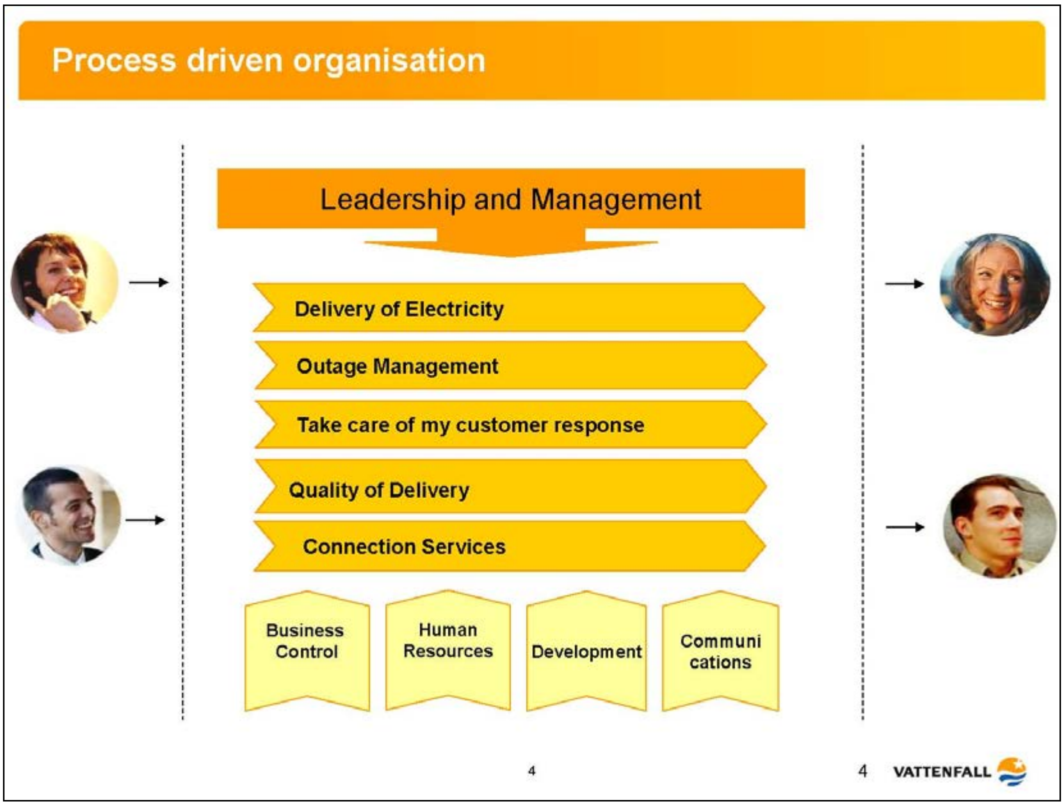
This work was carried out in the Smart Grids and Energy Markets (SGEM) research program coordinated by CLEEN Ltd. with funding from the Finnish Funding Agency for Technology and Innovation, Tekes. We also wish to thank all the speakers and especially the experts who came from University of Valencia and Tecnalia in Spain. We are also grateful to Ph.D Pentti Uuspää for checking the language of this report. Also the supporting attitude of the project and working package leaders helped to make this workshop possible.

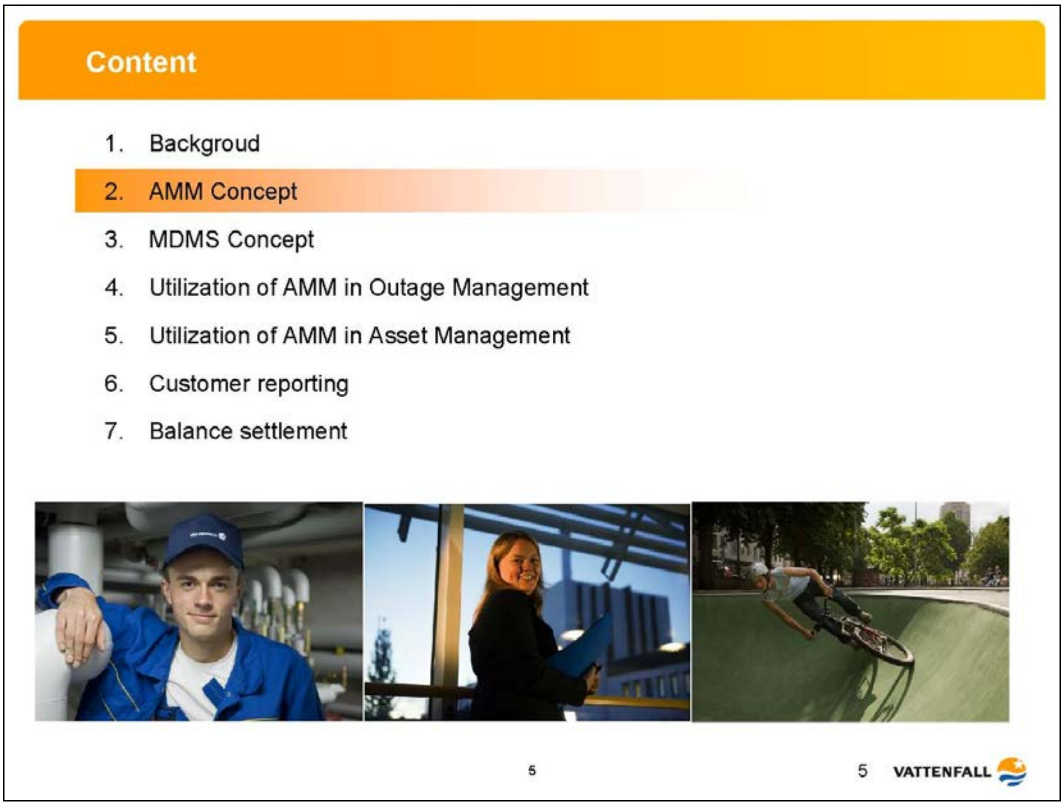
Appendix A: Utilizing AMR in network business



Appendix A: Utilizing AMR in network business






Content
1. Backgroud
2. AMM Concept
3. MDMS Concept
4. Utilization of AMM in Outage Management
5. Utilization of AMM in Asset Management
6. Customer reporting
7. Balance settlement
5
5
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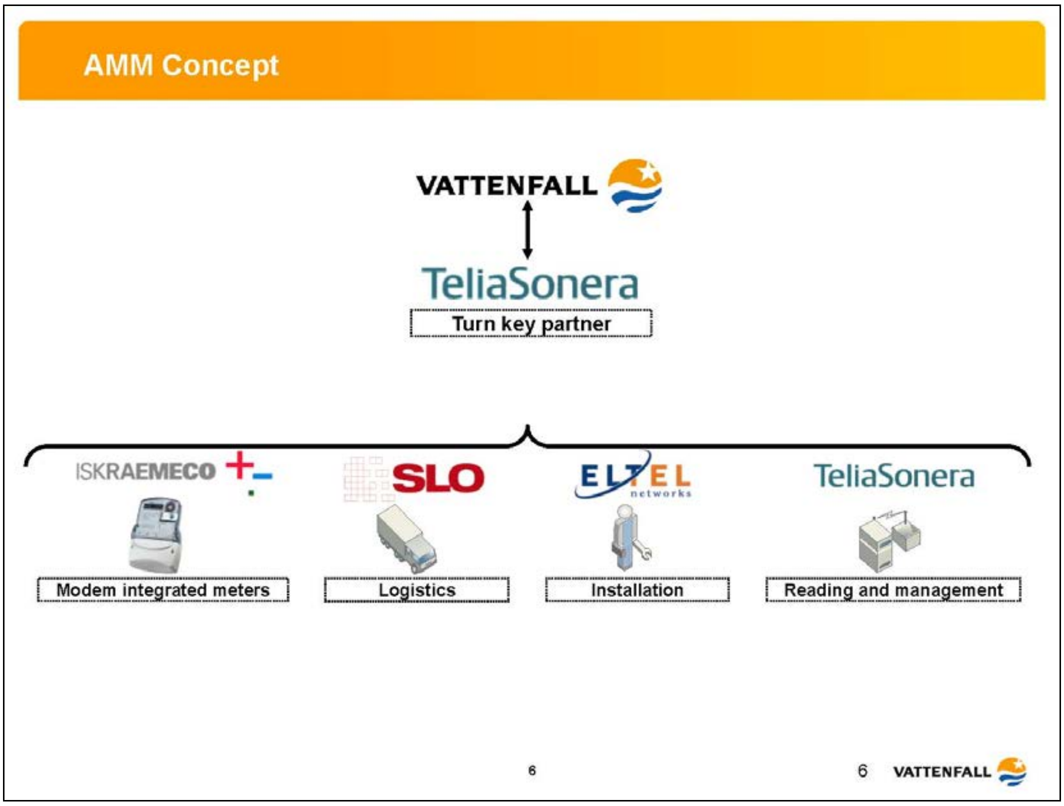
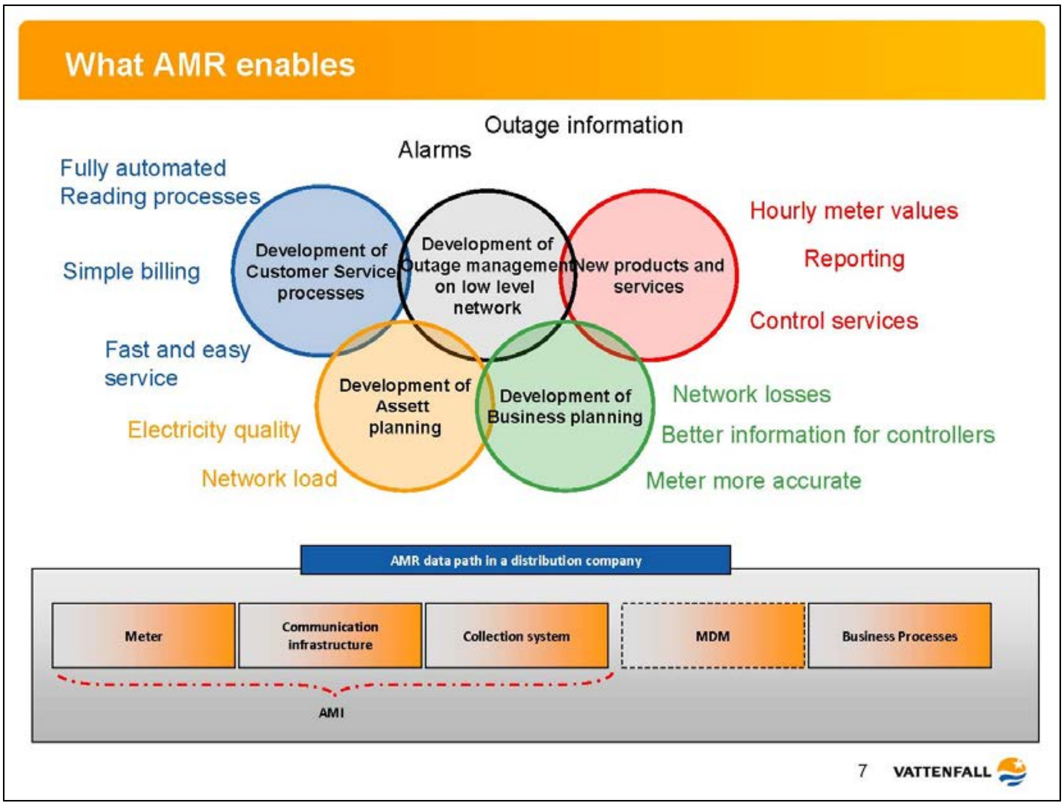
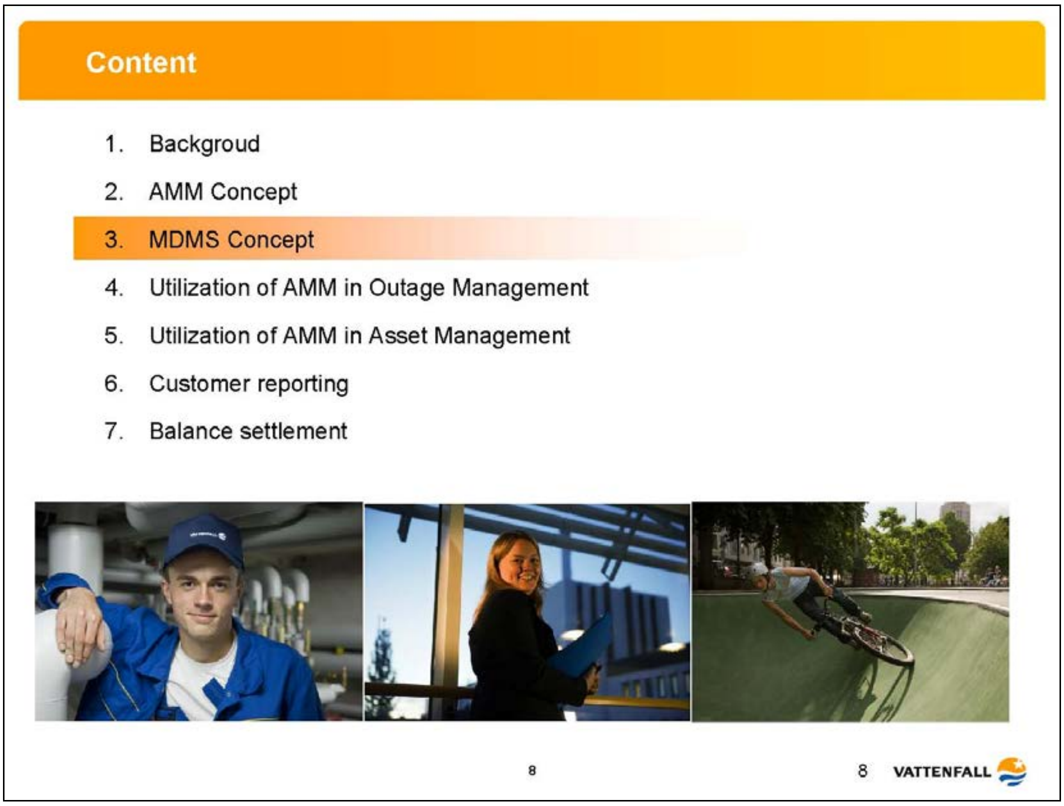

AMM Concept
VATTENFALL
TeliaSonera
Turn key partner
ISKRAEMECO
SLO
ELTEL networks
TeliaSonera
Modem integrated meters
Logistics
Installation
Reading and management
6
6
VATTENFALL

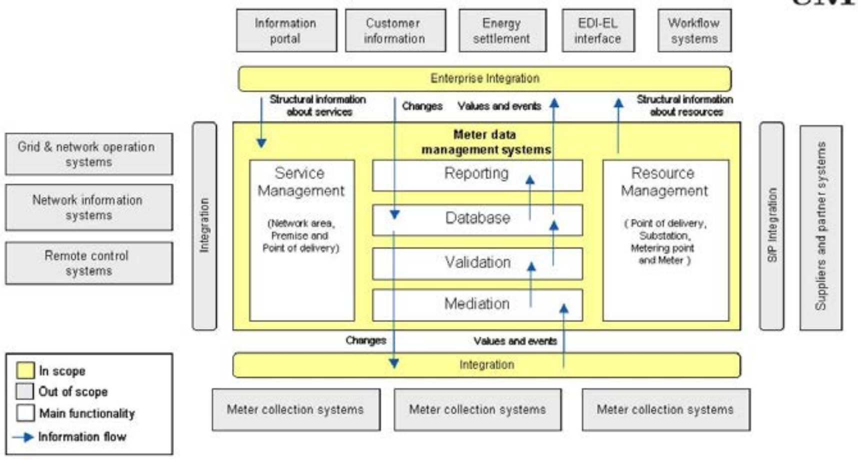
Appendix A: Utilizing AMR in network business





Architecture of MDMS

eMeter



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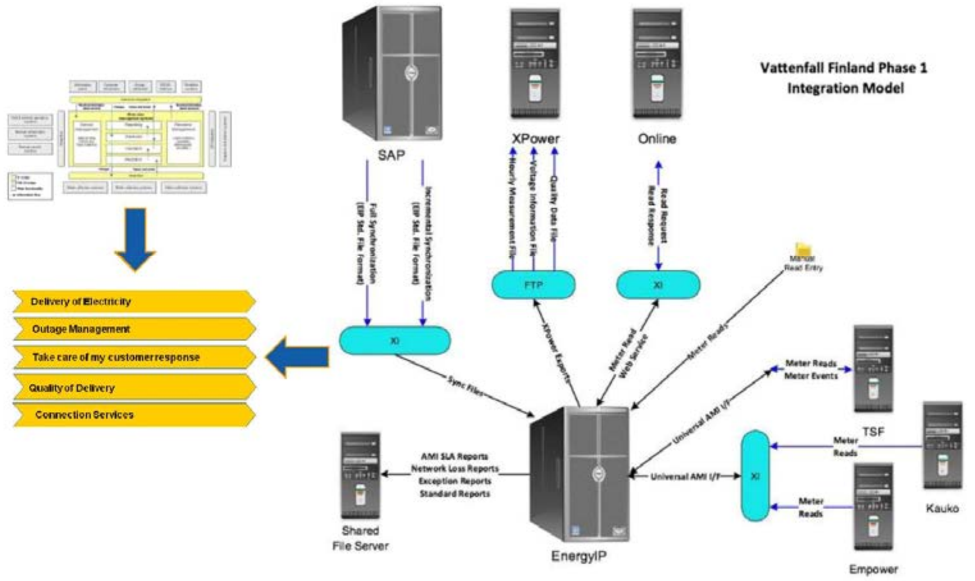
MDMS Main Functionality

- Supervision of received data
- Control of validation and estimation
- Control progress of billing and settmenent readiness
- Control of fuse size and connection demands
- Network loss calculation and reporting
- Control of distribution business periodization
- Power quality reports
- Service requests
- Self control
- Data quality monitoring

10 VATTENFALL

Solution concept of MDMS for Finland



11

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Custom development of MDMS

Custom

Reports
Consumption Greater than X% Fuse Size
Consumption Less than X% Fuse Size
Demand Greater than Contract
Consumption Less than X% Demand Contract
Meter Reading Summary Report
Hourly Product (>63A) Read Detail Report
Hourly Product (=<63A) Read Detail Report
Hourly Product Billing Not Ready Detail Report
Hourly Product Look Ahead Report
Network Loss Report
Monthly Tariff Summary Report
Monthly Special Summary Report
Finland Daily Maximum Voltage Deviation Report
Finland Weekly Excessive Voltage Alarm Report
First Read Validation Report
Production Premise Validation Error Report

Custom

	Meter Data Export Interfaces (Xpower):
17	Hourly Data Export
18	Voltage Data Export
19	Max/Min Voltage Data Export
	Sync Related Custom Components:
20	Main Switch Application
21	Record Creators
22	Custom Stored Procedures to support Record Creators and Provisioning
23	Report Configuration around custom reports interfaces
24	Custom Tables storing language for custom reports and interfaces
25	Custom Sync config xml files
26	Custom A12Seed Data
27	Record Creator Lookup Data
28	GAP to Auto Close SRs related to Events

Out of the box
- All basic functionalities

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Content

13

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Coverage of distribution automation

Remotely monitored network today

Remotely monitored network in the past

High voltage network
1 500 km

Substations
130 pcs

Medium voltage network
22 000 km

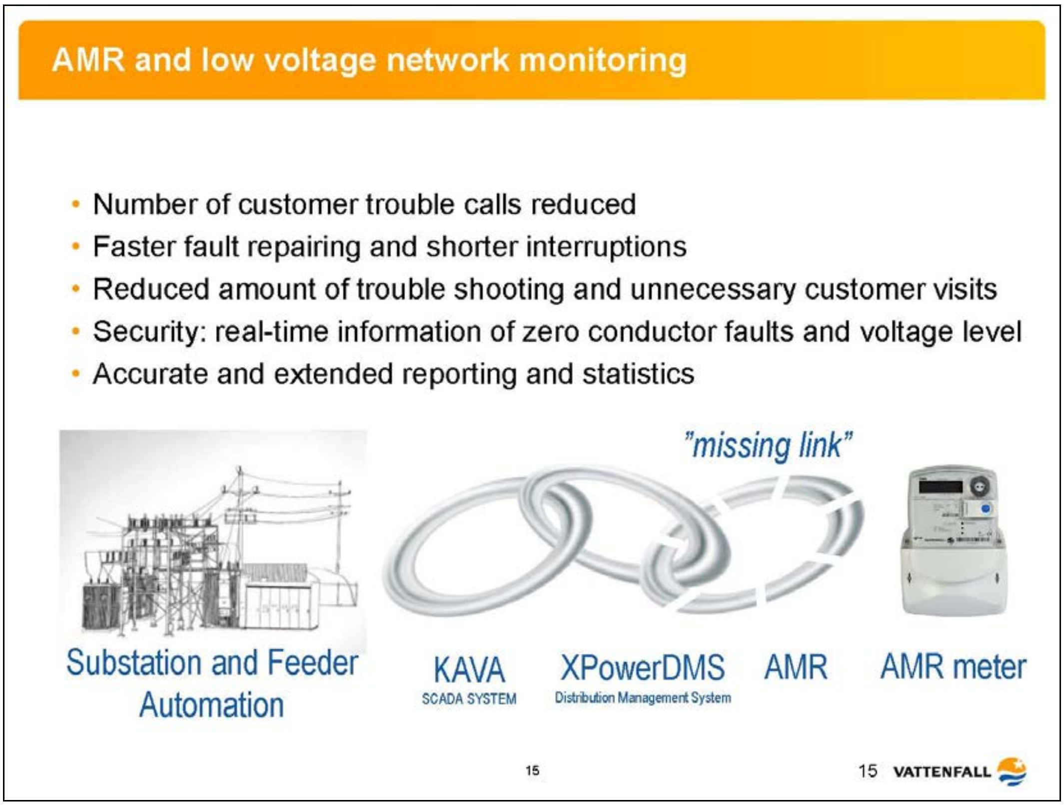
Distribution transformers
21 000 pcs

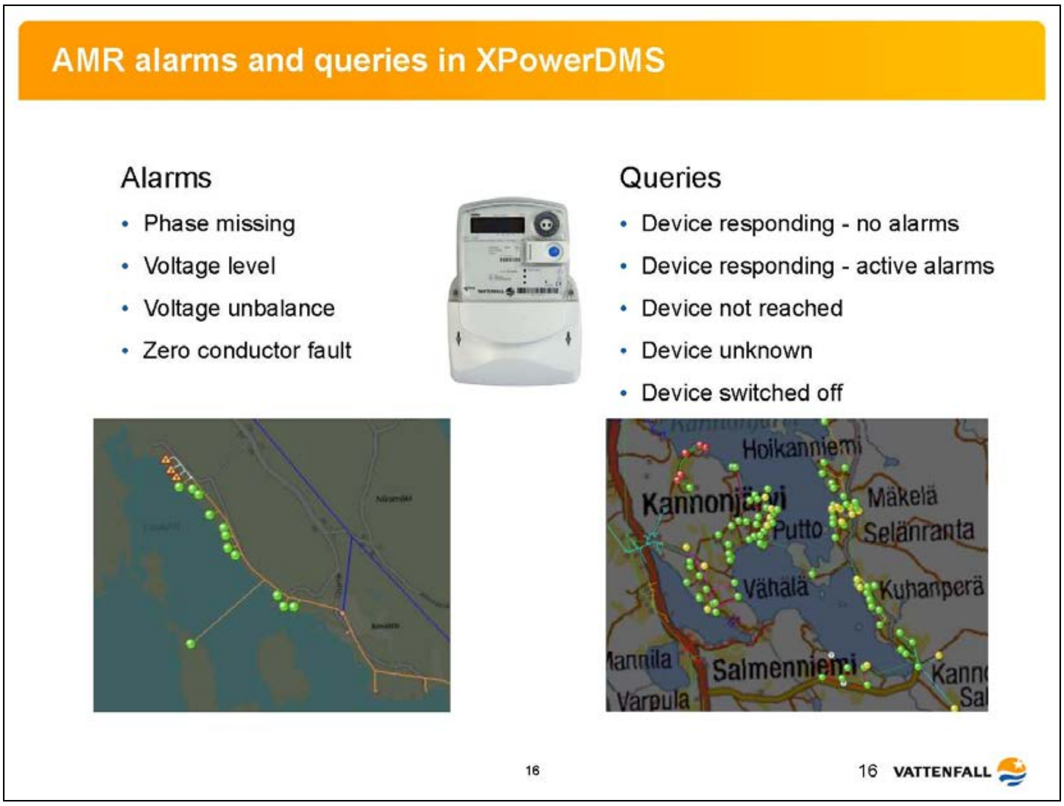
Low voltage network
38 000 km

Customers
390 000 pcs

14

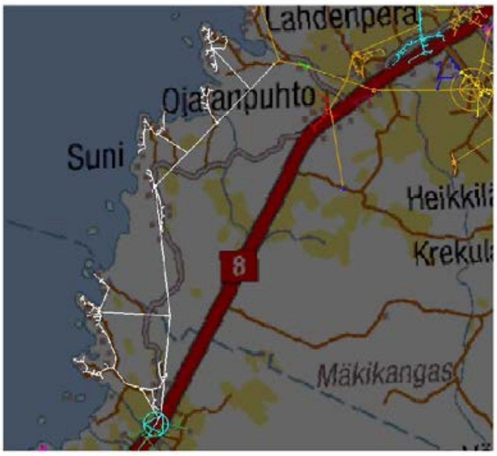
14 VATTENFALL

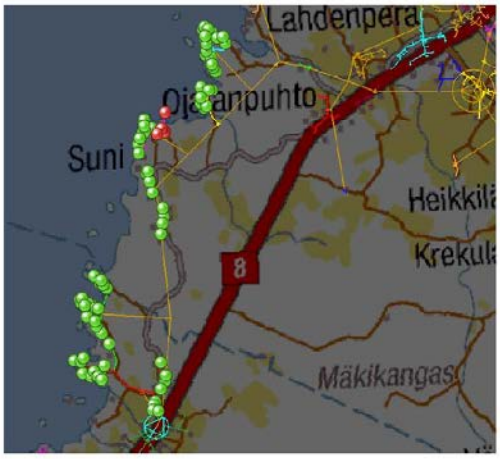

AMR and low voltage network monitoring
• Number of customer trouble calls reduced
• Faster fault repairing and shorter interruptions
• Reduced amount of trouble shooting and unnecessary customer visits
• Security: real-time information of zero conductor faults and voltage level
• Accurate and extended reporting and statistics
"missing link"
Substation and Feeder Automation
KAVA
SCADA SYSTEM
XPowerDMS
Distribution Management System
AMR
AMR meter
15
15 VATTENFALL


AMR alarms and queries in XPowerDMS
Alarms
• Phase missing
• Voltage level
• Voltage unbalance
• Zero conductor fault
Queries
• Device responding - no alarms
• Device responding - active alarms
• Device not reached
• Device unknown
• Device switched off
Hoikanniemi
Mäkelä
Putto
Selänranta
Vähälä
Kuhanperä
Salmenniemi
Varpula
16
16 VATTENFALL

Example: LV fault under MV fault

- System automatically proposes query after MV-fault
- Especially for finding LV-faults under MV-faults



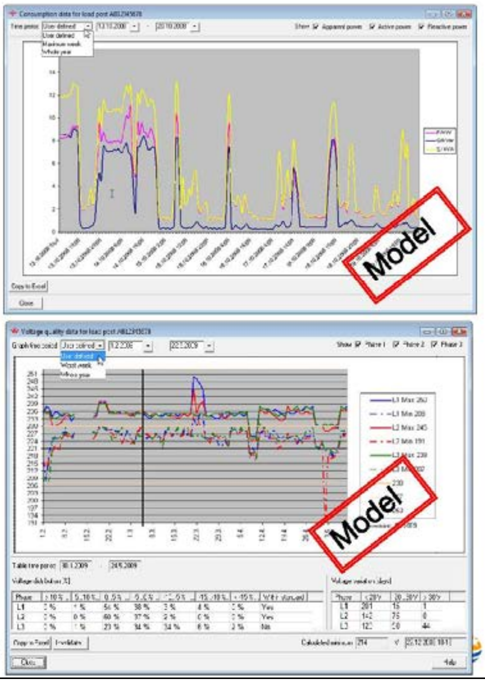


Content

1. Backgroud
2. AMM Concept
3. MDMS Concept
4. Utilization of AMM in Outage Management
5. Utilization of AMM in Asset Management
6. Customer reporting
7. Balance settlement

Examples of Utilizing MDMS data in Asset Management

- Hourly consumption series
  - Active and reactive power
  - More detailed load flow calculation compared to load curves
  - ➢ Network dimensioning and re-investment priorization
- Power quality information
  - Voltage level
  - Not necessarily compared to standard
  - ➢ Bringing forward and setting priority of "weakest" areas

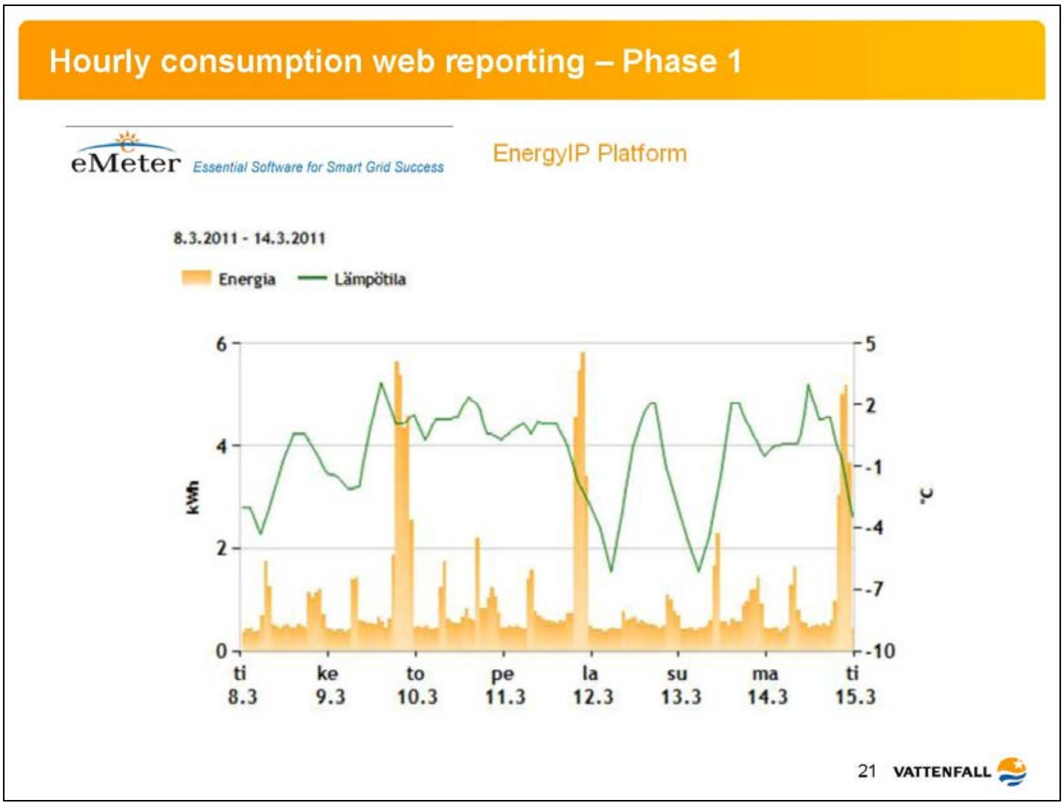


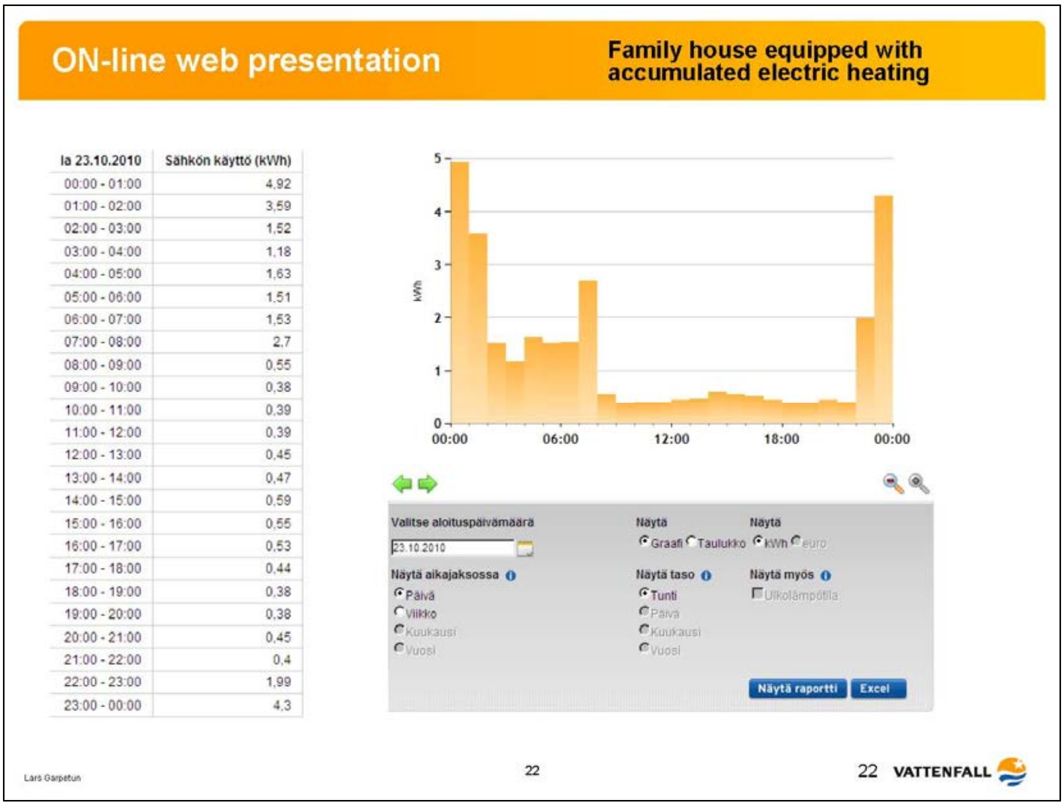
19

Content

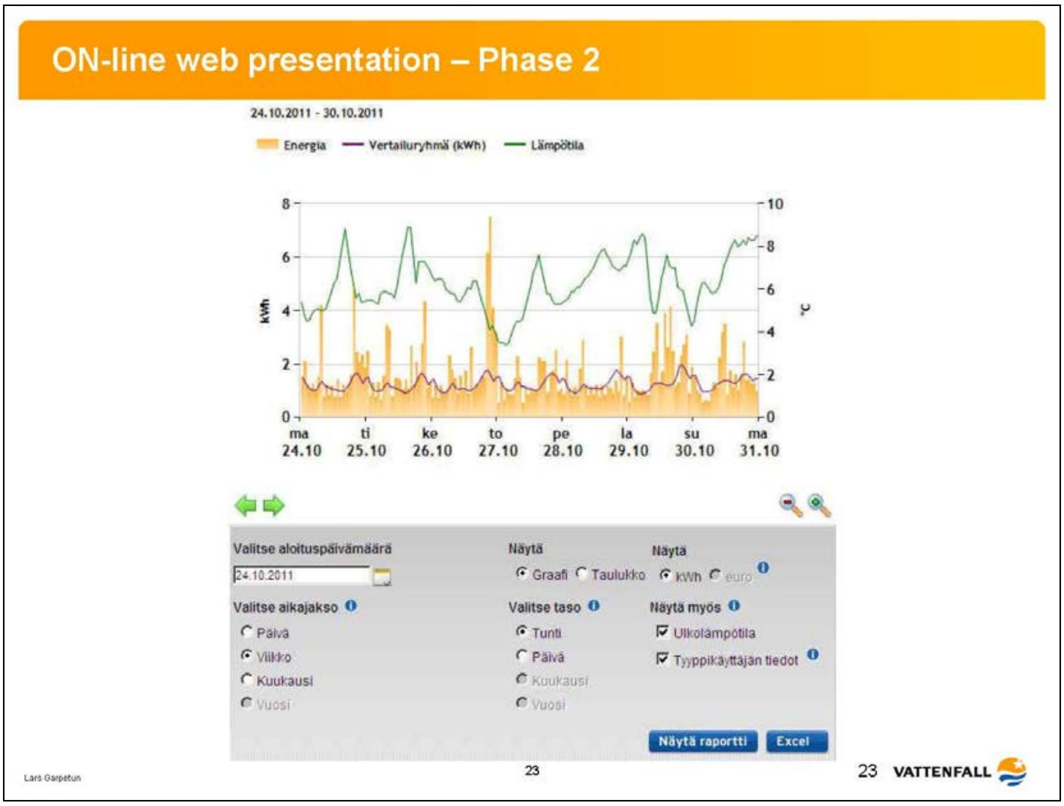
20

20 VATTENFALL





la 23.10.2010	Sähkön käyttö (kWh)
00:00 - 01:00	4,92
01:00 - 02:00	3,59
02:00 - 03:00	1,52
03:00 - 04:00	1,18
04:00 - 05:00	1,63
05:00 - 06:00	1,51
06:00 - 07:00	1,53
07:00 - 08:00	2,7
08:00 - 09:00	0,55
09:00 - 10:00	0,38
10:00 - 11:00	0,39
11:00 - 12:00	0,39
12:00 - 13:00	0,45
13:00 - 14:00	0,47
14:00 - 15:00	0,59
15:00 - 16:00	0,55
16:00 - 17:00	0,53
17:00 - 18:00	0,44
18:00 - 19:00	0,38
19:00 - 20:00	0,38
20:00 - 21:00	0,45
21:00 - 22:00	0,4
22:00 - 23:00	1,99
23:00 - 00:00	4,3


ON-line web presentation – Phase 2
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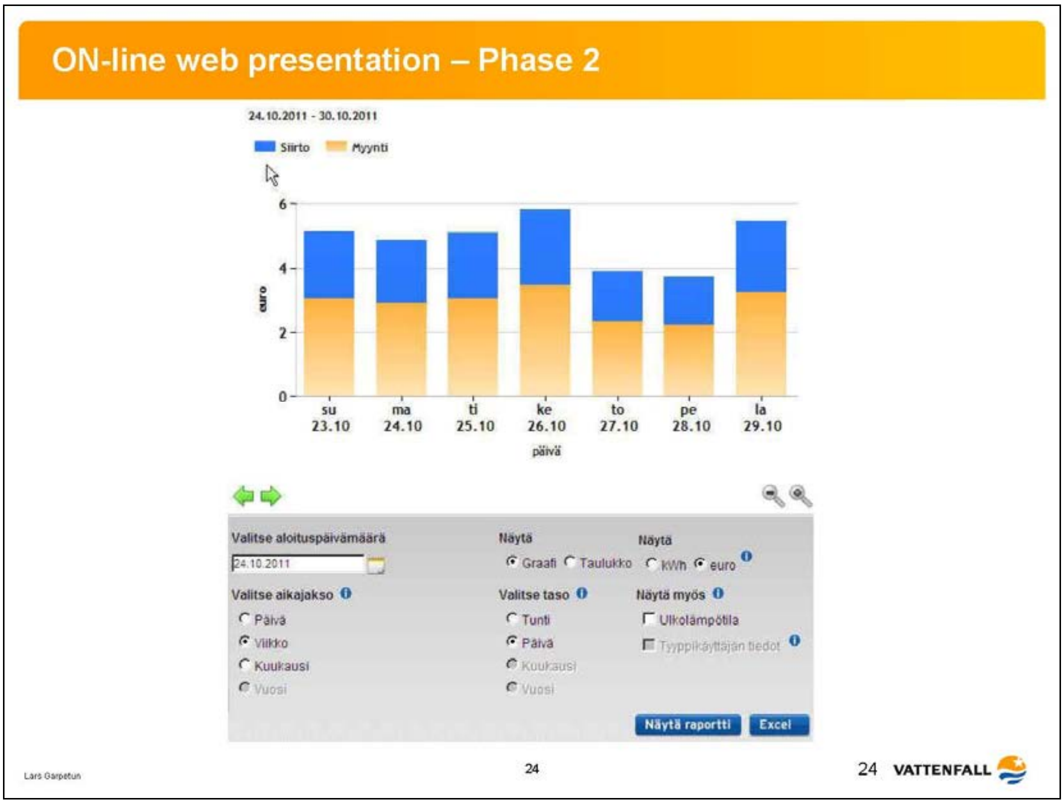
Valitse aloituspäivämäärä
24.10.2011
Näytä
Graafi
Taulukko
Näytä
kWh
euro
Valitse aikajakso
Päivä
Viikko
Kuukausi
Vuosi
Valitse taso
Tunti
Päivä
Kuukausi
Vuosi
Näytä myös
Ulkolämpötila
Tyyppikäyttäjän tiedot
Näytä raportti
Excel
Lars Garpetun
23
23 VATTENFALL


ON-line web presentation – Phase 2
24.10.2011 - 30.10.2011
Siirto
Myynti
euro
su 23.10
ma 24.10
ti 25.10
ke 26.10
to 27.10
pe 28.10
la 29.10
päivä
Valitse aloituspäivämäärä
24.10.2011
Näytä
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Tyyppikäyttäjän tiedot
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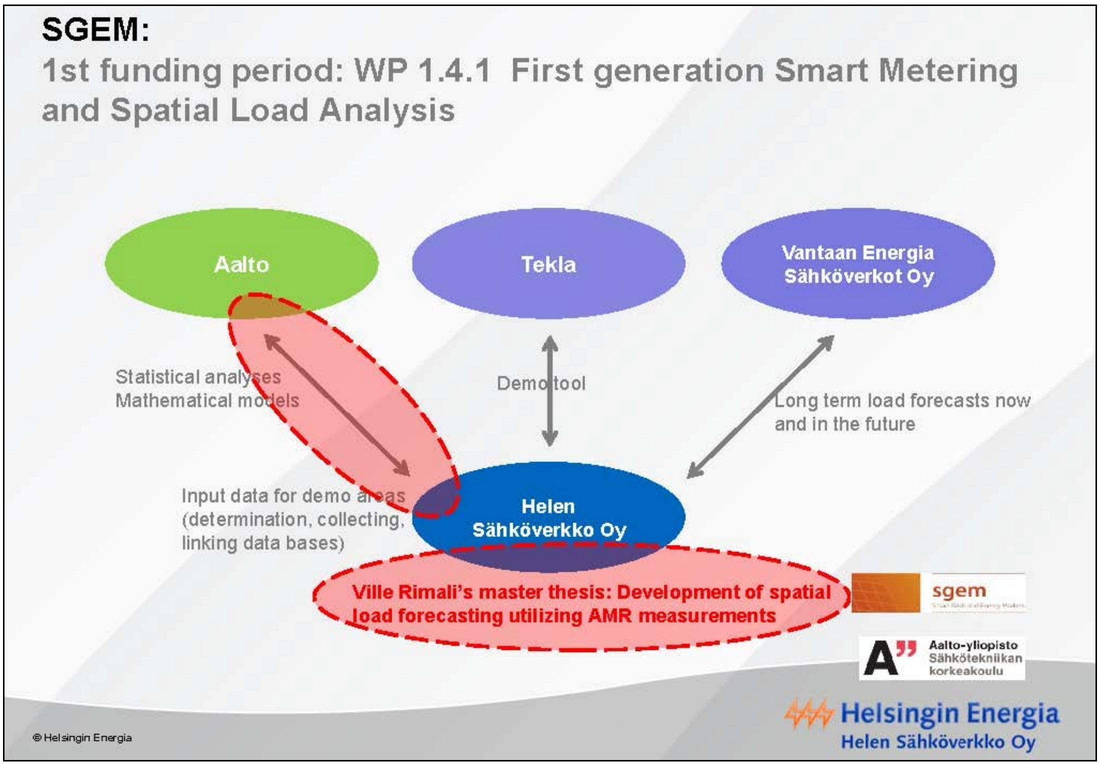
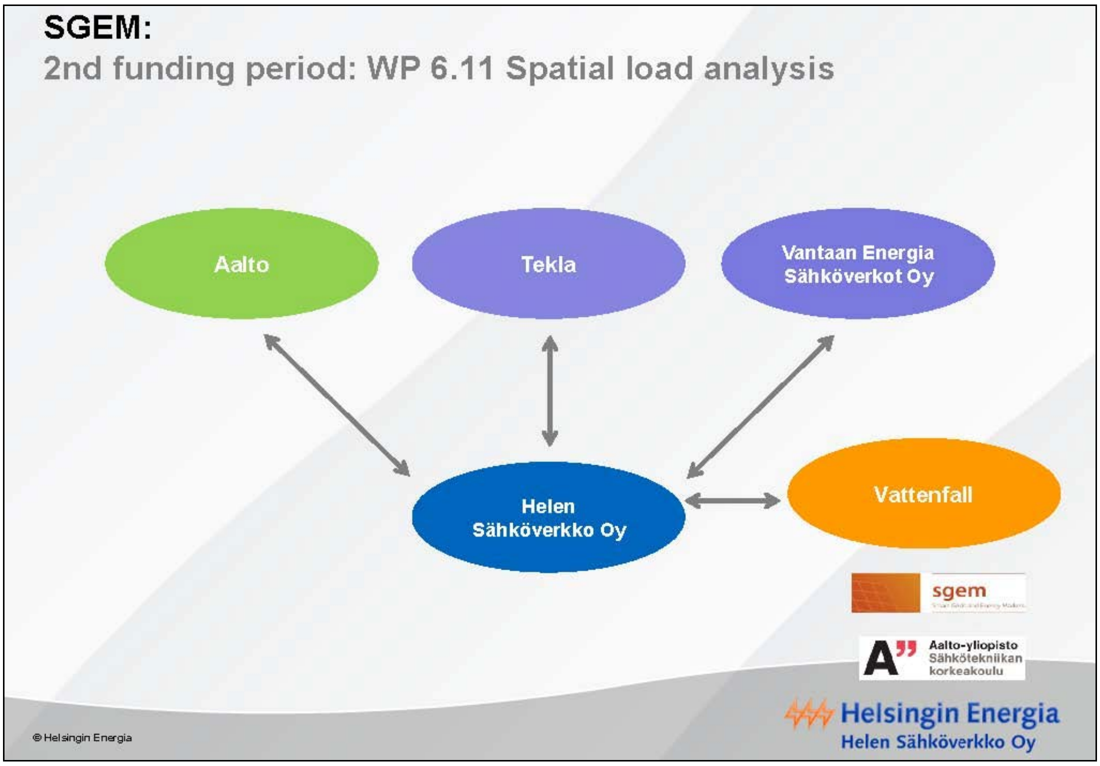
Excel
Lars Garpetun
24
24 VATTENFALL

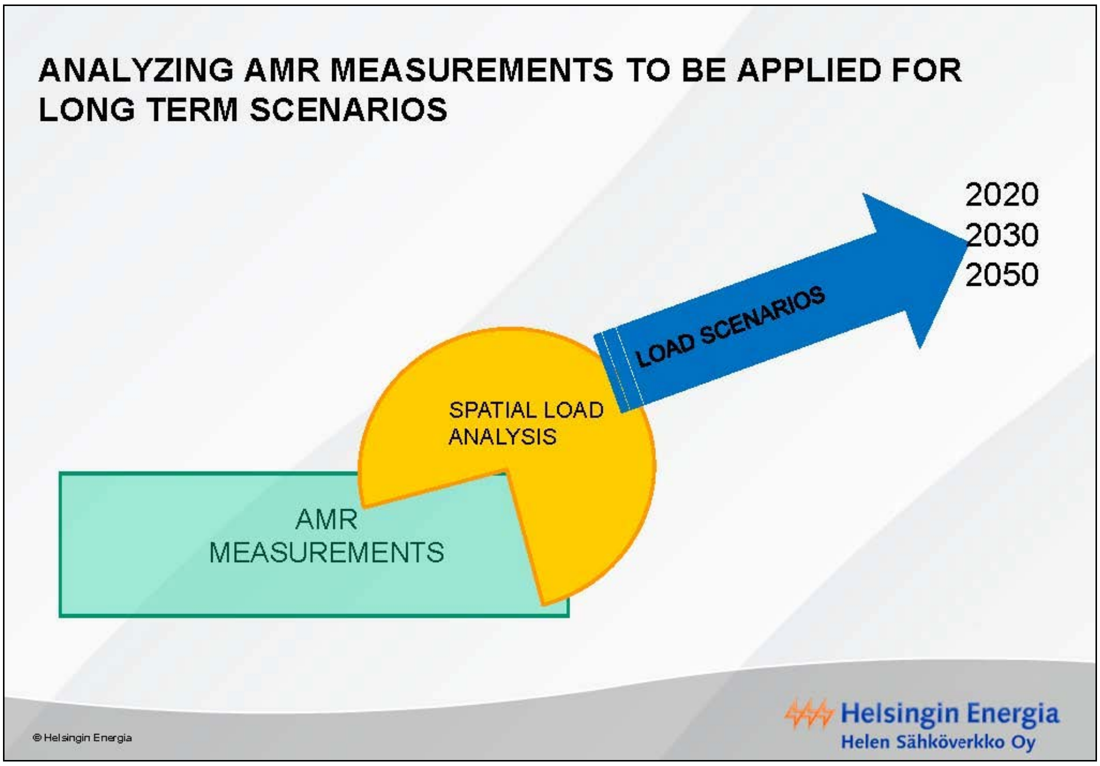

Thank you!

Appendix B: Analyzing AMR measurements to be applied for long term scenarios



Appendix B: Analyzing AMR measurements to be applied for long term scenarios





ANALYZING AMR MEASUREMENTS TO BE APPLIED FOR LONG TERM SCENARIOS

MOTIVATION: Why long term scenarios?

The planning and construction of power systems takes years, in case of cities and highest voltage levels even a decade. DSO has to be prepared for the future development of the city, society and use of electricity. This preparation includes in its early stages various scenarios how the load will develop in various parts of the city. Spatial load scenarios act as an input for long-term plans for the construction of the power system – where and when and what kind of new generation plants, new substations, new transmission lines etc. will be needed?

MOTIVATION: Why spatial load analysis?

To be able to make scenarios it will have to be known the present load in various parts of the city (spatial load). This acts as a starting point for future scenarios. To be able to model the future changes in the use of electricity it is needed to know how the present load is consisted of (e.g. shares, types and load curves of heating, air condition/ventilation, illumination).

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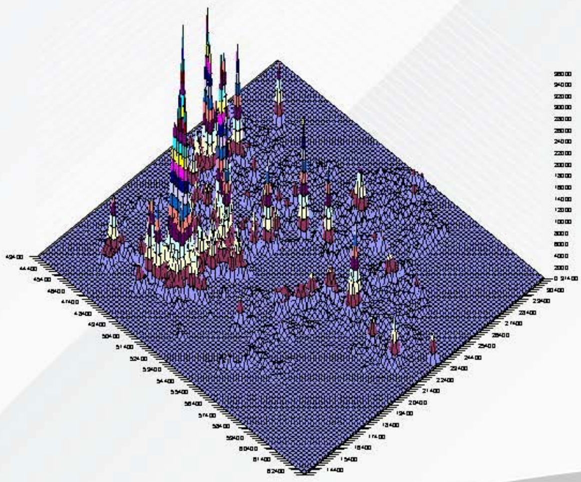
WHAT IS THE PRESENT SPATIAL LOAD ?



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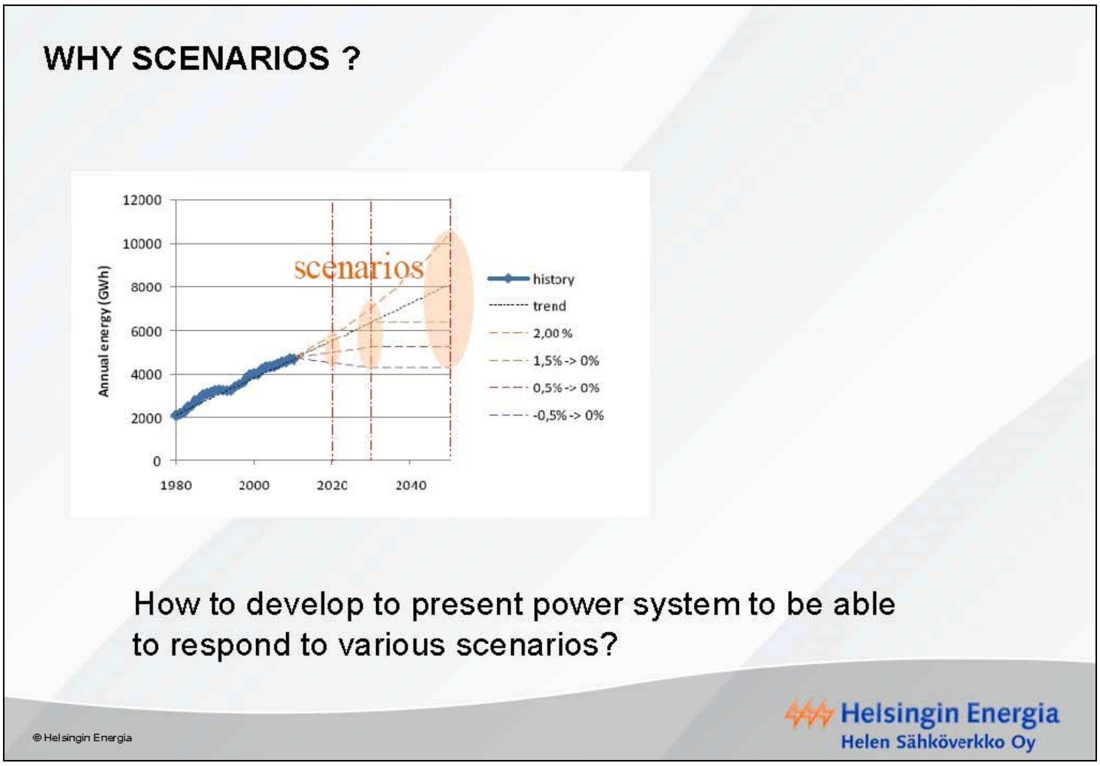
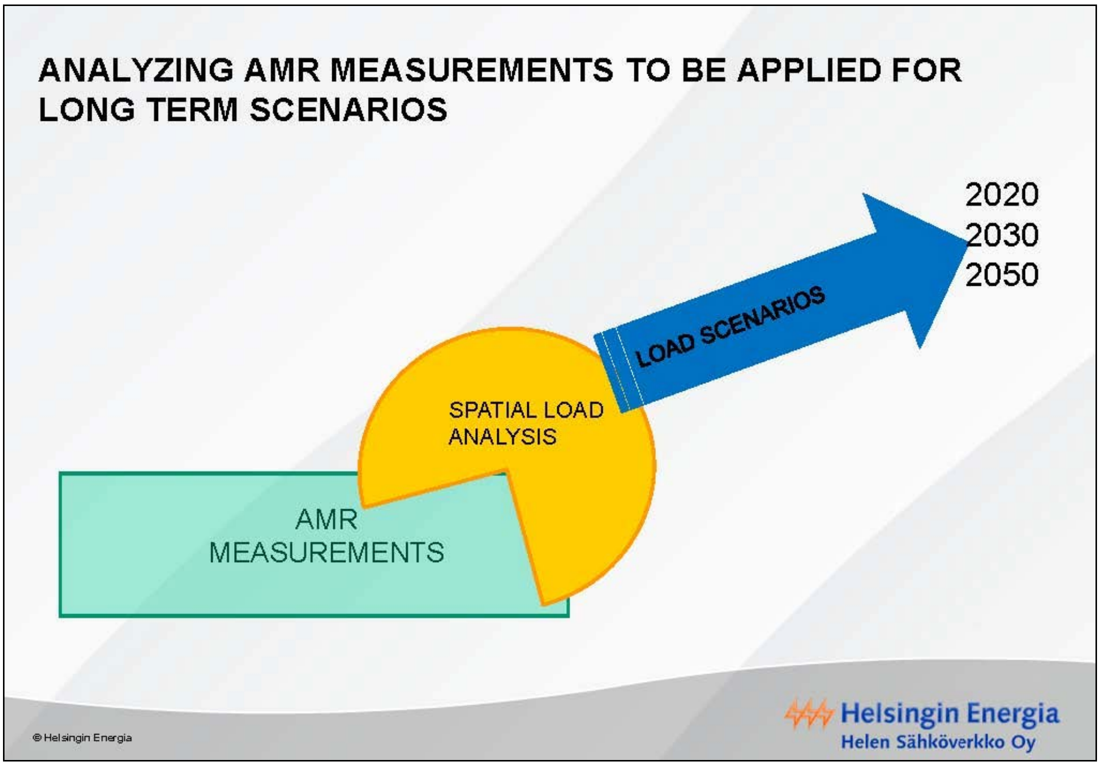
Appendix B: Analyzing AMR measurements to be applied for long term scenarios





ANALYZING AMR MEASUREMENTS TO BE APPLIED FOR LONG TERM SCENARIOS

ANALYSES

1. AMR measurements linked with background data
   - background data explains the electricity load
   - linking data from various data bases
   - input: AMR measurements and background data
   - output: spesific consumptions (kWh/FA-m2), e.g.
     - houses/offices with various heating / cooling
     - houses/offices of building of different ages

2. only AMR measurements
   - AMR measurements are analysed without any data of customers nor buildings etc.
   - input: AMR measurements and temperature
   - output: new load curves, temperature coefficients
   - two methods:
     - 2.1 principal component analysis + K-means clustering;
     - 2.2 key figure method + clustering

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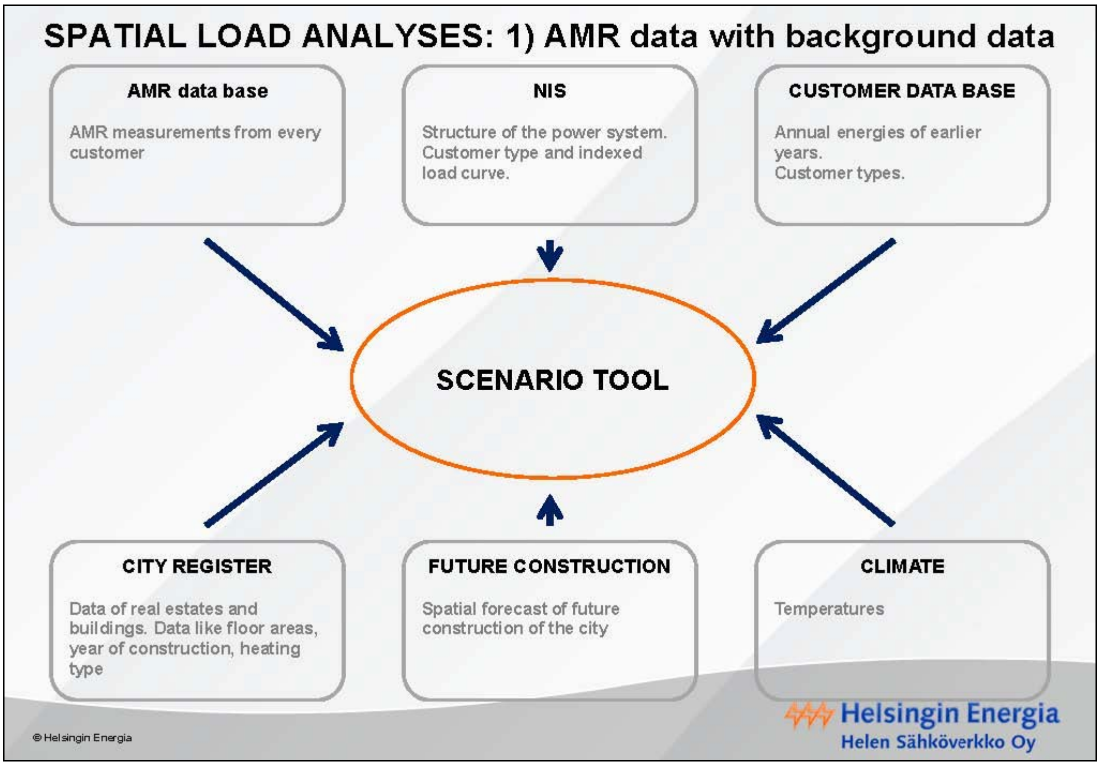
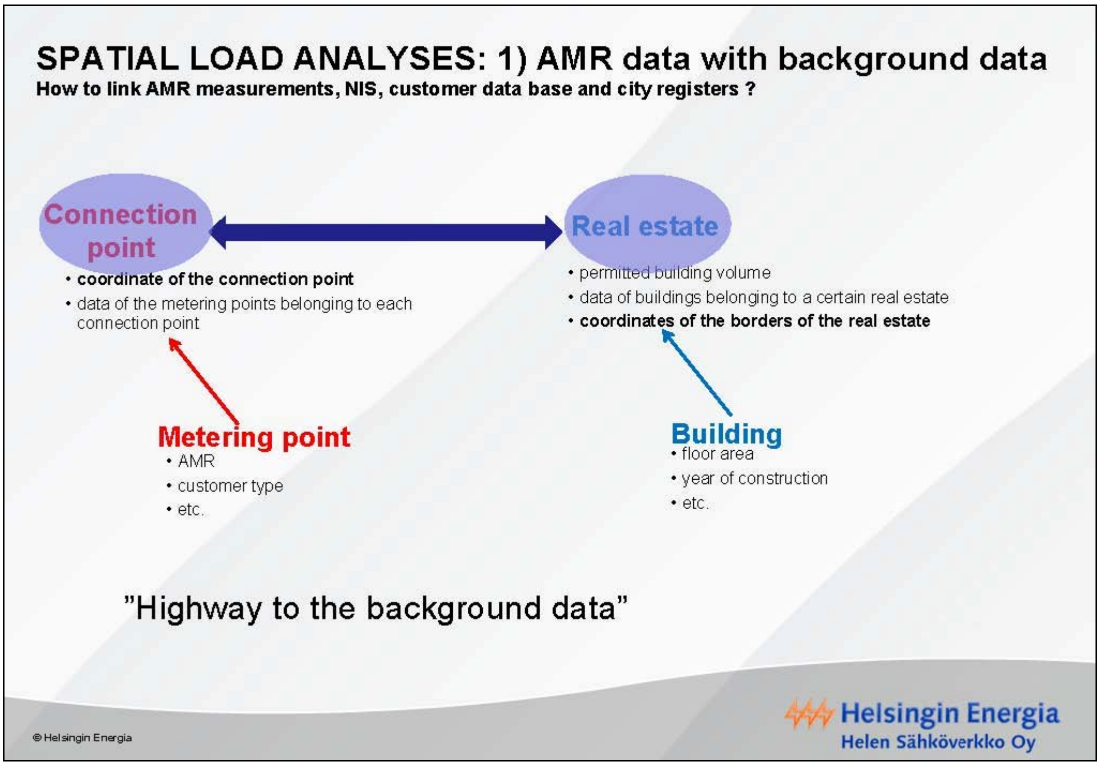
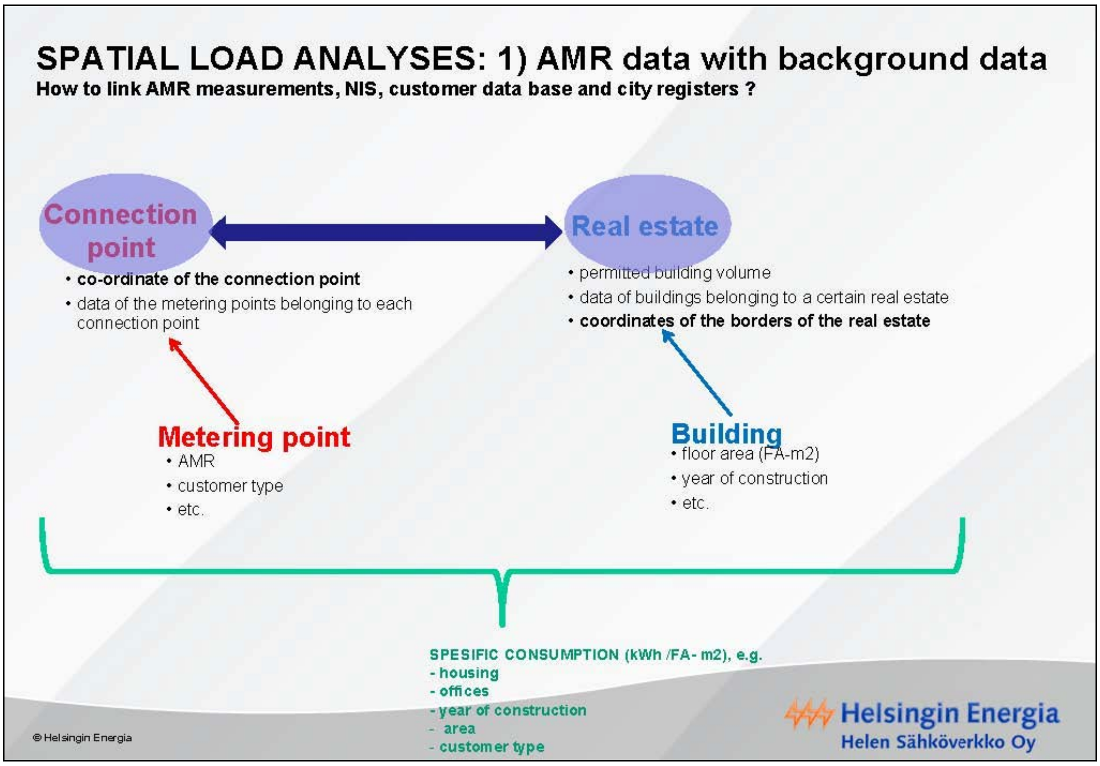
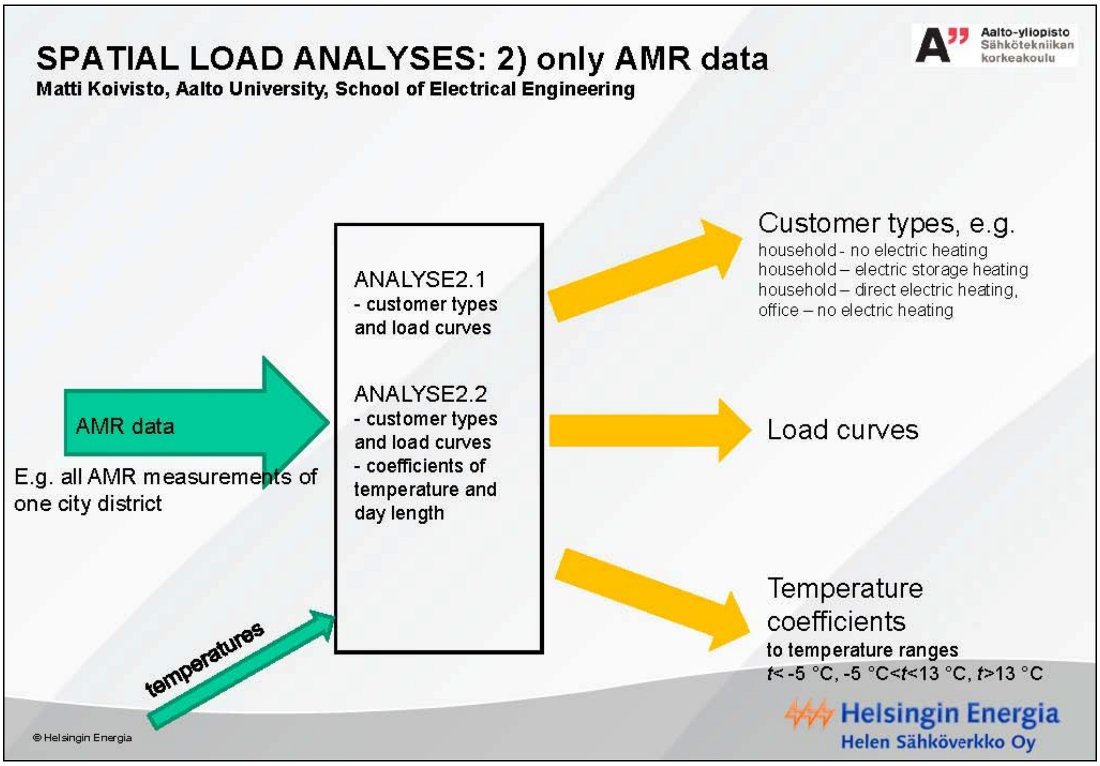


Appendix B: Analyzing AMR measurements to be applied for long term scenarios






SPATIAL LOAD ANALYSES: 2) only AMR data
Matti Koivisto, Aalto University, School of Electrical Engineering
Aalto-yliopisto Sähkötekniikan korkeakoulu
AMR data
E.g. all AMR measurements of one city district
temperatures
ANALYSE2.1
- customer types and load curves
ANALYSE2.2
- customer types and load curves
- coefficients of temperature and day length
Customer types, e.g.
household - no electric heating
household – electric storage heating
household – direct electric heating,
office – no electric heating
Load curves
Temperature coefficients
to temperature ranges
t< -5 °C, -5 °C<t<13 °C, t>13 °C
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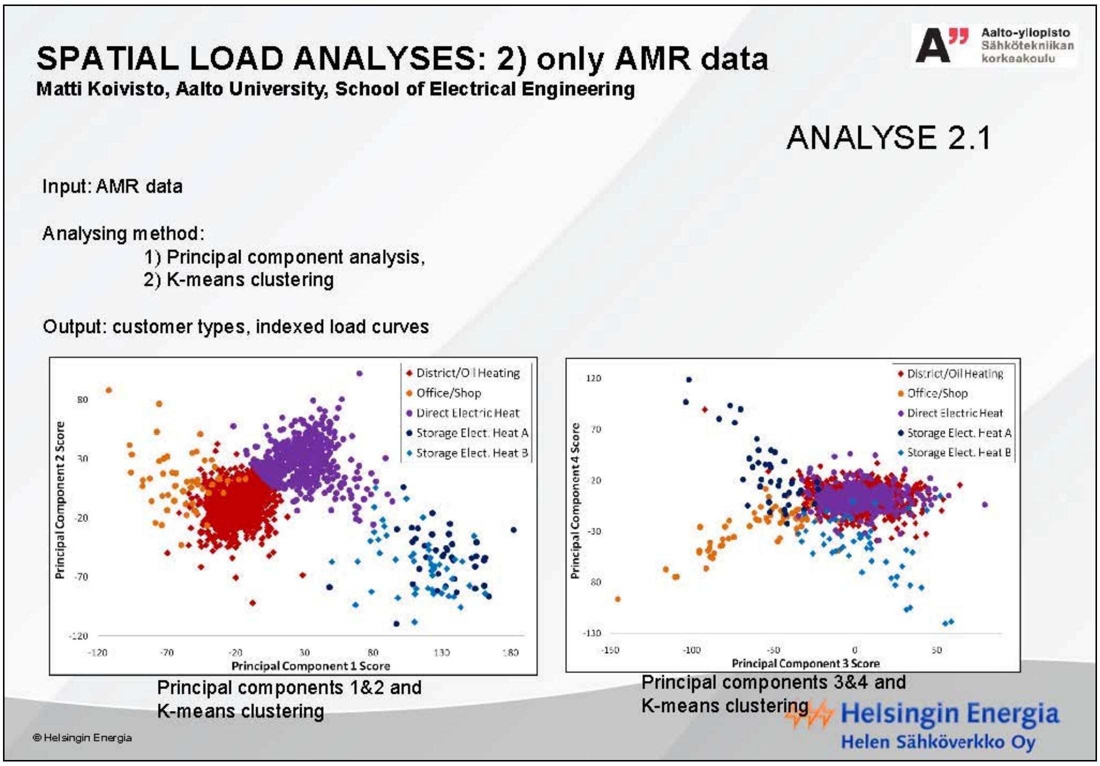
SPATIAL LOAD ANALYSES: 2) only AMR data
Matti Koivisto, Aalto University, School of Electrical Engineering
Aalto-yliopisto Sähkötekniikan korkeakoulu
ANALYSE 2.1
Input: AMR data
Analysing method:
1) Principal component analysis,
2) K-means clustering
Output: customer types, indexed load curves
District/Oil Heating
Office/Shop
Direct Electric Heat
Storage Elect. Heat A
Storage Elect. Heat B
Principal Component 2 Score
Principal Component 1 Score
Principal Component 4 Score
Principal Component 3 Score
Principal components 1&2 and K-means clustering
Principal components 3&4 and K-means clustering
Helsingin Energia
Helen Sähköverkko Oy
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Appendix B: Analyzing AMR measurements to be applied for long term scenarios

SPATIAL LOAD ANALYSES: 2) only AMR data

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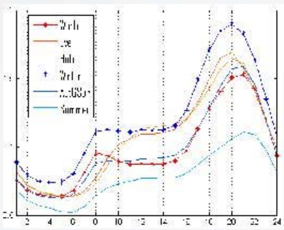
ANALYSE 2.1

- Principal component analysis
  - input matrix
    - rows: customers
    - columns: AMR hourly measurements
  - In principal, there will be as many principal components as there are columns. However, in Helsinki analysis of connection points, already with four principal components were found five various types (household and offices with various heating and air condition solutions)
- K-means clustering
- Determining load curves for each customer type

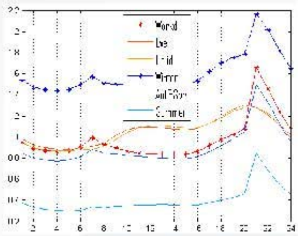
SPATIAL LOAD ANALYSES: 2) only AMR data

Matti Koivisto, Aalto University, School of Electrical Engineering

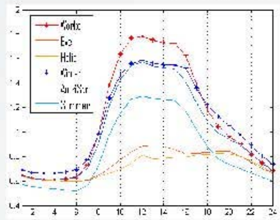
ANALYSE 2.1



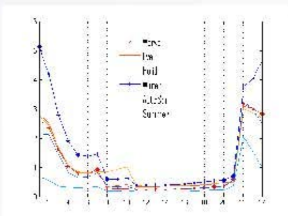
Household – district or oil heating



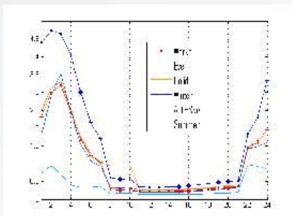
Household – direct electric heating



Office or shop – no electric heating



Household – electric storage heating A



Household – electric storage heating B

SPATIAL LOAD ANALYSES: 2) only AMR data

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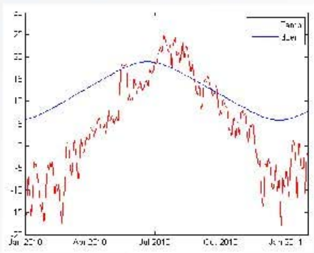
ANALYSE 2.2

Key figure method and clustering
Regression Using Day Length, Temperature and Day Type as Explanatory Variables



Temperature is a moving average of two days.

Day length is hours of light for a day.

Correlation between these two explanatory variables = 0.84.

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SPATIAL LOAD ANALYSES: 2) only AMR data

Matti Koivisto, Aalto University, School of Electrical Engineering

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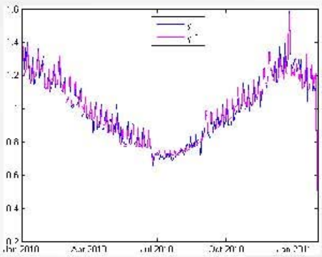
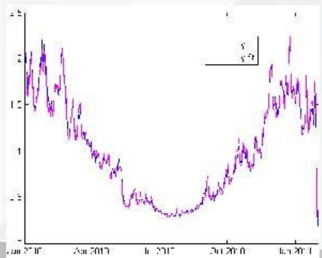
ANALYSE 2.2

Key figure method and clustering
Regression Using Day Length, Temperature and Day Type as Explanatory Variables



Direct Electric Heating:

Variable	b	b-standardized
b0	1.329439	1.000000
Temp	**-0.050326**	**-0.547933**
dLen	-0.015270	-0.068437
Eve	0.055730	0.019588
Holiday	0.067620	0.023766



Oil/District Heating:

Variable	b	b-standardized
b0	1.272928	1.000000
Temp	**-0.008875**	**-0.096626**
dLen	**-0.022192**	**-0.099462**
Eve	0.100533	0.035335
Holiday	0.104053	0.036572

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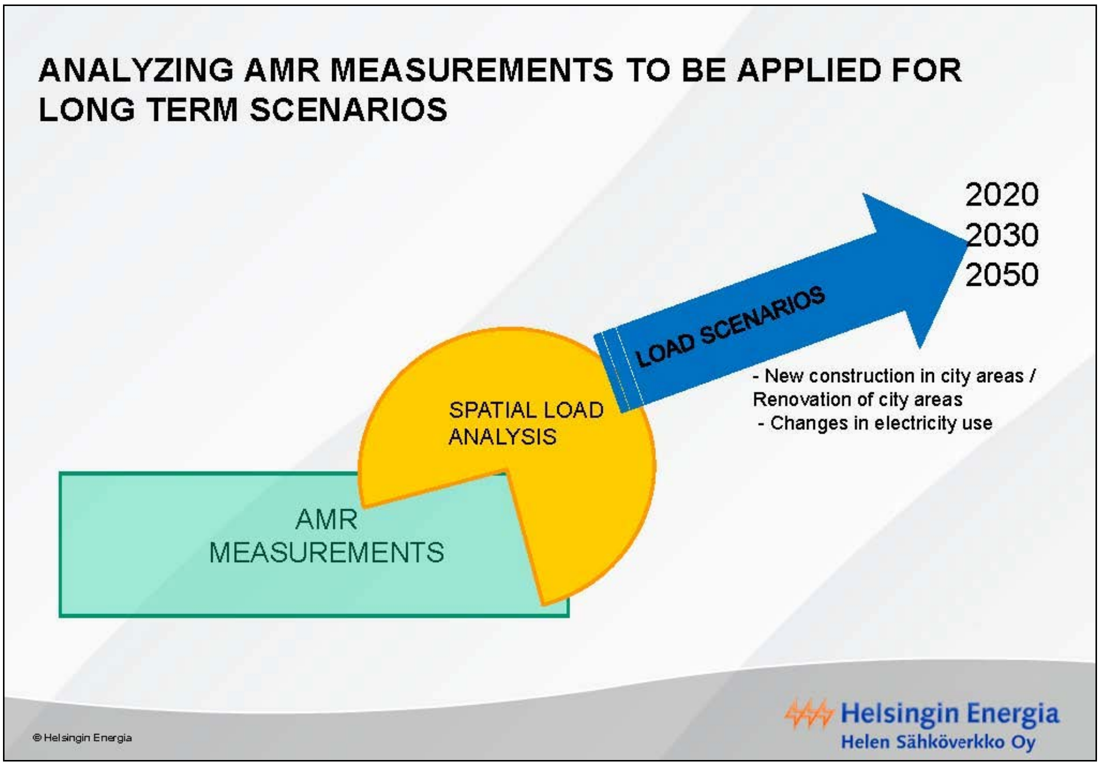
Appendix B: Analyzing AMR measurements to be applied for long term scenarios



SCENARIO: CHANGES IN THE USE OF ELECTRICITY

Analyses of the present consumption determines the basis for the modelling of the future changes. The future changes need to be modeled in scenarios.

+ air condition / ventilation
+ district cooling
+ electric cars, trains, metro, trams
+ ships at harbours connected to main land power system
+ serving centres
± heat pumps
± spesific consumption
- energy efficiency of equipment and buildings
- illumination
- energy efficiency
- small scale wind farms, solar panels,
- electric storages / demand side management
- political constraints

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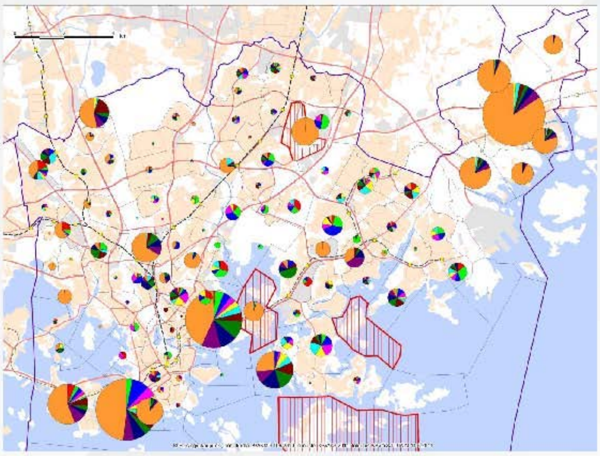

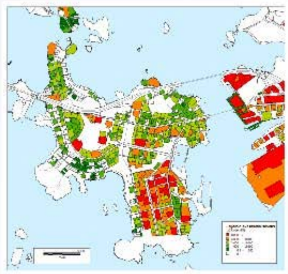

Forecast of new residential construction 2011 – 2030

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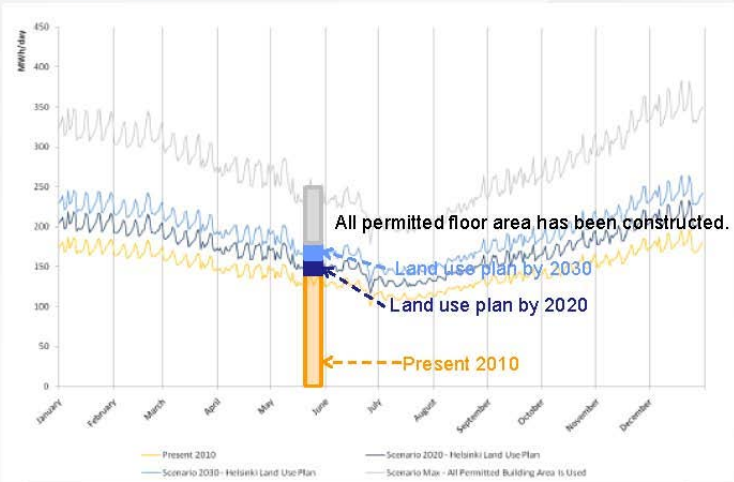
City district 1



Here, only the planned new construction is modeled. No changes in the electricity use is included in this model.

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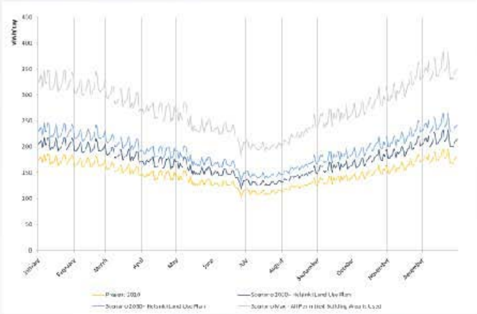
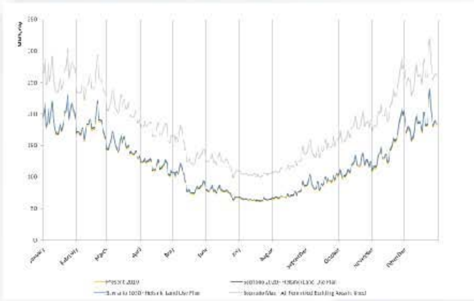
Appendix B: Analyzing AMR measurements to be applied for long term scenarios

SCENARIOS

City districts 1 and 2





Here, only the planned new construction is modeled. No changes in the electricity use is included in this model.

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ANALYZING AMR MEASUREMENTS TO BE APPLIED FOR LONG TERM SCENARIOS

ANALYSES

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   - linking data from various data bases
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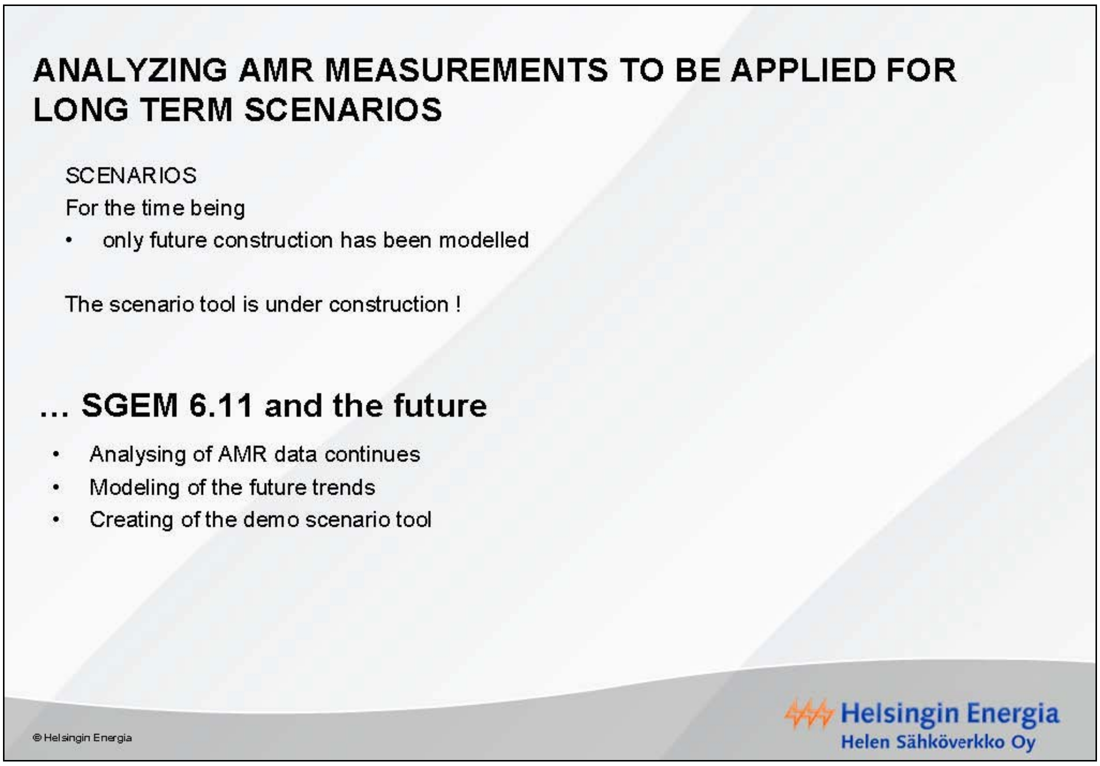
ANALYZING AMR MEASUREMENTS TO BE APPLIED FOR LONG TERM SCENARIOS
SCENARIOS
For the time being
• only future construction has been modelled
The scenario tool is under construction !
... SGEM 6.11 and the future
• Analysing of AMR data continues
• Modeling of the future trends
• Creating of the demo scenario tool
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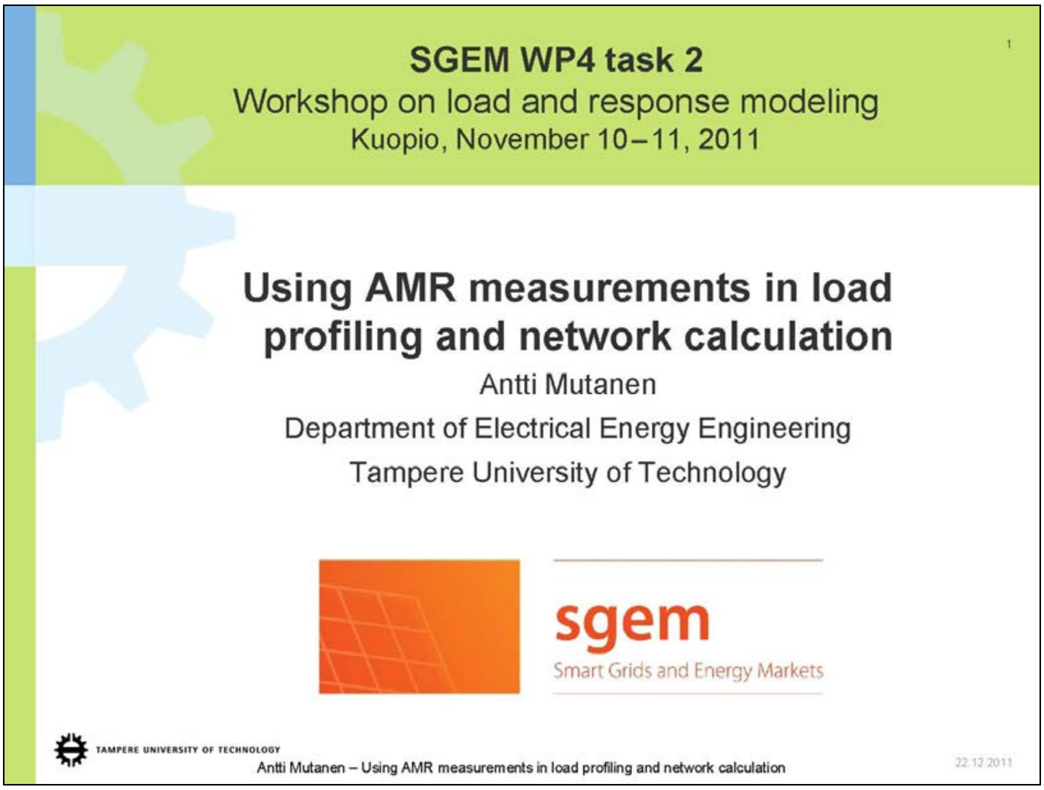
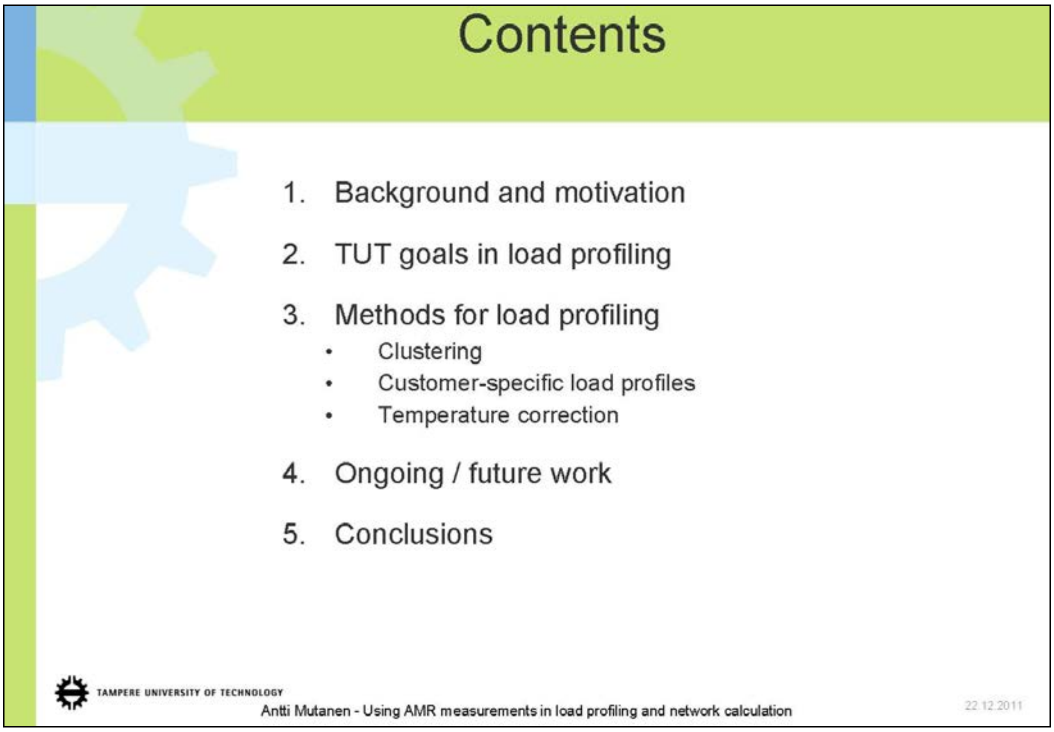
Appendix C: Using AMR measurements in load profiling and network calculation



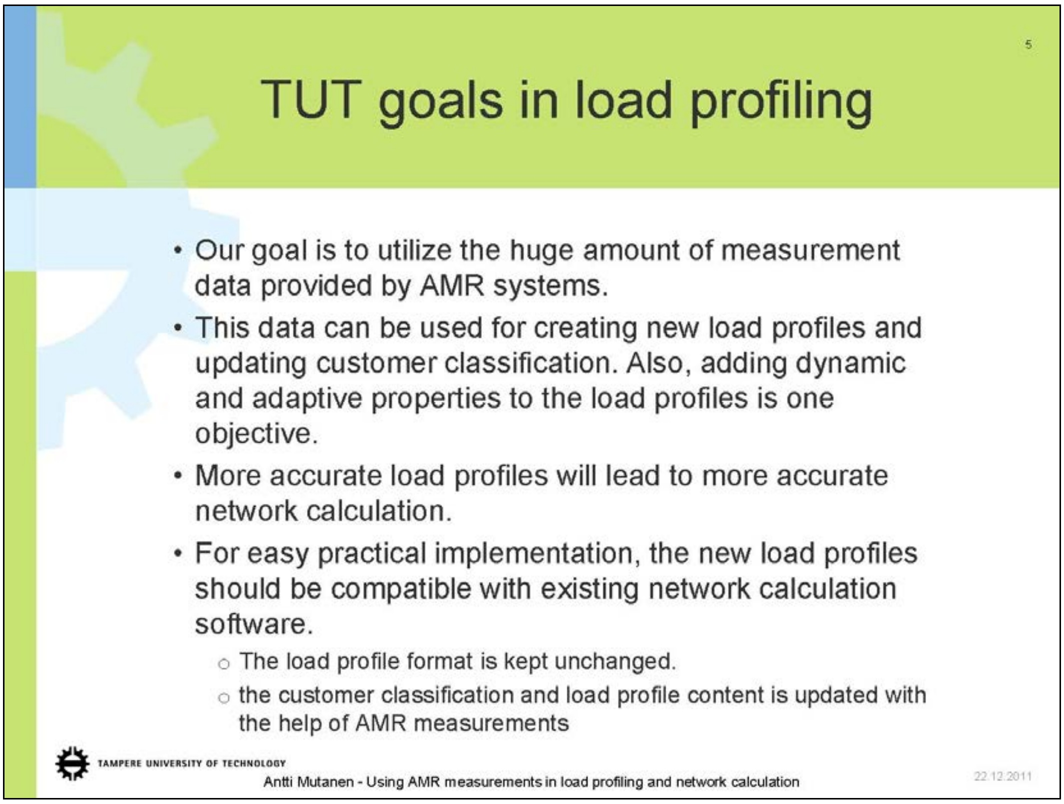


Background and motivation

- Finland has a long history in load profiling and network calculation with load profiles.
- Electric utilities started to co-operate in load research in the 1980's.
- In 1992, Finnish Electricity Association published customer class load profiles for 46 different customer classes.
- Since then, these load profiles have been used ***extensively*** in distribution network calculation
  - Load flow calculation
  - Planning calculation
  - State estimation
  - Pricing and tariff planning etc...

Background and motivation

- Large amounts of AMR data have recently become available
- Requirements for network calculation accuracy have become tighter
  - Active control of distribution networks is increasing => automatic control methods require accurate information on network states
  - Increasing the utilization rate of distribution networks requires better accuracy from planning calculation and state monitoring
- Defects in existing load models
  - Finnish load profiles are mostly based on 16–25 years old measurements
- Electricity consumption has changed over the years
  - Heat pumps and air-conditioners have multiplied
  - Entertainment electronics have multiplied
  - Electricity consumption in recreational dwellings is changing
  - Future technologies e.g. plug-in hybrids and customer-specific distributed generation will change the behaviour of electric loads


5
TUT goals in load profiling
• Our goal is to utilize the huge amount of measurement data provided by AMR systems.
• This data can be used for creating new load profiles and updating customer classification. Also, adding dynamic and adaptive properties to the load profiles is one objective.
• More accurate load profiles will lead to more accurate network calculation.
• For easy practical implementation, the new load profiles should be compatible with existing network calculation software.
○ The load profile format is kept unchanged.
○ the customer classification and load profile content is updated with the help of AMR measurements
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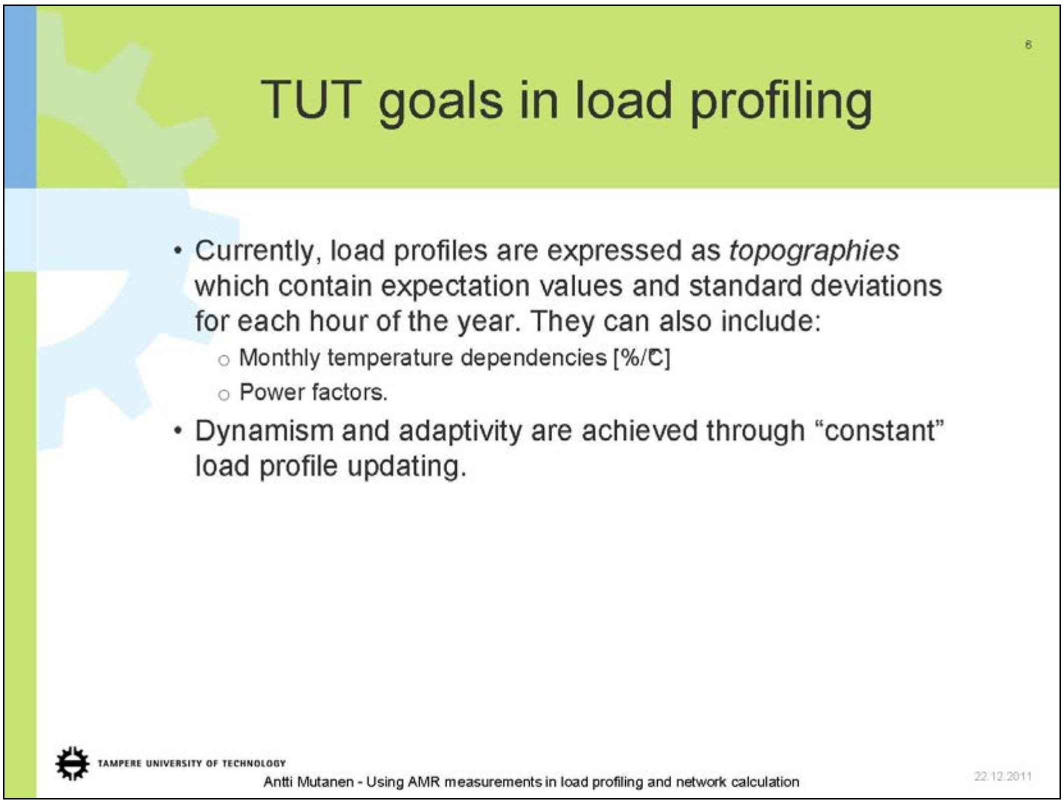
22.12.2011


6
TUT goals in load profiling
• Currently, load profiles are expressed as *topographies* which contain expectation values and standard deviations for each hour of the year. They can also include:
○ Monthly temperature dependencies [%/℃]
○ Power factors.
• Dynamism and adaptivity are achieved through “constant” load profile updating.
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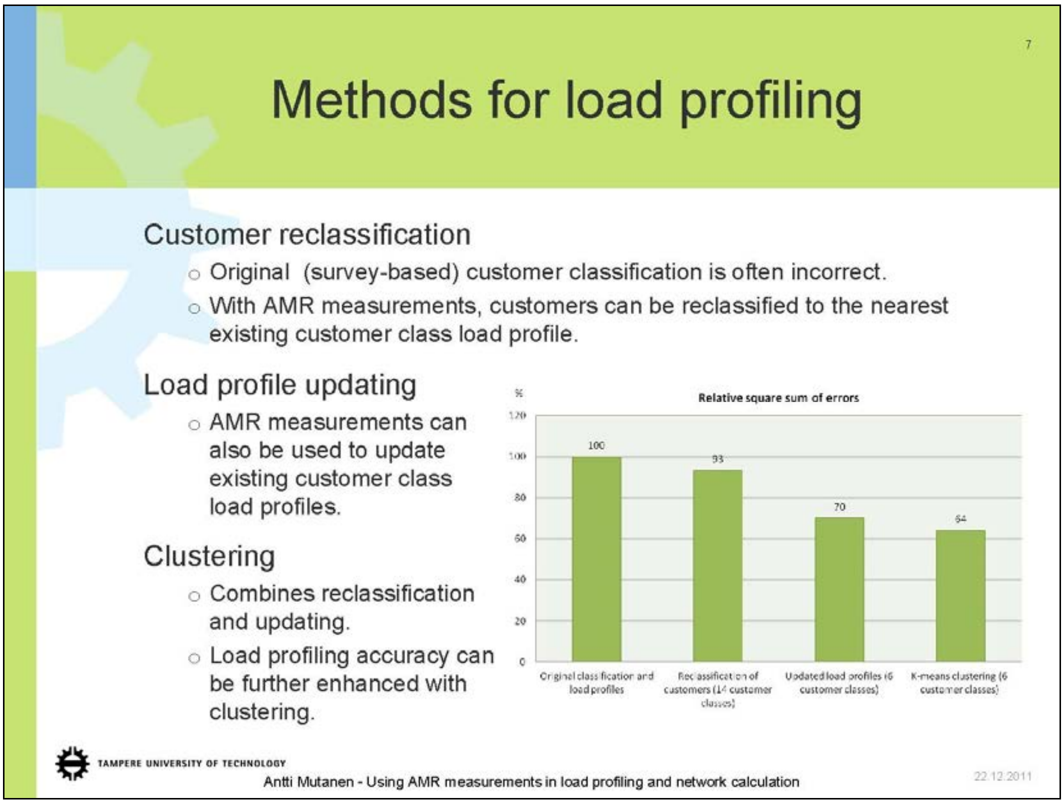
7
Methods for load profiling
Customer reclassification
Original (survey-based) customer classification is often incorrect.
With AMR measurements, customers can be reclassified to the nearest existing customer class load profile.
Load profile updating
AMR measurements can also be used to update existing customer class load profiles.
Clustering
Combines reclassification and updating.
Load profiling accuracy can be further enhanced with clustering.
Relative square sum of errors
%
120
100
80
60
40
20
0
100
93
70
64
Original classification and load profiles
Reclassification of customers (14 customer classes)
Updated load profiles (6 customer classes)
K-means clustering (6 customer classes)
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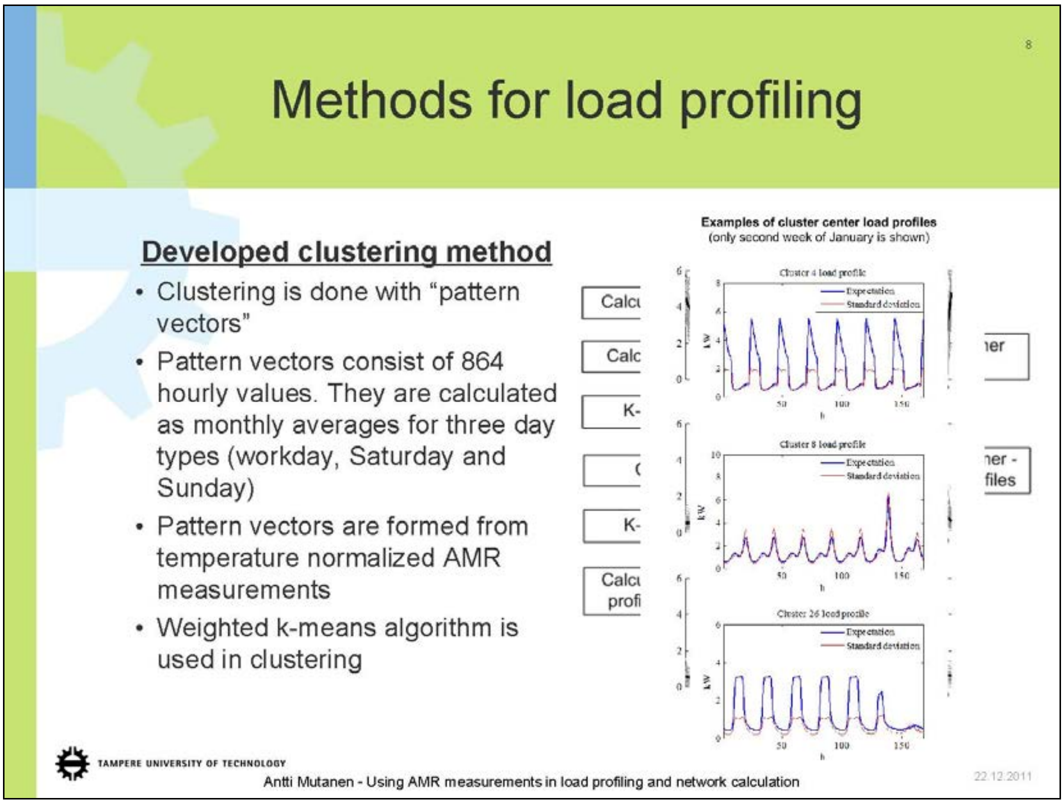
8
Methods for load profiling
Developed clustering method
Clustering is done with "pattern vectors"
Pattern vectors consist of 864 hourly values. They are calculated as monthly averages for three day types (workday, Saturday and Sunday)
Pattern vectors are formed from temperature normalized AMR measurements
Weighted k-means algorithm is used in clustering
Examples of cluster center load profiles
(only second week of January is shown)
Cluster 4 load profile
Cluster 8 load profile
Cluster 26 load profile
Expectation
Standard deviation
kW
h
Calcu
Calc
K-
K-
Calcu
profi
ner
ner -
files
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9

Customer-specific load profiles

- All customers can't be modelled accurately with customer class load profiles → customer-specific load profiles are needed for these customers
- The amount of load profiles that can be handled in current network calculation software is limited
  - The customer-specific load profiles must be selected with care
- The proposed outlier detection method:
  1. Calculate distances (squared Euclidean distance) to the nearest cluster center using pattern vectors
  2. Multiply the distance with the square of customers yearly energy consumption
  3. Select N customers with largest distances, where N is the desired number of customer-specific load profiles

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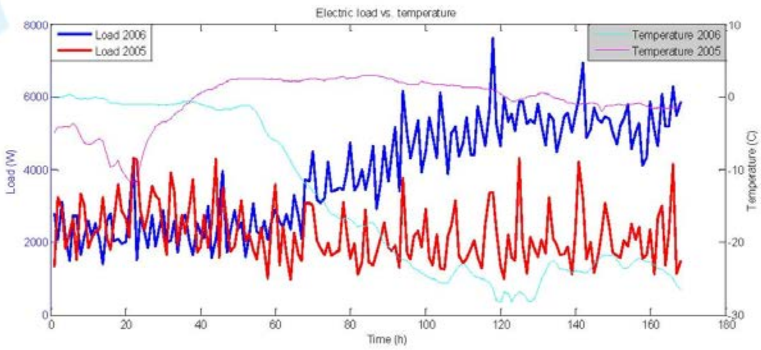
10

Customer-specific load profiles

- Customer-specific load profiles shouldn't be formed directly from AMR measurements. At least the following issues should be taken into account:
  1. Temperature dependency



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11

Customer-specific load profiles

2. Special days / holidays, especially the ones that don't have a fixed date (Eastern etc.)
3. Stochastic nature of the load
   → Use typedays to filter stochasticity and calculate means and standard deviations

- Proposed profiling method for customer-specific load profiles:
  1. Calculate temperature dependency
  2. Normalize measurements to the long term (monthly) average temperature
  3. Calculate average typedays (workday, Saturday, Sunday) for each month
  4. Form the load profile from typedays, taking into account special days.

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12

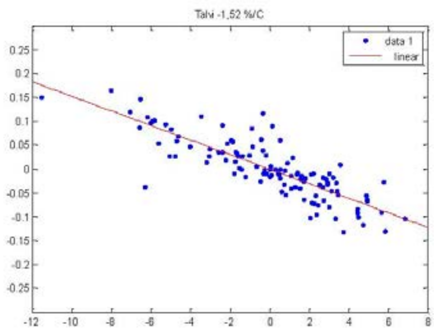
Temperature correction

Temperature dependency calculation:

- The temperature dependency parameters are calculated with linear regression analysis.
- The effects of daily and monthly fluctuations in electricity demand are eliminated by choosing the dependent and determining variables as follows:

Dependent variable (regressand):
the percent error between the daily energy consumption and the average daily energy consumption on a similar day (same day of the week and month).

Determining variable (regressor):
difference between the daily average temperature and the average temperature on a similar day.



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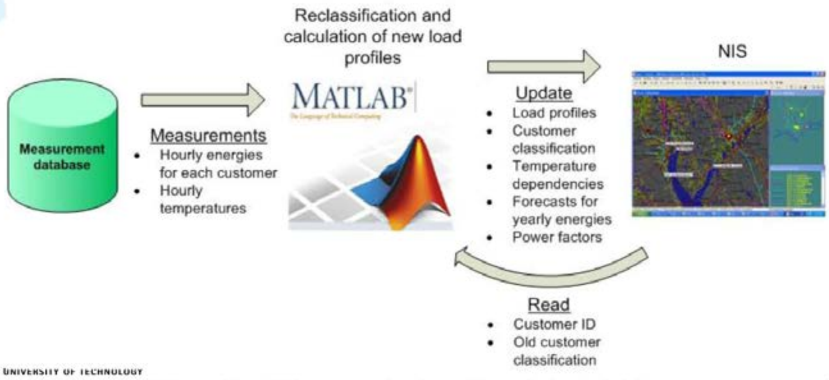
13

Ongoing / future work

- Demonstrative (Matlab) program that uses AMR data to reclassify customers and update load profiles
- Case studies how new load profiles affect network calculation and state estimation accuracy



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Antti Mutanen - Using AMR measurements in load profiling and network calculation
22.12.2011

14

Conclusions

- AMR data and existing load profile structure can be used to enhance load profiling accuracy
- Clustering is an effective tool for customer classification
- Customer-specific load profiles should be formed for large customers that do not fit to any customer class
- Including temperature dependencies in the load models is essential.

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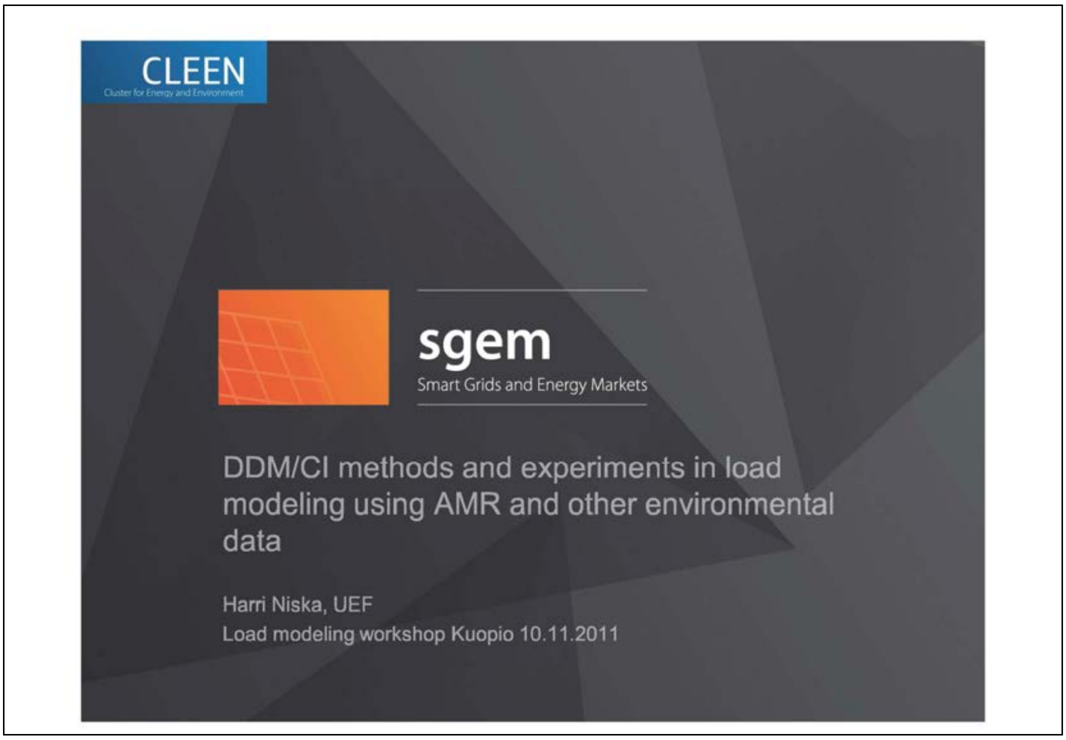
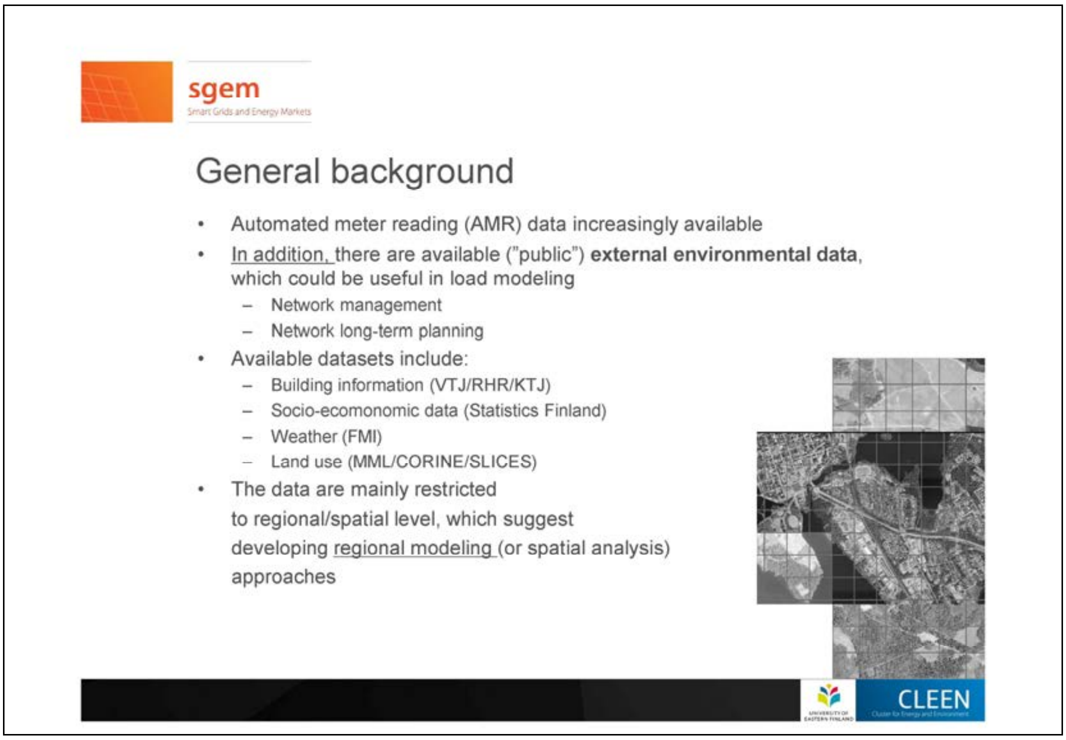
Appendix D: DDM/CI methods and experiments in load modelling using AMR and other environmental data





Appendix D: DDM/CI methods and experiments in load modelling using AMR and other environmental data

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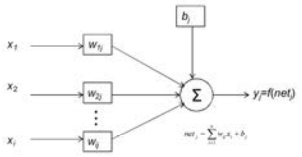
DDM/CI techniques

- In "data-rich" conditions:
  - *Data-driven modeling* (DDM) methods provide new possibilities for load modeling
- Main emphasis on novel data mining / computational techniques contributed by the field of *Computational Intelligence (CI)*
  - Neurocomputing
    - SOM, MLP, SVR/SVM, RBF
  - Evolutionary and genetic algorithms
  - Fuzzy logic
  - Clustering methods
    - K-means/fuzzy c-means/Isodata
- Conventional statistical methods
  - Linear regression
  - Principal component analysis (PCA)
  - PCR/PLS
- Combination with GIS



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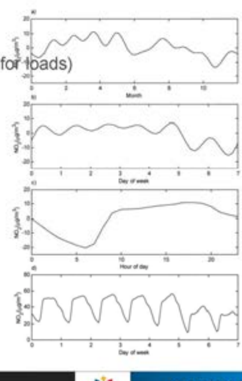
Possible advantages of DDM/CI methods

- Searching complex spatiotemporal patterns (clusters) in data
  - Constructing load curves at different levels of presentation (appliance…customer…region)
- Modeling non-linearity and temporal dynamics of loads
  - Complex interaction with external variables (e.g. socio-economic related variables)
  - System time-delays (e.g. influence of outdoor temperature for loads)
- Forecasting future behaviour of time-series
  - Short-term predictions required in load control
- Handling of measurement errors and noise and missing data



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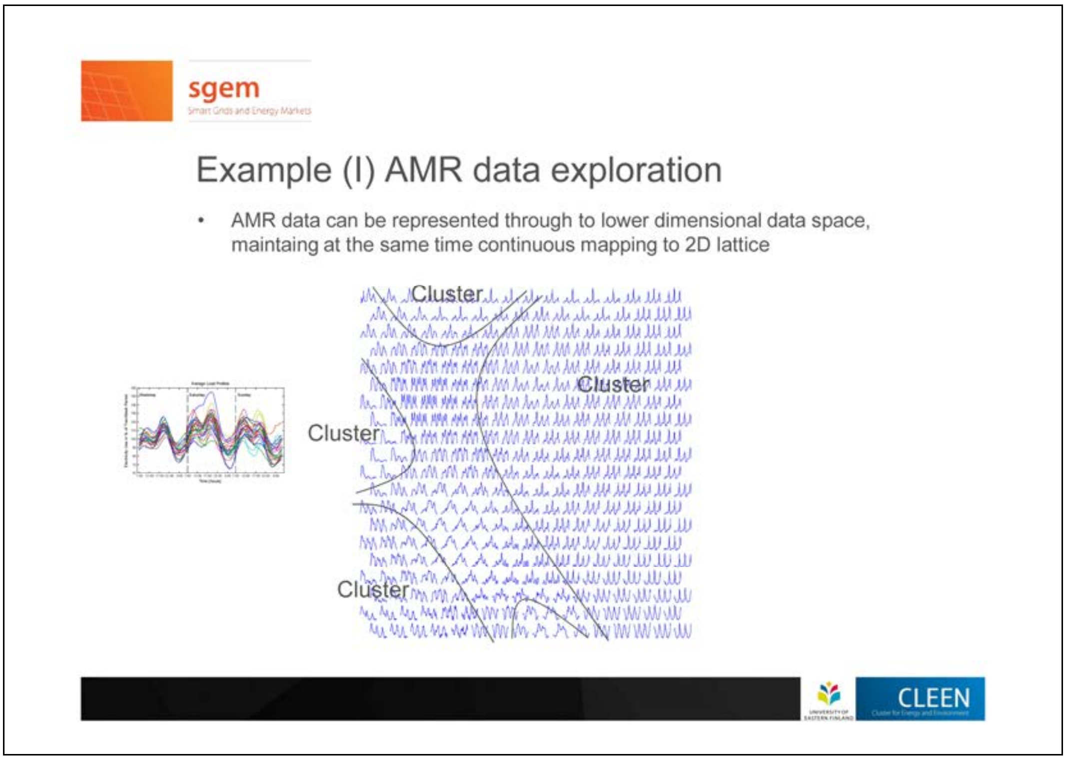
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Example (I) AMR data exploration
• AMR data can be represented through to lower dimensional data space, maintaing at the same time continuous mapping to 2D lattice
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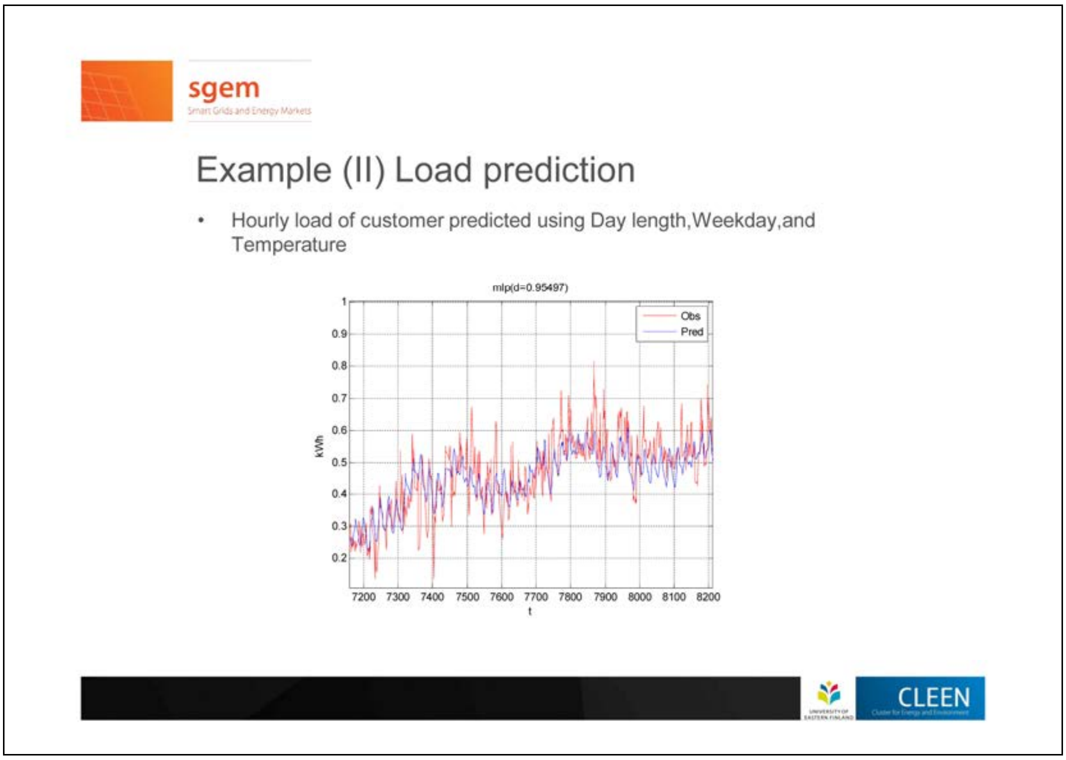
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Example (II) Load prediction
• Hourly load of customer predicted using Day length,Weekday,and Temperature
mlp(d=0.95497)
Obs
Pred
kWh
t
7200 7300 7400 7500 7600 7700 7800 7900 8000 8100 8200
0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1
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Main experiments so far…

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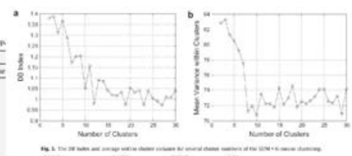
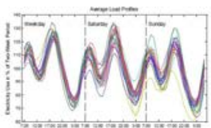
Re-definition of load curves

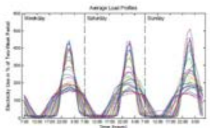
- Based on AMR data: 4454 small scale customers (Savon Voima) and the developed clustering approach with the following data processing:
  - Temperature corrections (based on customer specific temperature factors)
  - Feature extraction from AMR data
  - Clustering AMR data using the features extracted (SOM+k-means)
  - Extracting new load curves basis of cluster centers
  - Evaluating new load curves (NIS/PG)

Table 1
The index of agreement for the new customer groups and the ones used by the comp…

Company's customer groups							
Load curve	Mean IA	Std IA	No. of custome…				
LC1	0.671	0.097	796				
LC2	0.312	0.074	791				
LC3	0.316	0.102	379				
LC4	0.459	0.119	341				
LC5	0.681	0.098	327				
LC6	0.135	0.046	314				
LC7	0.590	0.090	156				
LC8	0.490	0.054	153				
LC9	0.562	0.101	133	NLC9	0.589	0.090	239
LC10	0.349	0.107	122	NLC10	0.458	0.089	194
LC11	0.498	0.139	120	NLC11	0.790	0.066	168
LC12	0.578	0.145	84	NLC12	0.302	0.084	160
LC13	0.617	0.160	80	NLC13	0.828	0.058	149
LC14	0.778	0.117	46	NLC14	0.939	0.087	144
LC15	0.941	0.109	36	NLC15	0.605	0.118	141
LC16	0.560	0.182	30	NLC16	0.804	0.083	135
LC17	0.589	0.187	17	NLC17	0.792	0.138	86
LC18	0.720	0.159	11	NLC18	0.722	0.113	84
Other	0.805	0.049	53	NLC19	0.909	0.072	82
Mean of all customers	0.478	0.209	3989		0.627	0.237	3989







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Regional modeling

- Mainly focused on:
  - **Heating system scenario modeling** using VTJ/RHR building data
  - **PHEV modeling**, modeling regional adoption potential based on socio-economic characteristics
- Basic hypothesis: similar customers have similar behaviour,

leads to question how to measure the similarity, and further under this:

- 1) *How to predict* which customers change their behavior (investigated in PHEV modeling)
- 2) *How to select* new load curve(s) when customers change their behavior (e.g. changing heating system)

- Of further interest:
  - Regional data available,

… Regional load curve approach?

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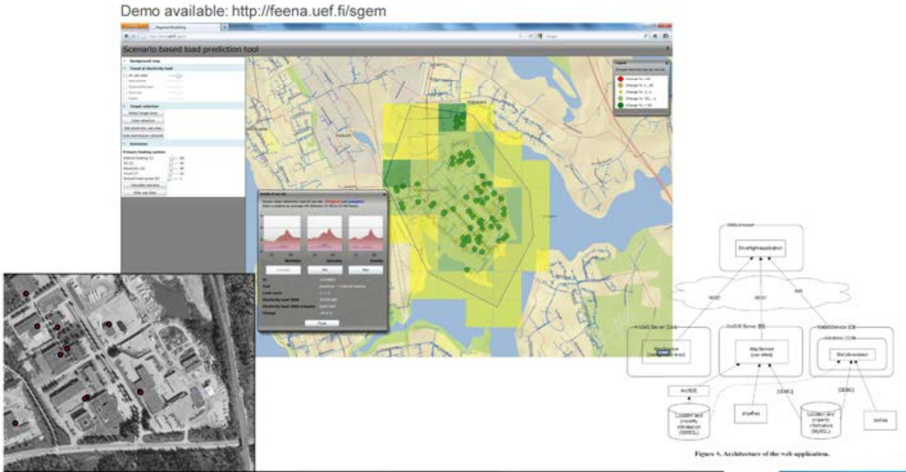
Regional modeling web application

Demo available: http://feena.uef.fi/sgem



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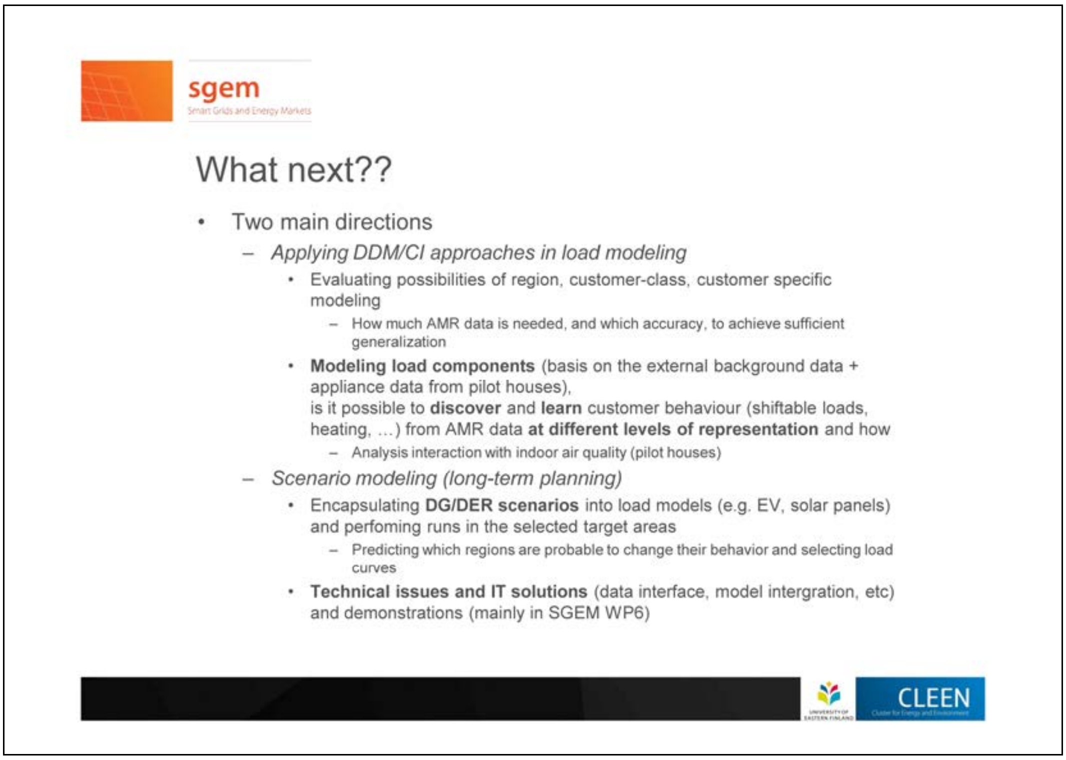
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What next??
• Two main directions
– *Applying DDM/CI approaches in load modeling*
• Evaluating possibilities of region, customer-class, customer specific modeling
– How much AMR data is needed, and which accuracy, to achieve sufficient generalization
• **Modeling load components** (basis on the external background data + appliance data from pilot houses), is it possible to **discover** and **learn** customer behaviour (shiftable loads, heating, …) from AMR data **at different levels of representation** and how
– Analysis interaction with indoor air quality (pilot houses)
– *Scenario modeling (long-term planning)*
• Encapsulating **DG/DER scenarios** into load models (e.g. EV, solar panels) and perfoming runs in the selected target areas
– Predicting which regions are probable to change their behavior and selecting load curves
• **Technical issues and IT solutions** (data interface, model intergration, etc) and demonstrations (mainly in SGEM WP6)
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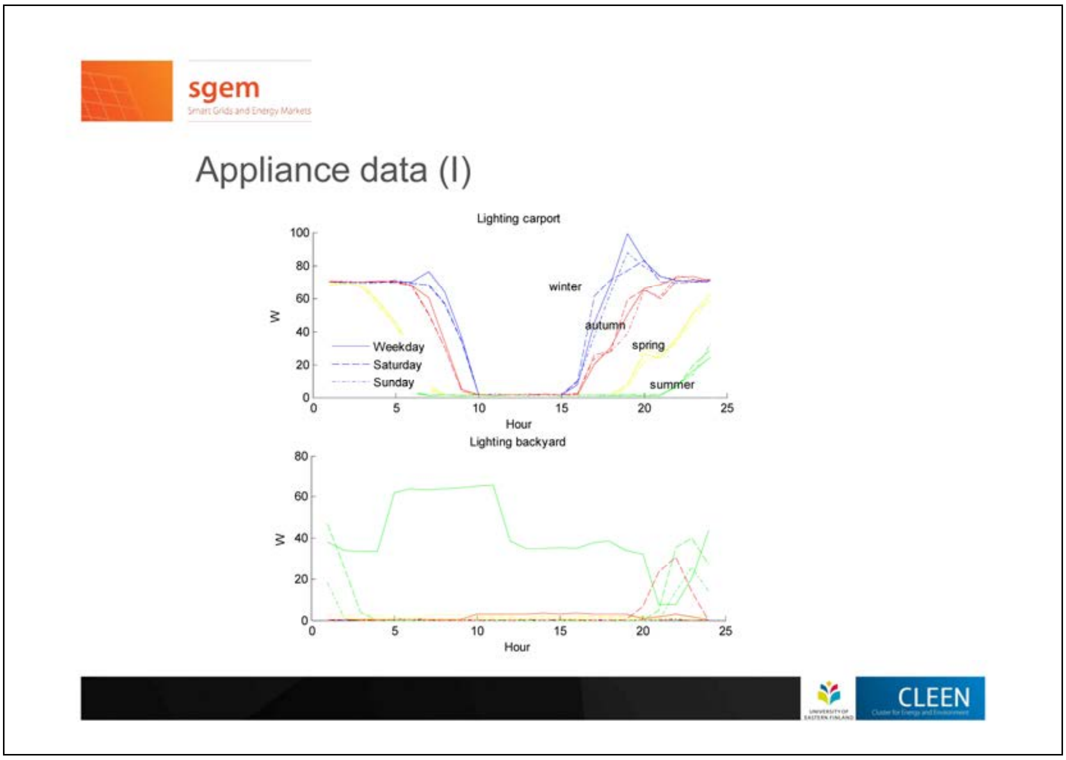
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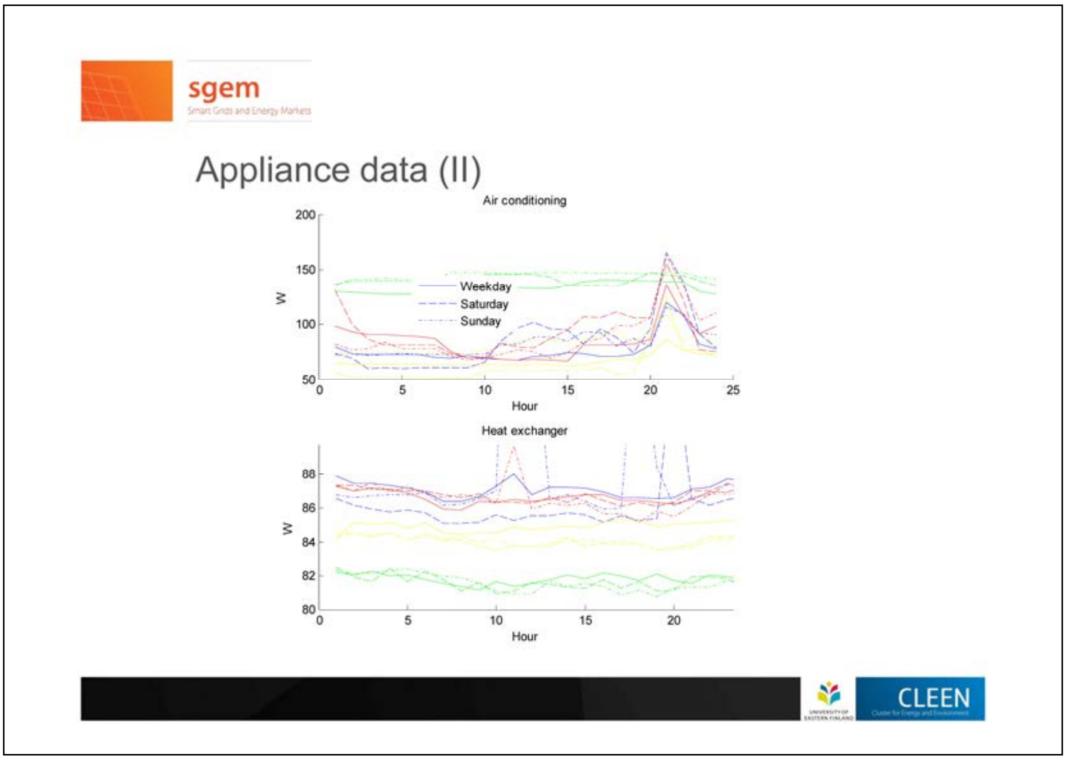
Appliance data (I)
Lighting carport
W
Hour
Weekday
Saturday
Sunday
winter
autumn
spring
summer
Lighting backyard
W
Hour
CLEEN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Appliance data (II)
Air conditioning
Weekday
Saturday
Sunday
W
Hour
Heat exchanger
W
Hour
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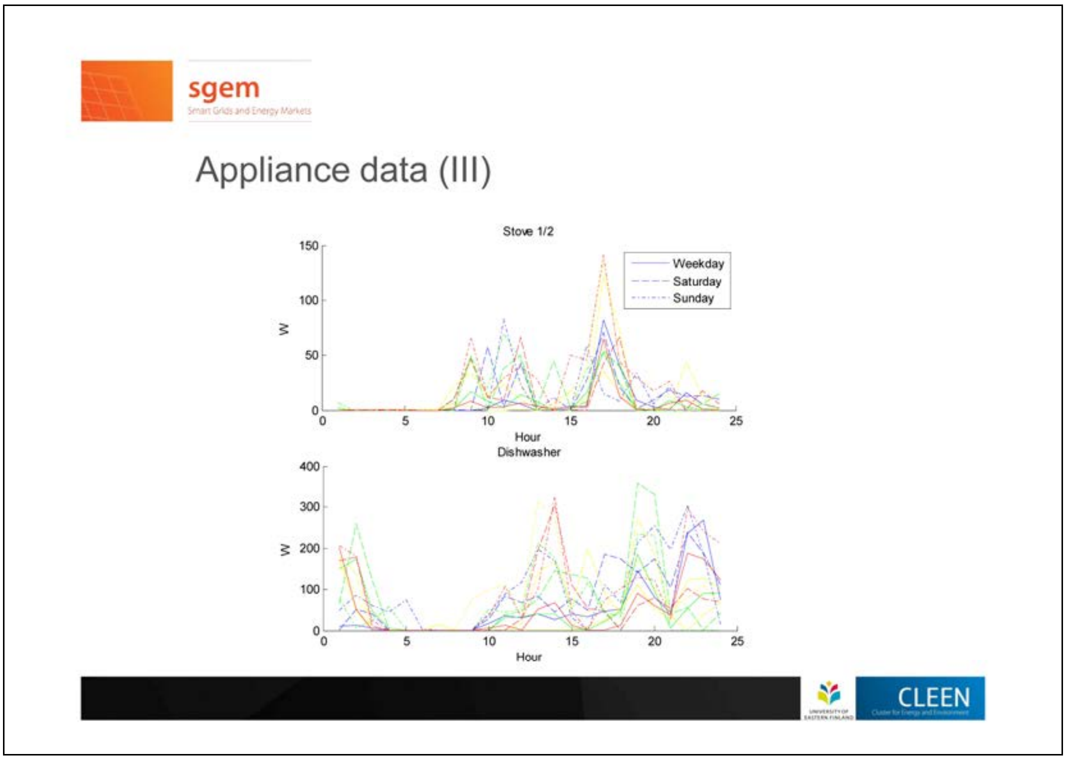
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Appliance data (III)
Stove 1/2
Weekday
Saturday
Sunday
W
Hour
Dishwasher
W
Hour
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Appendix D: DDM/CI methods and experiments in load modelling using AMR and other environmental data

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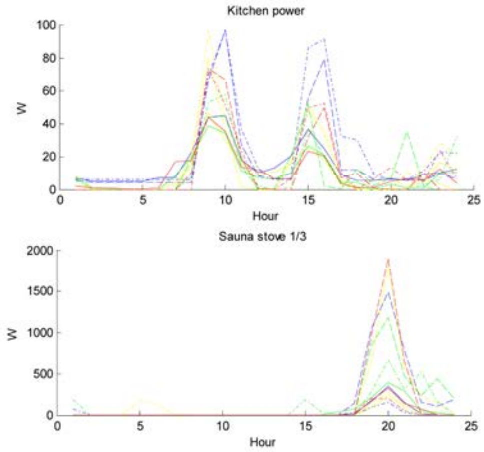
Appliance data (IV)



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General observations/challenges

- Proper validation of load models is somewhat difficult (e.g. the definition of load curves in NIS seems to be not fully automatised...)
- Availability of AMR data is so far limited for the research purposes
- Supporting information on customers are imperfect (incomplete, unreliable or totally missing)

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Thank you for your attention!

Harri Niska
Environmental Informatics
Department of Environmental Science
University of Eastern Finland
P.O.Box 1627, FI-70211 Kuopio, Finland

Phone: +358 44 2651 291
Email: harri.niska@uef.fi

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Recent publications

- Niska et al. (2011) *Scenario based electricity load prediction tool for distribution planning and management.* CIRED 2011.
- Saarenpää (2011) *Modeling electricity consumption using the self-organizing map.* M.Sc. Thesis. Computer Science.
- Räsänen et al. (2010) *Data-based method for creating electricity use load profiles using large amount of customer-specific hourly measured electricity use data.* Applied Energy 87 3538-3545
- Räsänen and Kolehmainen (2009) *Feature-based clustering for electricity use time series data.* Lecture Notes in Computer Science 5495 401-412.
- Räsänen et al. (2008) *Reducing energy consumption using self-organizing maps to create more personalized electricity use information.* Applied Energy 85 830-840

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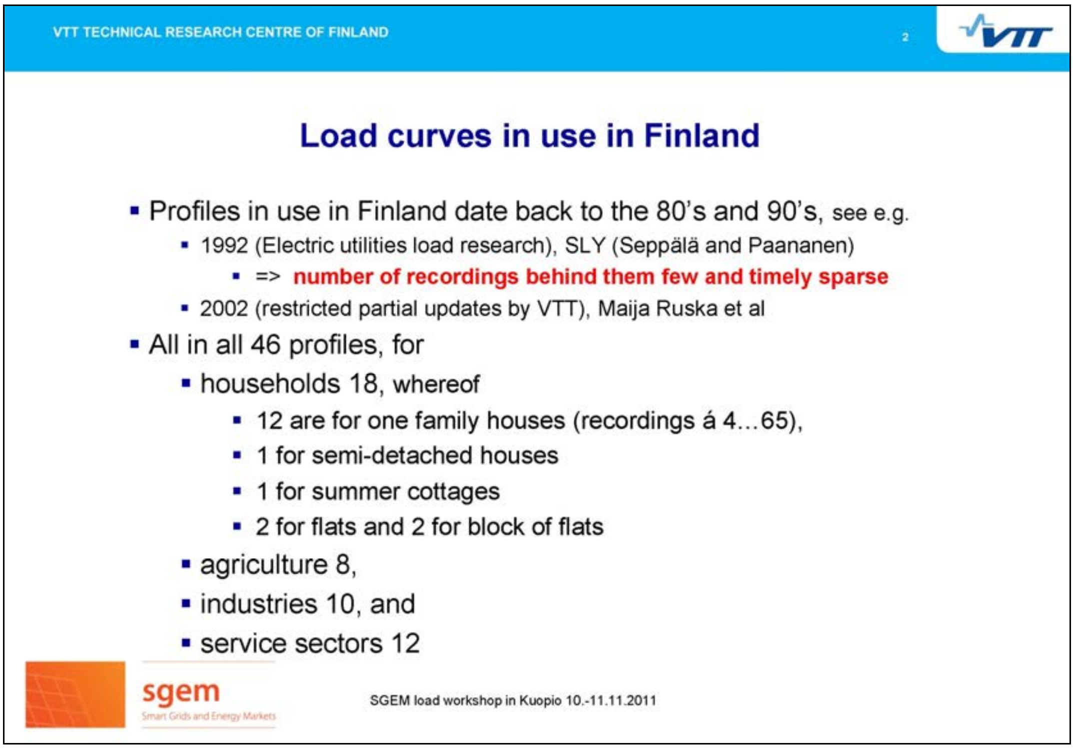
Appendix E: A new approach to load profiles: the use of building blocks



VTT TECHNICAL RESEARCH CENTRE OF FINLAND 3 VTT

Load curves for one family houses

- 110 direct electric heat, water boiler <300 liter
- 120 direct electric heat, water boiler =300 liter
- 130 direct electric heat, floor heating >2kW
- 210 partial storage electric heat, short disconnect periods
- 220 partial storage electric heat, long disconnect periods (7-22)
- 300 full storage electric heat, (7-22)
- 400 heat pump
- 510 dual heat, flat tariff
- 520 dual heat, night tariff
- 530 dual heat, seasonal tariff
- 601 no electric heat, no electric sauna
- 602 no electric heat, electric sauna

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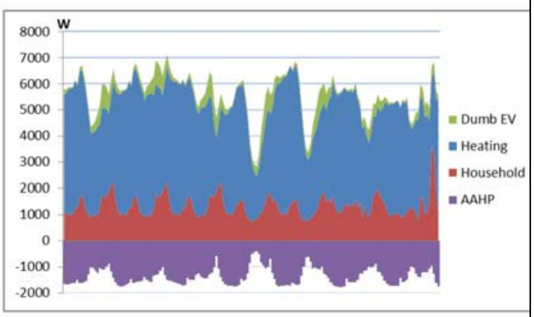
VTT TECHNICAL RESEARCH CENTRE OF FINLAND 4 VTT

Load profiles for one family houses – los problemos uno

Electricity use may be a sum of very differently behaving part loads, e.g.

- direct electric heating,
- auxiliary air-air heat pump
- hot water, and
- household electricity,….

- and in the future in addition maybe a solar heat collector, an electric sauna, a photovoltaic panel or one or several electric vehicles.



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…so, load profiles in the future for one

With all the new significant developments, we'll need a lot more profiles, e.g.:

- 4 types of basic one family houses heating modes (no electric heating, direct heating, partial storage heating, full storage heating)
- 4 types of basic electric heating sources with different behaviour (direct electric, GSHP, AWHP, EAHP)
- 5 additional heat sources sources possibilities with different behaviour (no additional, wood burning/kamin/stove/fire place, AAHP, AWHP, solar heat)
- different electric vehicles constellations (0…2 pieces, FEV or PHEV, smart or dumb charging)
- 3 types microgeneration slections (none, PV, some wind thingy)
- electric sauna or not

=(1 +3*4)*5*(3*2*2)*3*2 = **4680** new load curves for one family houses

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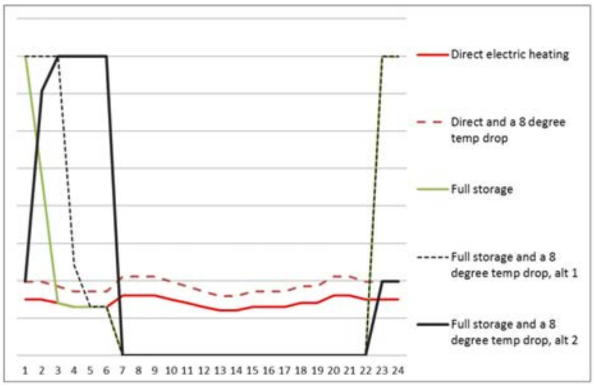
VTT TECHNICAL RESEARCH CENTRE OF FINLAND 6 VTT

Temp. related problems with existing load curves approach – los problemos due

Outside temperature dependency concerns electric heating, but not other parts of the load

- ⇒determination is a bit vaque and stetsonian
- ⇒4%/degree might be ok on a daysum level, but heat storages and/or night tariffs bring a long difficulties
- ⇒temp. dependency may vary with temperature (e.g. AAHP)



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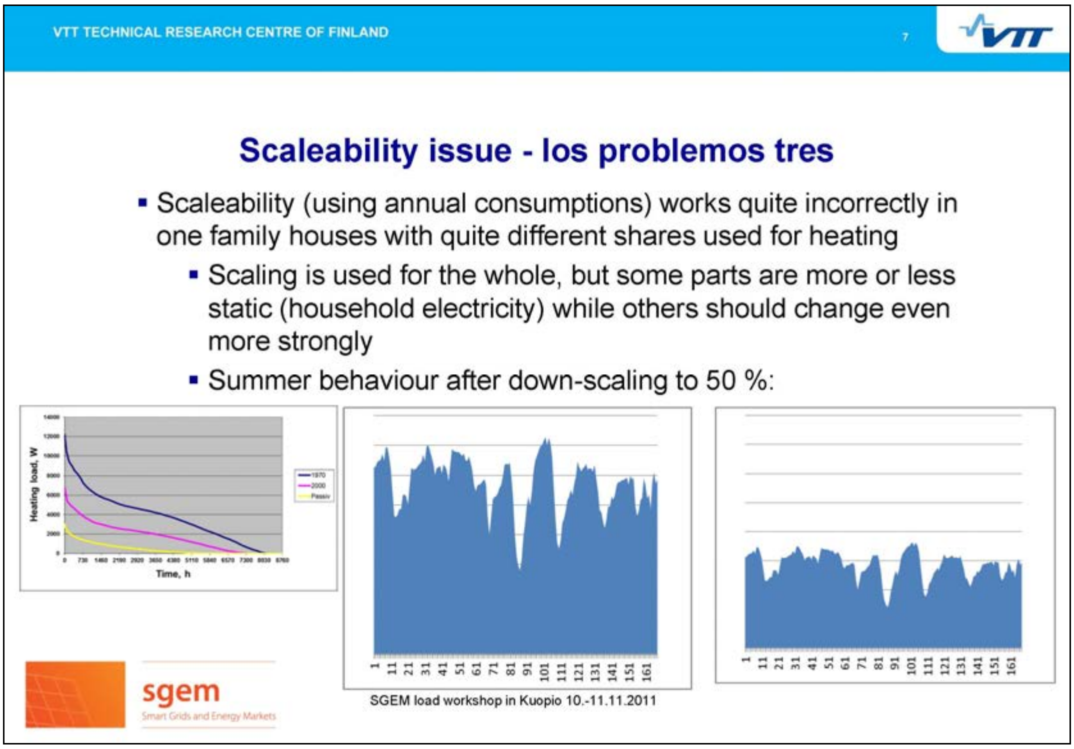
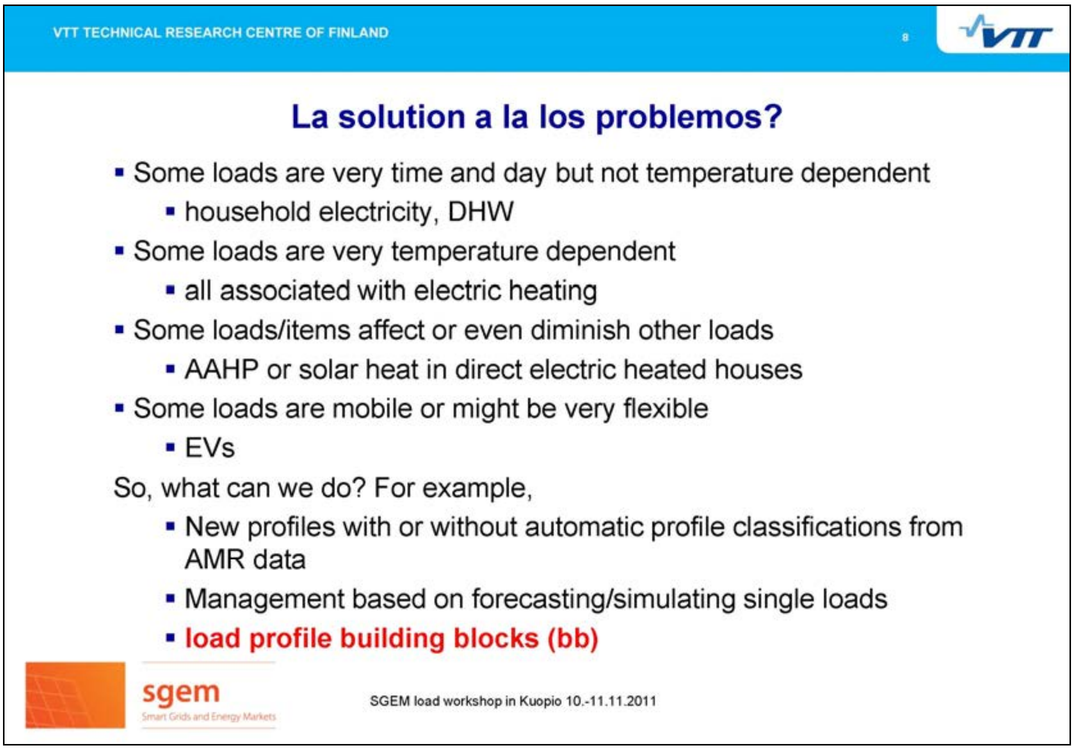
Appendix E: A new approach to load profiles: the use of building blocks





VTT TECHNICAL RESEARCH CENTRE OF FINLAND 9 VTT

Load profile building blocks - la solution a la los problemos!

THE MAIN IDEA

- Divide the load into feasible and more easily managed part loads
- Only the largest part load chunks, which also benefit the most from being treated separately
- For building blocks, models can be used instead of measurements
- The basic load, household electricity, should however be based on good and clean measurements
- Easy to add new building blocks

What is it not about?

- It is not atomic: it is not about single electric appliances or all the individual loads
- It is not NIALM (non-intrusive load modeling, see H.Pihala/WT4.2)

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Using load profile building blocks – how many are needed?

- Household: 1 bb; electricity used for appliances, lighting etc.,
- DHW: 1 bb
- Basic heating need: 1 bb; basic heating need is also the same as direct el
- Additional main electric heating curves or models: 4 bb; GSHP, AWHP, AAHP, EAHP, etc)
- Heat storage: 1-3 bb (zero, 3 load curves, or a model dependent of storage size and heat demand)
- Heating saving (negative) building blocks: 4 bb; AAHP, AWHP, stove, solar
- Electricity saving building blocks: 1-2 bb; PV, …
- Extra consumption blocks: 5 bb; EVs, directly heated sauna

1+1+(1+4) *(1…3)+4+2+5 = 26 building blocks takes you a long way

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Appendix E: A new approach to load profiles: the use of building blocks

Using load profile building blocks- example

Customer load =

+ household electricity
+ DHW
- solar heat panel (=savings)
+ direct electric heating
- AAHP in electric heated house (=savings)
+ AAHP during the summer
+ EV without smart charging
+ sauna 3 times/week

Research being done in SGEM WT4.2.2

- Build up the logical structure
- Gather building block materials and test the idea especially as a planning tool
- (WT 4.2.3) Will this approach be of help in the use of demand response models and estimations?

Future research in FP4&5 might include:

- Testing of online-usability, for example as tool for comparison to customer load.
- Knowledge of a customer's building blocks may be a problem for the CIS, but customer classification is a tremendous problem for normal load curve approach also! Customer load behaviour is not updated regularily.

  => we have some nice ideas in the back pocket for this niche!

VTT TECHNICAL RESEARCH CENTRE OF FINLAND 13

Conclusionas

Let’s see where the building block approach takes us!

Thank you for your attention & That’s all, folks!

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Appendix F: Physically based load modeling for distributed energy resources applications: EU-DEEP project

SMARTGRIDS and Energy markets

Physically Based Load Modeling for Distributed Energy resources Applications: EU-DEEP project

Carlos Álvarez
Institute for Energy Engineering
Universidad Politécnica de Valencia
calvarez@die.upv.es
November 10, 2011

p.1

Introduction

- **SmartGrids is user centric: Customer issues relevant.**
- **Customer Demand response is basic for a "homeostatic" electricity supply consumption systems**
- **Massive implementation of customer participation is required**
- **Up to now research efforts focused on:**
  - Technical issues
  - Translating traditional DSM structures into new market based

Research in EU-DEEP:
DER issues

p.2

Actual Approach to DR

- **Market structures allowing demand participation in different markets (energy, ancillary services, etc.)**
  - BETTA
  - Nordic counties
- **Structured programs triggered by operators and utilities**
  - USA
  - Europe

p.3

Innovative research in EU-DEEP

EUDEEP: **The birth of a European Distributed EnErgy Partnership that will help the large-scale implementation of distributed energy resources in Europe**

- A European Project supported within the Sixth Framework Program for Research and Technological Development
  - 2004-2008
  - 39 partners and 15 countries
- Objectives:
  - Large-scale implementation of distributed energy resources in Europe
  - Design, develop and validate an innovative approach to identify promising business models(*) based on market requirements, which will amplify, from 2010, the large scale penetration of DER in Europe.

  (*) Business model = market + technology + financing
- THREE CASES SELECTED TO IMPLEMENT THE BUSINESS MODELS

eu-deep

p.4

Innovative research in EU-DEEP

EUDEEP and the Customer

- **Segmentation in three levels (sector, activity and energy uses)**
  - Residential: 93 segments
  - Commercial 154 segments
  - Industrial 378 segments
- **Data base with detailed information about 40% of the segments (load curves, energy uses, flexibility, etc.)**
- **Ranking of segments according to DR possibilities**
- **Models of most promising segments**
  - **Segment characterization: Typical customer + Diversity**
  - **Aggregation**
  - **Simulation and verification of DER**
  - **Simulation and verification of DR**

p.5

IIE-UPV INVOLVEMENT

DEVELOPMENT OF INNOVATIVE CONCEPTS AND TOOLS APPLIED TO EU-DEEP

- Demand Description and Modeling
- Simulation and analysis tools
- Evaluation of scenarios of DER
- Validation

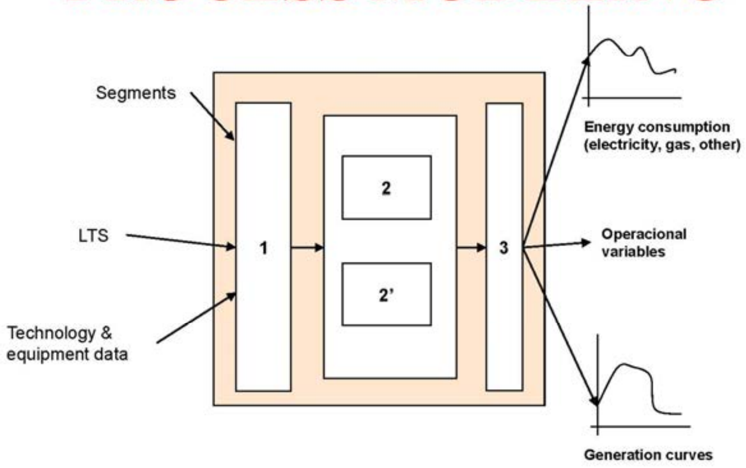
p.6

EU-DEEP BUSINESS CASES

- Priority on Distributed Energy Resources providing Balancing Mechanisms
  - Case 1: Aggregating Demand response and DER contracts to compensate imbalances caused by Renewable Energy Generation
  - Case 2: ESCO/Aggregator using customer flexibility and micro-CHP for selling Balancing Services
  - Case 3: ESCO internal balancing to cope with long term contracts

p.7

BASED ON CUSTOMER PROCESS MODELING



p.9

IIE APPROACH TO CUSTOMER RESEARCH FOR EACH BUSINESS CASE

- Flexibility evaluation in the customer belonging to the target portfolio: Commercial, Industrial and Residential
- Development of Offers to trade with the flexibility.
- Examples: Commercial and Industrial

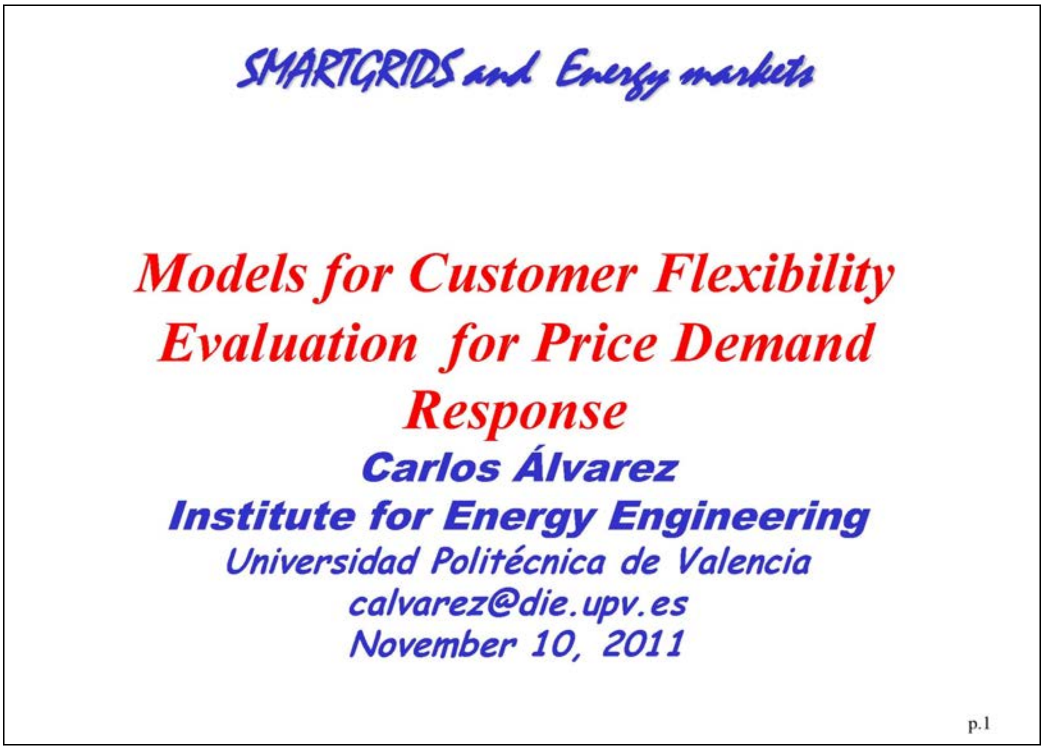
p.8

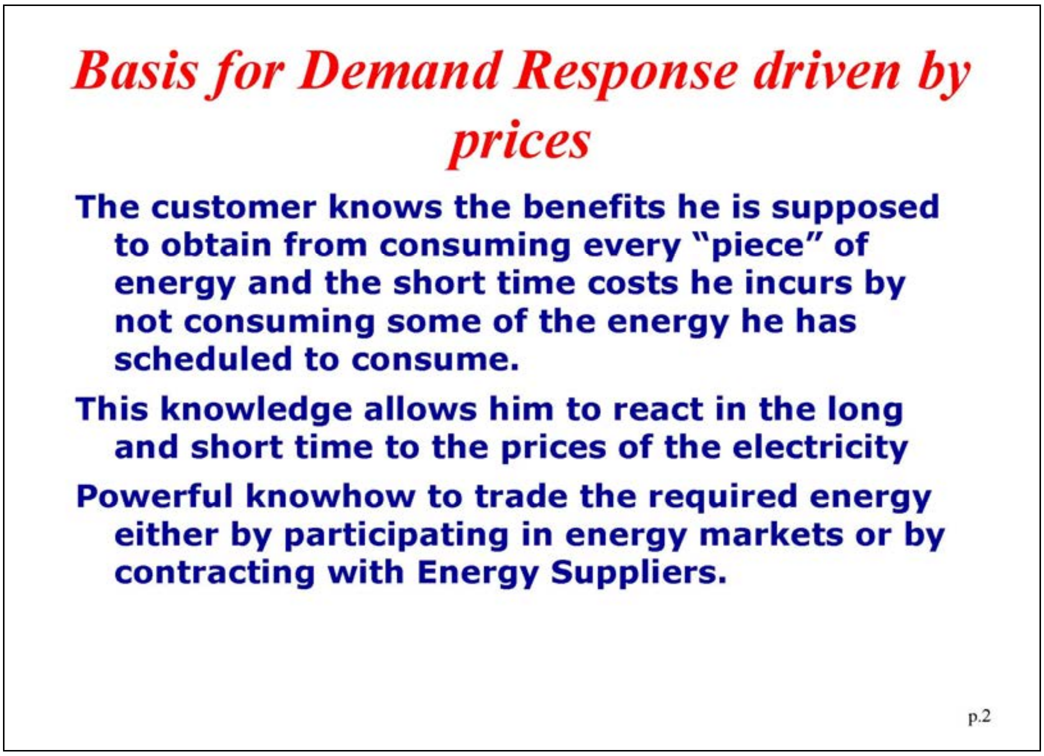
Evaluation of the impact of Distributed Energy Resources Implementation

Demo 1: Hotels
Demo 2: Apartments
Demo 3: Industrial

p.10

Appendix G: Models for customer flexibility evaluation for price demand response





Demand Organization (I)

- The demand has to be organized according to the specific uses (processes) the electricity is used for. Therefore, the identification of the flexibility in the energy consumption requires a detailed analysis of the processes in each customer facility, based on physical and economical concepts.
- The demand can be split into different "pieces" of energy each of them having associated specific properties
- The energy pieces (Demand Packages) can be different for energy buying purposes (Bids) or for demand reduction (offers)

p.3

Demand Organization (II)

- The organization of the demand requires detailed physical description of the processes that absorb the energy including the relation between the energy consumed and the "service" provided.
- Simulations relating the quality of the service/product provided and the energy used are necessary to identify the actual flexibility.
- The price assigned to each energy package depends on the impact in this quality/product.
- Commercial: a few processes repeated in the different customers (HVAC, lighting, water heating, etc.).
- Industrial: a few common processes and particular usually energy consuming processes.

p.4

DEMAND PACKAGES: BIDS

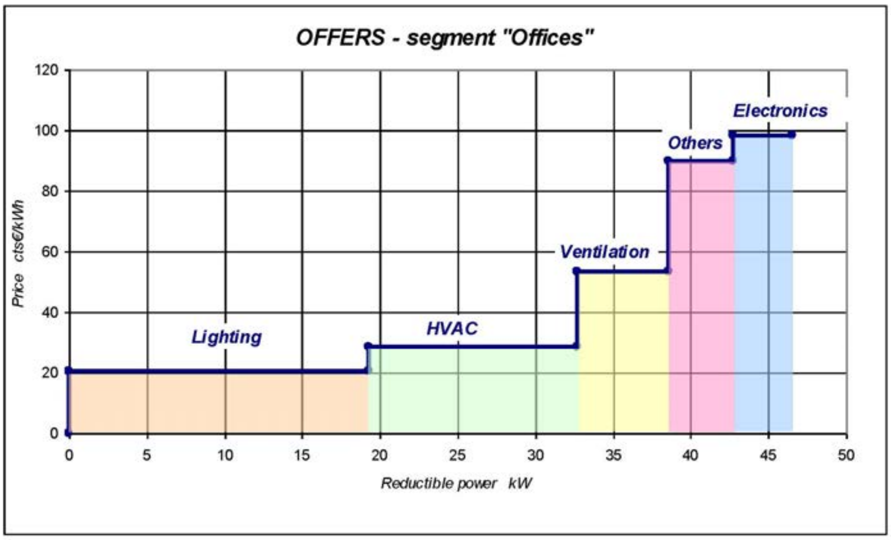
- Energy related to the different customer activities (production, commercial services, etc.).
  - Price: Benefit of the activity
    - Substitution costs
    - Stand by generation
    - Contracted insurances
    - Long term planning costs
    - Etc.
  - Size and shape of the DP.

p.5

DEMAND PACKAGES: OFFERS

- Energy related to customer process where some short term flexibility in the energy consumption can be found:
  - Trigger price: costs incurred by the reduction of the energy consumption
    - Direct costs
    - Costs of the control equipment
    - Cost of Storage
  - Size and shape of the DP block: (customer, load)
  - The notice time required for the change in the demand
  - Limitations
    - Reliability of the package (possible penalties once committed)
    - Number of occasions/season, year
    - Etc.

p.7



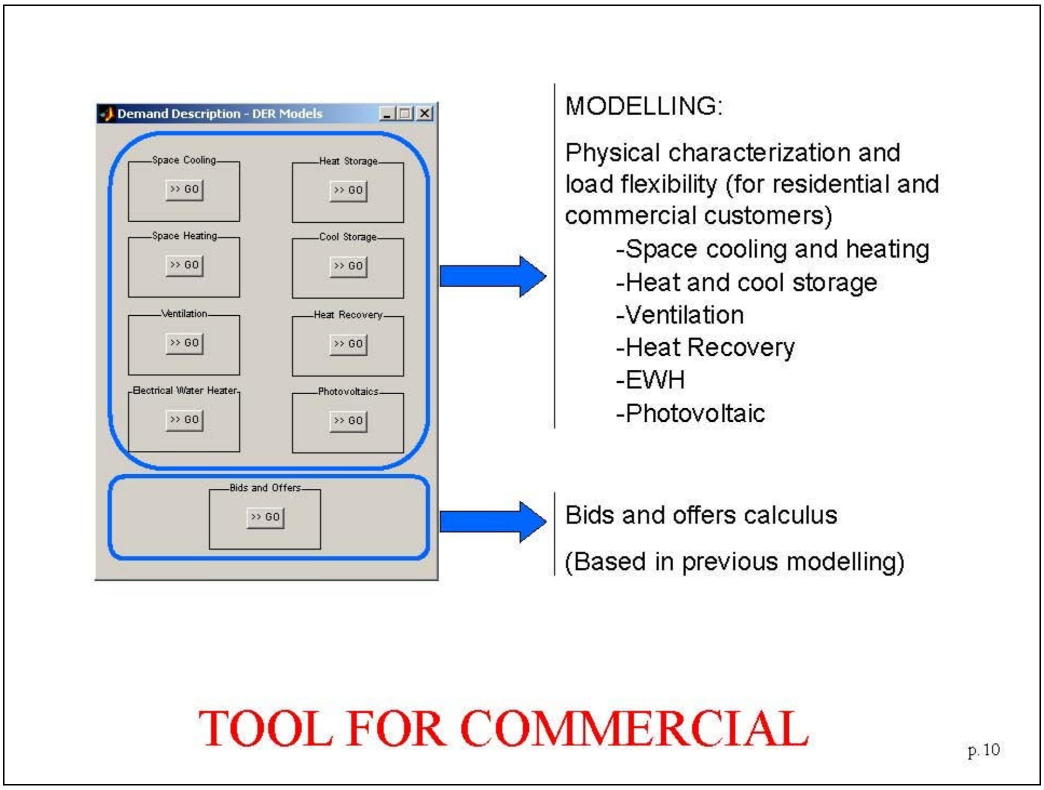
p.8

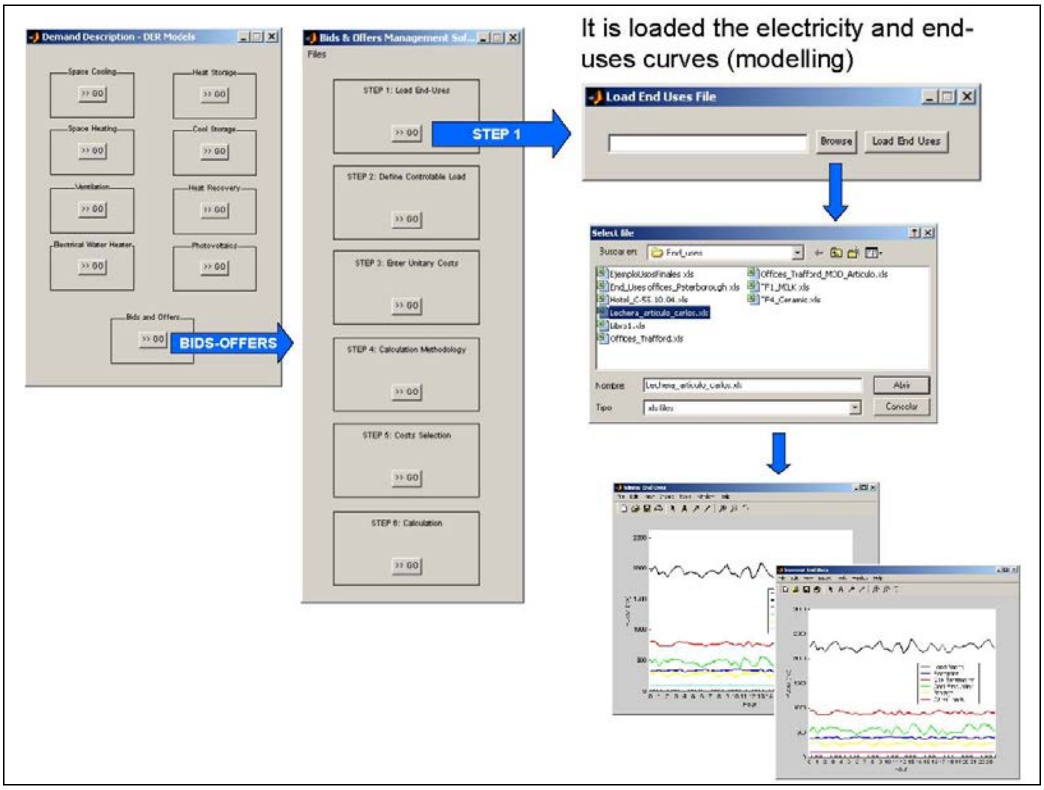
COSTS CONSIDERED FOR OFFERS

- Labour cost: depending on the impact of the reduction in the manpower. Difficult to assess in some cases
- Primary energy
  - Substitution of fuel
  - Back-up generation
- Storage cost:
  - Electricity
  - Thermal (heat, cold)
- Equipment to implement the reduction:
  - Control
  - Measurement and monitoring
  - Communication

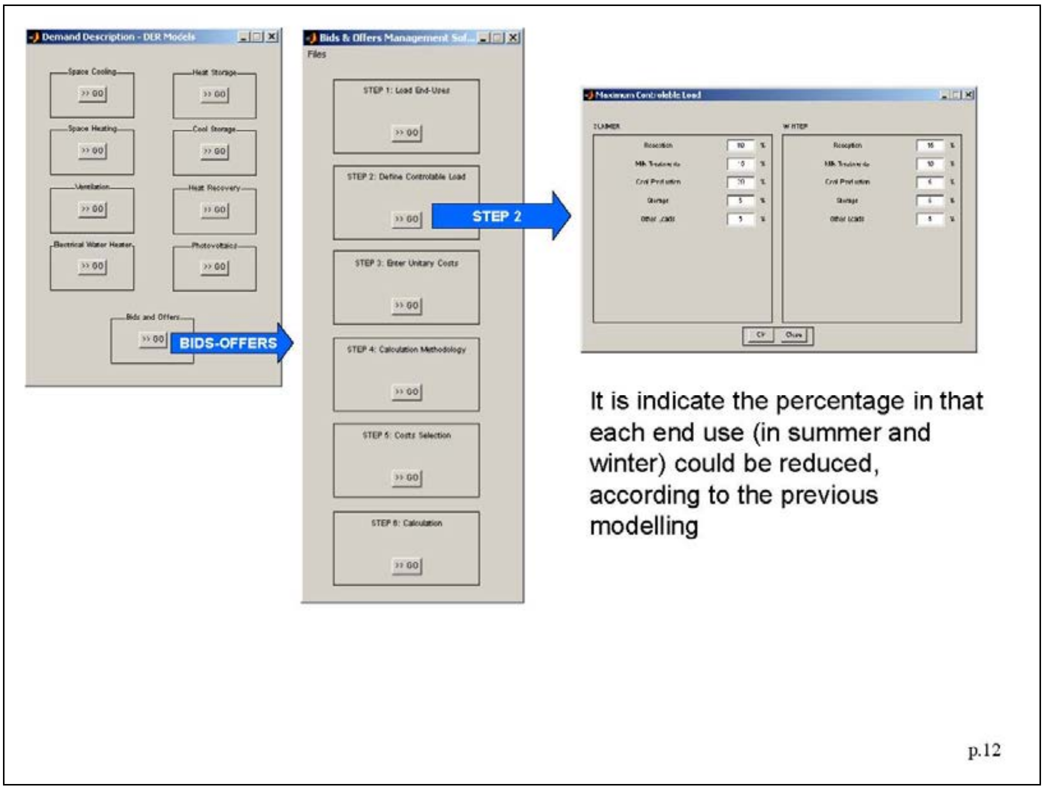
- IIE has developed a tool for that: Commercial and Industrial

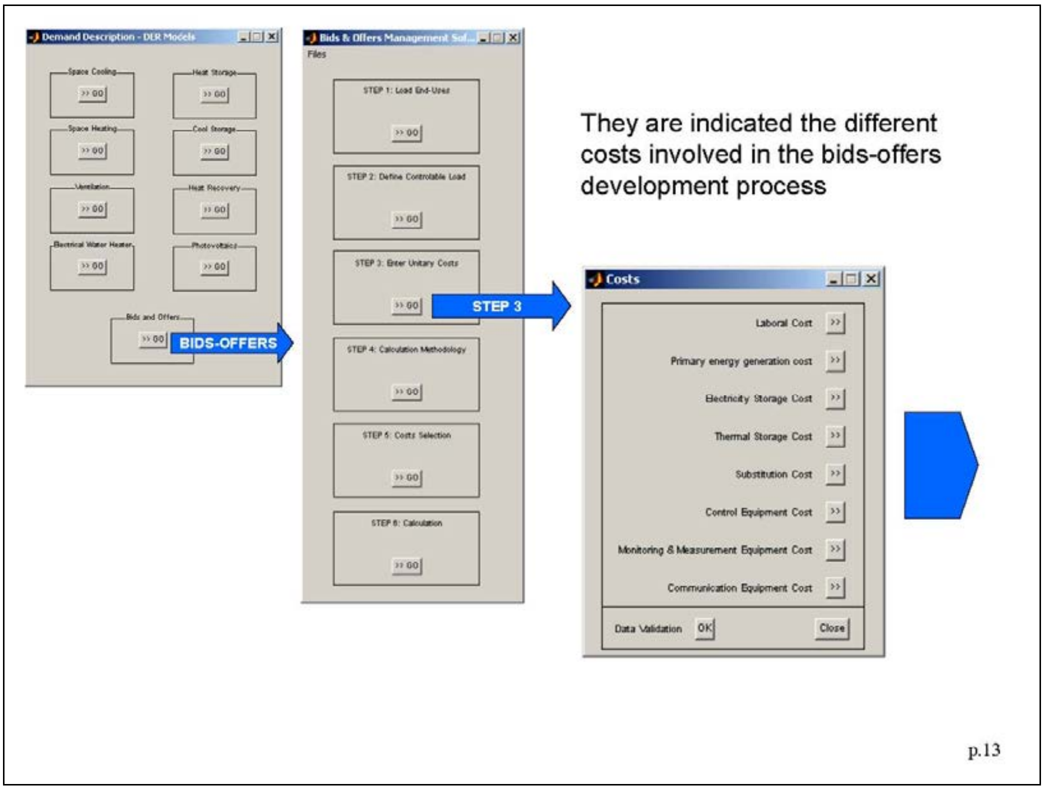
p.9

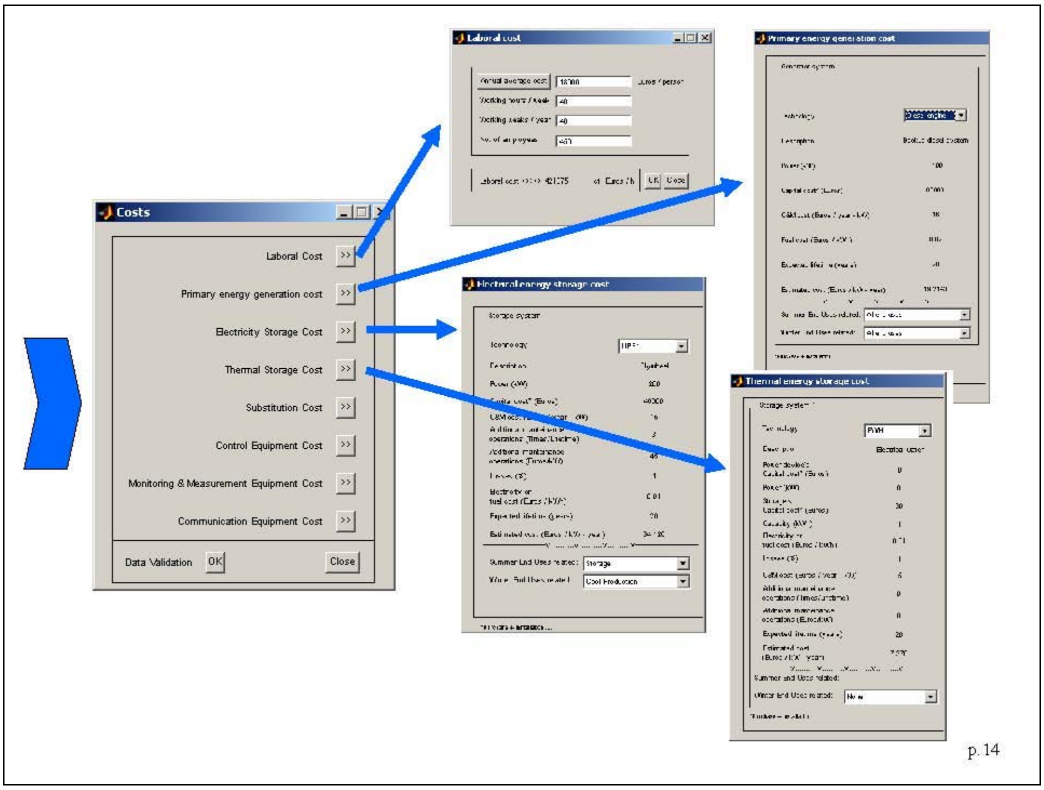

Demand Description - DER Models
Space Cooling
Heat Storage
Space Heating
Cool Storage
Ventilation
Heat Recovery
Electrical Water Heater
Photovoltaics
Bids and Offers
>> GO
MODELLING:
Physical characterization and load flexibility (for residential and commercial customers)
-Space cooling and heating
-Heat and cool storage
-Ventilation
-Heat Recovery
-EWH
-Photovoltaic
Bids and offers calculus
(Based in previous modelling)
TOOL FOR COMMERCIAL
p. 10

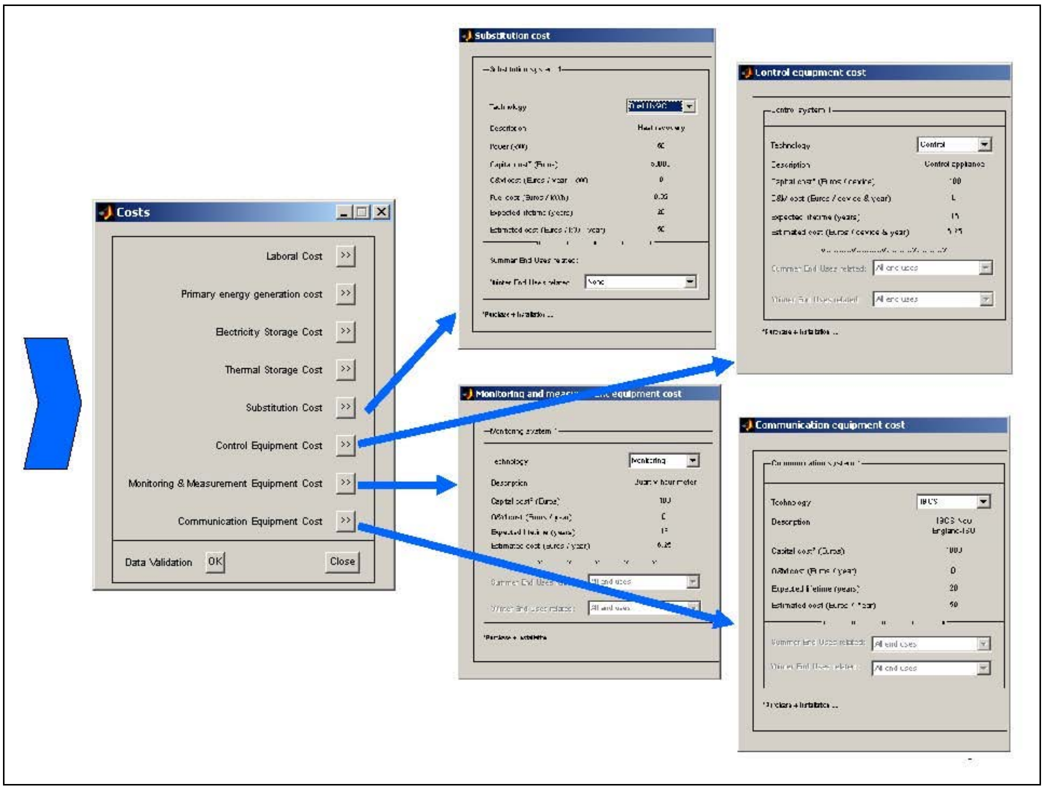

It is loaded the electricity and end-uses curves (modelling)
Demand Description - DER Models
BIDS-OFFERS
Bids & Offers Management
STEP 1: Load End-Uses
STEP 2: Define Controllable Load
STEP 3: Enter Unitary Costs
STEP 4: Calculation Methodology
STEP 5: Costs Selection
STEP 6: Calculation
STEP 1
Load End Uses File
Browse
Load End Uses
Select file

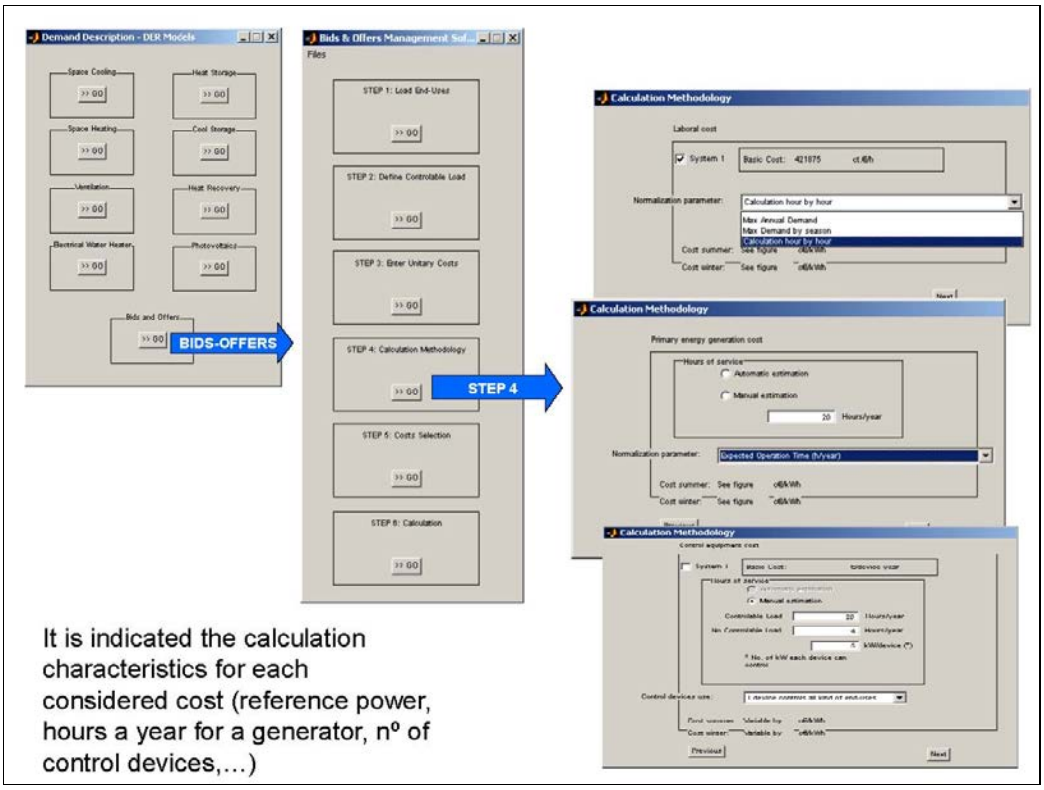
Appendix G: Models for customer flexibility evaluation for price demand response

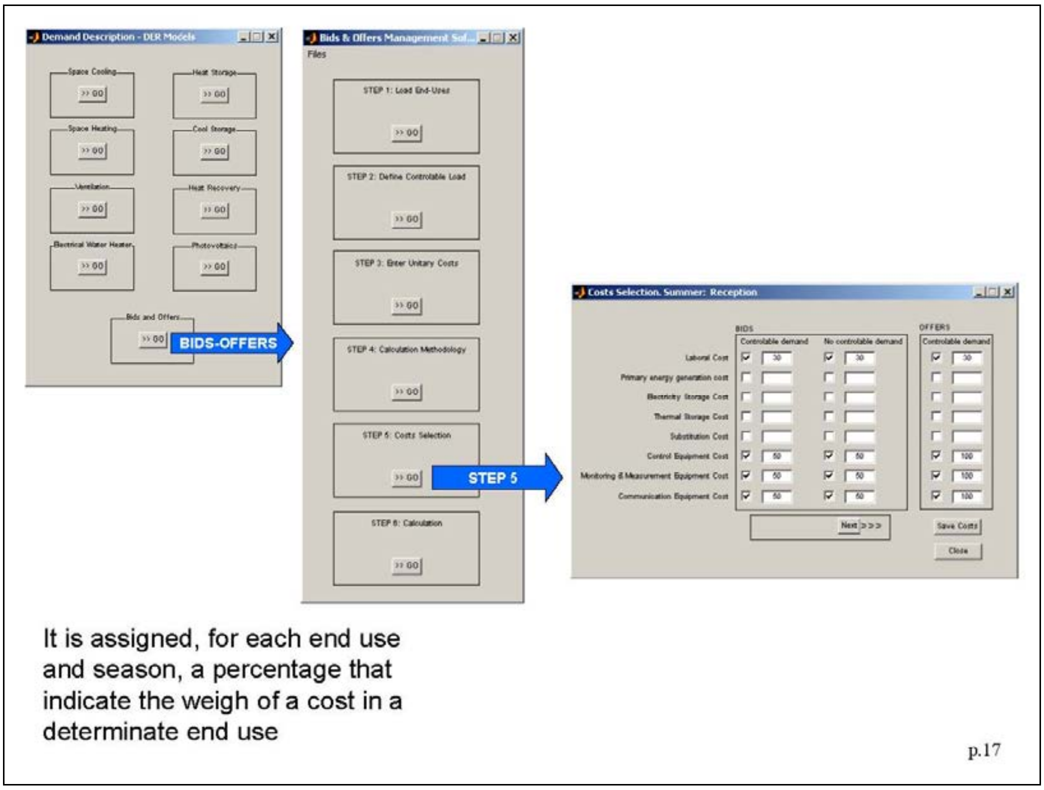


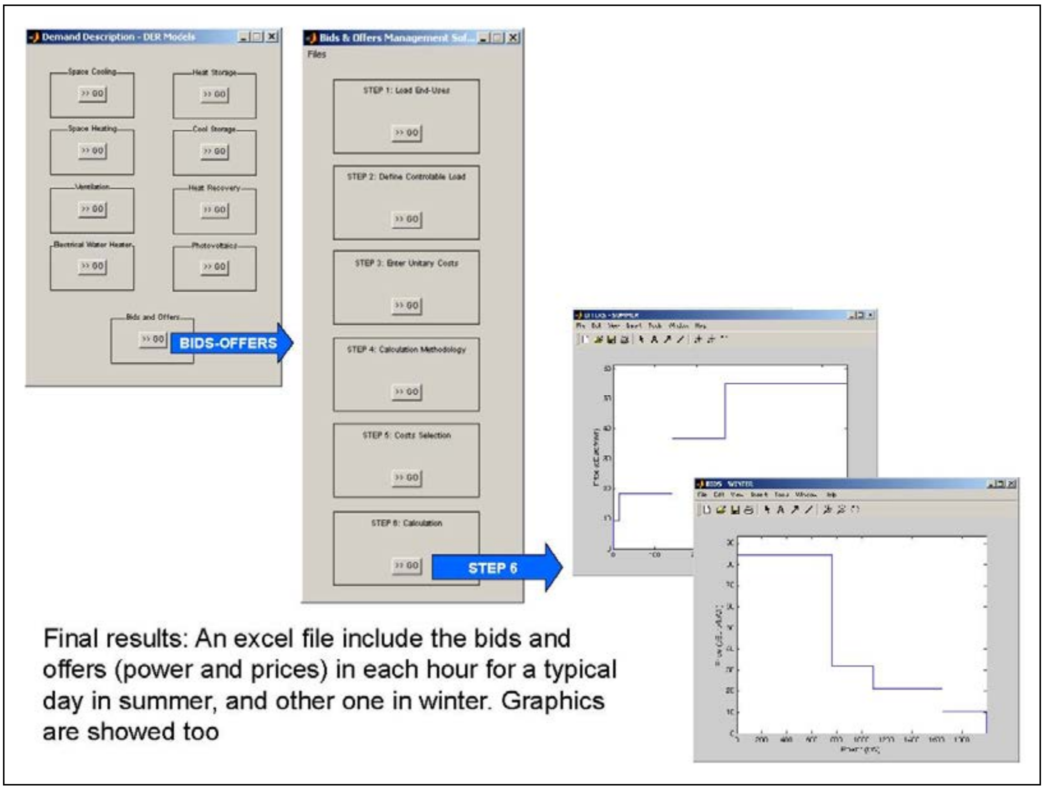



Costs
Laboral Cost
Primary energy generation cost
Electricity Storage Cost
Thermal Storage Cost
Substitution Cost
Control Equipment Cost
Monitoring & Measurement Equipment Cost
Communication Equipment Cost
Data Validation
OK
Close
Laboral cost
Primary energy generation cost
Electrical energy storage cost
Thermal energy storage cost
p. 14


Costs
Laboral Cost
Primary energy generation cost
Electricity Storage Cost
Thermal Storage Cost
Substitution Cost
Control Equipment Cost
Monitoring & Measurement Equipment Cost
Communication Equipment Cost
Data Validation
OK
Close
Substitution cost
Control equipment cost
Communication equipment cost


Demand Description - DER Models
Bids & Offers Management Sof...
STEP 1: Load End-Uses
STEP 2: Define Controllable Load
STEP 3: Enter Unitary Costs
STEP 4: Calculation Methodology
STEP 5: Costs Selection
STEP 6: Calculation
BIDS-OFFERS
STEP 4
Calculation Methodology
It is indicated the calculation
characteristics for each
considered cost (reference power,
hours a year for a generator, nº of
control devices,…)


Demand Description - DER Models
Bids & Offers Management Sof...
STEP 1: Load End-Uses
STEP 2: Define Controllable Load
STEP 3: Enter Unitary Costs
STEP 4: Calculation Methodology
STEP 5: Costs Selection
STEP 6: Calculation
BIDS-OFFERS
STEP 5
Costs Selection. Summer: Reception
It is assigned, for each end use
and season, a percentage that
indicate the weigh of a cost in a
determinate end use
p.17



RESULTS

- Demo 4: Hotel Offers
- Demo 5: Office offers

p.19

Conclusions

- Evaluation of the Demand response capacity of customers based on customer interaction to perform the evaluation of the impact (economic) of the energy in the customer processes.
- This allows to the ESCO to evaluate the aggregated response of its customer portfolio.
- Importance of Simulations and Modeling

p.20

Research needed in SmartGrids

- Customer evaluation and training to implement DR with economical parameters
  - Knowledge of the energy consumption and implications
  - Ability to evaluate benefits and costs
- ESCO Role definition
  - Full utilization of Customer Flexibility. How much DR is available in the Short term?
- Full integration of DR into the system:
  - How much DR is available in the long term? (Planning)
- Market mechanisms
  - How much DR is available in the Medium term? (Operation Planning)
  - Need to use a statistical approach

p.21

Appendix H: Load response models based on simple physical models of the response dynamics

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Load response models based on simple physical models of the response dynamics

Pekka Koponen
VTT

SGEM expert workshop on load modelling
Kuopio, 10 November 2011

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Smart Grids and Energy Markets

1

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Outline

- Overview: measurements + building data => model => prediction and optimization
- Why load response models based on simple physical models of the response dynamics?
- Simple physically based model of the heat dynamics
  - generic
  - an example model
  - a response with the example model
  - measurements used in identifying the example model parameters
- Where simple physically based models have so far been applied in Finland?

2

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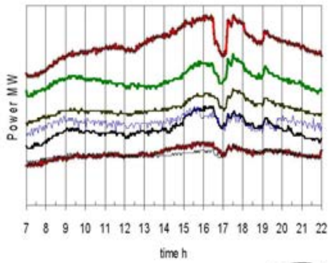
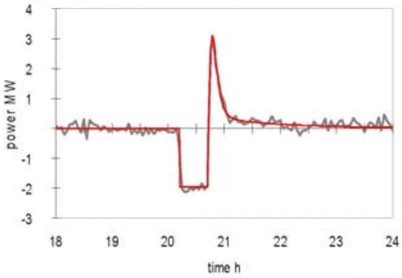
measurements + building data => model => prediction and optimization

measurements from smart meters and/or substations

simple physically based dynamic models



modelled response to load control



requirements on buildings

building type

other information on building properties

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3

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Why load response models based on simple physical models of the response dynamics?

They can be made more accurate than the load models applied today. (such as models described by Seppälä Anssi, 1996. Load research and load estimation in electricity distribution. VTT Publications, vol. 289. VTT: Espoo)

- traditional load models are poor in predicting the responses to outdoor temperature variations
- updating traditional load models to changes in loads is too slow
- traditional load models do not predict responses to control actions

Large scale demand response and smart grids makes predicting control responses necessary.

Predictability of loads is needed by in electricity markets, grid operation and system balancing.

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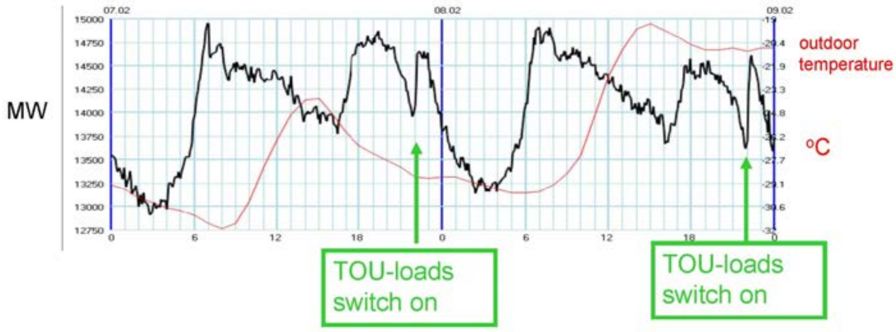
From time based TOU to dynamic market and grid based DR
What will happen, if we can not predict the responses?

Load profile and outdoor temperature in Finland in two cold winter days 2002,
source: www.tem.fi/files/18777/Sahkon_kysyntajouston_edistaminen.pdf



Now TOU levels peak but requires control resources to balance switching steps. If the responses become unpredictable, more balancing reserves are needed.

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5

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Simple physically based dynamic response models are suitable for modelling the heat dynamics related responses of houses

- direct electrical heating
- partially storing electrical heating
- full storage heating (rather trivial case)
- heat pumps for cooling and heating
- cool and cold storage

They do not help with predicting the load responses for

- appliances that do not have heat storage effects
- storage effects that are controlled in a way unknown to the model
- heating control systems that are not operating correctly
- multiple heating and cooling systems interacting in an uncoordinated way

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Simple physically based model of the heat dynamics

$d\underline{x}(t)/dt = f(C, K, \underline{x}(t), \underline{p}(t), T_{out}(t))$

$p(t) = f(\underline{x}(t), \underline{x}_{set}(t), \underline{u}(t))$

for example

$C\, d\underline{x}(t)/dt = K\, \underline{x} + p(t)$

$p(t) = f(\underline{x}(t), \underline{x}_{set}(t), \underline{u}(t))$

$\underline{x}(t)$	the state variable vector comprises lumped temperatures
C	heat storage capacities
K	thermal conductivities between the variables
$T_{out}(t)$	outdoor temperature
$\underline{p}(t)$	the power heating the house (Can be a vector)
$\underline{x}_{set(t)}$	set points for state variables
$\underline{u}$	control signals

7

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An example of the simple physically based heat dynamic model structure

$$
\begin{aligned}
C_1 \frac{dx_1}{dt} &= -k_{12}(x_1 - x_2) + P \\
C_2 \frac{dx_2}{dt} &= k_{12}(x_1 - x_2) \\
&\quad + k_{23}(x_3 - x_2) \\
&\quad + k_{24}(x_4 - x_2) \\
&\quad + k_{2o}(T_{out} - x_2) \\
C_3 \frac{dx_3}{dt} &= k_{23}(x_2 - x_3) \\
&\quad + k_{3o}(T_{out} - x_3) \\
C_4 \frac{dx_4}{dt} &= k_{24}(x_2 - x_4)
\end{aligned}
$$

Model of the temperature control is not shown here but is needed, of course.

The variables and parameters are explained on the next slide.

8

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The variables and parameters in the example model

The state variables were the following lumped temperatures:

- x1(t) temperature of the heating element e.g. in case of floor heating
- x2(t) temperature of the indoor air
- x3(t) temperature of the outside walls
- x4(t) temperature of the other heat storing masses of the building

The constant parameters were

- C1, C2, C3 and C4 the heat storage capacities related to each state variable
- k12, k23, k24, k2o, k3o the thermal conductivities between the state variables (temperatures in the model)

The time variable input variables were

- Tout(t) outdoor temperature
- P(t) the electrical power heating the house

After adding the control loop P(t) becomes the main output variable.

9

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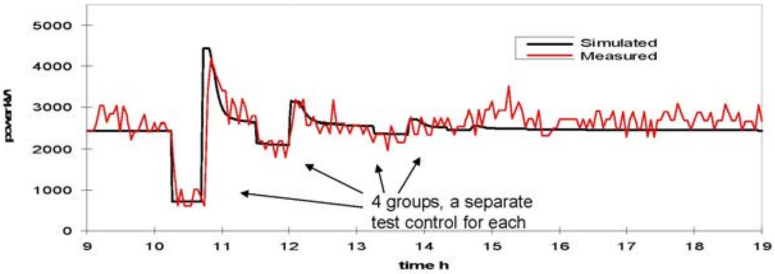
An example of a response identified in the direct load control field tests of electrically heated houses in winter 1996-1997



Comparison of the model response (simulation) with response estimated from measurements at substation for load control of 463 vacation house metering points in a resort. Outdoor temperature -19 C.

Regularly repeating load variations and impact of temperature variations are filtered out: The responses were identified from measurements at substations. The normal load profile was eliminated using both simultaneous measurements at non controlled reference substations and identified temperature dependency model. Normally the 4 groups were operated in a way that roughly cancelled the payback peaks, but in the test the timing is different to make the payback peaks visible and better identifiable.

Source: Koponen, Pekka. Sähkölämmityskuorman suoran ohjauksen mallit (= Load response models for direct control of electric heating) in Finnish, VTT report ENE6/9/97. Espoo 1997, 47 p. + app. 4p.

10

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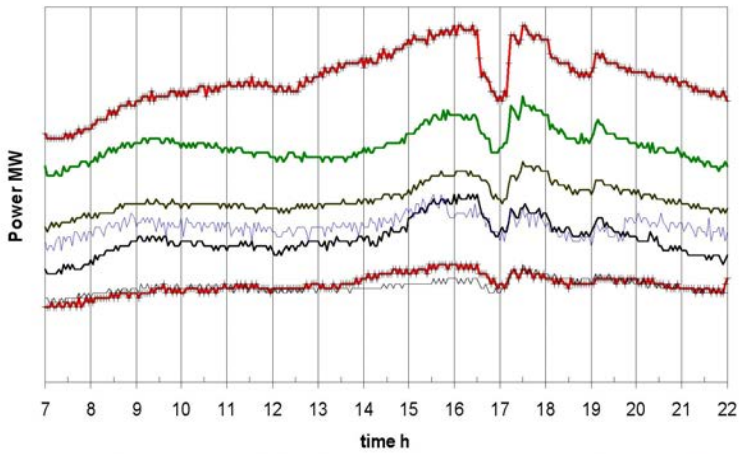
The model was identified from measurements at substations such as these



Source: Koponen, Pekka. Sähkölämmityskuorman suoran ohjauksen mallit (= Load response models for direct control of electric heating) in Finnish, VTT report ENE6/9/97. Espoo 1997, 47 p. + app. 4p.

11

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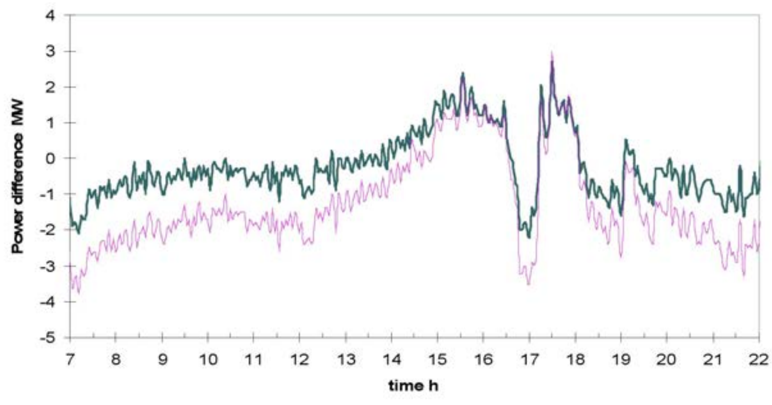
Measurements when power from reference substations is subtracted.



Source: Koponen, Pekka. Sähkölämmityskuorman suoran ohjauksen mallit (= Load response models for direct control of electric heating) in Finnish, VTT report ENE6/9/97. Espoo 1997, 47 p. + app. 4p.

12

The dynamic temperature dependency model

- Modelled the load responses to outdoor temperature variations.
- The same simple physically based model as the response model
- Was identified based on the measurements from substations over one year. (At least one year of data was needed)

The control response model

- The temperature dependency model parameters updated based on the load control field test measurements.

The same approach works even better, if power measurements for each house are summed and used. Notice also the possibility to combine measurements from different sources.

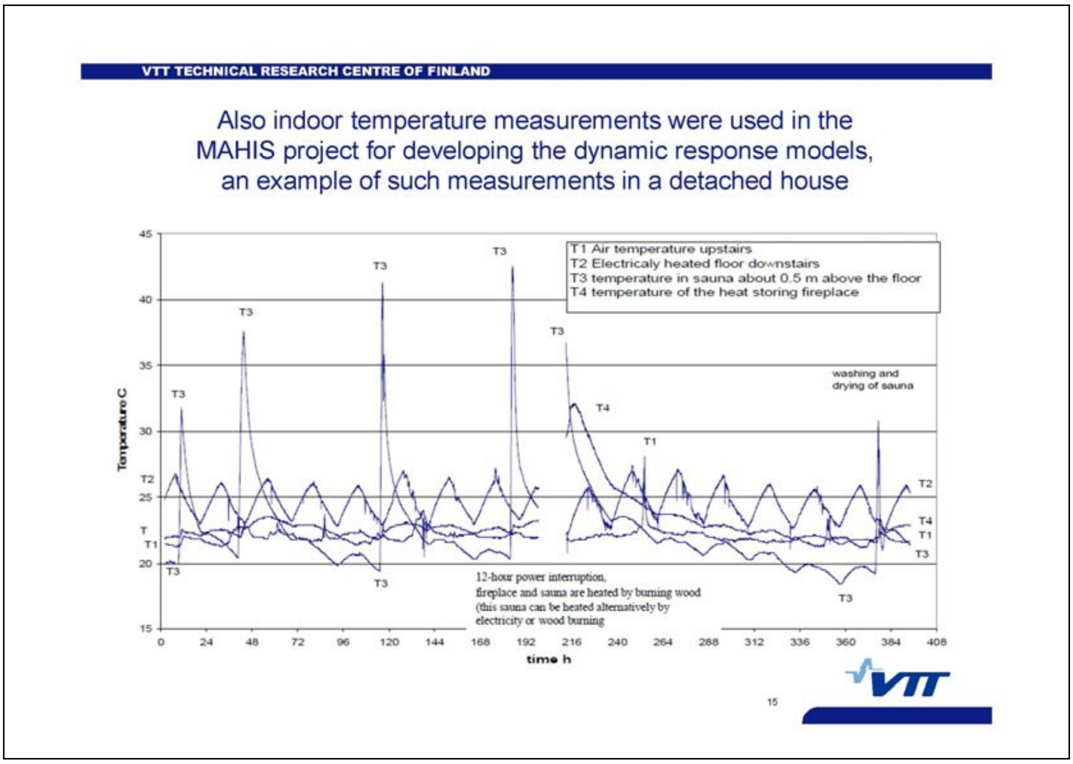
Where simple physically based models have so far been applied in DR in Finland

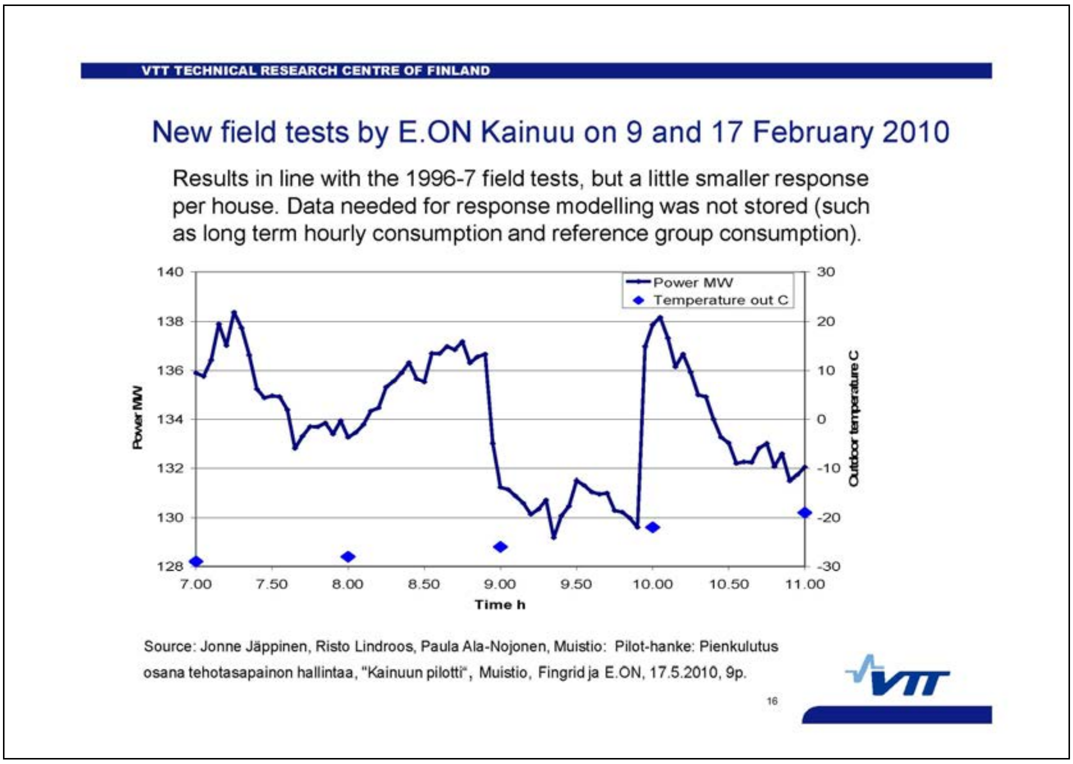
Only in DR research

1) First for response simulations in1971 by Haase and in 1987 by Martikainen. (Not as simple models as those applied for prediction and optimisation.)
2) Direct load control field tests in 1996-7 with over 6000 controlled houses and total controllable power was over 20 MW. (Koponen)
3) In MAHIS-project on spot price based control (Koponen 2006). Models were identified based on TOU-control + some tests and used in simulations of optimisation of the control responses of individual houses. 5 row house apartments, 5 detached houses, and two cold storages and comfort floor heating in some block houses.
4) In ENETE-project for optimising the load control responses of a full storage heating house by Koponen. (As a reference method for verifying the optimality of the control method to be applied.)

Other?

Appendix H: Load response models based on simple physical models of the response dynamics





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New enablers

- Smart metering data
- Improved simulation models
- Research collaboration within SGEM, within VTT and internationally

Critical enablers

- Smart metering data
- Data from well designed field tests. Models based on the old tests are not up to date.
- Information on the present and future properties of buildings and their heating and cooling systems
- Controllability of the relevant loads
- Good simulation models
- Experience on DR and related modelling, simulation, prediction and optimisation.
- Such load models that enable integration of response models in them.

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17

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Discussion and concluding remarks

- The need is increasing nationally and globally and we have potential to meet it. How can grids be smart, if they can not predict the responses of DR?
- Although the approach has demonstrated its potential in research projects, a systematic model development and maintenance methodology is needed to automate modelling and to reduce the burden and expertise needed.
- It is necessary to utilise synergies with modelling for other purposes.
- Loads are changing: energy efficiency improvements in heating and cooling, heat pumps, increase in other than heating loads, etc.

  This is a challenge for model development and maintenance but even more with the traditional load models.
- Finland is among the forerunners thanks to smart metering of all consumption, the long tradition in DR with electrical heating loads and collaboration of relevant stakeholders in R&D.

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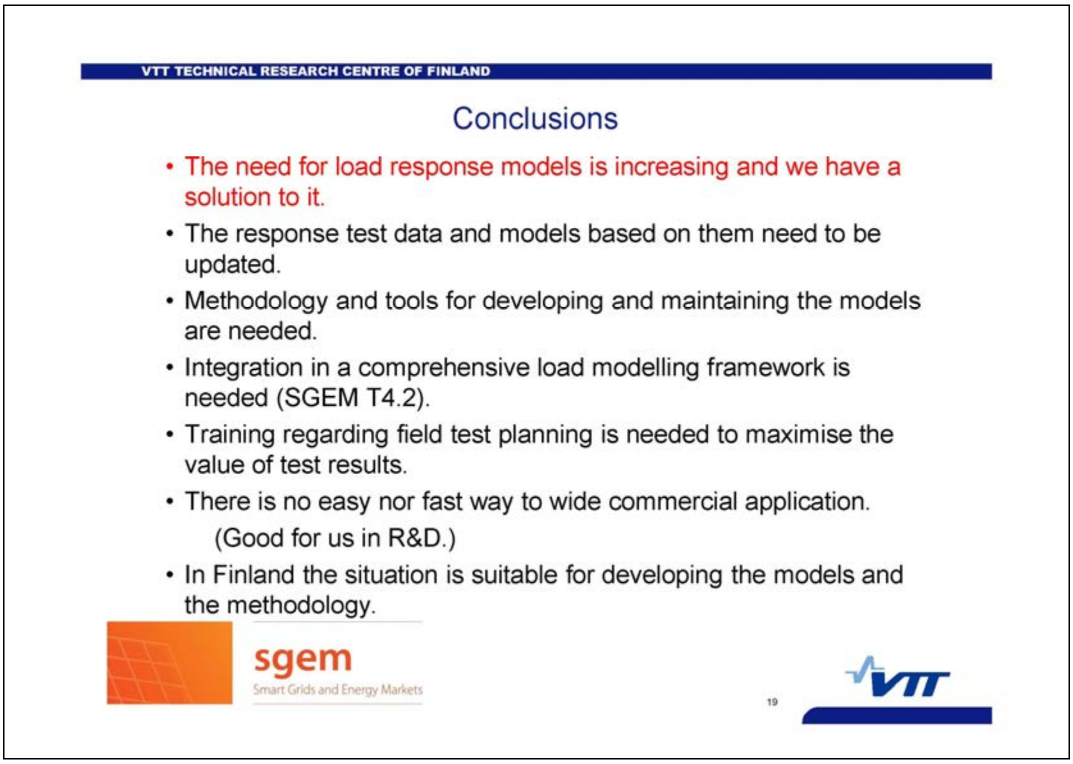
18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Conclusions
• The need for load response models is increasing and we have a solution to it.
• The response test data and models based on them need to be updated.
• Methodology and tools for developing and maintaining the models are needed.
• Integration in a comprehensive load modelling framework is needed (SGEM T4.2).
• Training regarding field test planning is needed to maximise the value of test results.
• There is no easy nor fast way to wide commercial application.
(Good for us in R&D.)
• In Finland the situation is suitable for developing the models and the methodology.
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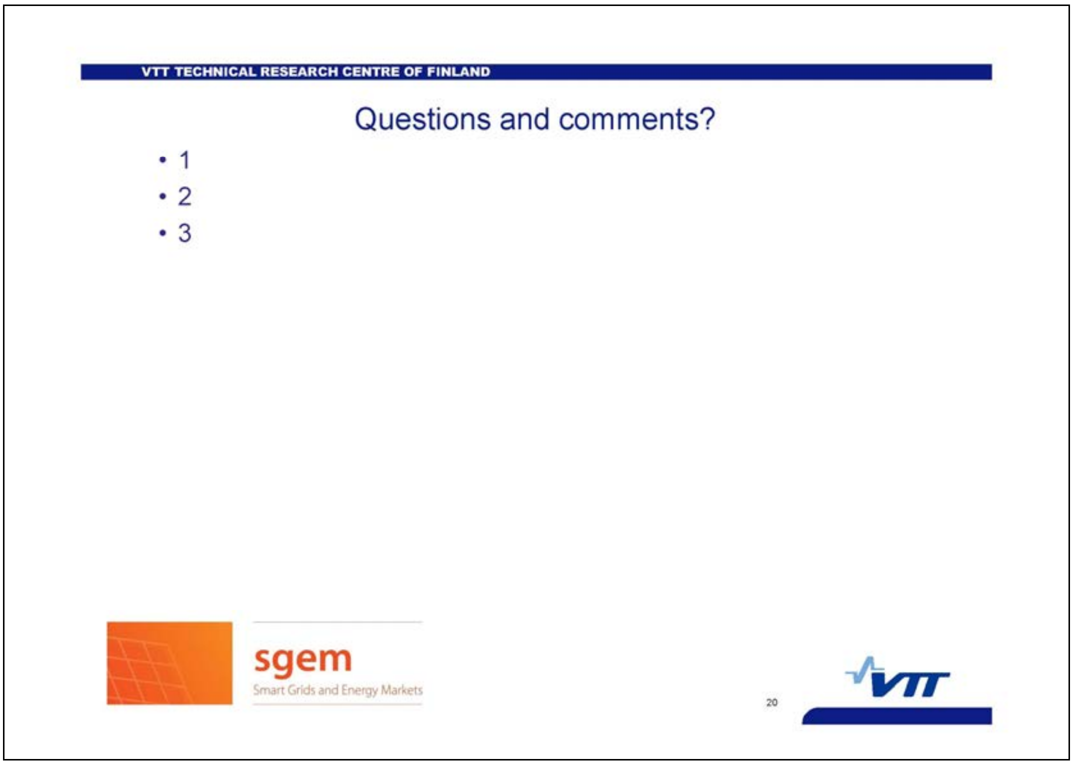
VTT TECHNICAL RESEARCH CENTRE OF FINLAND
Questions and comments?
• 1
• 2
• 3
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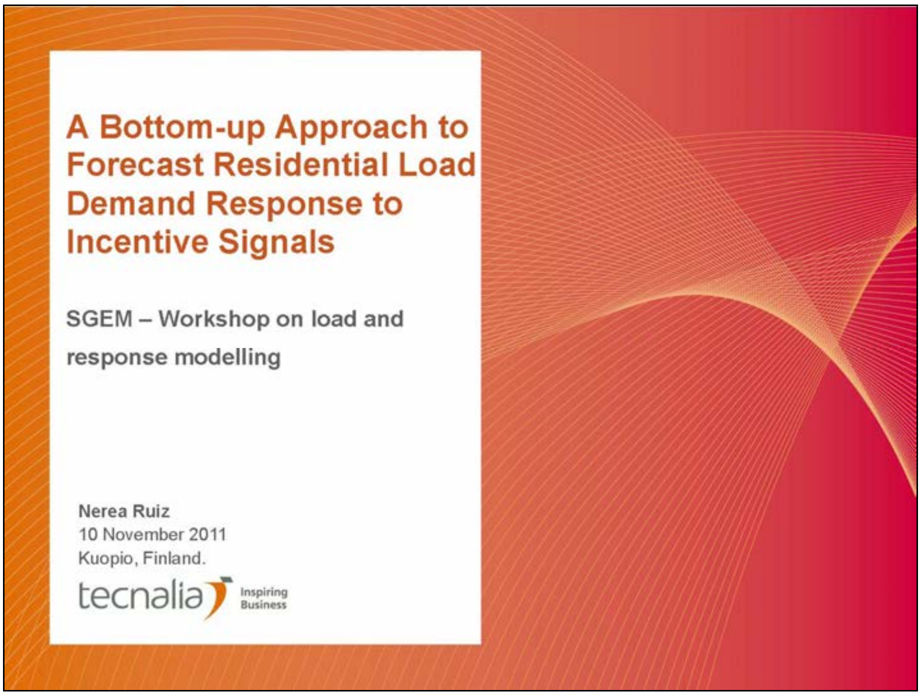
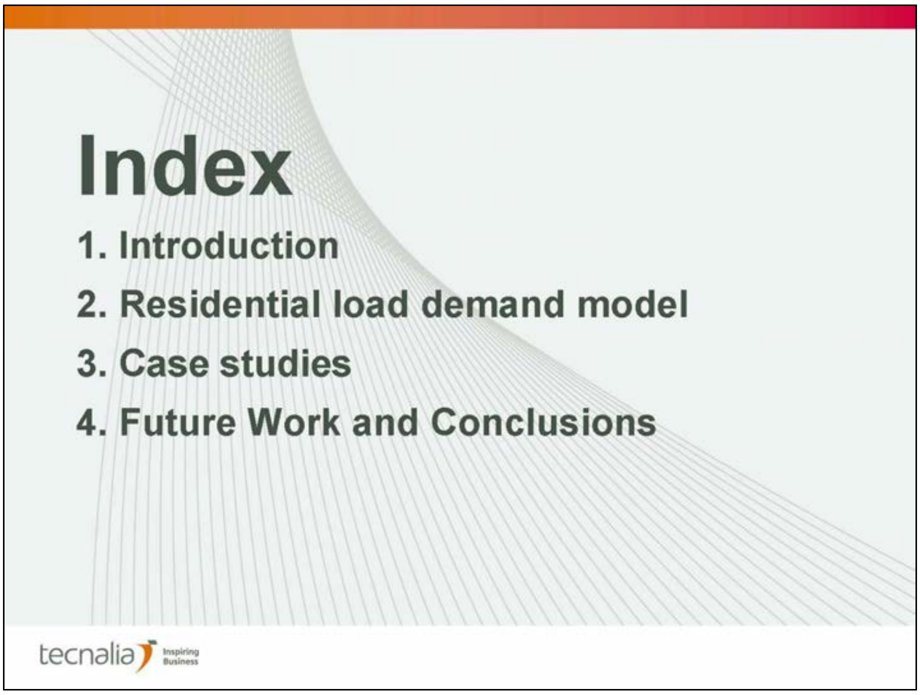
Appendix I: A bottom-up approach to forecast residential load demand response to incentive signals






1.Introduction
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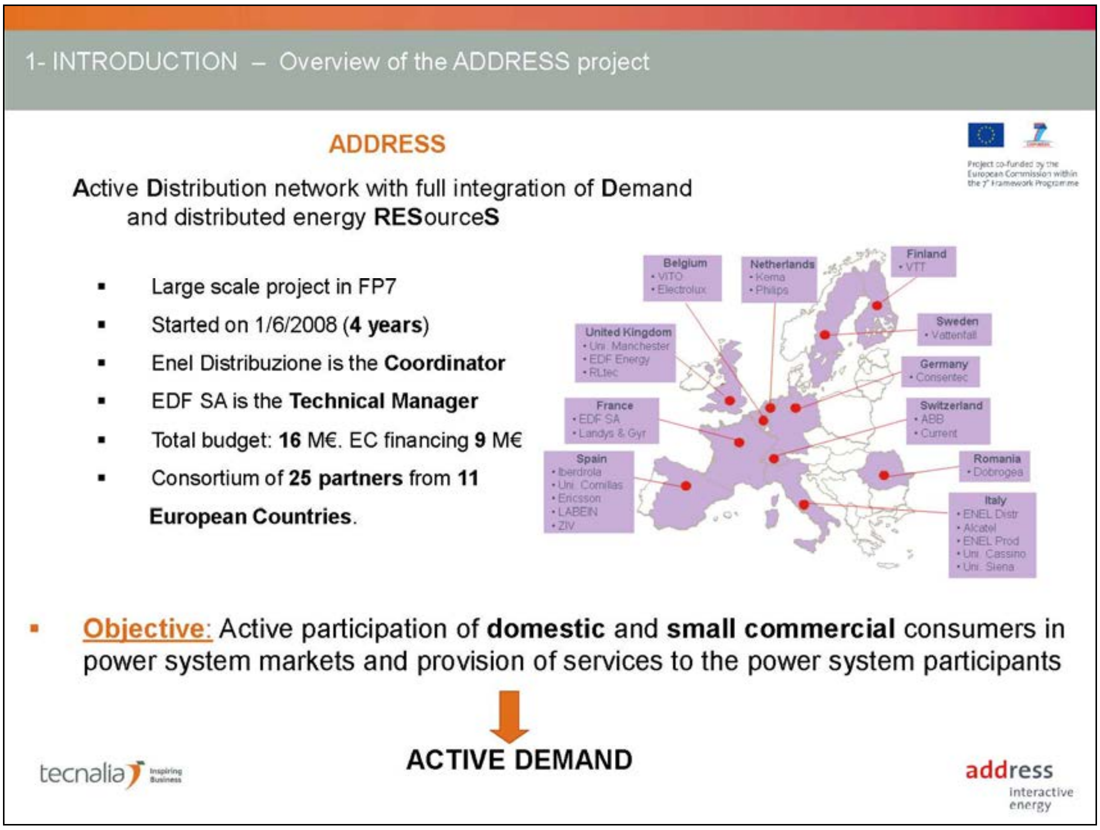
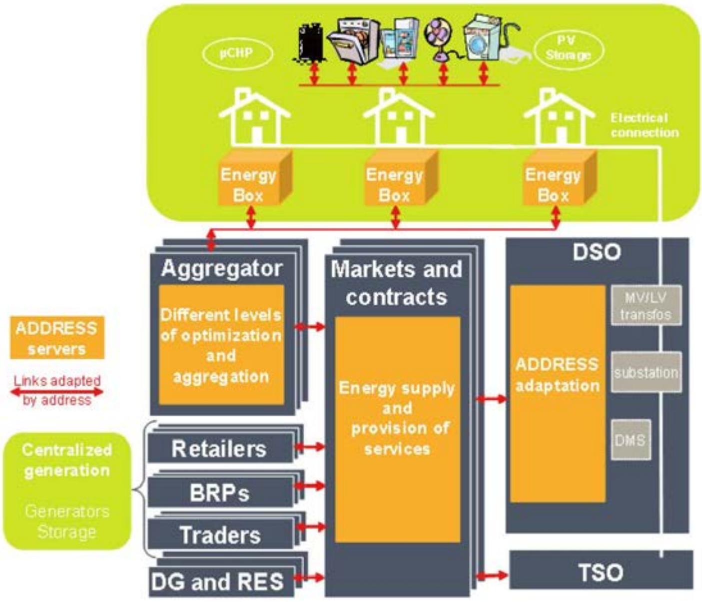

1- INTRODUCTION – Overview of the ADDRESS project
ADDRESS
Active Distribution network with full integration of Demand and distributed energy RESourceS
Project co-funded by the European Commission within the 7th Framework Programme
▪ Large scale project in FP7
▪ Started on 1/6/2008 (4 years)
▪ Enel Distribuzione is the Coordinator
▪ EDF SA is the Technical Manager
▪ Total budget: 16 M€. EC financing 9 M€
▪ Consortium of 25 partners from 11 European Countries.
Belgium • VITO • Electrolux
Netherlands • Kema • Philips
Finland • VTT
United Kingdom • Uni. Manchester • EDF Energy • RLtec
Sweden • Vattenfall
Germany • Consentec
France • EDF SA • Landys & Gyr
Switzerland • ABB • Current
Spain • Iberdrola • Uni. Comillas • Ericsson • LABEIN • ZIV
Romania • Dobrogea
Italy • ENEL Distr • Alcatel • ENEL Prod • Uni. Cassino • Uni. Siena
▪ Objective: Active participation of domestic and small commercial consumers in power system markets and provision of services to the power system participants
ACTIVE DEMAND
tecnalia Inspiring Business
address interactive energy

1- INTRODUCTION – ADDRESS conceptual architecture

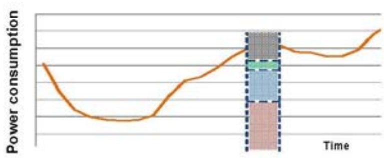


1 - INTRODUCTION – The ADDRESS main concepts

- **Aggregator:** key player for the activation and use of consumers flexibility
- **Energy Box:** - interface between consumers and the Aggregator.
  - linked to the appliances (optimises their power consumption)

- The Aggregator sends requests based on **Price & Volume signals**:
  - Short/long notice: 15 min,..., day-ahead.
  - Duration: up to several hours.
  - Consumers are rewarded as a function of their final power consumption (volume limits):
    ⇨ Indirect load control
  - Load demand reduction/increase requests.

	Average power consumed over time period	Price
	Less than 0,6 kW	Incentive of X (€)
	0,6 kW ≤ Power < 0,95 kW	Incentive of Y (€)
	0,95 kW ≤ Power < 1,05 kW	Incentive of Z (€)
	More than 1,05 kW	Incentive of W (€)



Appendix I: A bottom-up approach to forecast residential load demand response to incentive signals

2. Residential load demand model

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2 – RESIDENTIAL LOAD DEMAND MODEL – Introduction

Objective:

- Forecast the load demand curve of a group of consumers receiving a price/volume signal.

$$Flexibility = Forecasted\ Demand_{\ base\ case} - Forecasted\ Demand_{\ price/volume\ signal}$$

Approach:

- Consumers are classified into clusters or **prototypes**
- **Monte-Carlo simulations** (sample of random consumers of each prototype).
- Household load model based on an **optimization algorithm**.
- Aggregation of the response of all individual consumers → Aggregated response.
- Controllable loads: - shiftable loads (washing machine, dish-washer, dryer,…)
  - thermal loads (air-conditioner, space-heater)

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address interactive energy

2 – RESIDENTIAL LOAD DEMAND MODEL – Input data (I/II)

Input data:

- Prototype information:
  - Prototype ID
  - Electricity tariff (contractual power and tariff)
  - Building thermal characteristics
  - Penetration percentage of shiftable and thermal loads
  - Controllable equipment technical characteristics:
    - Shiftable loads: power consumption cycle
    - Thermal loads: nominal power, efficiency
  - Controllable equipment usage:
    - Shiftable loads: start-time likelihood profile
    - Thermal loads: temperature schedule
  - Flexibility characteristics: price-sensitivity factors

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2 – RESIDENTIAL LOAD DEMAND MODEL – Input data (II/II)

Input data:

- Simulation information:
  - Prototype ID
  - Simulation time period
  - Sample size
  - Price/volume signal
  - Forecasts:
    - Outdoor temperature
    - Consumption curve in the base case

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Appendix I: A bottom-up approach to forecast residential load demand response to incentive signals

2 – RESIDENTIAL LOAD DEMAND MODEL – Algorithm formulation (I/II)

Optimization algorithm

- **EBox emulator:** Optimizes the power consumption of the household for the next 24 h.
- Goal: Minimize the **cost** of electricity while user **comfort** preferences are maintained.
- Comfort preferences: **price-sensitivity factors**:
  - Shiftable loads: λ_s (€/h)
  - Thermal loads: λ_t (€/ºC)
- The optimization algorithm includes **physical models:**
  - Thermal loads: thermal model describing the dynamics of the house.
  - Shiftable loads: power consumption profiles
- **Control actions**:
  - Thermal loads: changes on the temperature set-points
  - Shiftable loads: delays on their starting-times

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2 – RESIDENTIAL LOAD DEMAND MODEL – Algorithm formulation (II/II)

Optimization algorithm

Inputs:

- Controllable appliances owned and usage characteristics
- Building thermal parameters (α, β)
- Contractual power and energy price
- Forecasted non-controllable load profile
- Forecasted outdoor temperature profile
- Price-sensitivities of the consumer (λ_s, λ_t)
- Price-volume signal

Objective function (MILP):

$$Minimize \quad \sum_{i=1}^{N}(Cost_i - Incentive_i) + \sum_{k=1}^{K}\lambda_s \cdot |\Delta Time|_k + \sum_{i=1}^{N}\lambda_t \cdot |\Delta Temp|_i$$

N Number of time-steps in the scheduling period

K Number of shiftable appliances

$|\Delta time|_k$ Delay applied to the starting time of the shiftable appliance *k* (h).

$|\Delta Temp|_i$ Deviation between the initial temperature set-point and the final one (°C).

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2 – RESIDENTIAL LOAD DEMAND MODEL – Output data

Outputs: - Optimal **control actions** to be applied to controllable loads:

- Thermal loads: temperature set-points
- Shiftable loads: starting times

- Forecasted **load demand curve** of the house for the next 24 hours.

Residential Load Demand Model:

Outputs: - Forecasted consumption curve of the all consumers in the prototype under the effect of the considered price/volume signal

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3. Case studies

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Appendix I: A bottom-up approach to forecast residential load demand response to incentive signals

3 – CASE STUDIES – Tests description

Overview

- Two case studies:
  - Load demand **reduction** request during a peak period
  - Load demand **increase** request during a period of low consumption
- Three price/volume signals:
  - Two price-steps and high incentives
  - Two price-steps and low incentives
  - Three price-steps
- Sources of information:
  - Spanish segmentation analysis (ADDRESS IR1.2)
  - European studies on residential energy consumption (Smart-A project,…)

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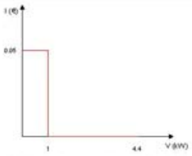
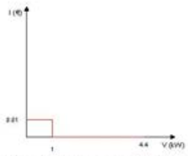
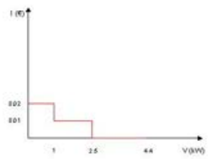
3 – CASE STUDIES – Load demand reduction request



Price/volume signal with two price-steps and high incentives



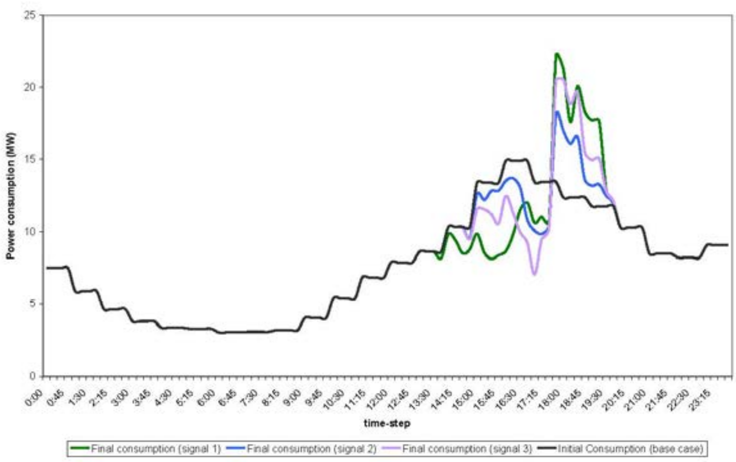
Price/volume signal with two price-steps and low incentives



Price/volume signal with three price-steps

Case study 1

Load demand reduction request from 15:00-17:45



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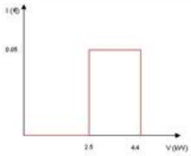
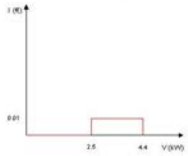
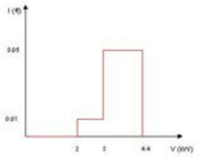
3 – CASE STUDIES – Load demand increase request



Price/volume signal with two price-steps and high incentives



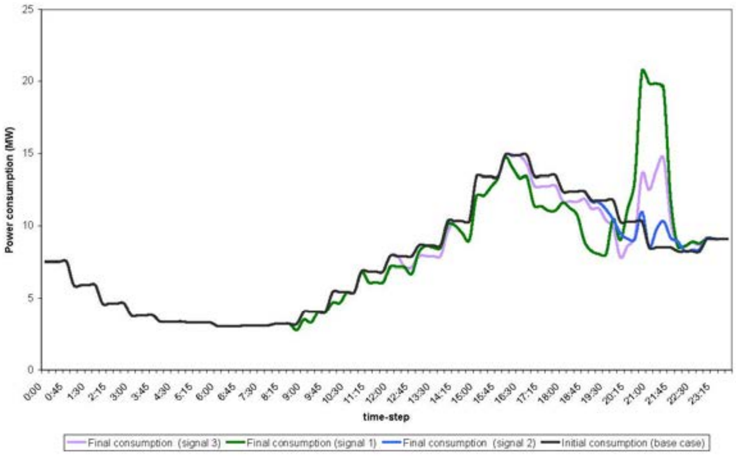
Price/volume signal with two price-steps and low incentives



Price/volume signal with three price-steps

Case study 2

Load demand increase request from 20:45-22:00



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3. Future Work and Conclusions

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4 – FUTURE WORK AND CONCLUSIONS

Conclusions

- A tool based on end-use models has been developed for forecasting the flexibility of the aggregator.
- The tool includes an optimization algorithm based on MILP for simulating the consumption of an individual household according to electricity prices and incentives.
- Simulation tests show that the developed model can provide an effective approach for forecasting the response of a group of consumers.

Future work

- Validation of the model in the field tests of the ADDRESS project:
  - Spain: Castellón, 300 domestic consumers, IBERDROLA.
  - France: Brittany Region, 50-100 domestic consumers, EDF.

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4 – REFERENCES

- ADDRESS web site: **http://addressfp7.org**

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www.tecnalia.com
Thank you for your attention!
Nerea Ruiz
nerea.ruiz@tecnalia.com
Parque Tecnológico de Bizkaia
C/Geldo, Edificio 700
48160 Derio (Spain)
T +34 946 430 850
M +34 667 178 870
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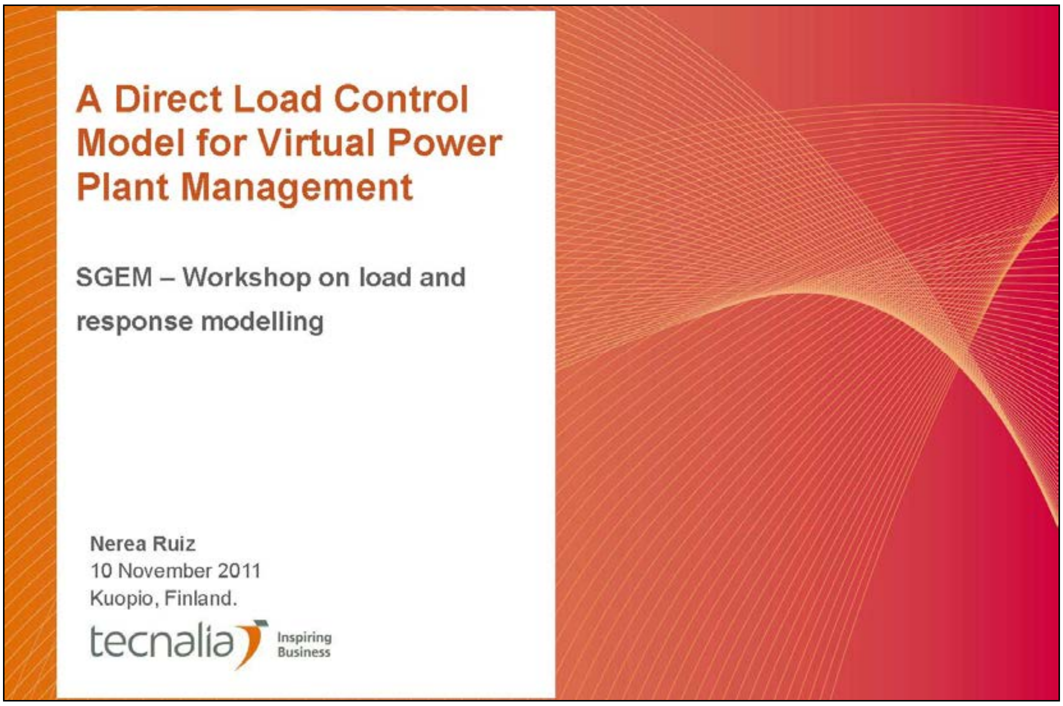
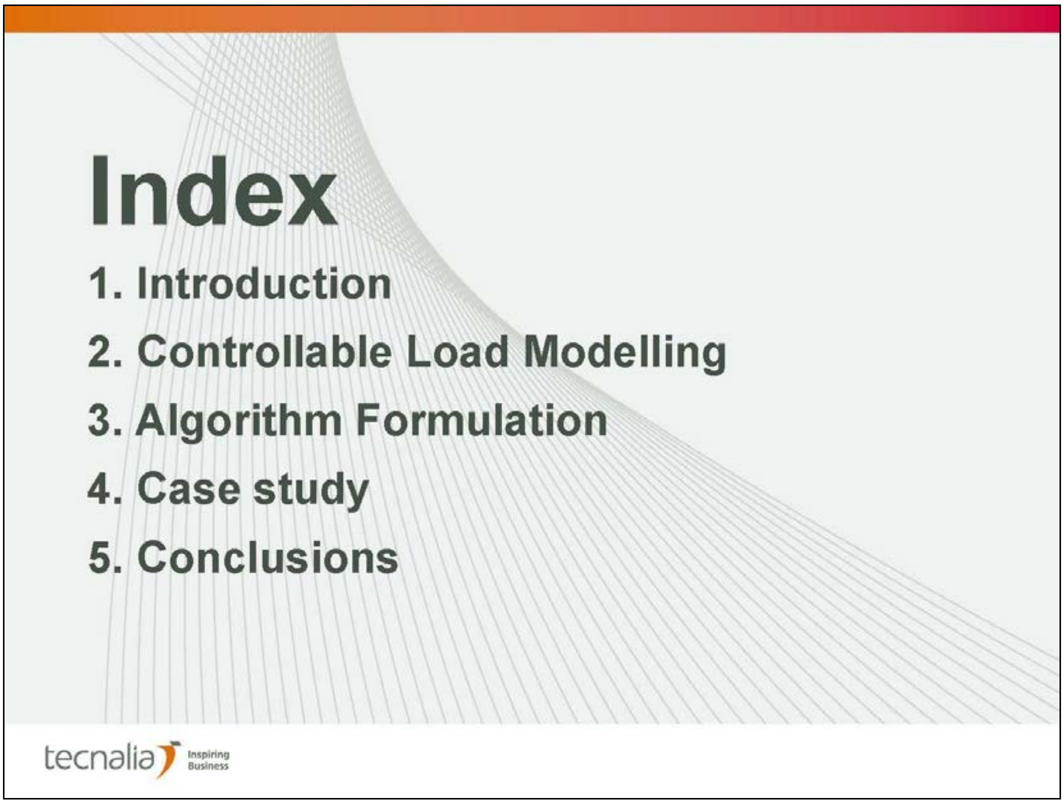
Appendix J: A direct load control model for virtual power plant management





1.Introduction

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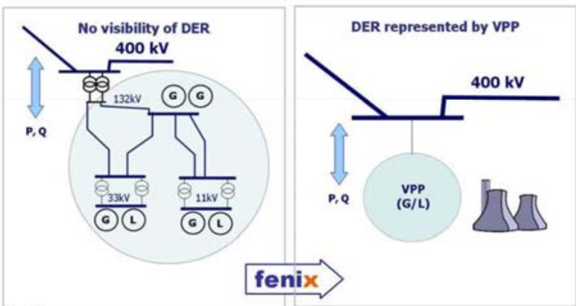
1- INTRODUCTION (I/II)

Flexible **E**lectricity **N**etwork to **I**ntegrate the e**X**pected 'energy evolution' fenix

Virtual Power Plant (VPP)

- Aggregation of the capacity of many diverse DER (generation, storage, demand)
- It creates a single operating profile
- Individual DER gain visibility and manageability to SO, optimizing their position and maximizing their revenue opportunities.
- It can be used to:
  - Make contracts in the wholesale market
  - Offer services to SO



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1 – INTRODUCTION (II/II)

Overview of the model

- Tool for managing a **demand based VPP**
- Aggregation of **domestic & small commercial** customers
- **Direct Load Control** of electrical loads with thermal inertia:
  - Space-heating system
  - Air-conditioning system
- Control actions:
  - Change on thermostat reference temperature setting
  - Short-term disconnections (30, 60, 90, 120 min.)
- **Output**: load reduction capability of the VPP

  ⟶ **load reduction bid (market)**

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2. Controllable load modelling

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2 – CONTROLLABLE LOAD MODELING

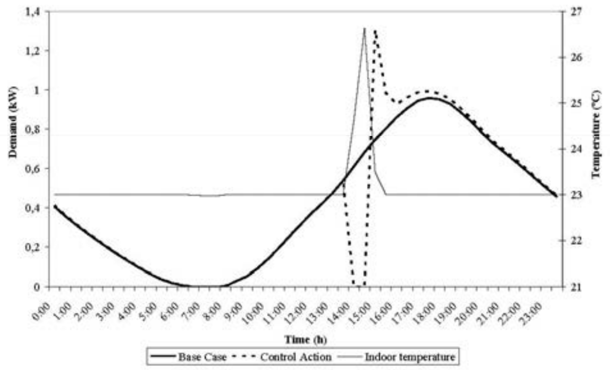
Objective

- Simulate the load consumption curves of the loads: - Base case
  - Control actions

Approach

- Employment of a Building Energy Simulation tool (**EnergyPlus**)
- Definition of typical **model buildings** (e.g. flat, office building,...)

Example :
- flat
- 90 m2
- west oriented
- construction materials fulfil Spanish legislation
- Temp. setting AC: 23°C all day



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3. Algorithm Formulation

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3 – ALGORITHM FORMULATION (I/II)

Objective

- Maximize load reduction of the VPP through the selection of the optimal control strategies

Input parameters

- Forecast load demand of the VPP
- Types of customers
- Number of controllable devices (AC or SH) within each customer type
- Available control actions for each customer type
- Load consumption curves of controllable devices: - base case
  - control actions

Decision variables

-Y_{kst} number of devices of the type K customer which are controlled after the optimization with the strategy s starting at time-step t

-Y_{k0} number of devices of the type k customer no controlled after the optimization

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2 – ALGORITHM FORMULATION (II/II)

Objective function (ILP)

$$\text{Min} \sum_{z=1}^{n} load_z = \sum_{z=1}^{n} (forecLoad_z + \Delta Load_z)$$

$$\text{Min} \sum_{z=1}^{n} [forecLoad_z + \sum_{k=1}^{m} \sum_{s=1}^{p_{kz}} Y_{ksz} e_{ksz}(z) + \sum_{k=1}^{m} \sum_{t=1}^{z-1} \sum_{s=1}^{p_{kt}} Y_{kst} e_{kst}(z)]$$

Constrains:

Payback limitation $\quad load_z \leq loadLimit, \quad \forall z$

Outputs:

- Optimal **combination of control actions** and number of devices that should be controlled with each of them.
- Resulting **daily load demand curve**.

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3. Case study

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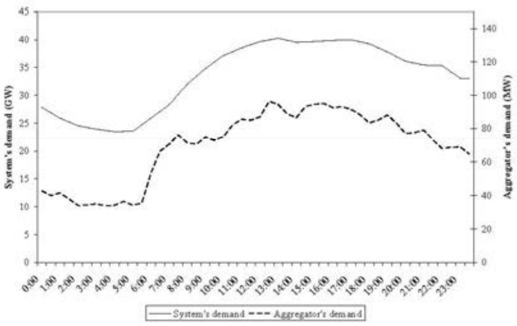
3 – CASE STUDY (I/IV)

Overview

- Actual power system in the north of Spain (residential & commercial loads)
- Participation in the Spanish Deviation Management Market (DMM) participation

Input Data

- TSO calls the DMM from 14:00-16:00
- Summer scenario: AC
- Daily load curve of the aggregator:



- Number of customers

Customer type	Number
domestic customers	6295
supermarkets	12
offices	197

- Payback limit: 96 MW

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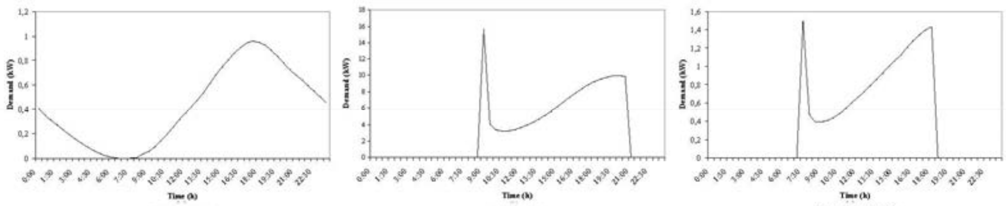
3 – CASE STUDY (II/IV)

- Load consumption curves (base case):



Residential AC — Office AC — Supermarket AC

- Control strategies:
  - disconnecting the AC for a maximum of 1 h
  - increasing the tª setting by a maximum of 2ºC for a maximum of 2 h
  - increasing the tª setting by a maximum of 3ºC for a maximum of 1.5 h
  - increasing the tª setting by a maximum of 4ºC for a maximum of 1 h

Action	Duration	Start time
OFF	30 min.	14:00
OFF	30 min.	14:30
OFF	30 min.	15:00
OFF	30 min.	15:30
OFF	60 min.	14:00
OFF	60 min.	14:30
OFF	60 min.	15:00

Breakdown of Control actions (44 possibilities)

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3 – CASE STUDY (III/IV)

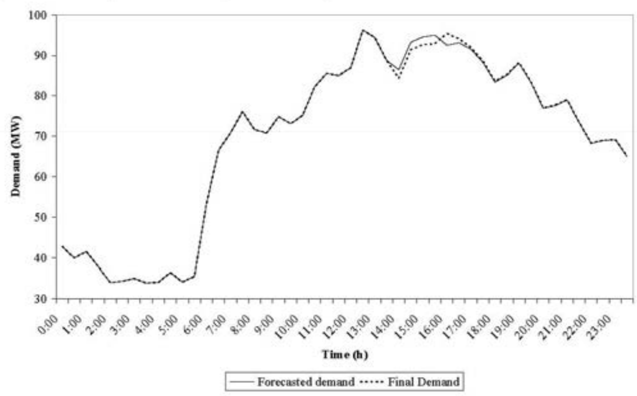
Results

Optimal control actions

Type	Action	Duration	Start time	Number of customers
Domestic customers	OFF	60 min.	14:00	1544
	+ 2ºC	120 min.	14:00	1830
	+ 3ºC	90 min.	14:30	2917
	+ 4ºC	30 min.	15:30	3
Supermarkets	+ 3ºC	90 min.	14:30	12
Offices	+ 3ºC	90 min.	14:00	197

Load reduction capacity of the VPP

Time-step	Load reduction (kW)	Reduction (%)
14:00 – 14:30	2128	2.46
14:30 – 15:00	1864	2.00
15:00 – 15:30	1940	2.06
15:30 – 16:00	2123	2.24



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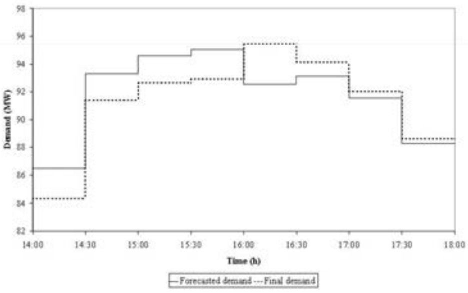
3 – CASE STUDY (IV/IV)

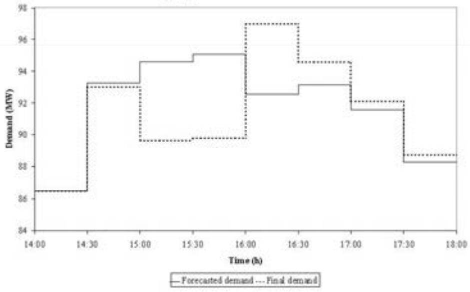
Results

Detail of the load variation obtained



Detail of the load variation obtained

- No payback limitation-



Load reduction bid

	14:00-15:00	15:00-16:00
Energy (MWh)	1.996	2.032
Price (€/MWh)	P1	P2

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3.Conclusions

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4 – CONCLUSIONS

Conclusions

- A DLC algorithm based on LP is developed for operating a VPP with load reduction capabilities.
- It is intended to enable aggregators

  - managing portfolios of residential and small commercial controllable customers

  - participating in electricity markets (provide bids to the TSO/DSO)
- The thermal behaviour of AC or SH is accurately obtained with a building energy simulation tool.
- Simulation tests show that the developed model can provide an effective approach for generating load reduction bids

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Thank you for your attention!

Nerea Ruiz
nerea.ruiz@tecnalia.com
Parque Tecnológico de Bizkaia
C/Geldo, Edificio 700
48160 Derio (Spain)
T +34 946 430 850
M +34 667 178 870

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