Smart Metering Based Demand Response in Finland

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SUMMARY

Research on residential smart metering based demand response in Finland is presented. Hourly interval metering and settlement of practically every customer started in the beginning of 2014 as required by the electricity market legislation that aimed at enabling new forms of demand response. To some extent this already happened. 1) Customers are now offered home automation based demand response, including fuel switching. 2) There is about 1 GW of Time of Use (ToU) load, and new smart metering and settlement made it possible to make a substantial part of it dynamically respond to situations in the electricity market and network. Helsinki Energy and its partners developed an operational model for market based dynamic load control to replace static ToU load controls, and implemented it with smart meters. 3) Loiste in Kainuu has implemented smart metering based direct load control of residential ToU customers and the response is used as system reserve.
The value of demand response depends very much on the accuracy of response forecasting. Both in Helsinki and Kainuu field tests to support response modelling were completed in winter 2014. This paper describes the field tests and related model development for forecasting and optimising the load responses.

KEYWORDS

Demand Response, Load modelling, Forecasting

1. INTRODUCTION

Hourly interval metering and settlement of electricity consumption for practically all residential customers is required in Finland. This requirement came to effect in the beginning of 2014. Thus very large and increasing amounts of data are becoming available for load research in Finland. Shortages of controllable resources and reserve power in the electricity system are expected due to 1) high proportion of heat demand driven cogeneration of electricity and heat (CHP), 2) dependence on imported electricity, 3) growing penetration of intermittent generation from renewables, 4) increase in the distribution of energy system, 5) new loads such as electrical vehicles, and 6) big base load nuclear power plants. For solving this challenge, dynamic demand side responses offer a cost and energy efficient and environmentally friendly alternative to investments in networks and centralised generation and storage. But successful utilisation of this underused resource is not trivial and requires some testing, modelling and learning.

Several field trials have been implemented in Finland in order to better understand and demonstrate how to get maximum benefit from the demand response potential available. The field tests give experience and data on the possibilities, limitations and challenges of different technologies. It turns out that the value of demand response depends very much on how accurately the responses can be forecast when planning load control actions, electricity market transactions and network operations. In Finland most of the residential demand response potential is in thermal storage type loads comprising mainly heating, but there may also be significant amounts of potentially flexible cooling loads. The heating and cooling loads and their responses depend much on the ambient temperature and its variations. That makes forecasting the load control responses challenging, because in Finland the annual and daily temperature variations can be large and irregular. The data sets used for model identification and verification must be long in order to adequately cover all the relevant conditions. It is especially important to model accurately the loads and the responses during the extreme peak load situations. Thus the models need to be accurate also outside the ambient temperature range that was available for the model identification.

This paper focuses on tests on the residential customer segment that are adequately large for statistical relevance. Only smart metering based dynamic demand response has reached such a scale early enough for this paper. Its implementing and operating do not cost as much as home automation based demand response and it requires very little customer involvement and engagement. The penetration of home automation based demand response is increasing so much that starting large scale tests can be considered. Background for the research described here is explained in [1] and [2].

The usefulness of the demand side responses depends much on how accurately the loads and their control responses can be forecasted. Field trials for developing models of demand side responses of residential heating and cooling loads are described. Also measured and forecasted responses are compared. The modelling approaches being developed include neural networks, clustering load profiles and partially physically based models. Also hybrid methods are considered.

2. SMART METERING DATA AND DEMAND RESPONSE FIELD TRIALS

In addition to large scale implementation of dynamic controls the field trials comprise collection, analysis and modelling of hourly interval metered data from smart meters, weather measurements, weather forecasts and 3 minute interval power measurements from the network. Also results from some earlier demand response field trials in 1996-1997 will be used to complement the analysis and modelling. In the project SGEM (Smart Grids and Electricity Markets), for short-term load forecasting model development, the following sources of hourly interval measurement data were used:

- Smart metering data of about 3000 customers in 2009 and 2010 in Koillis-Satakunnan Sähkö (KSS, a rural DSO) were provided by Tampere University of Technology (TUT). Dynamic load controls were not applied but traditional static time-of use controls were included.

- Direct load control field trials of about 7000 electrically heated houses in early 2012 and 2014 by network operator Loiste in Kainuu area. Traditional static time-of use control was also applied.
- Field trials of dynamic smart metering based demand response for full storage heated houses in Helsinki. The trial comprised about 700 houses and about 16 MW of controllable power during night time.

Each measurement set and its objectives are briefly described in the following.

2.1 Koillis-Satakunnan Sähkö Oy (KSS)

The measurement data from KSS were used for the development and comparison of methods for short-term forecasting the responses to outdoor temperature variations of electrically heated customers by VTT Technical Research Centre of Finland, UEF (University of Eastern Finland), and TUT. Fig. 1 shows the summed hourly interval measurement data for 2009. Similar data were also available for 2010. Thus one year could be used for model identification and another for verification. Also temperature forecasts for the area and time period were acquired.

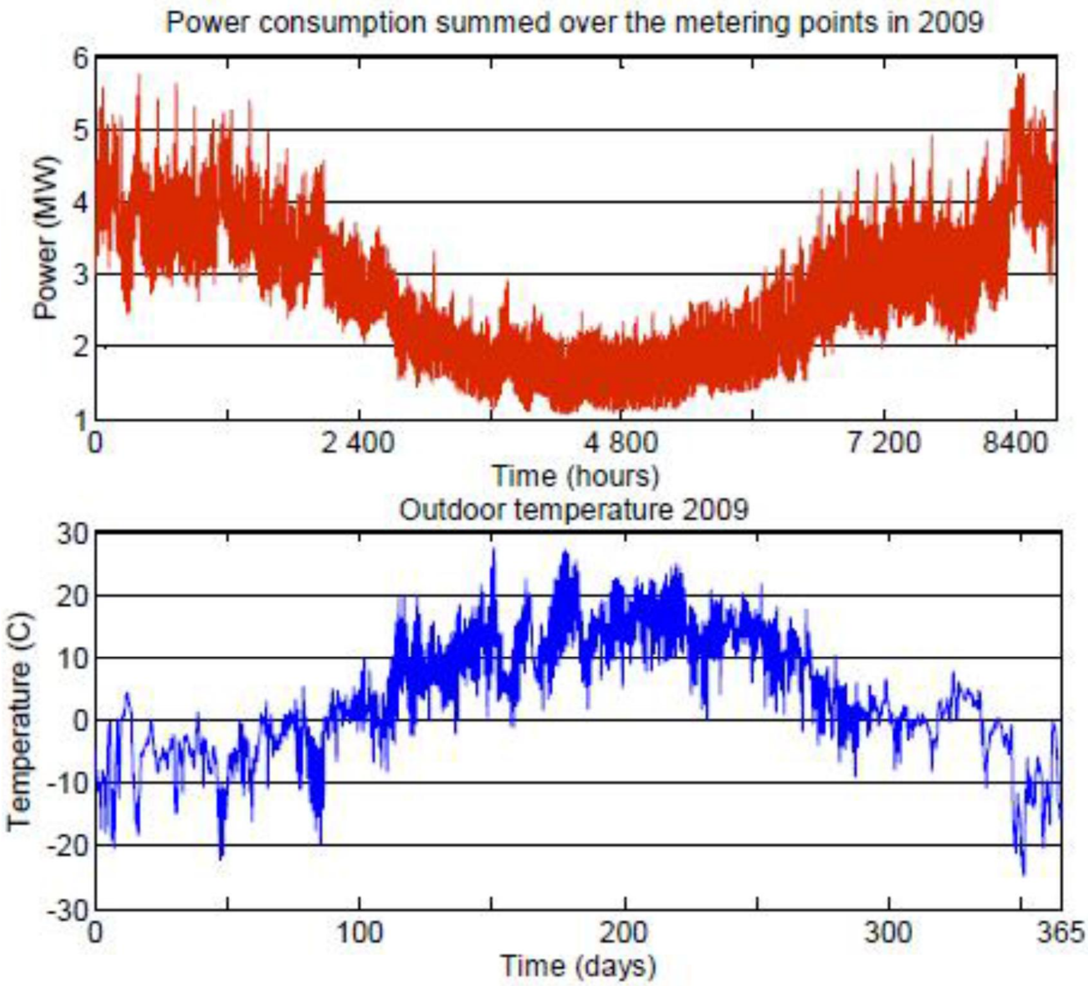

Fig 1. Summed measurement data of 2009 for the KSS measurement.

2.2 Loiste Sähköverkko Oy (electricity distribution) in Kainuu

VTT in project SGEM helps Loiste in Kainuu in direct load control field tests comprising about 7000 partial heating storage houses that are also in time of use control. This help includes test planning, and data analysis and modelling. The objective is to develop short-term load forecasting models of the load responses to outdoor temperature variations and load control actions. In addition to the hourly interval data, also 3 minute interval data from the distribution network were recorded, see Fig. 2.

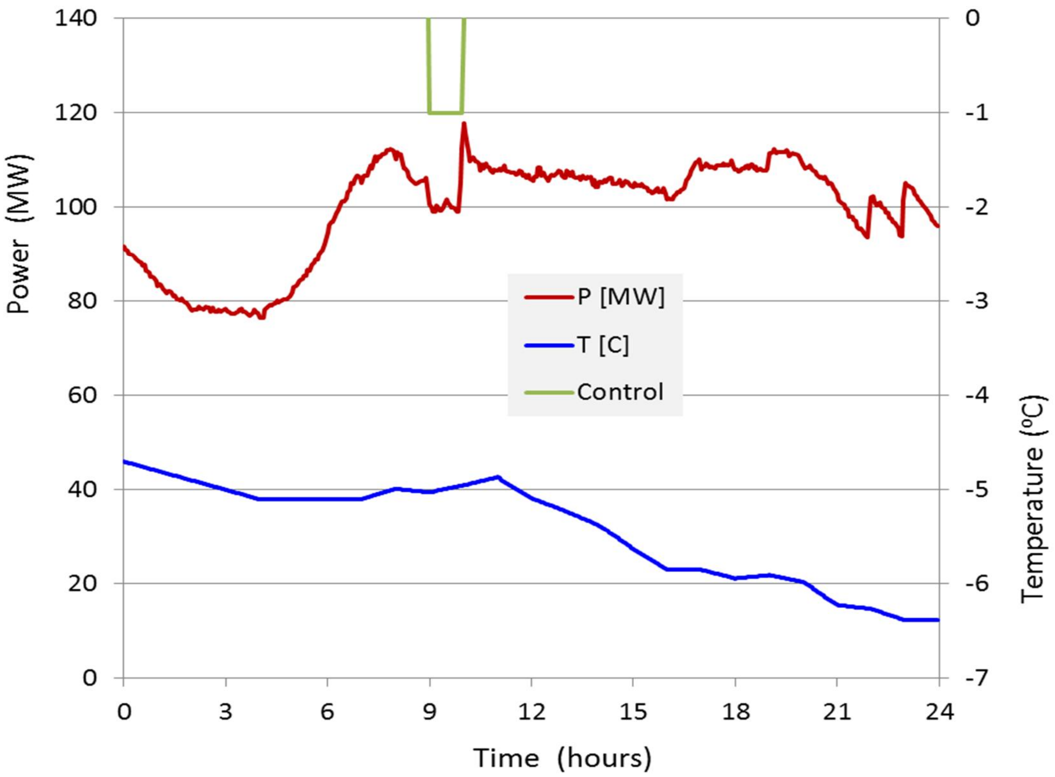

Fig. 2. Load control response in the 3 minute interval power of the distribution area in 6 Feb 2014.

2.3 Helsingin Energia

According to [3] the use of static time of use control of electrically heated houses started in large scale in Helsinki in 1964. In Finland now over 1 GW of Time of Use (ToU) controlled loads are switched on in the evenings of the system peak load days. The need to make a large part of ToU controls dynamic is increasing due to the developments in the electricity supply infrastructure and electricity market.

A dynamic demand response operating model and specification were developed and two smart metering system vendors implemented it. The model defines how electricity retailers control the loads based on their needs using the messaging developed. Helen Electricity Network started field trials in 2010-2011. By February 2012 about 500 consumers (10 MW) were connected and in February 2013 about 35 MW. All are full storage electrical heating houses. In December 2012 dynamic load control started with about 1000 consumers. Observed controlled power was about 17 MW and the total power of the customers was about 20 MW. The 3 MW difference was due to non-controllable consumption and lost control messages. Vantaa Energy Electricity Networks completed tests with 1 house and has started new tests with some more houses that have partial heating storage. Fortum Electricity Networks made a study on how the developed dynamic demand response model fits to their smart metering system.

Fig. 3 shows observed load responses of a full storage heated house to a spot market prise and outdoor temperature variation. The heat demand to be met increases as the ambient temperature drops. Heating is scheduled to the hours that have the lowest electricity prices. In practice the retailers take into account also other aspects of the electricity market such as intraday markets and balancing. The retailers also need to monitor from the measurements and forecasts that every customer always gets enough heating time to keep the house and domestic hot water warm enough.

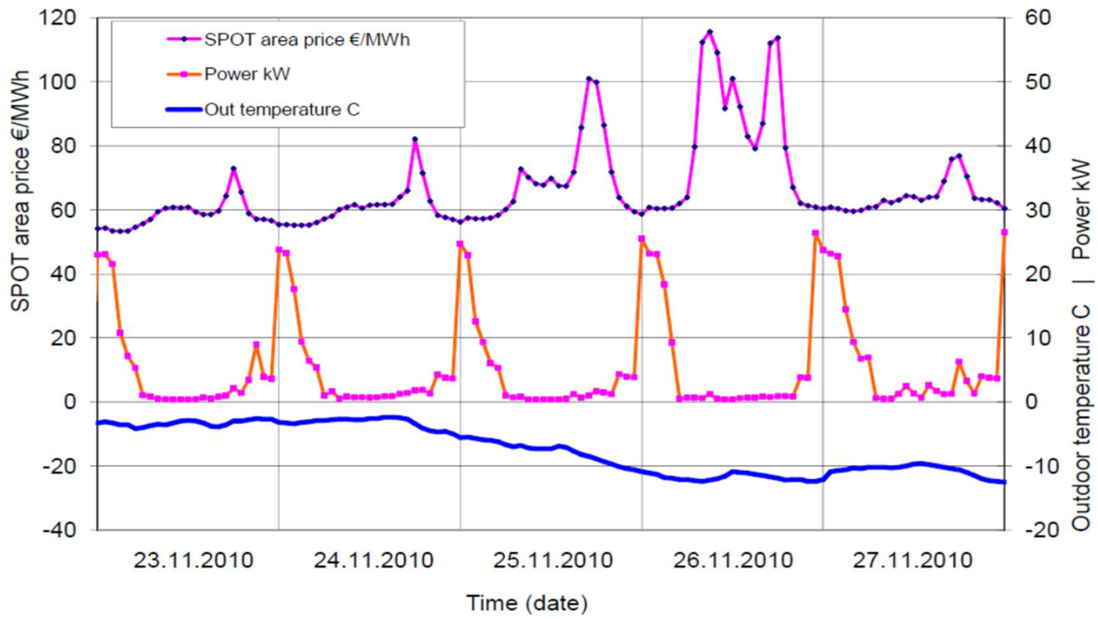

Fig.3. Responses to dynamic market base control of full storage heated houses in March 2011.

3. A COMPARISON OF SHORT TERM LOAD FORECASTING APPROACHES

First short term load forecasting methods were studied, developed and compared by VTT, TUT and UEF. These methods do not yet model dynamic control responses. Nevertheless they provide a useful starting and reference point for the development and analysis of the control response models. The compared methods included 1) traditional load profiling, 2) a fitted temperature dependency with a lag, 3) a smart metering based load profiling with and without clustering [4], 4) a model that has simple partially physically based model structure and includes a Kalman-filter predictor [5], and 5) a neural network model. It will be useful to add to the comparison some more models such as classical time series models with certain input nonlinearities, more advanced neural network models and hybrid models and develop new comparison criteria that reflect the actual priorities of this particular forecasting task. The performance of the models was compared in forecasting 9 a. m. in the morning the energy demand during a 24 hour period covering roughly the next day, and in forecasting the power of each hour during the same period.

It was found out that using a short term ambient temperature forecast for the network area as input to forecasting improves the short term load forecasting performance very much. Thus in the comparison the ambient temperature short-term forecast was always used as an input. The other inputs were the measurement histories of temperature and hourly powers as available at the time of forecasting 9 a.m.

The forecasting task for the comparison was motivated as follows. The load and response forecasts and the control responses are needed for planning the actions in the day ahead and intraday electricity markets. Forecasting before the day ahead market closure was chosen because it is particularly interesting in this context due to both a challenging forecasting horizon and the importance in the electricity market. The energy demand forecast is often used as an input for the control response forecast. The hourly interval power forecast gives a reference and an alternative for the forecasting of the base case situation where no load control is applied.

The neural network approach performed best in the comparison, but also the new load profiling methods and the model with a physically based model structure performed very much better than the traditional load profiling. Thus at least these approaches are the main candidates to be considered when proceeding to response forecasting in future projects. We have earlier identified, from only substation measurements, simple partially physically based models [1, chapter 4.]. In the same tasks the identification of classical linear time series models always more or less failed. We have not yet studied control response modelling with the other types of models. In addition to substation measurements, we now can use hourly interval data from smart metering for model identification.

4. SHORT-TERM FORECASTING MODELS OF DYNAMIC CONTROL RESPONSES

4.1 Direct load control responses

Fig. 4 shows the response to one hour long control action as identified from measured hourly interval powers of the test groups and reference groups in the tests in 2014. During 2012 and 2014 altogether four load control tests were made, three of them around -5 C and one in about -23 C. Fig. 5 shows the size of the identified responses in hourly power as a function of ambient temperature. Thus some more tests are still needed to get better temperature coverage and it remains a subject for future research to develop direct load control response models that provide minute level time resolution, take into account the temperature dependence of the responses, and integrate into an accurate short term load forecasting model.

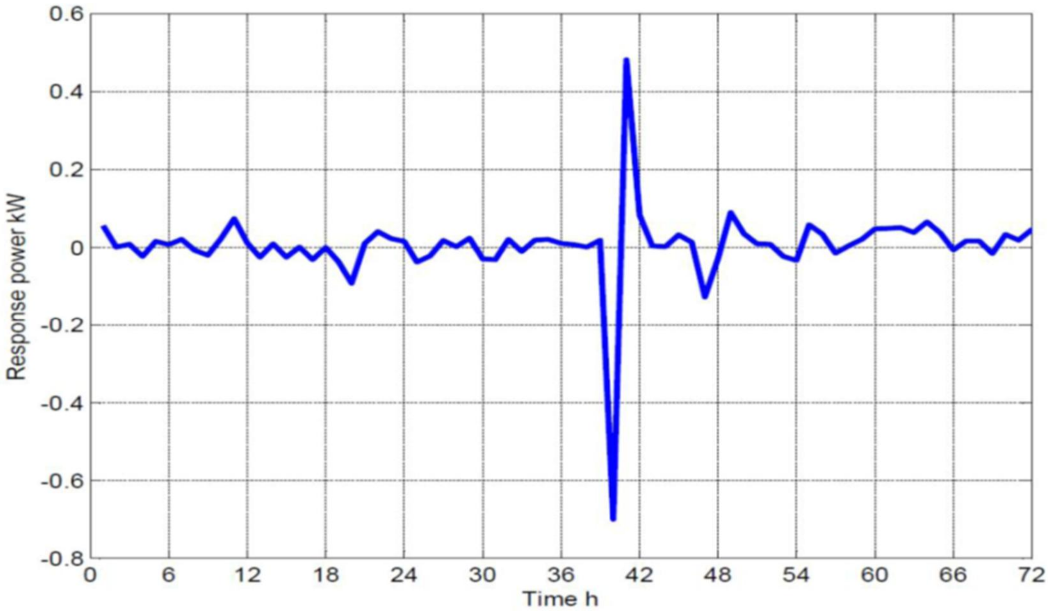

Fig.4. Daytime direct load control response identified from measured hourly powers.

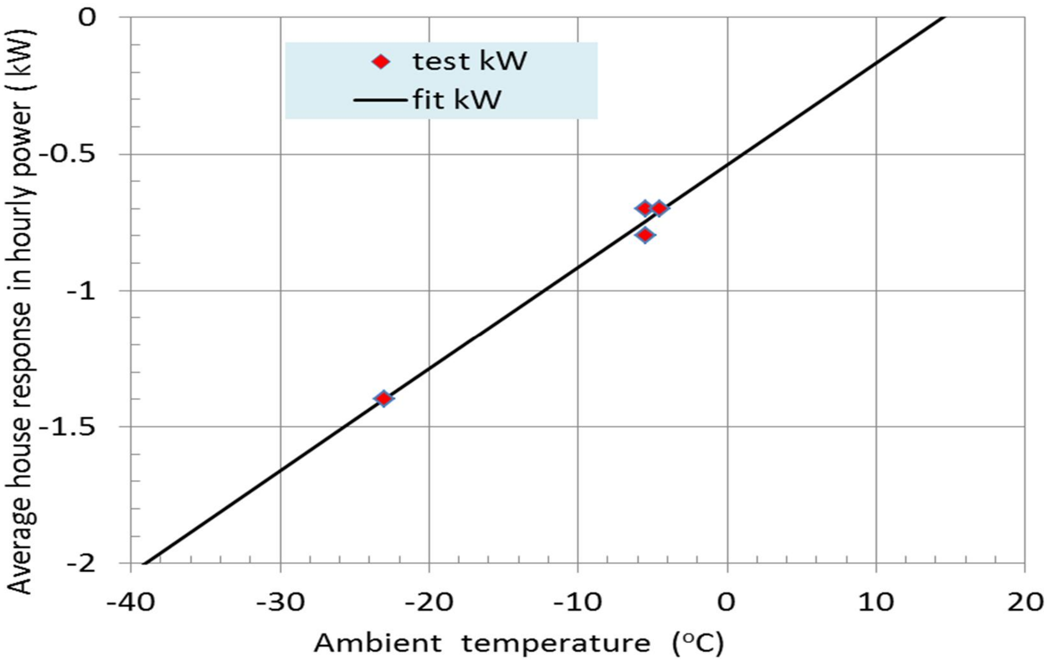

Fig.5. Some more tests are still needed at cold temperatures.

4.2 *Responses of dynamic load control of full storage heated houses*

Based on the field test described above in Chapter 2.3, a model for forecasting the responses of dynamic load control of full storage heated houses was developed and some of its responses are shown in Fig. 6. The performance is always roughly as good [6], which can be seen from Fig. 7 that shows the forecasting error over the year. Collection of separate verification data completes at the end of May 2014 so they were not yet available for Figs. 6 and 7. The inputs for the model are the control commands, forecasted outdoor temperature, measurements of outdoor temperature, and power of both two load control groups, which are available at the forecasting moment 9 a.m. The model output includes the hourly powers for the following 48 hours. In the Figs. 6 and 7 the forecast is the hourly powers for the 24 hours from 9 p.m. till 9 p.m. that span 12 to 36 hours ahead of the moment of making the forecast. In SGEM also new better models are being developed for the forecasting of the other loads. Integrating them is expected to improve the accuracy of the forecasting outside night time.

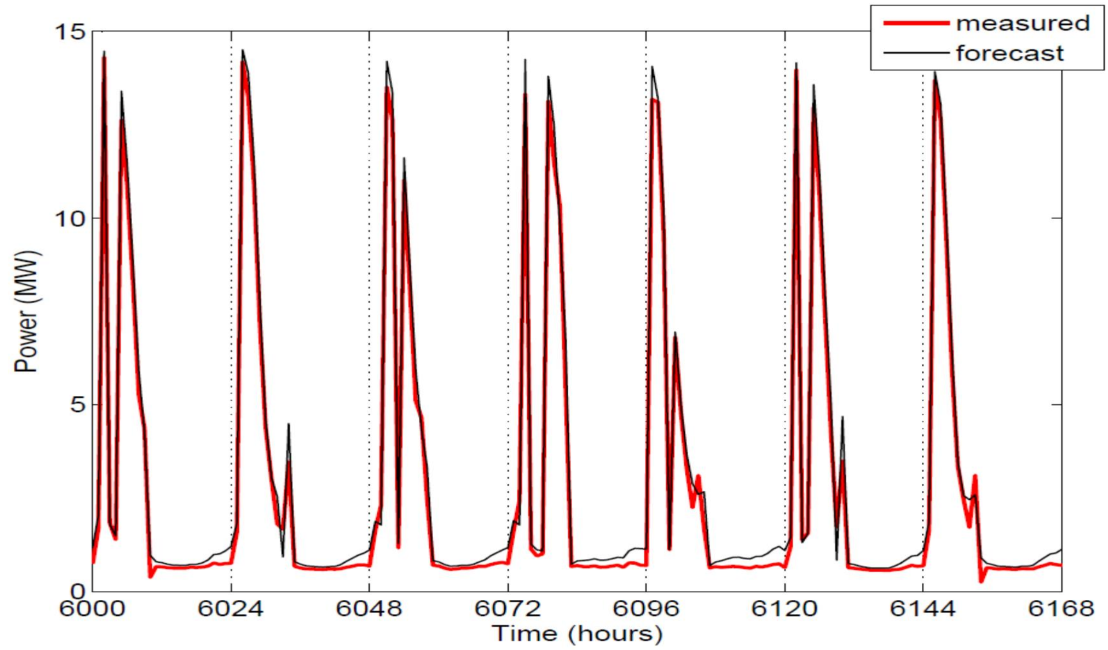

Fig.6. The responses to load control actions can be accurately forecast [6].

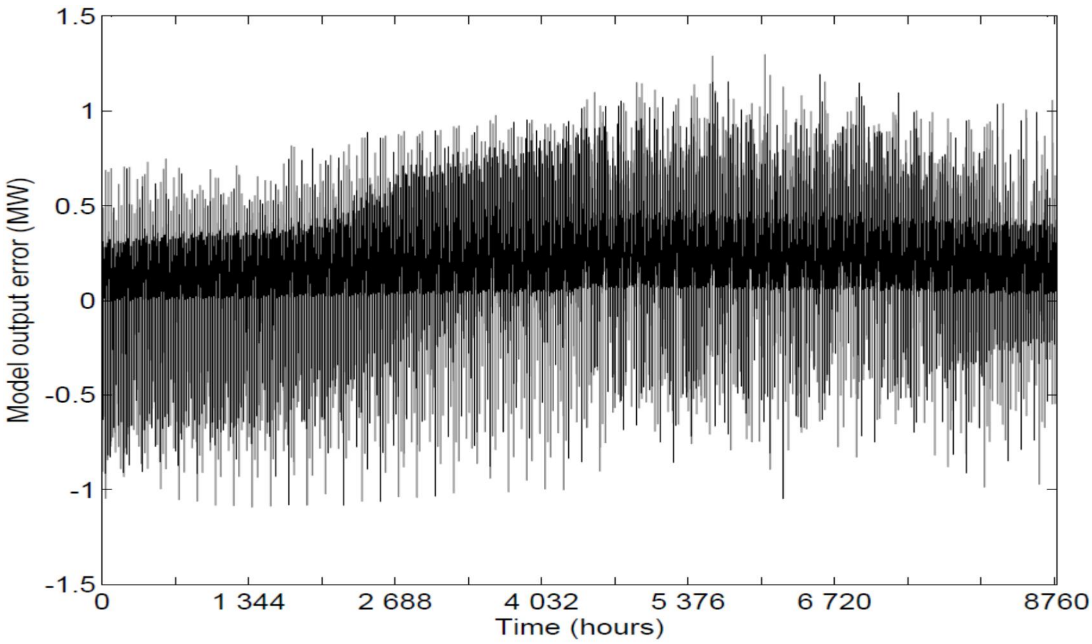

Fig.7. Forecasting was accurate over the whole year [6], (error = measurement - forecast).

5. IMPACTS OF DEMAND RESPONSE ON THE ENERGY SYSTEM

In order to achieve the expected benefits of demand response, it is necessary to forecast the responses accurately. When dynamic market based load control of full storage heated houses was applied without response forecasting models the benefits were largely cancelled by increased costs due to the balancing errors. At least equally critical is accurate forecasting of the responses, if demand response is applied for the network management or as reserves for the system operator. Then the responses need to be forecast with time resolution and accuracy of some minutes instead of the hourly resolution of the Nordic electricity markets.

6. CONCLUSION

Hourly interval consumption data from smart meters enable improved load modelling. Different approaches have been studied and compared to provide basis for load response modelling. Models for load responses have been developed but the models still need more completion and verification.

Field trials have succeeded in providing data that enables modelling the dynamics of the control responses. Some data from very cold weather are still needed for making more complete the models that can forecast the loads and responses for even much more extreme weather conditions.

Electrically heated houses can provide useful amounts of well predictable direct load control response even though most such houses are also time-of-use controlled. Time-of-use controls of electrical heating houses have been replaced or are being replaced by dynamic controls in some electricity distribution areas.

7. ACKNOWLEDGEMENT

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