FORECASTING THE RESPONSES OF MARKET BASED CONTROL OF RESIDENTIAL ELECTRICAL HEATING LOADS

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ABSTRACT

The value of demand responses depends much on their predictability. In Helsinki dynamic smart metering based dynamic demand response can control about 35 MW of residential full storage heating. A partly physically based model for forecasting this aggregated load and its responses to control signals and ambient air temperature is being developed. Also interval measured consumption is used as model input. The initial results show that the control response model developed improves the forecasting accuracy very much. This research and its initial results are reported in this paper.

INTRODUCTION

Hourly interval metered electricity consumption of practically every consumer must be collected for the settlement in Finland starting from the beginning of the year 2014. The interval data enables improving the accuracy of load models and forecasts. The interval settlement also makes it possible to connect the small customers' demand response to the electricity market. Thus it is becoming necessary to accurately short-term forecast the aggregated control responses, too. Load forecasting methods are reviewed in [1] except physically based load response models that are initially reviewed in [2]. There are also more recent papers, such as [3].

The subject addressed is short term forecasting the loads and responses of customers that have electrical heating and are subject to market based dynamic load control. Helen Electricity Network has implemented dynamic smart metering based load control functionality for its time of use customers [4]. The electricity retailers can control the loads based on the electricity market prices and the balancing situation. Also the network operator will be able to control the loads as soon as a non-discriminatory and fair scheme for compensations for the retailers has been defined and agreed on. Accurate forecasting of loads and their responses helps the retailers to reduce their power purchase and balancing costs, and the network operator to better avoid overloading of the network. In this contribution the focus is on forecasting before the day ahead market gate closure the load behaviour for the following 38 hours. The same forecasting approach may be applied again inside the intraday market context. Accurately forecasting the heating demand is needed for defining load control schedules that minimize the electricity costs and maintain the customer comfort.

Now about 1500 customers with about 35 MW total power are connected to the dynamic load control system in Helsinki. Since June 2012 dynamic market based load control has been applied to nearly 800 customers and we develop and identify forecasting models using their hourly interval data, weather data and weather forecast of the first year. The model development is now being completed and the data of the second winter (June 2013-May 2014) will be used for model verification and comparison. Thus all the results reported here are only initial, because they are based on identification data that covers June 2012 to May 2013.

This paper describes the forecasting methods and the performance indices applied. It will also show the results of the verification and comparisons of forecasted and actual load responses. The method has two main steps that are described separately. These steps are 1) forecasting the heat demand for the next night and 2) forecasting the responses to the control signals so that the forecasted night heat energy demand is met exactly. Also the needs and requirements for load and response forecasting will be discussed.

OVERVIEW OF THE RESPONSE FORECASTING METHOD

The main structure of the load forecasting algorithm developed is shown in Fig. 1. First the daily demand for both heating energy and other energy are forecast and based on them and the control signal the hourly powers are forecast. Inputs include weather measurement and forecasts and the load control signal. Also time is used as an input for removing remaining weekly rhythms and day length dependencies.

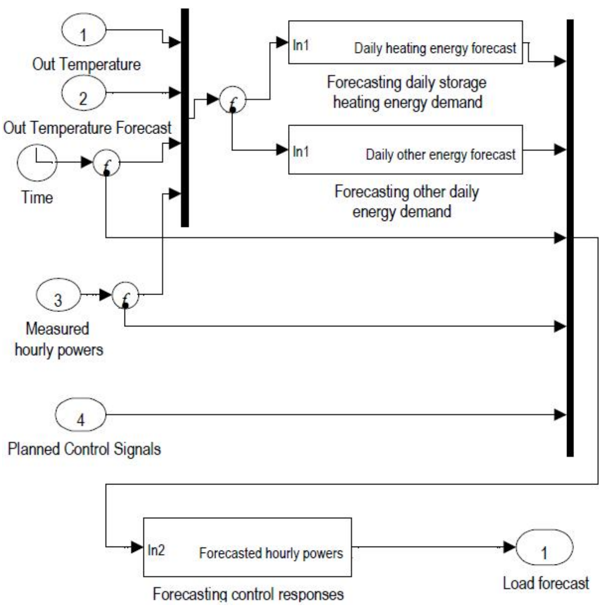

Fig. 1. Simplified overview of the load response forecasting approach

FORECASTING HEATING ENERGY DEMAND

Method

The energy demand forecasting model uses past weather data, weather forecast, day length, and weekday as inputs. It includes simple linear dynamics and some nonlinear elements. Special days and the transitions between standard time and summer time are not yet included in the model.

A simplified version of the applied method was developed and analysed in [5]. Now identification data covers a wider ambient air temperature (outdoor temperature) range where polynomial fit is more appropriate than the original linear fit. Adding mild low pass filtering of the input also improved the fit. The inputs of the model are the measured and forecasted ambient air temperature. The temperature forecast is used where the measurement is not yet available. The output is the heating energy demand of the night time. The method comprises a polynomial with input saturation limits, lag and a first order low pass filter. The model also includes a filter for removing constant or slowly varying bias. All of those parameters were together fitted so that the variance between the model output and measured heating energy demand were minimised. After that the weekly rhythm and a day length dependent component were also identified from the residual and added to the model. That slightly improved the fit, and verification analysis is needed to know, if those model components are adequately useful to outweigh the added complexity.

For forecasting the daytime energy demand, and the daily minimum and maximum hourly powers from the ambient air temperature, we developed similar but even less complex models.

In earlier studies, such as [6], we found out that using ambient air temperature forecast improves the forecasting performance substantially. Short term temperature forecasts are available without additional costs. Thus in this paper we always use ambient air temperature forecasts as inputs.

Performance indices

Then the following performance indices were used:

Root Mean Square Error (RMSE) = root(mean(e_t^2))
Std. (Standard Deviation) = root(mean(e_t-mean(e_t))^2)
Mean Absolute Error (MAE) = mean (|e_t|)
Range = max(e_t)-min(e_t)

Here e_t is the forecasting error at time t. For more information on measures of forecast accuracy read [7]. The performance indices mentioned above do not take into account the monetary cost of the errors. Thus also weighting the errors with electricity spot-price was implemented but the results are left for later publishing. For the same reason percentage errors that weight more the errors during low loads are not useful performance indices here.

Results

Selected indices of night energy forecasting performance are shown in Table 1. The absolute error is given as divided by the number of houses. Also the indices normalised to the yearly mean night energy, which is 64.8 kWh/house, are given. The performance is practically the same, when separately modelled group forecasts are summed (G1+G2 as clusters) or when the combined croup is modelled and forecast as such (G1+G2 combined.).

Table 1. Performance of night energy demand forecasting.

a) Absolute error divided by the number of houses (kWh)				
	Group 1	Group 2	G1 + G2 as clusters	G1 + G2 combined
RMSE	5.583	5.544	3.719	3.722
Std.	4.129	4.445	3.713	3.716
MAE	4.305	4.344	2.760	2.758
Range	30.476	25.855	26.291	26.366
b) Error normalised by the yearly mean night energy				
	Group 1	Group 2	G1 + G2 as clusters	G1 + G2 combined
RMSE	0.0862	0.0856	0.0574	0.0575
Std.	0.0637	0.0686	0.0573	0.0574
MAE	0.0665	0.0671	0.0426	0.0426
Range	0.4705	0.3991	0.4059	0.4070

The best night energy forecast is compared with the measurement in Fig. 2. For scalability the energy is averaged over the 694 houses that belong to the two separately forecasted groups. The forecast is the sum of the forecasts of two groups. These results give

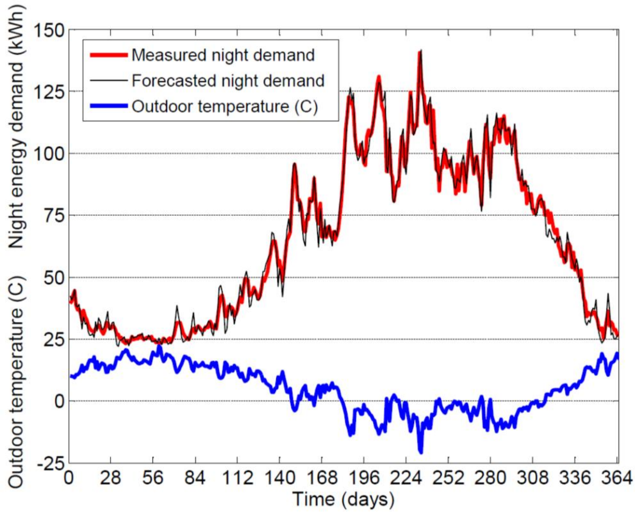

Fig. 2. Comparison of energy demand of the next night forecasted at 10 a.m. with the measured energy demand.

confidence that forecasting of the heating demand can be improved much compared to the method that is now used online.

The forecasting error time series for Fig. 2 is shown in Fig. 3. Its standard deviation (Std.) is 3.71 kWh. One sigma confidence interval of the Std. is about 0.14 kWh, because the identification data comprises 365 days and the errors can be assumed to be nearly independent with normal distribution.

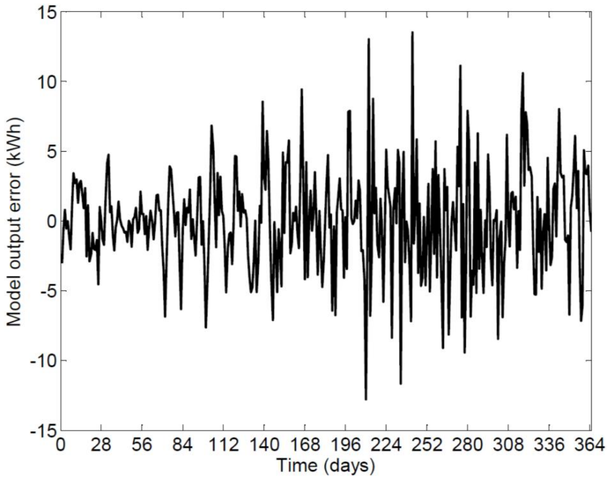

Fig. 3. Night energy forecasting error per house for the sum of separate group forecasts (G1+G2 as clusters).

The control signals for the two groups are different, mainly because the houses in group 2 need a longer heating time. Thus forecasting of the control responses requires that the heat demands of the groups are modelled separately. Table 1 shows that this approach does not compromise the accuracy of heat demand forecasting.

FORECASTING CONTROL RESPONSES

Method

Sometimes rather detailed physically based response models are applied so that the responses of a representative large number of houses are simulated [8]. This can be too time-consuming for real time operation such as planning and optimizing the use of controllable resources for the day-ahead and intra-day market. If the set of situations to be considered is limited, the responses can be calculated in advance. When the control actions and responses depend strongly both on the variations of spot prices and ambient weather, such an approach is not practical for online use. It can also be expected that both the prediction performance and the model updating suffer from the big number of parameters that need to be identified before the simulations. Such a top down simulation approach is more useful for other types of uses such as studies for testing and verification of the online forecasting and control algorithms. Here we focus on simple models where tuning is easy to update or even to make adaptable in response to the changes in the heating systems and buildings.

The applied dynamic control response model models the aggregated load of each controlled group using a simple physically based model structure that is fitted to the measured data. So the model does not describe any individual house. The structure is based on a typical full storage heated house but the dynamics are modified slightly so that the model better reflects the smoothness of the behaviour of a big group of houses. The model parameters were fitted so that the error between the model output and the measured hourly powers were minimised.

The input signals to the model are:
- the predicted night energy demand,
- the maximum and minimum power predicted based on the measured and forecast ambient air temperature
- the control signal.

The output of the model is the hourly power time series up to the forecasting time horizon. That covers the following night tariff period and the day tariff time period after that. Here the tariff periods are applied both for the Time-Of-Use network tariff and for most customers also the contractual limits that define the admissible heating period within which the dynamic load control is allowed to control loads on.

Results

The heating load is the biggest load component and it is controlled dynamically. Thus all load forecasting models that do not model the control responses are doomed to fail. This is demonstrated in Table 2.

Table 2. Load response model improves the forecasting performance very much

a) Absolute error divided by the number of houses (kW)

	no control response model	with control response model
RMSE	3.1701	0.5303
Std.	3.1701	0.4687
MAE	1.5238	0.3896
Range	35.2233	3.7385

b) Error normalised with the yearly mean power

	no control response model	with control response model
RMSE	0.9880	0.1653
Std.	0.9880	0.1461
MAE	0.4749	0.1214
Range	10.9774	1.1651

There one model has a dynamic control response model but the other one does not. Otherwise both models have

similar model structures and similar tuning procedures. Both models have the same ambient air temperature dependency model and both models have the same performance in predicting night time energies and daytime energies. When the Std. is 0.4687 kW the estimated confidence interval for the Std. is about 3.5W, because there are 8760 hours in the identification data.
Fig. 4 and Fig. 5 show examples of a comparison between the forecast and the measurement. They are the sum of two separately controlled groups. The night time starts at the vertical gridlines (9 p.m.) and the time when heating turns loads on and off varies according to the market situation.

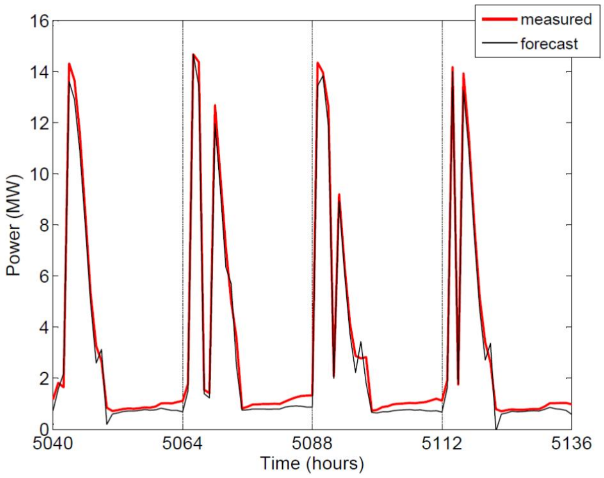

Fig. 4. A sample of a comparison of hourly power forecasted at 10 a.m. with the measured energy demand.

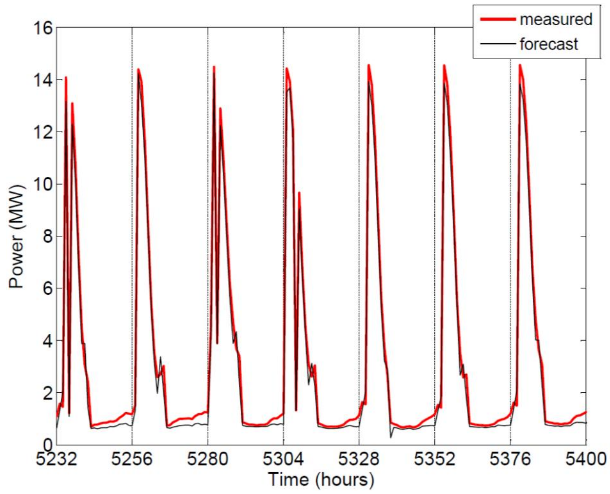

Fig. 5. Another sample of a comparison of hourly power forecasted at 10 a.m. with the measured energy demand.

The hourly power forecasting error is shown in Fig. 6. Its Std. is 0.315 MW.

The focus was on forecasting the control responses. Some possibilities to further improve forecasting of the daily energy demands and the daytime hourly powers are compared in [9] for a partial storage heating customer segment of a rural DSO.

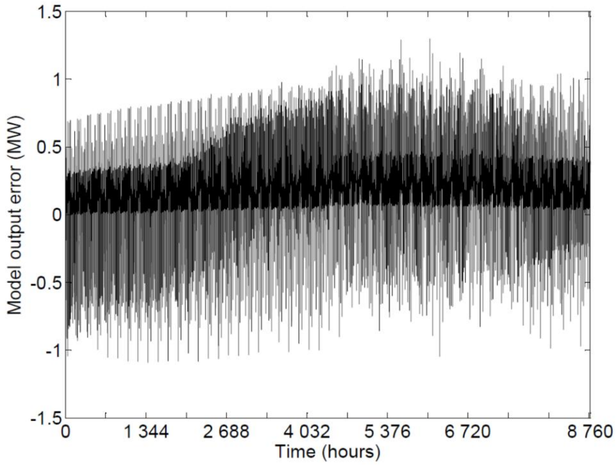

Fig. 6. Hourly power forecasting error

DISCUSSION

Needs and requirements for control response forecasting

The power flows and balances in modern power systems are increasingly dynamic due to changes in the generation mix towards intermittent renewables, heat load following CHP, and distributed generation. Strengthening the networks to accommodate these variations is expensive and needs space. Large scale electricity storages can buffer the variations but are still rather expensive and cause energy losses. Smart network automation enables operation closer to the network capacity constraints but depends on dynamic demand side responses and the ability to forecast these responses accurately.

Load control response models are needed for forecasting and optimising the control responses. When market based control or system based control is applied to very many new controllable loads, the risk of exceeding network capacity constraints increases. With accurate load response forecasts it is possible to detect such problematic situations in time and correct the control signals accordingly before sending them to execution. During recovery of faults situations it is useful to forecast and control the load pick up. For market based control, short term forecasts are needed with various time horizons such as before day-ahead market gate closure, after day-ahead market clearing, and during planning of intra-day market operations. Load control actions combined with poor control response forecasts lead to large and costly balancing errors that cancel much of the benefits of load control. Accurate response forecasts are necessary also when load control is used for provision of system reserves or management of network capacity constraints.

For the optimisation of the responses, nonlinear constrained dynamic optimisation explained in [10] can be used. However, it was observed that for full storage heating simply selecting the hours with the lowest price as explained in [4] gives results that are close to the optimum [11]. Thus the very simple method is preferred. For partial storage heating the dynamic nonlinear optimisation clearly outperforms heuristics, even when the heuristics are designed and tuned with the help of the optimisation method [10, 11].

The forecasting algorithm must be suitable for online use, because the responses depend on ambient air temperature and its variations.

Plans for the future development

Because the same identification data was used for model identification and performance analysis, the reliability of the results is somewhat questionable. In our earlier short term load forecasting studies the verification data has given almost as good values for the performance indices as identification data. When we have collected enough verification data by June 2014, we can complete the forecasting performance analysis.

The analysis and tuning of the methods continues. A preliminary plan is to apply neural networks and hybrid models to response forecasting and compare the performance in the case of dynamic load control. In our recent comparison of short term load forecasting methods [9], a neural network model to some extent outperformed a partly physically based model that included a Kalman-filter. There the loads were partially storing electrical heating loads and dynamic load control was not applied. It is not yet completely clear how neural network models can be made to predict the responses of dynamic load control more accurately than the partly physically based approach.

In this paper the focus was on forecasting the control responses of the heating loads. Thus the possible impacts of wind speed and solar radiation on the heat demand was left to future studies. Also the forecasting of the daytime hourly household loads was kept simple and we have some ideas on how it could be rather easily improved from that shown low in Figures 4 and 5.

CONCLUSION

A partly physically based model for the aggregated load was developed and its parameters were fitted to the identification data. When dynamic load controls are applied the inclusion of a control response model improved the forecasting performance very much. We expect that it is possible to develop even more accurate response models, for example using neural networks. There are also aspects other than accuracy that are relevant when selecting the model, but these were not considered in this study.

Acknowledgments

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