



Contents

- 1. Information about feeders and its customers**
- 2. Energy cost optimization algorithm based on spot prices**
- 3. Implementation of the optimization algorithm on the customers**
 - 3.1 Initial assumptions**
 - 3.2 Sensitivity analysis**
 - 3.3 Results**
- 4. Analysing the impacts**
 - 4.1 On the energy cost of the retailer**
 - 4.2 On the distribution network**



In this report a methodology to define the impact of unpredicted customer behavior on the retailer energy sales and distribution network is presented. The unpredicted customer behavior means that a part of customers follows the market-based load control, while the rest of the customers consume electricity without following the load control signals. The results are interesting from the perspective of peak power changes on the feeder level as well as energy cost savings of the electricity supplier (retailer), depending on participation rate of customers in the load control.

1. Information about feeders and customer types

The impact of unpredicted customer behavior has been analyzed on the example of a rural and urban feeder. The rural feeder supplies 1119 customers, among which 248 customers are with direct electric heating (Fig.1.1). The urban feeder supplies 358 customers, among which 61 customers are with direct electric heating loads (Fig.1.2).

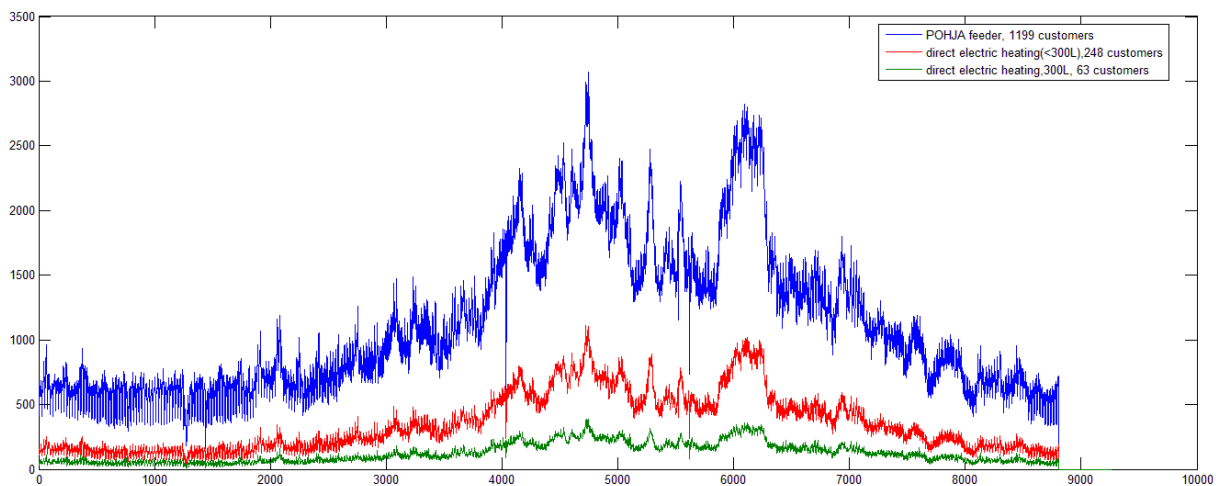


Fig.1.1 . Annual load curve (power in kW) of the rural feeder, AMR measurements 29.06.2010 – 01.07.2011

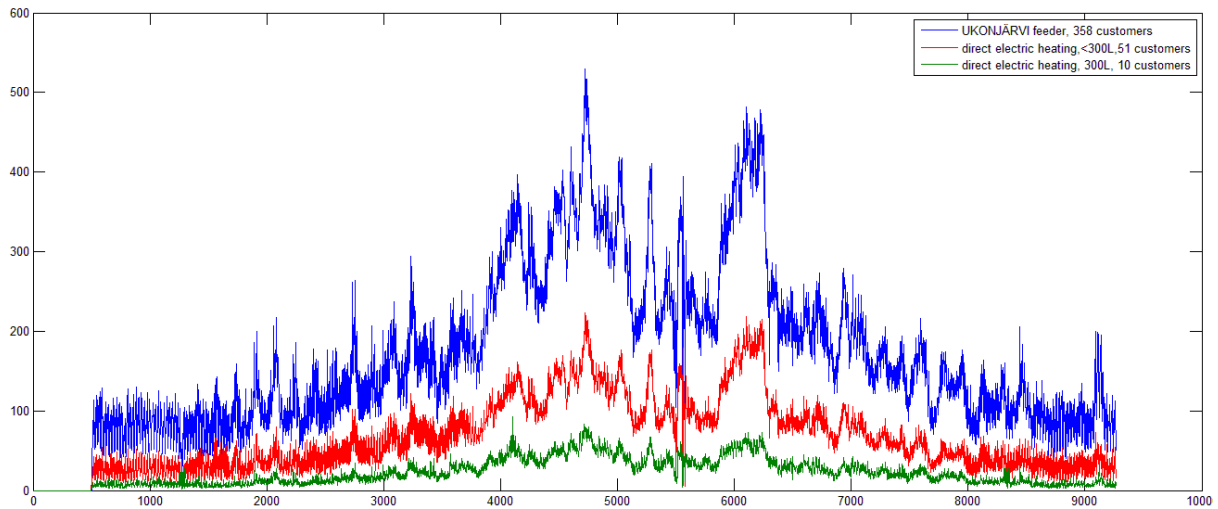


Fig.1.2 . Annual load curve (power in kW) of the urban feeder, AMR measurements 29.06.2010 – 01.07.2011

The coldest month, when the electric heating loads were at the highest, has been chosen for load control simulations in order to see the changes in the peak power compared to the annual peak power.

2. Energy cost optimization algorithm based on spot prices

The data needed for the load control simulation of space electric heating include outdoor temperatures, electricity spot market prices and electricity consumption forecasts.

Load control signals for customers are formed based on spot market price forecasts for the day-ahead. The electricity retailer estimates the heating demand at every hour based on outdoor temperature forecasts for the next day. The forecasted heating demand provides the information for the retailer about the controllable power on an hourly basis. Based on this, the retailer bids electricity demand for the next day according to the spot prices. The objective of the retailer's portfolio optimization is to minimize the electricity procurement costs from the spot market by shifting the energy from high-price to low-price hours. The energy cost savings maximization function can be presented as :

$$E_{\text{savings}} = \max \int_0^T (E_{\text{contr}}(t) \cdot P(t) - E_{\text{payback}}(t+1) \cdot P(t+1)) dt \quad (1)$$

E_{cost} energy cost during a period T, €

$E_{\text{contr}}(t)$ controllable energy during the hour t, MWh

$E_{\text{payback}}(t+1)$ recovered payback energy at the hour t+1, MWh

$P(t)$ price at hour t on the electricity spot market, €/MWh



The flow chart describing the optimization algorithm is presented in Fig.2.1

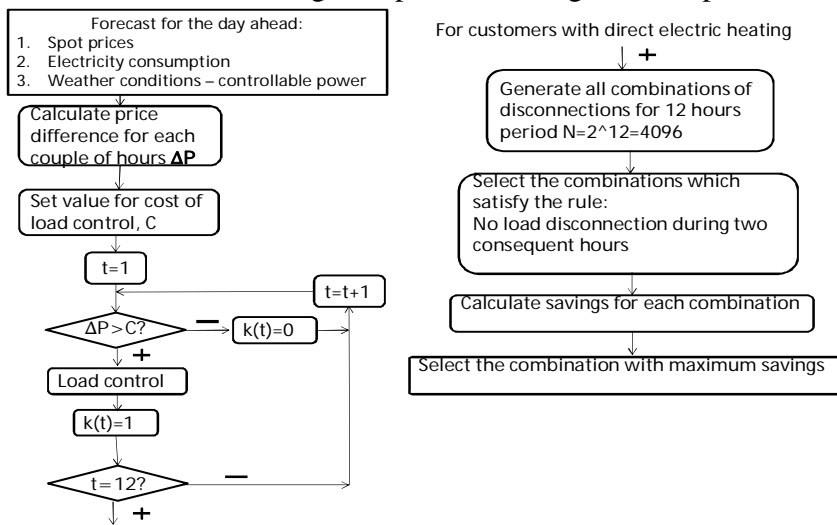


Fig.2.1 Price-based optimization flow chart for the customers with direct electric heating loads [1]

3. Implementation of the optimization algorithm

3.1 Initial assumptions

The algorithm was implemented in MATLAB environment, and the following assumptions were considered:

1. Cost of load control – 3€/MWh. The marginal value of the load control cost depends on the cost of the home automation technology, information communication technology (ICT), the retailer's hedging state in the long term and the frequency and number of load control events. In this paper, the cost of load control is assumed to be a fixed value, the study of which is beyond the scope of this paper.
2. Controllable heating power
The electric heating power is estimated based on the measurement data. The hourly powers have been grouped based on the outdoor temperature (Fig.3.1 and 3.2) .
Next, it has been assumed that the electric heating loads are turned on when the outdoor temperature is lower than +10°C.

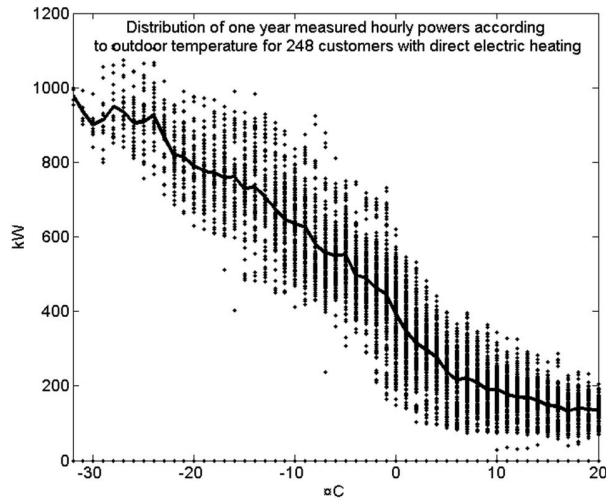


Figure 3.1 Distribution of hourly powers for the customers supplied by the urban feeder [2]

For the mean power load curve presented in Fig.3.1 and 3.2, the dependency of hourly power on the outdoor temperature has been defined using the following equation:

$$P(T) = P(T = +10^{\circ}\text{C}) - k * T \quad (2)$$

where

$P(T=+10^{\circ}\text{C})$ average power when the outdoor temperature is $+10^{\circ}\text{C}$;

$k = \frac{\Delta P}{\Delta T}$ angle of the curve line for the case feeder, $\text{kW}/^{\circ}\text{C}$

T outdoor temperature, $^{\circ}\text{C}$

For the urban feeder customers:

$$P(T) = 190 - 17.8 * T$$

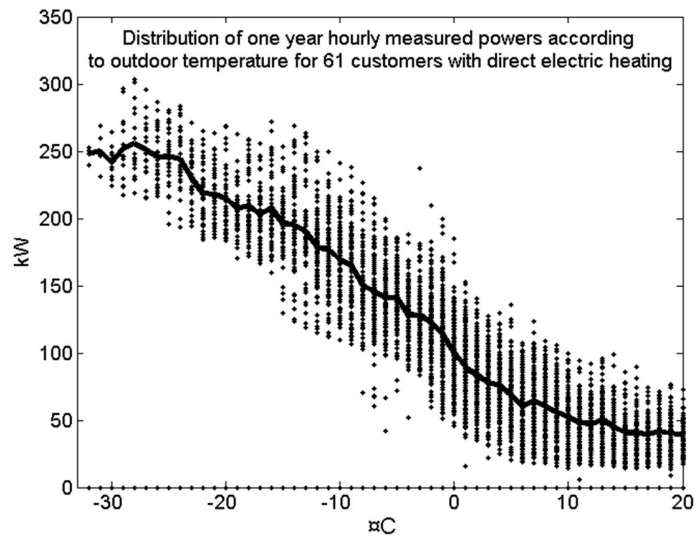


Figure 3.2 Distribution of hourly powers for the customers supplied by the rural feeder

For the rural feeder customers:

$$P(T) = 52 - 4.7 * T$$

3. payback effect: disconnected energy are equal to the reconnected energy

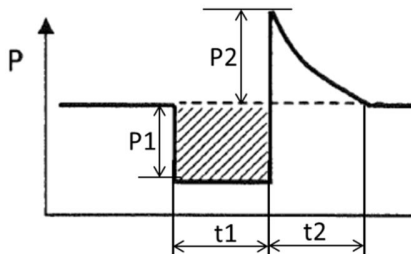


Figure 3.3. Illustration of the payback phenomenon[2]

4. The payback power shape is modeled according to the following rules [3]:
1. Payback power during the first 20 min after reconnection $P2 = 0.8 P1$
 2. Payback power during the following time $P2 = 0.3 P1$
 3. The duration of the payback power is defined by the disconnected energy

In reality, during the cold winter days, the payback power is limited by the capacity of the space heaters of the customers whose loads are controlled. In other words, the payback power calculated based on the disconnected power cannot be higher than the sum of the space heaters of the customers under load control. Finding this limit is a further research question.



3.2 Sensitivity analysis

The participation rate of customers in load control events was varied from 10% to 70%. The peak power changes on the feeder level and also on the level of group of customers were calculated. Energy cost savings were also calculated. The results are presented in Table I and Table II. Figures 3.4 and 3.5 illustrate results for participation rate 60% for the urban and rural feeders, respectively.

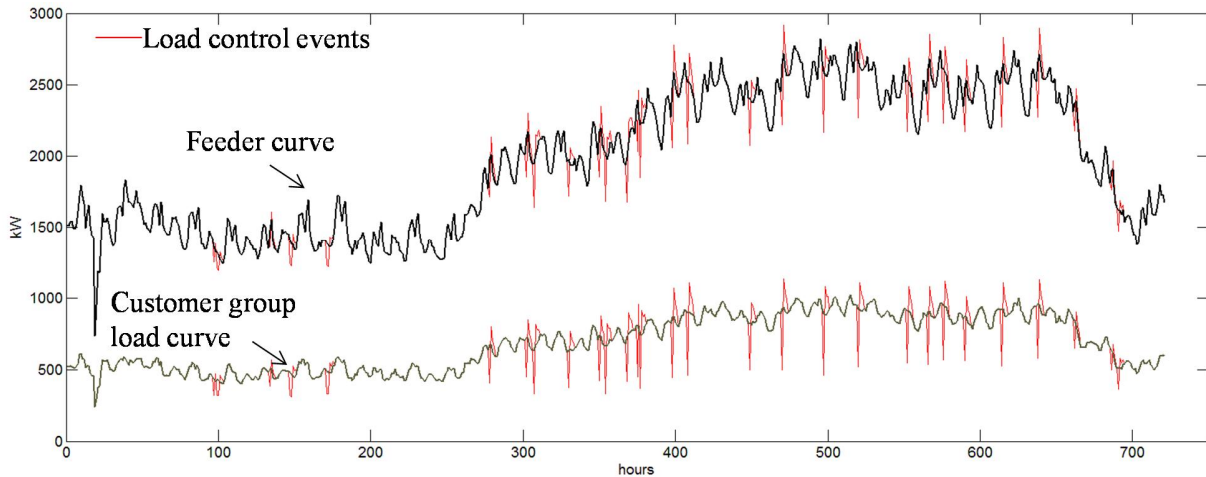


Fig. 3.4 Urban feeder, one month load control period, load curves before and after load control events on the feeder and customer group level

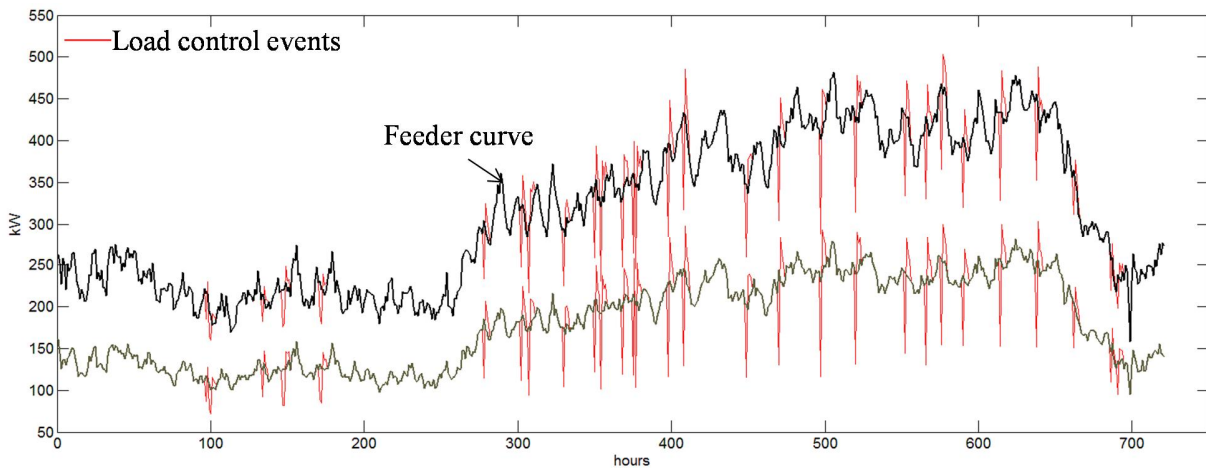


Fig. 3.5. Urban feeder, one month load control period, load curves before and after load control events on the feeder and customer group level



Table I. Energy cost difference (before – after the load control) / peak power increase for the urban feeder

Participation rate, %	Peak power increase, kW		Energy cost savings, €/ %
	feeder level	customer group level	
20	0	0	32 / 1
30	0	18	50 / 1.6
40	32	50	65 / 2
50	65	80	82 / 2.5
60	97	110	98 / 3
70	129	146	115 / 4

Table II. Energy cost difference (before – after the load control) / peak power increase for the rural feeder

Participation rate, %	Exceeding of peak power, kW		Energy cost savings, €/ %
	feeder level	customer group level	
20	0	0	9 / 1
30	0	0	13 / 1.6
40	5	7	18 / 2
50	13	15	22 / 2.5
60	21	19	26 / 3
70	30	27	31 / 4

It should be borne in mind that the results are case-sensitive and depend much on the initial assumptions, primarily on the cost of load control and controllable power.

Nevertheless, the general trend is the more customers participate in the load control, the higher are the energy cost savings and the higher is the exceeding of peak power. This brings up the further research task to find the optimum balance between the savings of the retailer from load control and optimum level of peak power in the distribution network.

4. Further research

Further research questions are:

1. One way to avoid payback peak power after loads reconnection as well as achieve higher energy cost savings, cycling of the load control events should be integrated in the optimization algorithm. The basic scheme is illustrated in Fig.4.1

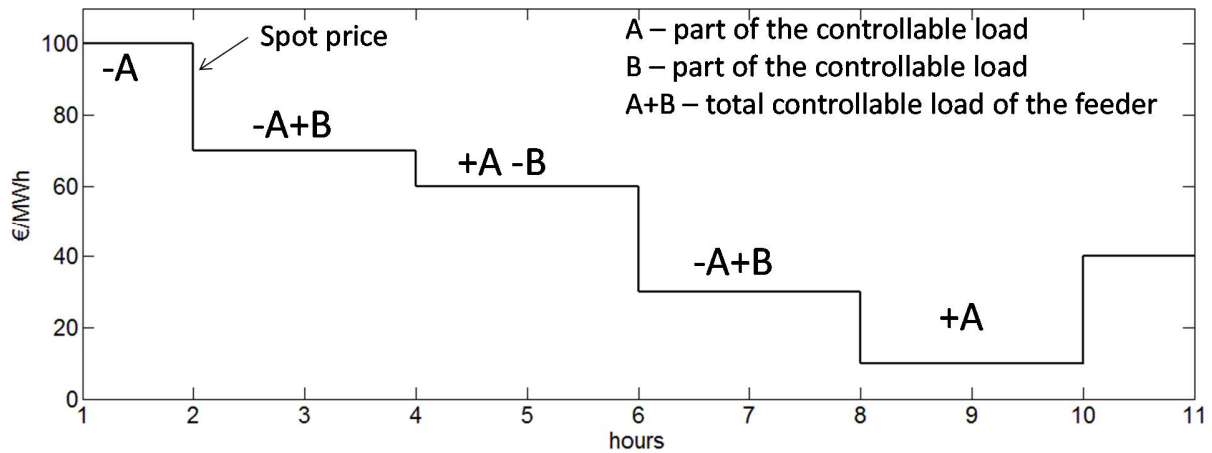


Fig.4.1 Illustration of cycling principle of the load control events

2. Another further research question is to consider the possibility of turning electric heating loads ON before the price peak hour (“pre-heat” mode). For this purpose, price difference between the peak price hour and the previous price hour has to be included in the optimization algorithm. In addition, amount of power that can be turned ON in the pre-heat mode should be estimated, as well as payback energy after the peak price hour.
3. The optimization algorithm has to be adopted to other types of customers (stored and partially stored electric heating). For this, assumptions about duration of disconnection have to be set for each customer type.
4. Varying cost of load control and analysing its impact on the load control events

References

- [1] N.Belonogova, P. Valtonen, J. Tuunanen, S. Honkapuro, J. Partanen, and A. Mutanen “Forecasting of an active customer load in the smart grid environment”, IEEE Transactions on Smart Grid, Special Issue on Analytics for Energy Forecasting with Applications to Smart Grid, submitted in 2013 for review
- [2] N.Belonogova, P. Valtonen, J. Tuunanen, S. Honkapuro, and J. Partanen, “Impact of market-based residential load control on the distribution network business”, CIRED 2013, Stockholm
- [3] Eero Tamminen and Jorma Aho-Mantila, “Suoran sähkölämmityksen ohjaamisen kannattavuus” 1977