# Forecasting of an Active Customer Load in the Smart Grid Environment

N. Belonogova, P. Valtonen, J. Tuunanen, S. Honkapuro, J. Partanen, *Member, IEEE*, and A. Mutanen

***Abstract*-- A methodology to forecast the load of an active customer is developed in the paper. The objective of the methodology is to show how an active customer behaves in the smart grid environment under the impact of the electricity market and the network operators, and having distributed generation and energy storages on his/her premises. First, the base electric load is modeled without control actions or distributed energy resources. Next, the load behavior is forecasted under the impact of global factors. Finally, the effect of local factors on the load curve and the load reduction potential is analyzed. The resulting forecasted load curve shows how the electricity consumption behavior of a single residential customer may be influenced in the smart grid environment. The core elements of the paper are modeling of the electric heating loads and developing a flow chart for energy cost optimization.**

***IndexTerms*—clustering methods, energy storage, K-means, load management, optimization methods, smart grid, solar power generation**

## I. INTRODUCTION

### *A. Background*

The smart grid environment is emerging as a solution to the electricity supply and distribution. In the residential sector this means that the rational end-customer is both motivated and able to act in the interests of the electricity supplier and the network operator. Traditionally, in the electricity market, the amount of generated power was adjusted to the consumption patterns of end-customers. With the development of technology, information communication technology (ICT), and penetration of smart meters, an end-customer is becoming an active customer, a new market player [1]. The transition from passive into active end-customers is gradually progressing. In the emerging smart grid environment, the need for load control has re-emerged. Because of the globally growing electricity consumption and an increase in the energy cost, the electricity market prices are steadily growing. In addition, the volatility of prices has become more frequent over the recent years primarily because of cold winters, intermittent renewable generation, and lack of local generation. In such a market environment, the electricity retailer is exposed to a risk of volatile market prices. Therefore, the focus of the retailer's business has been turned to the portfolio optimization strategy. Such tools as long-term hedging and trading in the short-term markets have been used up to this moment. In today's smart grid environment, controllable distributed energy resources (DER) also present a potential tool for the retailer's optimization strategy. The DER may include load control, micro generation, and energy storages in the strategy. Therefore, it is important to understand the impacts of load control on a single customer. Among distribution network customers, the domestic sector represents the most difficult one to analyze the load control opportunities when compared with the industrial, commercial, or public sectors, because of the probabilistic consumption patterns of the consumers. Moreover, the research task is challenging owing to different housing types, heating methods, the dependence of the residential consumption on weather conditions and duration of daylight, and individual consumption habits. It has been shown that there is a potential for load reduction in the residential sector [2]–[4]. One of the common reasons for this is the large number of customers, the growing demand for energy efficiency in households, and flexible loads, which can be shifted or shed without the customer noticing it. In the future, when micro generation units and local energy storages will spread also in the residential sector, their impact on the load curve, the load control potential, and changes in the tariff structure at the single customer level will be of interest.

### *B. Description of the methodology*

The flow of the methodology is as follows (Fig.1). First, the electricity consumption is modeled by dividing a large group of customers into groups, clusters, with a similar behavior. The idea of Monte Carlo simulations is described to show the limits within which the electricity consumption of a single customer may vary. The clusters obtained this way represent the typical behavior of the customers in the cluster and provide the input information for the analysis of the impact of load control and distributed energy resources on the load shape. Next, micro generation on the customer's premises is integrated into the base load curve. Based on the weather

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.

N. Belonogova, P. Valtonen, J. Tuunanen, S. Honkapuro, and J. Partanen are with the Department of Electrical Engineering, Lappeenranta University of Technology, 53851 Lappeenranta, Finland, (e-mail: Nadezda.Belonogova@lut.fi;Petri.Valtonen@lut.fi;Jussi.Tuunanen@lut.fi; Samuli.Honkapuro@lut.fi;Jarmo.Partanen@lut.fi).

A.Mutanen is with the Department of Electrical Energy Engineering, Tampere University of Technology, 33101 Tampere, Finland(e-mail:Antti.Mutanen@tut.fi).

forecasts (solar irradiation, wind speed) the power generation output can be estimated for every day. After that, the case when the local energy storage is available is also considered.

At the following step, the electricity market based energy cost optimization algorithm is developed. It is shown, how the electricity consumption profile, with possible availability of micro generation and energy storage, may be influenced according to the electricity market prices and network capacity limits signals. The focus of the paper is on the base electricity consumption modeling and energy cost optimization algorithm development.

The outline of the paper is structured as follows. In Section II, the main clusters of residential customers are obtained for further analysis. Section III presents the market-price-based optimization algorithm and demonstrates its implementation on the different customer types. In Section IV, the need for power signals from the distribution network capacity limits is explained. Section V discusses the integration of micro generation into load control, and Section VI shows the optimization principles for the use of local energy storages on the customer's premises. In Section VII, conclusions are drawn and further research questions are brought up.

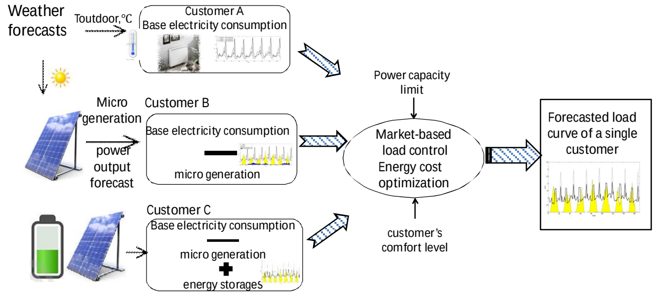


Fig. 1. The flow of the methodology

## II. LOAD MODELING

### A. Data

The automatic meter reading (AMR) measurements which were used to define electric heating load models were supplied by Elenia Networks Ltd. The available measurements contained hourly energy values for 7558 customers measured between 10th of June 2010 and 31st of October 2012. In this paper, the case of direct electric heated houses was studied in detail. Using the available customer classification information, 1338 such customers were found in the set of measured customers. The Nordic electricity market prices have been used in the methodology.

### B. Clustering

Customer classifications used in electric utilities are often rough in nature, contain classification errors and do not retain all possible subclasses. In this study, there was a need to divide the customers into groups with similar behaviour. For this reason, the customer class of electrically heated houses was further divided into similarly behaving subgroups with the help of a clustering algorithm. There are many clustering algorithms suitable for electrical customer classification, for instance K-means, ISODATA, and hierarchical clustering [4],[5]. In this study, the K-means algorithm has been implemented using MATLAB.

Before the clustering, seasonal temperature dependency parameter were calculated for each customer using the method presented in [6]. The temperature dependency parameters were then used to normalize the measurements in to the long time average monthly temperatures. The temperature normalization was made so that measurements from several different years could be treated equally. Pattern vectors describing the consumption of each customer were calculated from the normalized measurements. The pattern vectors consisted of 864 values (12 months × 3 day types × 24 hours = 864) describing the average hourly consumption. The day types were working day, Saturday and Sunday.

The clustering procedure was divided into two parts. First, initial clusters were calculated with all pattern vectors. Then, customers with the largest distances (10 % of the total population) to the cluster centers were removed. Finally, the clustering was redone without the outliers. A more detailed description of the used clustering method can be found in [7].

Three distinct subclasses were found during the clustering. These are shown Fig. 2 (one week load curves). It can be clearly seen that customers in cluster 3 are using cheap night-time electricity to heat up their domestic hot water. Due to utility misclassification, it is also possible that there are some customers with partial storage heaters in this cluster. When a customer has a dual-tariff electricity contract, the hot water boilers and storage heaters are switched on after 10pm when the cheaper night tariff begins. Customers in clusters 1 and 2 are heating their domestic hot water according to the temporal hot water consumption. The differences between these two clusters could be explained with different electricity usage habits and needs or with different space heating area. Some of the customer may also have heat pumps. Nowadays it is common that customers in electrically heated detached houses install air-to-air heat pumps to supplement their main heating system. It is also possible that some of these customers have changed their main heating system to ground source heat pumps. Electric utilities are rarely informed about such changes.

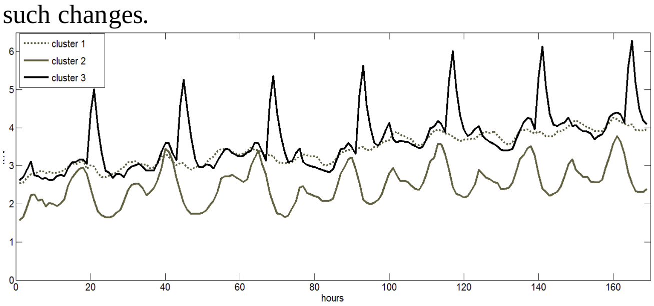


Fig. 2b. Load profiles of typical customer of three clusters during the coldest winter week

Heat pumps are often installed in addition to a direct electric space heating load. Theoretically, heat pumps can be controlled in the same way as the space heating load. However, restrictions are placed on the frequency of the switching on/off of the heat pumps, which affect the lifetime of the device. Therefore, in this work, the impact of a heat pump will be considered in terms of its impact on the controllable space heating load.

Depending on the type of heat pumps, their impact on the controllable heating power is different. Air-air heat pumps mostly serve as auxiliary heating for a direct electric heating solution, while ground source heat pumps may in some cases serve as the main heating source [8]. If direct electric heating is partly replaced by heat pumps, the amount of controllable space heating load will decrease. Table I presents the impacts of heat pumps on controllable heating power.

TABLE I

| Heat pump type | Heating method | Impact |
|---|---|---|
| Air-air | Local, room-based | Less controllable load |
| Ground-source | 100% space heating | No controllable load |
| Ground-source | 50%space heating | Less controllable load |

Characteristic parameters describing the clusters such as the load factor and the maximum annual hourly power are presented in Table II. These values give preliminary information about the consumption behavior patterns, and thereby on the load reduction opportunities for a single customer in each cluster.

TABLE II

| Cluster | 1 | 2 | 3 |
|---|---|---|---|
| **Pmax, kW, customer** | 1.8 | 2.5 | 4 |
| **Load factor, Pmax/Paverage** | 1.3 | 1.6 | 2.2 |

Recalculate table values for obtained clusters!

The load factor shows how much capacity there is for shifting the energy within the same peak power limitation.

## C. *Monte Carlo simulations*

The objective of Monte Carlo simulations is to generate a load curve for a single customer in a specific cluster within the probability distribution function of peak power values and hours. Fig. 3 presents the distribution of hourly powers and the hourly peak power occurrences based on the measurements. This information provides input boundary parameters for the Monte Carlo simulations of the single customer load curve.

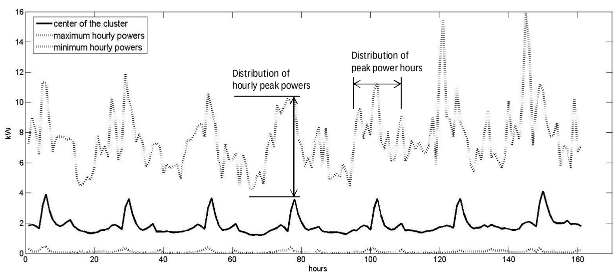


Fig. 3. Distribution of hourly powers and peak power hours of the customers belonging to cluster 3, based on AMR-measurements

The idea is to generate the same load pattern as for the center of the cluster, but the peak powers may occur at different hours, and their size may also differ as shown in Fig. 3. The result of the simulations is the load curve of a single customer in a specific cluster (Fig.4). The purpose of estimating the peak power size and hour is to give information to the retailer about the time when the load control potential is at highest and when it should be avoided.

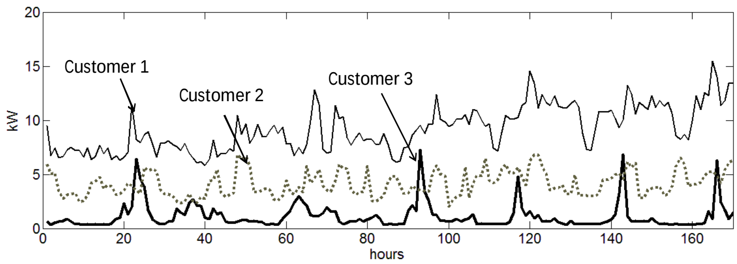


Fig.4. Electricity consumption of a random customer (customer 1 from cluster 1, customer 2 from cluster 2 and customer 3 from cluster 3) during the coldest winter week

# III. Impact of Price Signals from the Electricity Spot Market

In this section, the forming of load control signals based on the day-ahead spot prices is discussed. The control period is assumed to be a winter period so that the effect on peak powers can be estimated.

It is assumed that a retailer controls the load based on the electricity spot market prices. Before liberalisation of the electricity market, the responsible party for load control was the distribution system operator (DSO), which controlled the load according to the network condition. However, in a competitive market environment, network-based load control may severely disturb the retailer's profit optimisation strategy. On the other hand, the load control initiated by the retailer could meet the interests of the DSO and the customer because the retailer can take into account their interests.

## A. *Optimization function*

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 generated based on spot market price forecasts for the day-ahead. The electricity retailer estimates the heating demand at every hour based on the 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 maximization of energy savings from the load control actions can be presented as

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

| | |
|---|---|
| $E_{savings}$ | energy cost savings during a period T, € |
| $E_{contr}\ (t)$ | controllable energy during the hour t, MWh |
| $E_{payback}(t+1)$ | recovered payback energy at the hour t+1, MWh |
| $P\ (t)$ | price at the hour t on the electricity spot market, €/MWh |

Within the constraints:

1. E(t)>customer's comfort
2. E(t)< maximum annual power

According to (1), the energy savings are higher, the greater is the price difference between the adjacent hours. The main idea of the price difference approach is that the load control takes place if the price difference between the following hours is larger than the marginal cost of the load control. Therefore, the frequency of load control events depends on the volatility of spot prices and the cost of the load control. 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.

The payback effect of electric heating load control also has an impact on the load shape and the energy savings. In this work, it is assumed that the payback energy is equal to the disconnected energy.

### *B. Price difference approach*

The price difference approach defines the following rules to be implemented on the market-based load control:

1. Controllable power is turned off at the hour when the price difference between that hour and the following hour is higher than the value given for the load control cost.
2. It is not allowed to disconnect the load during the hour of load reconnection for the sake of customer's comfort. If the price difference is high enough also between the following couple of hours, the following combinations of disconnection are possible:
   a) All controllable power is disconnected during the hour t, no load disconnection occurs during the hour t+1
   b) All controllable power is disconnected during the hour t+1, no load disconnection occurs during the hour t

For this combinatorial optimization task the day is divided into 12-hour periods. The vector k consisting of 0 and 1 is formed for each hour, where 1 corresponds to the case when load control could take place due to the high enough price compared to the price of the following hour. After that, the iterative process generates all the possible combinations of disconnections and selects the one with maximum savings from the load control actions according to (1). The optimization algorithm is illustrated in Fig.5.

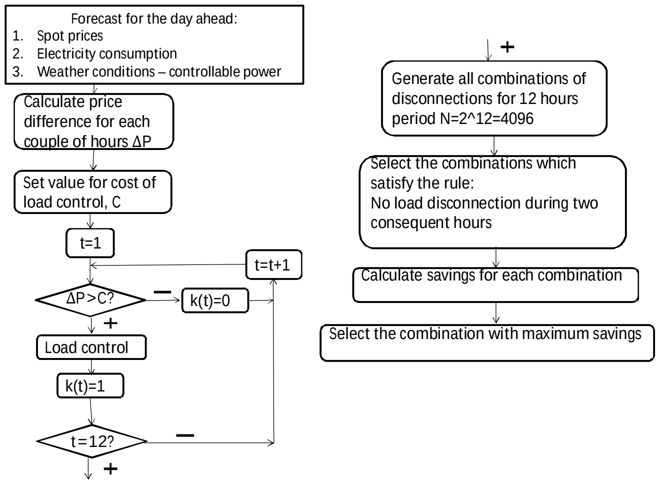


Fig. 5. Energy cost optimization flow chart

The results of the spot-price-based load control for the customers whose load curves were shown in the Fig.4, are presented in Figs.6(a), (b) and (c).

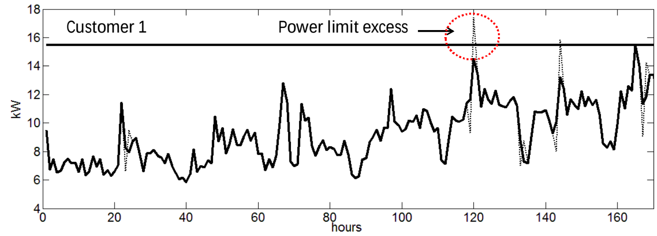


Fig. 6a. Example of a customer's consumption behavior from the cluster 1, price-based load control causes peak power level excess

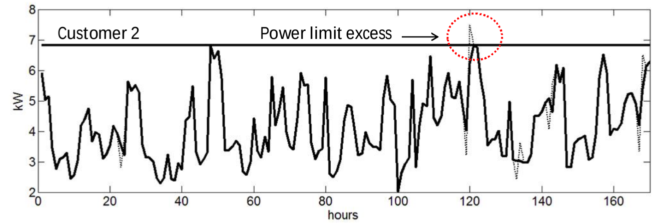


Fig. 6b. Example of a customer's consumption behaviour from the cluster 2, price-based load control causes peak power level excess

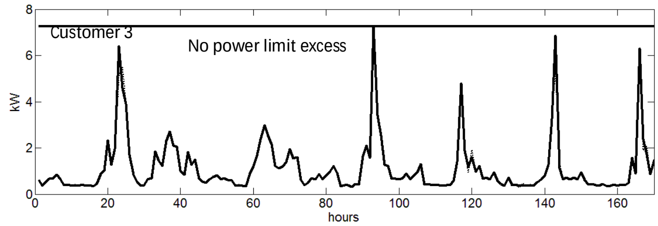


Fig. 6c. Example of a customer's consumption behavior from the cluster 3, price-based load control does not cause peak power limit excess

The results show that for the customers with a low load factor (customer 1 and 2), i.e., with a peak power value close to the average power consumption, the risk of exceeding the peak power limit is higher. For load curves with the high load factor instead (customer 3), the risk of exceeding the maximum peak power is low. It has to be borne in mind that the demonstrated results are case-sensitive. The risk of higher annual peak powers depends primarily on the weather conditions and price volatility. The risk is higher during cold weathers when the electric heating load level is high, as well as during high price volatility periods when the load control is likely to occur. Also there is higher probability to exceed the peak power when controllable heating power is high.

In practice, controllable heating power varies in time according to the outdoor temperature as well as the customer's comfort requirements (indoor temperature, thermostat set point). It is also dependent on the insulation of a house and its space heating area. In this study, the controllable power is assumed to be constant and equal to 30 % of the hourly consumption. In order to see, how the amount of controllable power affects the load curve, the sensitivity analysis was executed. For the group of 1200 customers who participated in the clustering procedure, controllable power was varied from 10% to 30%. The spot-price-based load control was carried out during the coldest winter week. Table III presents the results of the calculations.

TABLE III

| **Controllable power,%** | **% of customers, for whom the maximum annual power level was exceeded** | **Maximum size of power excess, kW** |
|---|---|---|
| 10 | 20 | 2.2 |
| 20 | 32 | 4.2 |
| 30 | 44 | 6.3 |

It is difficult to estimate how much of heating power will be controllable in future. With higher penetration of heat pumps, amount of controllable power is expected to decrease. On the other hand, with improving insulation of new houses, heat losses are lower and therefore the duration of heating load disconnection can be longer. However, improved insulation also means lower heating demand and hence lower controllable power.

Finally, it has to be kept in mind that the fact of exceeding peak power level is not problematic on the customer as well as on the feeder level, if it has a stochastic nature and happens rather rarely and occasionally during the year. However, if it happens regularly, some means have to be undertaken in order to motivate customer to keep the consumption under the specified level and thus avoid peak powers on the feeder level.

## IV. IMPACT OF POWER CAPACITY LIMITS FROM THE DISTRIBUTION NETWORK COMPANY

As it was discussed in the previous chapter, shifting the load to off-peak price hours may overload the network and result into a new peak power. Electric heating load control presents a challenge for the network due to the payback effect when the loads are reconnected. In case the annual peak power of the single customer electricity consumption is exceeded because of the price-based load control, the risk of new power peaks on the feeder level is also high. On this basis, conflict of interests may occur between the DSO and the retailer. The size of the conflict depends on:

1. The excess of annual peak power, kW
2. Duration of peak power, minutes
3. Frequency of peak power, times / year
4. Power capacity of distribution network, its capability to endure peak powers.

The conflict means that the distribution company would have to invest additional money into the network so that it can withstand the new peak powers. The need for additional investment costs has to be reflected in the end-user distribution fees. Thus, to enable market-oriented residential customer load control on a large scale and to avoid conflicts of interest between the parties involved, appropriate operation and pricing models are needed. The pricing model should provide adequate incentives for all market parties and ensure that the principle of non-discrimination is applied. Power Band Pricing (PBP) [9] is suggested as a way to settle the conflict of interests between the retailer and the DSO in a market-based load control.

The basic idea of the proposed tariff structure follows the principle of power-based pricing. A power band is an element of the electricity distribution tariff. The customer orders it from the DSO according to the required maximum power capacity, which is approximately the maximum value of the average hourly powers from the AMR data. The pricing is based on kilowatts, which means that the customer pays for the network capacity.

From the DSO's and retailer's perspectives, a tariff structure should support market-based demand response so that it motivates customers to consume electricity in retailer's and DSO's interests. PBP can meet this requirement and includes many desirable elements from the perspective of the electricity markets.

The power band level depends mainly on

a) Distribution network capacity limits: the load level in the distribution network; during low-load hours, a high power limit is permitted, while during high-level hours, a low power level is allowed.
b) Requirements of the customer for the level of comfort depending on his/her daily activities.
c) Availability of distributed generation and/or energy storage.

The benefit of load control for the retailer is much higher if all the above-mentioned factors are considered, and the power band value changes according to them. However, for simplification, the maximum annual peak power is assumed to be the power limitation for each customer.

When the retailer gets information about the contracted power limit of each customer, he can take them into account when executing price-based load control. This way, also the interests of customer and DSO will be taken into account.

## V. MICRO GENERATION

The objective of the third step is to discuss the principles of the integration of local energy storages and micro generation units into the load control in electricity retailer, DSO and customer interests. Micro generation on the customer's premises is one of the elements of the smart grid environment. Among the challenges is the intermittent nature of micro generation; it is not always available at the moments when it is needed, and there is often excess of it in the hours when the need for energy is low. For instance, micro generation can cause unacceptably high voltage levels in the low-voltage networks during low- load hours. In this case, energy storages could provide a solution to avoid this problem.

The load control potential in summer time in Finland is rather low because electric heating loads are off and air-conditioning units in the residential area are not so commonly used in Finland and therefore an insignificant part of electric load in the grid. In Finland the annual peak powers are achieved in winter time unlike for instance in the USA or Australia, where air-conditioning units in the residential sector might cause overloading problems in the distribution network [10]-[12].

Moreover, the volatility of spot prices in summertime in Finland is usually insignificant compared with wintertime. Therefore, solar power units, which generate most of the energy during the daytime, could be used either for selling power to the grid or charging the local energy storage during the day. In this paper, the example of solar power units of 3 kWp and a 600W wind turbine has been considered. The wind power output has been generated applying wind speed forecasts for the next day and the technical characteristics of a wind turbine. In Fig. 7, the excess of generated energy during the day can be seen for all customer types.

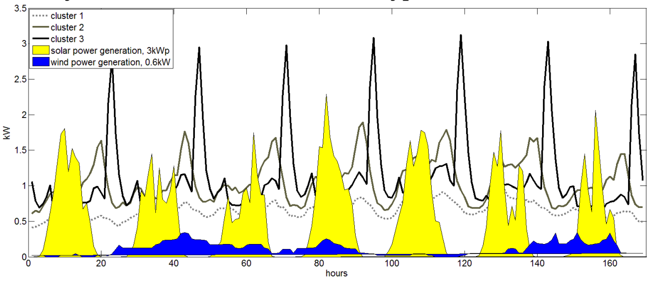


Fig. 7. Load curves of the clusters and small scale solar and wind power generation curves during a summer week

The measurements of the generated solar energy have been carried out in summer time. The daily generated energy varies from 0.5 to 18 kWh, depending on the irradiation.

The investment costs of the small-scale wind power generation units are rather high compared with the energy they generate. The investments into solar panels instead are directly proportional to the generated energy. However, in this section, the focus is on the technical aspects while the economic feasibility of micro generation units for a single residential house is beyond the scope of the research question.

## VI. ENERGY STORAGES

Energy storages can be integrated in the market-based load control optimization, which makes the total load and storage optimization more complex. The control algorithm for energy storages is similar to the load control optimization scheme.

The difference is that the energy storage charging and discharging cycles do not have to take place at consequent hours, and the price difference level is defined according to the price of the battery and the number of charging/discharging cycles. In this regard, the price difference refers to the hours of local maximum and minimum prices. In [13], it is shown that the price level at which it is economically feasible to discharge storage is higher than 100€/MWh. This means that the market-price-based optimization of energy storage use is not feasible for the present spot price levels. In the future, the spot price level is expected to rise because of the increasing energy cost, or for instance as a result of a dependency on generation from other countries; at the same time, the cost of energy storages is expected to decrease thanks to the progress in battery technology.

Even more challenging task is to optimize energy storage charging and discharging cycles not only based on electricity market price signals, but also taking into account electricity network power needs. It is pointed out that in most cases, high spot price hours correspond to high load level hours, most often at the system level. In this regard, market-based control of energy storages would deliver benefits also to the network, if discharging of the energy storage during the high price hour coincides with a high load level in the grid. This way, congestion in the network may be relieved. The possible impacts of the market-based control of energy storages on the network are qualitatively analyzed in Table IV.

However, the main idea of this section is to present the principle for the optimization of the energy storage use rather than analyze its feasibility on the customer's premises.

TABLE IV

| **Energy storage mode** | **Spot price** | **Load level in the grid** | **Impact on network*** | **Comments** |
|---|---|---|---|---|
| **Discharge** | High | High | + | Avoid overloading |
| **Discharge** | High | Low | - | Risk of over voltages |
| **Charge** | Low | Low | + | Smooth load shape |
| **Charge** | Low | High | - | Risk of overloading |

(*+ positive impact , - negative impact)

As mentioned in the previous section, the local energy storage could be useful to charge in summertime the excess solar energy and discharge it, for instance during low spot price hours or peak power hours at the customer or feeder level.

The residential water heater can be considered as a local heating energy storage. The impact of the charging and discharging of such heating storage using own solar power generation on the load curve of a single customer is illustrated in Fig.8.

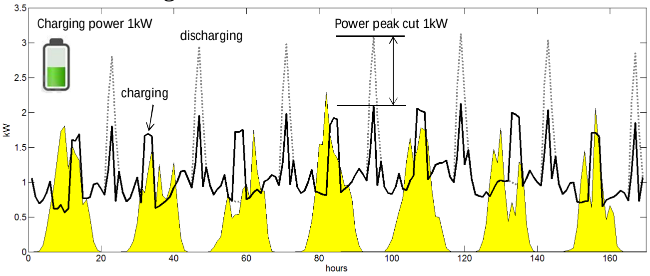


Fig.8. Water heater charging and discharging cycle optimization for the customer in the cluster 3, with 3 kWp solar panels on the customer's premises.

As the results show, the energy storage may bring positive smoothing impact on the load curve for the customers with high load factor, when having own local generation. However, for the customers with low load factor, the charging may cause higher peak powers and therefore customer may have to shift to the higher power band level.

To sum up, micro generation on the customer's premises together with local energy storages can deliver the following benefits:

1. A lower power band level can be chosen for the customers with a power band pricing tariff.
2. The energy cost at the single customer level can be optimized, avoiding purchasing electricity at high spot price hours.

## VII. Conclusions and Further Research

The main contribution of the paper is the development of the methodology to forecast the load of a single customer in the smart grid environment. The principal objective was to establish a general methodology, which is not fixed to any specific environment and is flexible to the input data.

The main results of this paper are:

1. Development of the load forecast methodology for a single customer load in a smart grid environment
2. Demonstration of the energy cost optimization algorithm
3. Proposal of the power band pricing mechanism as a way to motivate customer to keep the electricity consumption under the contracted level.
4. Discussion on the benefits and threats of micro generation
5. An analysis of the impact of a local energy storage on the grid and the customer's load shape

One of the further research questions is to define the optimum level for the power limit for each customer type so that the investment costs in the distribution network, the retailer's savings from the load control, and thereby the customer's total energy costs are minimized.

The implementation of retailer's portfolio optimization algorithm using load control, energy storage and micro generation on the customer's premises brings up several further research questions. One of them is analyzing the impact of customers' response to load control on the spot market prices. Another one is estimating the impact of customers' participation in load control events on the distribution network peak powers and therefore network investment costs in the long-term.

## References

[1] Livik, K., "From passive consumer to active customer" Power Engineering Society Winter Meeting, IEEE, vol.2, pp.835–837, Jan. 2000

[2] Mohsenian-Rad, A.-H. and Leon-Garcia, A., "Optimal Residential Load Control With Price Prediction in Real-Time Electricity Pricing Environments," *Smart Grid, IEEE Transactions on* , vol.1, no.2, pp.120–133, Sept. 2010

[3] Moholkar, A., Klinkhachorn, P., and Feliachi, A., "Effects of dynamic pricing on residential electricity bill," *Power Systems Conference and Exposition, 2004. IEEE PES* , vol., no., pp. 1030- 1035 vol.2, Oct. 2004

[4] Koponen, P. and Kärkkäinen, S., "Experiences from Spot-Market Based Price Response of Residential Customers" 19th International Conference on Electricity Distribution, CIRED, Vienna, May 2007

[5] G. Chicco, R. Napoli, and F. Piglione, "Comparisons Among Clustering Techniques for Electricity Customer Classification", *IEEE Trans. On Power Systems*, vol. 21, no. 2, May 2006

[6] Mutanen, A.; Ruska, M.; Repo, S.; Jarventausta, P.; , "Customer Classification and Load Profiling Method for Distribution Systems," *Power Delivery, IEEE Transactions on* , vol.26, no.3, pp.1755-1763, July 2011

[7] A. Mutanen, P. Järventausta, M. Kärenlampi & P. Juuti, "Improving Distribution Network Analysis with New AMR-Based Load Profiles", 22nd International Conference on Electricity Distribution, CIRED, Stockholm, June 2013.

[8] A. Laitinen, M. Ruska, G. Koreneff "Impacts of large penetration of heat pumps on the electricity use", VTT, 2011

[9] J. Tuunanen, S. Honkapuro and J. Partanen "Managing Impacts of Distributed Energy Resources and Demand Response by Tariff Planning", 10th Nordic Conference on Electricity Distribution System Management and Development, Nordac 2012, September 2012

[10] Nordell, Daniel E.; , "Forced Duty Cycling of Air Conditioning Units for Load Management," Power Systems, IEEE Transactions on , vol.2, no.4, pp.1110-1116, Nov. 1987

[11] Ilic, M.; Black, J.W.; Watz, J.L.; , "Potential benefits of implementing load control," *Power Engineering Society Winter Meeting, 2002. IEEE* , vol.1, no., pp. 177- 182 vol.1, 2002

[12] Khanna, I.; , "Smart Grid application: Peak demand management trial - the Western Australian experience," *Innovative Smart Grid Technologies Asia (ISGT), 2011 IEEE PES* , vol., no., pp.1-6, 13-16 Nov. 2011

[13] J. Lassila, J. Haakana, V. Tikka, and J. Partanen "Methodology to Analyze the Economic Effects of Electric Cars as Energy Storages", *IEEE Trans. On Smart Grid*, vol. 3, no. 1, pp 506-516, March 2012

## Biographies

**Nadezda Belonogova** was born in Moscow region, Russia, December 1986. She received her M.Sc. in electrical engineering from Lappeenranta University of Technology and from Moscow Power Engineering Institute in 2009 and 2010, respectively. Since then she has been a research engineer and a postgraduate student at Lappeenranta University of Technology. Her main field of interests is demand response of residential customers.

**Petri Valtonen** was born in Punkaharju, Finland, in March 1983. He received his M.Sc. degree from Lappeenranta University of Technology in 2009.
Since then he has been post graduate student and a research engineer in Lappeenranta University of Technology. His main areas of interests are smart grids and electricity markets.

**Jussi Tuunanen** was in 1988. He received Lappeenranta (LUT), Lappeenranta, 2011, he has been a postgraduate student at interest are customers' and electricity

born in Parikkala, Finland, the M.Sc. degree from University of Technology Finland, in 2009. Since Research Engineer and a LUT. His main areas of role in electricity markets distribution business.

**Samuli Honkapuro** was born in Siilinjärvi, Finland, September 1977. He received his M.Sc. and D.Sc. degrees in electrical engineering from Lappeenranta University of Technology (LUT) in 2002 and 2008, respectively. Currently he is working as associate professor at LUT Energy. His main research interests are smart grids and electricity distribution business.

**Prof. Jarmo Partanen** degree in electrical Tampere University of has been a professor at of Technology (LUT) Prof. Partanen is the Energy Technology at interest are smart grids, and regulation of business

received his D.Sc. (Tech.) engineering from Technology in 1991. He Lappeenranta University since 1994. At present Head of the Institute of LUT. His main fields of electricity market, RES electricity distribution

**Antti Mutanen** received his M.Sc. degree in electrical engineering from Tampere University of Technology in 2008. At present, he is a Researcher and a post-graduate student at the Department of Electrical Engineering of Tampere University of Technology. His main research interests are load research and distribution network state estimation.