FINDING DEMAND RESPONSE FROM SMART METER DATA

Antti RAUTIAINEN, Antti MUTANEN, Pertti JÄRVENTAUSTA
Tampere University
antti.rautiainen@tuni.fi

Tomi TURUNEN, Veli-Matti LAAKKONEN
Pohjois-Karjalan Sähkö Inc.
tomi.turunen@pks.fi

ABSTRACT

Demand response (DR) is widely seen as an element bringing needed flexibility to the sustainable power system of the future. In Finland, all electricity consumers, including small ones, have smart meters enabling DR based on the electricity contracts with dynamic hourly energy prices. With these contracts, electricity has its own price every hour based on the prices of the day-ahead market of the Nordic power exchange. Consumers can shift part of the consumption to low-price hours leading to lower electricity costs. A very interesting question is that does the volatile price influence on the real consumers' consumption patterns today. In this paper, we seek answer to this question by first discussing the proper methodology for observing DR from a retailer's data and secondly by making a case study in which smart meter data of real customers having dynamic electricity contracts is used. The results of the case study show that tiny indications of possible DR can be found, but more research is needed.

INTRODUCTION

Electrical energy related demand response (DR) has long traditions both in practice and in research. However, the real DR applications of small electricity consumers have been restricted mostly to time-of-use, mainly two-time type, products in the Nordic countries. During the past few years, DR has appeared in the spotlight in a new way. This is due to general technological advancement, development of electricity infrastructure, especially rollout of smart meters, and rapidly increasing amount of renewable intermittent energy sources like wind and solar power.

Due to the act in 2009 set by the Finnish government almost all consumers (>99%) [1] are now provided by a smart meter that features hourly energy measurements as well as registrations of quality of supply and DR functionality. Remote readable smart meters enable e.g. more fluent competition in retailer business, new kind of dynamic contracts of energy retailers and dynamic distribution tariffs [2] by distribution system operators (DSOs). The hourly electricity consumption data can be read from the meters once a day or even more often if needed. In addition, the balance settlement of the electricity market is made using the hourly smart meter data in Finland today. This enables e.g. the hourly electricity retail pricing based on the *Elspot* day-ahead market prices of the North-European power exchange run by *Nord Pool*. At the end of 2017, roughly 9% of Finnish consumers had such a contract [1], and the proportion is expected to increase in the future.

If a consumer has an Elspot based hourly electricity contract, it enables demand response in the way that if a consumer shifts part of the electricity consumption to low price hours, the consumer can save money. The saving possibilities depend on many things but especially on volatility of the prices and the load control possibilities [3]. As these kinds of contracts are already in use, a very interesting question is that does the varying price affect on the consumption of the consumers. In other words, are the consumers doing Elspot based demand response? If a retailer would have large mass of customers whose electricity consumption would be affected by the varying price, understanding the impacts of the price on the consumption would be valuable for the retailer from the risk management viewpoint. In this paper, we discuss the practical ways electricity retailers could observe Elspot based demand response, and we present a case study. The research literature lacks these kinds of studies.

The paper is organized as follows. In the second section, the methodology for observing DR from smart meter and other data, which a typical retailer in Finland has, is discussed. In the third section, a case study using smart meter data of real consumers with Elspot based dynamic electricity contract is made. In the last section, conclusions are made and future work is proposed.

METHODOLOGY FOR FINDING DEMAND RESPONSE FROM SMART METER DATA

Factors affecting consumption patterns

Figure 1 illustrates the main factors affecting to the electricity consumption pattern of a household electricity consumer.

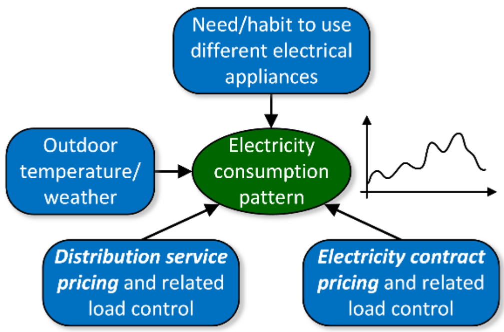

Fig. 1. Factors affecting the consumption pattern of a single electricity consumer.

Needs and habits to use of different electrical appliances is one factor. This includes all the household appliances like oven, coffee maker, washing machine, entertainment electronics etc., but also different types of heating/cooling appliances. Different houses have different kinds of heating/cooling systems, and different consumers prefer different indoor temperatures.

Outdoor temperature and weather in general is another factor affecting the consumption pattern especially if the consumer has electric heating, some kind of a heat pump system or an air conditioner. Heating and cooling energy need is determined mostly by the insulation level of the house and the outdoor temperature.

Third factor is related to the distribution tariff of DSOs. In Finland, there is a long tradition of using time-of-use tariffs, which means that the distribution fee (in cent/kWh) is lower during nighttime than in the daytime. In accordance, there are plenty of houses in Finland where electric heating and water heating is shifted partly or as a whole to the nighttime. This has a significant effect on the electricity consumption profile of these consumers. One thing, which has started to emerge in Finland over the last few years, is the power-based distribution pricing [2]. This means that in addition to the traditional monthly fee (in €/month) and volumetric energy fee (in cents/kWh) with or without time-of-use component, there is a peak power based fee (in €/kW) calculated and billed monthly based e.g. on the highest hourly power (average power of the hour) of the month [2]. Power-based distribution tariffs affect on the load profiles of the consumers if the consumers try to lower the peak demand.

The fourth factor affecting the consumption profile is the electricity contract of the retailer. Retailer can also offer time-of-use type contracts like day/night tariff, but also the hourly electricity pricing based on the Elspot prices. In this paper, the latter contract type is in our attention.

Methods for a retailer to observe DR

In order to observe Elspot pricing based demand response of the customers, the retailer has to have proper data. The hourly price data is of course known by the retailer. In Finland, the retailers typically have also at least the following information of the household customers:

- Geographical location
- Hourly electricity consumption pattern from the contract period
- Information on whether the customer has day/night type load shifting in use
- Customer type (e.g. dwelling type)

In addition, a retailer might have other information on the customers, like type of the heating system.

Using the data a retailer typically has, there is in practice only one way to observe the demand response of customers: to investigate the dependency/correlation between the hourly consumption and the hourly prices. In order to observe the impact of prices on the consumption, the effects of all the other factors than the price should be filtered out. If all the non-price factors were filtered out, demand response would be observed as a negative correlation between the price and the consumption: when the hourly price increases, the hourly consumption decreases. If there were no demand response, there would be no correlation between the price and the consumption. This theoretical concept is illustrated in Fig. 2.

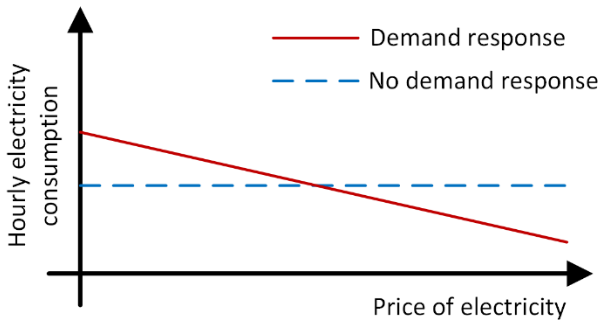

Fig. 2. The principle of observing demand response as a correlation between the price and consumption in the theoretical case where the effects all the factors affecting to the consumption excluding the price would be filtered out.

Filtering the non-price factors out of the consumption data is a challenging task when considering a case where the retailer would only have the regular customer data described above. If the customer had some kind of a home energy management system (HEMS) or a home automation (HA) system, which would carry out the load control actions based on the dynamic pricing, the load control data would provide the necessary information on the impact of the prices on the consumption. The availability of this kind of data depends on the case. If a HEMS/HA system is provided by the retailer, the retailer typically has the data, but if the HEMS/HA is not provided by the retailer, the data is not available for the retailer. HEMSs and HA systems are quite rare today and hence typically there is no such data available for the retailer. Therefore, this is not a way to go in a typical case.

A way to overcome this problem is to compare the correlation of the price and the consumption of two different customer groups. In this approach, the customers in different groups should be selected to be as similar as possible with the exception, that in one group, the customers have and in another group, the customers do not have a dynamic electricity contract. This means that considering the factors illustrated in Fig. 1, all the other factors besides the dynamic contract would be as identical as possible. This principle is applied in the case study of this paper.

Another question is that what kind of correlation or dependency should be sought from the data. The first guess would be linear dependency. Although the real dependency could also be non-linear, in the case study of this paper we consider the linear dependency because its simplicity, and other types of dependencies are addressed in the future studies. In the case study, standard linear regression methodology is used.

There are many options how to calculate and compare the price-consumption-dependencies of two customer groups. One questions is that how to use the consumption data. Possible approaches for this are the following.

- For both of the customer groups, carry out dependency analysis for a set of hourly consumption-price pairs so that all the data points (consumption-price pairs of individual hours) of individual customers would be aggregated into one set.
- Sum up the hourly consumptions of all the customers and carry out the dependency analysis for the hourly total consumption for both of the customer groups.
- Do the dependency analysis for every customer separately and calculate an average dependency for both of the groups.

As the total energy consumption or the peak powers of different customers are not the same, it is necessary to scale the consumption energies so that they could be more easily compared. One can scale the hourly energies e.g. by dividing each energy by the average or maximum energy of the set.

CASE STUDY

Data and assumptions

In the case study, we searched signs of demand response from the data of real customers of a Finnish electricity retailer Pohjois-Karjalan Sähkö Inc. (PKS). Data of electricity consumption and prices were analysed using data covering January 2016. In that time, there was quite high volatility in the Elspot prices and in the outdoor temperature. This means that there were also cold days with plenty of need for heating. Almost all the customers of in this case study locate in the same region experiencing pretty much the same outdoor temperature. The customers represent household customers living in detached houses. In detached houses, the consumption is typically significantly higher than e.g. in apartment houses, and in many cases, detached houses have more possibilities to control the load compared to other apartment types.

There are two types of customers in the case study data:

- Customers with dynamic electricity contract
- Customers without dynamic electricity contract.

Within these two groups, there are also two different types of customers:

- Customers who have static load shifting to night-time
- Customers who have not static load shifting to night-time.

Most of the customers who shift their consumption to the night-time would do the shifting even without the Elspot price based electricity contract. The load shifting has impact on the dependency between the consumption and the price. Typically, the electricity prices in the Elspot market are lowest during night-time, and shifting part of consumption to the night-time means also a change in the consumption-price correlation. The customer data sets used in the case study are summarized in Table 1.

Table 1. Customer groups of the case study.

Group	Dynamic electricity contract	Static load shifting	Number of customers in the group
1	No	No	1153
2	Yes	No	766
3	No	Yes	407
4	Yes	Yes	625

Figure 3 presents the outdoor temperature in the case study, and figures 4 and 5 illustrate the hourly sum consumptions of the customer groups together with the hourly customer prices in January 2016.

Fig. 3. Outdoor temperatures in the case study (small portion of the data was missing and had to be interpolated).

In the case study, an affine function (of a form $y = ax + b$) was fitted to different price-consumption data sets using the least squares method. The idea is that the price is the independent variable x, and y represents the consumption. This function is called linear predictor. In the analysis, the attention was mostly paid on the slope a of the curve, as it describes the sensitivity of the consumption on the price. The case study comprises four different comparisons of linear predictor functions. The comparisons are made using the following linear predictors.

A. Linear predictors that are calculated from the sum consumptions of the customers of groups 1 and 2. To make the groups comparable, the hourly consumptions are divided by the average consumption. The number of data points is *the number of the hours*.
B. Same as the previous but with the groups 3 and 4.
C. Linear predictors that are calculated from all the individual hourly consumption-price pairs of all the customers of groups 1 and 2. To make the groups comparable, the hourly consumptions of each

customer are divided by the average consumption of the customer. The number of data points is *the number of the customers × the number of the hours*.

D. Same as the previous but with the groups 3 and 4.

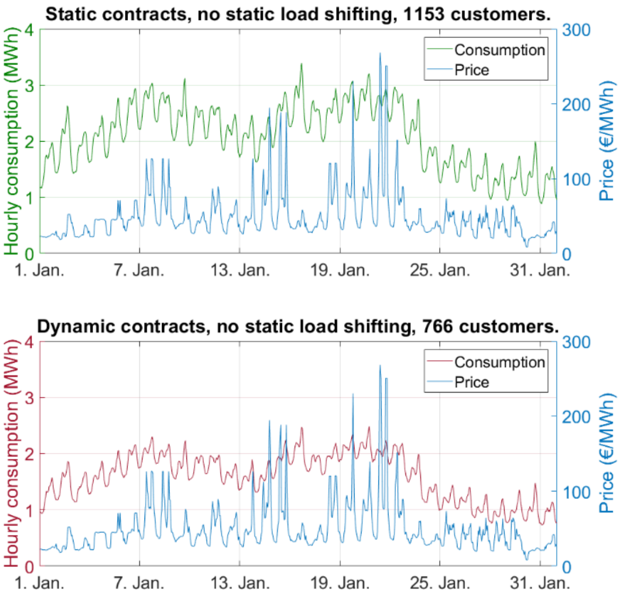

Fig. 4. Total consumption of customer groups 1 and 2 and the hourly end customer electricity prices.

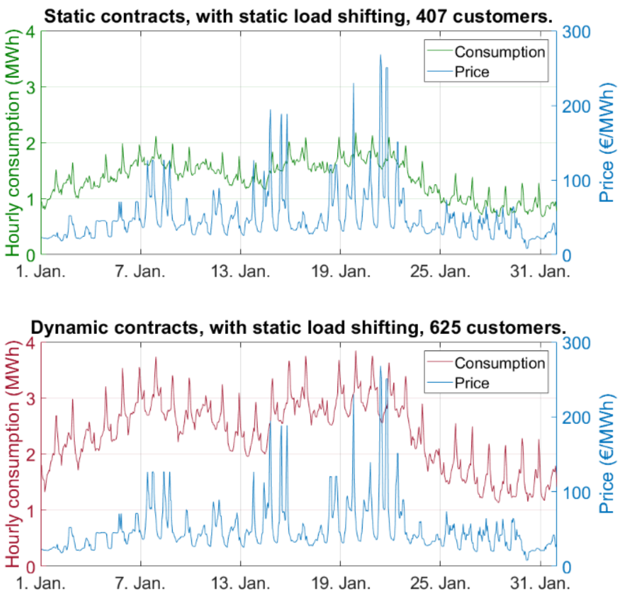

Fig. 5. Total consumption of customer groups 3 and 4 and the hourly end customer electricity prices.

Results

Figures 6 and 7 present the scatterplots of the data points and the linear predictors of comparisons A and B (see above). Figures 8 and 9 present the same thing for the comparisons C and D. The figures also show the parameters of the linear predictors. The first thing to see from the figures is that the fit of the data points to the line is not very good. The Pearson correlation coefficient, which describes the goodness of the fit, was around 0.3–0.5 for the fits of the figures 6 and 7 and around 0.2 for the fits in the figures 8 and 9. Therefore, the linear regression can be treated here only as a rough indicator.

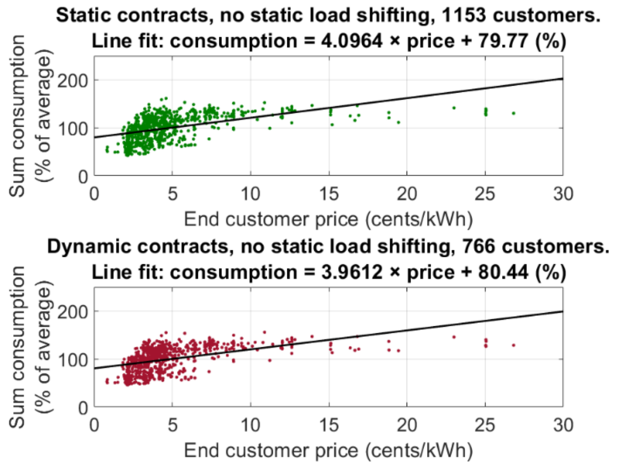

Fig. 6. Scatterplots of the correlation comparison A with fitted lines.

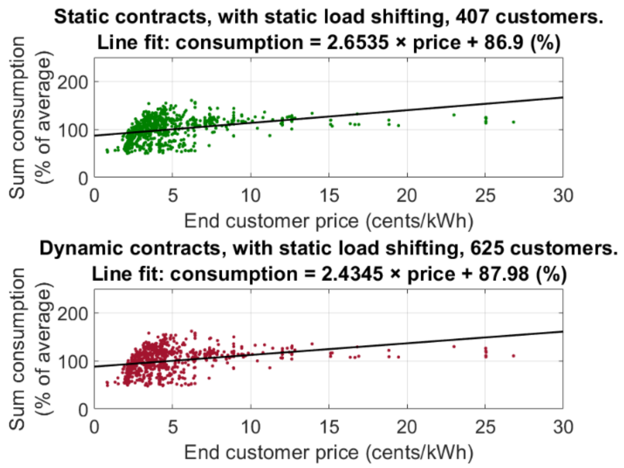

Fig. 7. Scatterplots of the correlation comparison B with fitted lines.

If the individual data points of figures 6 and 7 are investigated, it can be seen that there are significant similarities in the data points between the groups although the customer groups comprise different customers. One explanation to this could be that when large and very similar customer groups experiencing the same outdoor temperature are investigated, the sum consumptions (scaled as percentage of the average of the sum consumption) become very similar due to the similar consumption patterns of the customers.

In all of the figures, there is positive slope in the fitted lines, which means that when the price is high, also the consumption tends to be high. This is due to many factors. It is very natural that there is a positive correlation between the consumption and the price. This is because of the general law of supply and demand to which the Elspot market is based on; when the consumption on the system level is high, the prices tend to be high. This shows the importance of filtering out the other factors than the price from the dependency between the consumption and the price. As mentioned above, in our case this is made by comparing the two groups of customers.

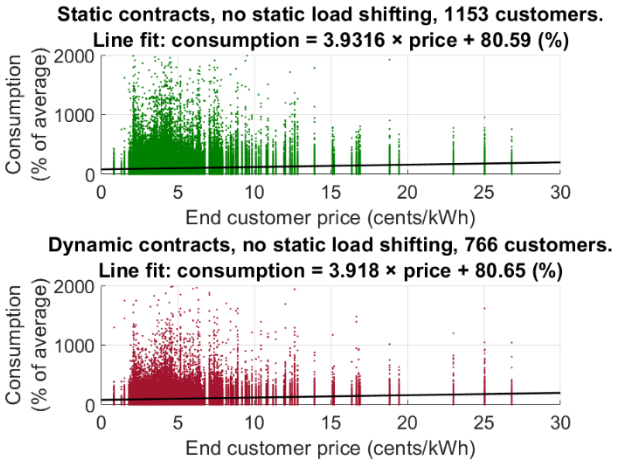

Fig. 8. Scatterplots of the correlation comparison C with fitted lines.

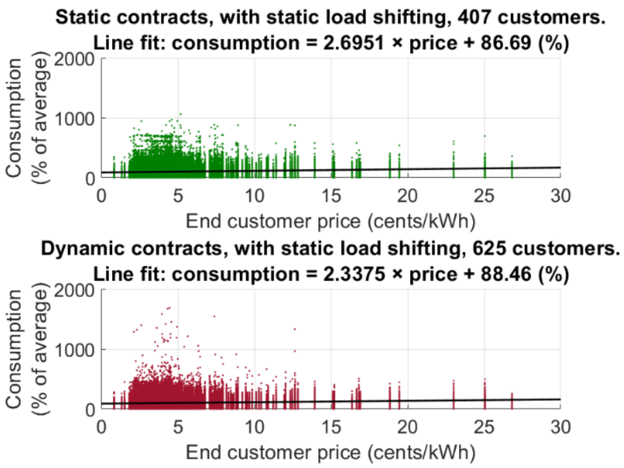

Fig. 9. Scatterplots of the correlation comparison D with fitted lines.

Another common thing for all of the correlation comparisons is that the slopes of the linear predictors of the customer groups with dynamic electricity contracts (hourly pricing based on the Elspot prices) have smaller positive slope than the ones with static (non-dynamic) contracts. We tested the statistical significance of the difference using the test procedure and the calculator found in [4]. The test showed that the differences in the slopes were statistically significant ($p < 0.05$) in the comparison cases A, B and D, and not significant in comparison case C (the slope difference is very small in case C). This implies that in comparison cases A, B and D there is > 95% probability that the difference in the slopes is not just a statistical coincidence. *One possibility is that the difference is induced by demand response of the customers.* This is not, however, the only possible explanation. The customers having dynamic electricity contract might also be such that their natural (no demand response) consumption pattern is more focused on the low price hours even without any DR involved.

CONCLUSIONS AND FUTURE WORK

In this paper, methodology for observing hourly pricing based demand response using the typical data, which a retailer has of its own customers, was discussed. In addition, a case study was made using real smart meter data of about 3000 real consumers. The result of the case study was that tiny indications of possible demand response were found, but more research is needed in order to have a better understanding of the matter.

Many ideas for the future work rose during the research. It would be good to use larger data sets in terms of the amount of customers and the length of the investigation period. A deeper understanding and analysis of the consumption patterns of different customers and customer groups would also be necessary. In addition, more sophisticated statistical tools like multivariable regression or mixed linear effects modeling could be used in the analysis.

REFERENCES

[1] Energy Authority, 2018, "National Report 2018 to the Agency for the Cooperation of Energy Regulators and to the European Commission," Available: https://www.energiavirasto.fi/documents/10191/0/National+Report+2018+Finland+1411-480-2018_20180726.pdf/10b8e538-2eef-4e97-8629-aafd4ad9ee02

[2] Rautiainen, A., Lummi, K., Supponen, A., Järventausta, P., Repo, S., Honkapuro, S., Partanen, J., Haapaniemi, J., Lassila, J., Haakana, J., Belonogova, N., 2017, Reforming Distribution Tariffs of Small Customers – Challenges, Targets and Impacts of Implementing Novel Tariff Structures. In proc. 24th International Conference on Electricity Distribution (CIRED 2017), Glasgow, UK, June 2017.

[3] Rautiainen A., Koskela J., Vilppo O., Supponen A., Kojo M., Toivanen P., Rinne E., Järventausta P., Attractiveness of demand response in the Nordic electricity market – present state and future prospects. In proc. 14th International Conference on European Energy Market (EEM), June 2017, Dresden.

[4] https://www.danielsoper.com/statcalc/calculator.aspx?id=103