ASSESSMENT OF POSSIBILITIES FOR DEMAND RESPONSE RESOURCES IDENTIFICATION IN SMALL AND MEDIUM CUSTOMER SEGMENTS

Antonio GABALDÓN
U.P. de Cartagena – Spain
antonio.gabaldon@upct.es

Antonio GUILLAMÓN
U.P. de Cartagena – Spain
antonio.guillamon@upct.es

Mari Carmen RUIZ
U.P. de Cartagena – Spain
maricarmen.ruiz@upct.es

Sergio VALERO
U. Miguel Hernández – Spain
svalero@umh.es

Francisco J. Gª FRANCO; Carlos ALVAREZ
IIE-UPV – Spain
garfrafr@iie.ipv.es

Mario ORTIZ
U. Miguel Hernández – Spain
mortiz@umh.es

ABSTRACT

The objective of this research is to show the capacity of Self-Organizing Maps to classify customer and their response potential from electrical demand databases with the help of Non-Parametric Estimation and Physically Load Based modelling as support tools. The searching of customer suitability is focussed to real time products, whose interest is growing in developed countries. In this way customer demand and response have been tested and compared with energy price curves extracting patterns from these curves. Results show the capability of this approach to improve data management and select coherent policies to accomplish cleared demand offers amongst different prices scenarios in an easy way.

INTRODUCTION

The participation of customers in electricity markets is an important concern to achieve a better market operation. Market will not be complete until demand and supply sides could compete in an equal foot and have a "similar" possibilities and products to participate in energy and ancillary markets. Obviously, small and medium customers have serious barriers to participate: the minimum size of demand, the complexity of market rules and procedures, and finally how (customer driven approach) and why (electricity usually is a small part in customer budget) to change their demand.

In this way, the role of "energy aggregators" becomes a necessity. These aggregators should decide: the set of options that best suits the demand patterns and flexibility of those customers, and how to aggregate demands because a segment of customers is not an "homogeneous group" of demand, i.e. they do not respond identically, have different loads and take a different service from the electricity.

This situation promotes the search of "simple" tools, mechanisms and procedures which allow demand aggregators to identify customer groups in the market and determine the market products that best suit each customer segment, from the economic point of view, using elemental data, such as customers daily demand profiles, load flexibility simulation, and the results of market prices in the past to obtain "price patterns". Moreover, the demand response portfolio to be developed for customers should be easy to understand and apply in their homes or business.

The first step of the methodology is to classify customers, then it will be developed a process oriented to find "price patterns" in daily energy markets but specifically in balance markets. Some patterns were found through statistical Non-Parametric Estimation (NPE) approaches both in energy and in balance markets. The third step was to simulate a mix of policies for demand response –cycling in HVAC, thermal storage, small photovoltaic and thermal generation…-, according to these patterns, in some selected customer segments through physically based load models. The final step was to develop a mechanism to evaluate the policy that produce the highest benefit for each customer in the market when a "price pattern" appears in the energy or balance market (taking into account the need for energy recovery).

THE GROWTH OF OPPORTUNITIES FOR LOAD RESPONSE PROGRAMS

At present, different Independent System Operators (ISO) in Europe, Oceania and North America are continuing the development of Load Response Programs (LRP) with the objective of changing electricity demand of large power users. Nevertheless some medium commercial or industrial customers could submit offers and bids in new energy markets thanks to lighter requirements for demand reduction with levels of about 100kW (New York ISO or New England ISO). Besides, some ISO encourage the possibility of demand aggregation through commercializer entities [1] to reach the minimum level for the participation of users. These aggregators have several responsibilities: to provide the necessary load level according to the parameters of the cleared offer; to notify customers the necessary demand rescheduling resulting from accepted offers, and to assist users in the determination of the best demand response policies mix according to demand curtailment period and price levels.

The present problem is how to detect the more suitable customers to achieve a minimum change in demand level to comply with energy reductions in short and medium-term markets with a fast time response. The methodology proposed in this paper is oriented to find opportunities in

Real-Time Price Market (RTPM).
In the first case it is necessary to find customers with interest and capacity to bid load curtailments through an aggregator. Notice that these curtailments, if any elasticity is possible and expected [2], can be obtained through on-site small generation or by a change in the technology of the loads (for example the use of dual-fuel loads). Apparently, the customer segments more interested in these policies should be those whose demand follows day-ahead prices. The first objective of this paper is to show the capability of Self-Organizing Maps (SOM) to find the maximum potential of the customer segments. Obviously, the participation of these customers depends on some additional sociological, technological and economical aspects. The second task consists of proving that this demand can be reduced during the periods when an offer is more interesting or feasible to be cleared. This task can be performed through models such as the one described in [3]. Besides, it is necessary to evaluate monitoring, control, communication costs and loss of commodity [3].
Customers or participants enrolled in Real-Time Load Response programs agree to achieve a certain level of load reduction at the discretion of the ISO in a short term notice period (from 30 to 120 minutes) involving demand control, backup or self-generation. This notice period requires a fast response and the development of new tools to achieve mandatory curtailments without penalties.
Demand relief needs are sent from the ISO through, for example, Internet Based Customer Service provider [1]. This load relief may last from two to four hours and generally, the shorter the notification period is the higher the revenues are (for example from 100$/MWh to 500$/MWh). Obviously these prices appear as a very interesting opportunity to manage energy cost while they contribute to system performance.
Again in this case, the aggregator must be able to select customers and adequate demand response policies to achieve the greatest benefit. This involves the management of some RTPM forecasts to find the best DER combination.

DETERMINATION OF DER POLICIES IN REAL-TIME MARKET PROGRAMS

Customer clustering through the use of SOM maps.

To evaluate the above mentioned markets and explore the possibilities of the participants, a set of winter season measurements corresponding to a representative sample of industrial, institutional, commercial and small residential loads was used. The annual peak demand of the sample ranges from 100 kW to 10MW. The input space database is formed by about a hundred Spanish customers. Table I shows the description and the label related to the daily load curves (the same label number for all the load curves).

TABLE I. CUSTOMER SPECTRUM

Customer description	Label
Industries	1,2,3,4,5,6,7,8,9, and from 24 to 73
Universities	10,11,12,13 and from 74 to 89
Hotels	14,15, and from 90 to 93
High Schools	16, and from 94 to 97
Hospitals and Medical Centers	17,18,19,20 and from 98 to113
Retailers	21,22, and from114 to 117
Residential C.T.	23,118 and 119

A SOM was trained with these load curves to achieve a customer clustering. The characteristics of similar maps are presented in [6], and a specific application devoted to customer clustering is presented in a previous paper [7]. Figure 1 shows the map and the clusters obtained (for example Universities whit labels 10,11,12,13, 77, 79, 86...).

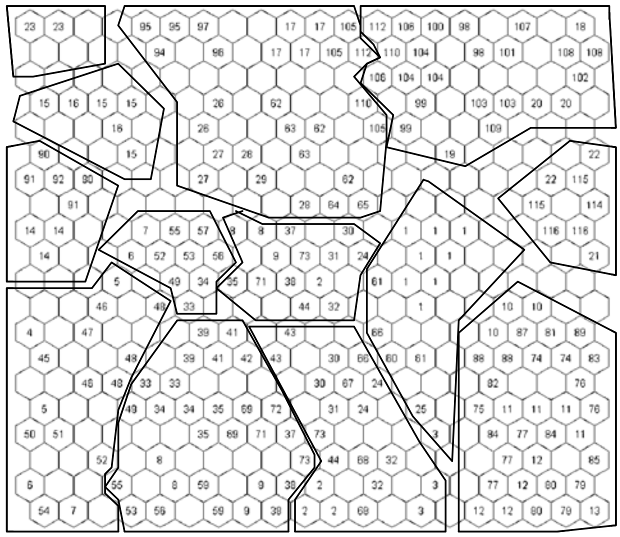

Figure 1. Customer clustering (thirteen clusters)

Notice that some pilot projects in California [8] show a real potential for demand response amongst small and medium users with Critical Peak and RTPM options with Day-Ahead notification (Residential and Commercial < 200kW).

Founding Energy Price Patterns

Participation in these short-term programs needs to know customer response and probable curtailment periods to define when demand should be reduced and also when energy recovery is allowed.
To extract patterns from some annual price series (Spanish balance services market [10]) from 2001 to 2002, a new SOM was trained. The SOM detected four clusters or zones. The zone 1 is the widest one (number of days), but in there appeared prices lower than 10 cent€/kWh. This zone was not considered for the next analysis step because it was supposed that an ISO would not initiate a notification, opening and interruption period with a RTP lower or equal to 10-12c€/kWh. Nevertheless, zones 2, 3 and 4 are considered to extract RTP patterns for simulation purposes.

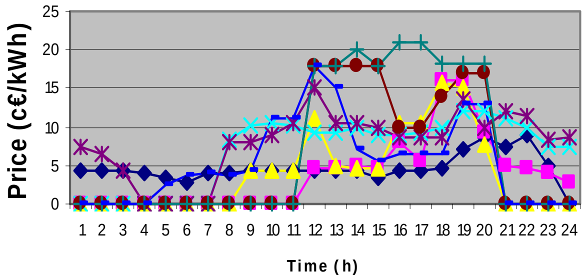

Figure 2. Balance prices in zone 2

Figure 2 shows the prices in zone 2 for six days of this cluster (the maximum price is about 20-25cent €/kWh).

Non Parametric Estimation (NPE)

Non Parametric estimation [9] are statistical methods that allow obtaining the functional form of a data set in absence of any guidance or constraints from theory. As a result, the procedures of non parametric estimation have no meaningful associated parameters. The two types of nonparametric techniques are neural networks and kernel estimation. In this case we will apply kernel estimation to obtain the RTPM patterns to reinforce and validate the value of the former results obtained through SOM (patterns in customer demands and segmentation).
The non parametric regression used here to obtain and validate "price-pattern" is a model such as:

$$Y = m(X) + \varepsilon; E(Y|X) = m(X)$$

Where Y is the output variable (prices), X is the input variable (time of the day), m(X) is the conditional expectation of Y with non parametric form whatsoever, and the density of the error ε is completely unspecified. The n observations yi, xi (price vs. time) are used to estimate a joint density function for Y and X. The density at a point (yk, xk) is estimating seeing what proportion of the n observations are close to (yk, xk). This procedure implies the use of a kernel function to assign weights to nearby observations.
The first attempt of non parametric regression is credited to Nadarya and Watson (1964). Their estimator was given by:

$$\hat{m}_h(x) = \frac{\sum_{i=1}^{n} K\left(\frac{x_i - x}{h}\right) y_i}{\sum_{i=1}^{n} K\left(\frac{xi - x}{h}\right)}$$

Where K(u) is the kernel function used, and h the bandwidth (a nonnegative number controlling the size of the local neighbourhood).
This kernel function is a real value weight function, and in practice it is most often assigned a symmetric density function. For this research a Gaussian kernel is used:

$$K(u) = \frac{e^{-u^2/2}}{\sqrt{2\pi}} I_u(\Re)$$

Also two confidence bands were proposed to show the accuracy of these price-patterns (bandwidth h=0.78).

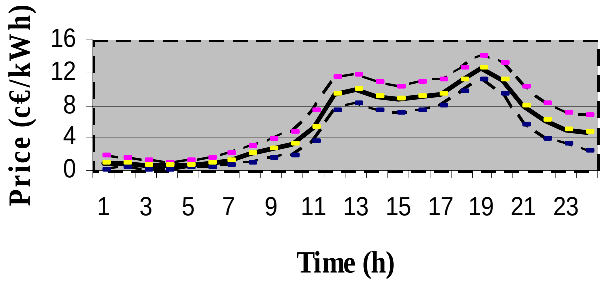

Figure 3. NPE Estimation and confidence bands

In this figure3, two confidence bands were proposed (dashed lines) showing the accuracy of NPE estimation. It can be stated that customers should expect two curtailments periods a day in zone 2 (from 11h to 13h and from 18h to 21h). For example, pattern of zone 3 is high but quite flat (in the afternoon and evening), so the participant would apply different DER policies (for example thermal storage) to overcome energy recovery costs (from 13 to 18h in zone 2) and maximize benefits during ISO curtailment requests.

DER Policies Simulation for a customer segment

Once selected the representative pattern price in the balance service market (in this case in "zone 2), it was evaluated the participation potential of the customers depending on the specific RTPM. This pattern price was used and several strategies of control and management of demand were designed based on the shape of this curve. The seven DER policies studied were: 1&2-Load Trade Strategies (HVAC and WH control), 3-Distributed Generation (PV) and 4-7 some Strategies Combination (SC) of LTS and DG.
The design was based on the load curve shape of the corresponding end-use, but trying to follow estimation and confidence bands (figure 3) in order to get higher economic profits.

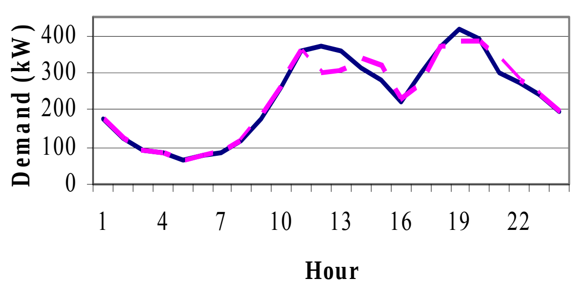

Figure 4. Residential Customer before and after LTS

Notice this price trend (two separate peak period of about two/three hours a day) allows aggregators or customers to apply an easy DER portfolio when such a trend is forecasted. Figure 4 shows a daily load curve for a

Residential customer segment and a new demand with an LTS strategy applied to HVAC loads (60% duty cycle from 11 to 13h and from 18h30 to 20h, dashed line).
PBLM software [3] was employed allowing reproducing the real behaviour of end-uses (HVAC, Water Heaters, Lighting, PV panels…). Customer end-uses were estimated using this software taking into account their geographical locations and the physical features of their facilities.

DER POLICIES SELECTION

Once defined the DER policies, it was time to choose the possible products the user can select to achieve ISO curtailment request in RTPM. Demand reductions (power generation) are seen from the market point as a demand offer. The load growth due to the recovery phenomenon after ISO request periods is managed as an additional purchase of energy at RTP. With the policies simulated in the way indicated in the previous paragraph, a new SOM was used as a quick detection tool for choosing the DER policies in function of market energy pattern forecast. The data for these maps are the reduction (gains) in demand profiles, i.e. the difference between curves in figure 4 (different of simulations were performed with several individual policies and also, some mix of policies).
Analyzing the way the Kohonen algorithm works [5], it seemed clear that the network matched the price vector with the energy reduction vector that had the shortest distance. The best solution for network training was to change the scale of both curves (demand reduction and price). The RTPM curves were rearranged in per unit value taking as a base the maximum value of price for each zone before to be presented to the SOM map to select a DER policy.
With this treatment the reduction curves of higher values were placed near the average of the prices eliminating the disadvantage produced by the different scales. This allowed the SOM to properly match the curves from the economical profit viewpoint. In order to validate this concept, a map with the seven DER strategies selected (Table II) was trained for each user. Figure 5 shows the clustered strategies for customer 23 (the labels correspond to the strategies).

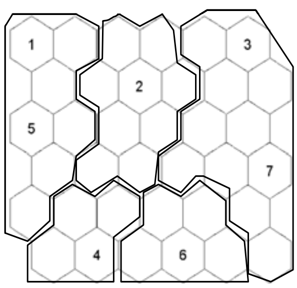

Figure 5. SOM for DER Strategies in a Residential Customer

The results of these tests are presented in table II. Notice that the best alternative (BMU) usually is LTS&DG combination. The worst alternative (WMU) for the hypothetical participant also appears in the same table.

TABLE II. DR+DG SELECTION PERFORMED THROUGH SOMS

Day (mm/dd)	10/30	11/15	11/16	12/11
BMU	6	7	4	6
WMU	2	1	2	2

CONCLUSIONS

Customers could obtain interesting benefits from the energy trading with the help of an aggregator acting as an enrolling participant in ISO Load Response Programs. Unfortunately, it is difficult to directly participate in the electricity market due to its complexity. Through the proposed integration of tools such as SOM, NPE and PBLM methodologies, a third part agent can identify in RTPM (or Day-Ahead) markets the customer segments and DER strategies with better possibilities to manage and reduce energy costs. With these and other tools, the integration of demand-side and supply-side options in the market will obtain growing benefits and therefore a better market operation.

Acknowledgments

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REFERENCES

[1] ISO New England Load Response Program Manual [On line].Available:http://www.isone.com/rules_proceds/isone_mnls/index.html June 2005.
[2] Neenan Associates, Lawrence Berkeley Nat. Lab, "How and Why Customers Respond to Electricity Price Variability", LBNL Report 52209, January 2003.
[3] C. Alvarez, A. Gabaldón et al., 2004, "Assessment and Simulation of The Responsive Demand Potential in End-User Facilities : Application to a University Customer " *IEEE Trans. On PWRS*, vol. 19, n 2,1223-1231.
[4] E. Hirst, 2002, " Reliability benefits of price-responsive demand", *IEEE Power Eng. Review*, vol 22, n 11, 16-21
[5] T. Kohonen, *Self-Organisation and associative memory (3rd ed.)*,Springer-Verlag, Berlin, 1989.
[6] G. Chicco, R. Napoli et al., 2004, "Load Pattern-Based Classification of Electricity Customers", *IEEE Trans. On Power Systems*, vol. 19, n 2, pp. 1232-1238.
[7] S. Valero, M. Ortiz, Fco. García et al., 2006, "Classification, Filtering and Identification of Electrical Customer Load Patterns Through the Use of SOM Maps", *IEEE Trans. On PWRS, vol.21, n 4, 1672-1682* .
[8] A. Rosenfeld, K. Herter et al., California Energy Commission, "Demand Response Hardware and Tariffs: California´s Vision and Reality", ACEE Summer Study, Available: www.energy.ca.gov/papers, 2004
[9] E.A. Nadaraya. *Nonparametric Estimation of Probability Densities and Regression Curves*. Kluwer Academic Publishers, Dordretch, 1989.
[10] Spanish Electricity Market Operator (OMEL); www.omel.es/frames/es/resultados/resultados_index.htm.