ASSESSMENT OF THE POSSIBILITIES OF DEMAND RESPONSE RESOURCES IN ENERGY AND CAPACITY MARKETS

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

Monique HERNÁNDEZ
U.P. de Cartagena – Spain
monique.hdez.rabbat@gmail.com

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

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

Carlos ÁLVAREZ
IIE-UPV – Spain
calvarez@die.upv.es

Sergio VALERO, Mario ORTIZ
U. Miguel Hernández – Spain
svalero@umh.es, mortiz@umh.es

ABSTRACT

A principal objective of electricity regulators when establishing electricity markets was to decrease the cost of electricity through competition. However, this possibility is quite limited for some customer segments (small and medium customers): they are not able to reduce and manage their energy costs because they can have high opportunity costs (the time they should spent in understanding the market and submit the energy bids and offers and, finally, the processing of market information).

The aim of this paper is to propose a responsive load economic model in order to manage the participation of customers in standard Demand Response programs. This procedure could help energy aggregators to integrate small customers in Electricity Markets and overcome technical and educational barriers and risks.

INTRODUCTION

The literature largely addresses the benefits of capacity markets relative to energy markets: for the customer a higher payment for availability of its capacity resources; for the Independent System Operator (ISO) the increased level of reliability, a reduced volatility, lower investment costs and mitigation of power markets. An example of Capacity Markets expansion is PJM and New England (USA) [1]. The auctions' results of these markets support the argument that Forward Capacity Markets foster competition (1800 MW of DR resources are interested by this new market in the first auctions). The paper explores through simulation with Physically Based Load Modeling (PBLM), the customer bidding possibilities in energy and capacity markets. Most customers do not sign long term contracts with the aggregators due the uncertainty about their business longevity, opportunity costs and the frequency with which they would be activated in four years. This social pattern creates a special risk for load aggregators. Due to this fact, the aggregators must be compensated for taking on the financial risk and this could increase the price at which Demand Response (DR) bids into the auction while decreasing the amount of DR, and creating a technical barrier for DR in these emerging markets.

By the use of the models proposed in the paper, the aggregator and ISO can simulate the behavior of customers when different elasticities, incentives and penalties are applied, considering the customer and loads that best fit the aggregator or system capacity objectives under each environment. These simulation results can improve the load profile characteristics as well as customer economy while decreasing peak prices. The performance of the proposed model was investigated through a numerical study using NE-ISO market data.

CHARACTERISTICS OF THE CUSTOMERS

A group of residential customers in the North of Spain have been selected for simulation purposes. This group of customers corresponds to real residential customers in Europe, and the average rated power per customer ranges from 4 to 10kW. The temperature in winter ranges from -5 to 10ºC. Figure 1 shows the winter and summer loads for two selected workdays in the primary feeder (transformer centre, CT) that supplies power in 400V to the customers.

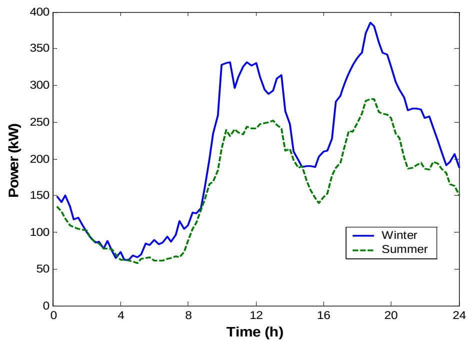

Figure. 1. "Typical" Load Curves in CT(winter/summer).

End Uses for a residential "average" customer have been estimated according to European Union EU-27 data (Joint Research Centre, 2007, [2]). Main end uses according to energy consumption are: heating systems (18.7%), Cold appliances (15.2%), Lighting (10.5%), Water heaters (8.6%), Air Conditioning (4.4%), i.e. typical targets for DR programs in this segment, also in USA, see [3]. In these customers heat storage is not unusual due to government incentives in last decade. Notice that in Mediterranean regions (in Europe), the Air Conditioning load represents a higher percent, but we have assumed those percentages [2] to better represent for simulation purposes a continental climate (Europe, East Coast in USA) where heat storage is possible and cost-effective.

STRUCTURE OF THE MODEL

The proposed model has five blocks: customer elasticity, peak price forecasting, a responsive load economic model, the classification of the load according its suitability for response, and the modeling of load response. We will explain the data and assumptions for each of these parts of the model in next paragraphs.

Step 1 : Customer elasticities

First submodel represents the changes in customer's demand with respect to changes of the electricity prices in Day-Ahead and Real-Time Markets through the use of own and substitution elasticities found in the bibliography.
Own price elasticity E_{ii} : the percentage of change in demand (D_i) at time t=i as a result of a percentage of change in the price (Pi) at the same time (remark: own elasticity should be a negative number):

$$E_{ii}(D_i) = \frac{\Delta D / Di}{\Delta P / Pi} \quad (1)$$

Elasticity of substitution E_{ik}: is a measure of the percentage of change in the ratio of the peak (hour i) to peak-off (hour k) demand as a result of a percentage of change in the ratio of the peak to the off-peak prices (this elasticity should be a positive number).

$$E_{ik}(D_i) = \frac{\Delta D / Di}{\Delta P / Pk} \quad (2)$$

It is important to consider that price elasticity of demand is non-linear and the responsiveness to price changes is not symmetrical, i.e. Eik≠Eki.
It is necessary to clarify that this change in demand from time i to time k can be due to energy payback (recovery of energy that was not supplied before the load is switched on again after a DR response in the time i. This energy is necessary to reach the level of service previously lost, for example in HVAC loads) or can be produced by a change in the time of use of the load (for example the use of a water heater (WH) or a dishwasher (DW)).
For this work we have considered data from USA, Australia and European Union extracted from pilot studies in small/medium customers. For example, in 2006 Federal Energy Regulatory Commission, reported some data about the value of the elasticity of substitution analyzed in some large customer segments ([12], RTP Tariff in Niagara Mohawk Co). These segments are high demand customers, but some insight appears about commercial and retail segments (elasticity ≈ 0.05). California Critical Peak Pricing Project [4] presents elasticity studies for small and medium residential/commercial customers (20kW, 200kW segments). These own elasticities are higher when an automated system for response is applied [4]. Aubin has studied [5] the effect of "tempo" tariff (Eléctricité de France EdF, France) in customers. The conclusions of this research are that RTP tariff improves the welfare of the majority of customers participating in the experiment and achieves significant demand reductions (up to 45% in high price days). Aubin concludes that the peak price elasticity is about -0.79 and an off-peak elasticity reaches +0.28. These data and other studies for EU countries [6] are used for simulation purposes to built a theoretical elasticity E24x24 matrix for a residential customer group.

Step 2: Peak-price forecasting

There are many papers in the bibliography concerning the forecast of price series, but it requires data information from nearly 45 previous days in order to forecast one or two weeks of daily prices (see [7]).
We propose an alternative for forecasting energy price series based on what happened in the markets the previous day. The procedure of clustering and forecasting is proposed in a previous paper [8] and is the following:

- We consider two-consecutive-day price series; a series of size 48 corresponding to the price of the 48 hours of the two consecutive days. In the first stage, we classify and extract patterns of the two consecutive days from some annual Real Time Locational Marginal Price (LMP) database, corresponding to the previous year.
- Then, we identify each daily-price series (current year) with one of the price patterns obtained in the first stage (previous year): at the end of a day, the daily price series (size 24) is identified with one of the price patterns comparing the first 24 hours. Then the price series of the following day (day-ahead forecasting) is estimated by hours 25 to 48 of the price pattern selected.

Obviously, the objective of the method is not to provide an accurate estimation for each day, but helping customers or aggregator to take decisions through a model. Figure 2 show the high-price cluster (48h series) used to forecast high prices periods. The data correspond to New England (USA) 2006 Real Time LMP price series [1].

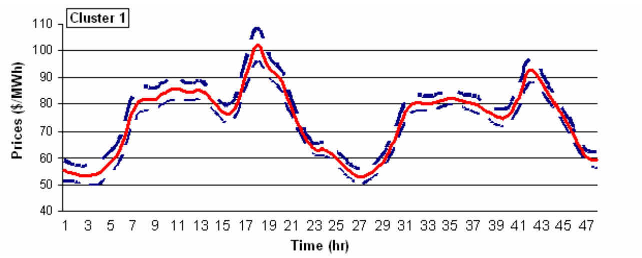

Figure 2. Estimation values and confidence bands for Real Time Prices (high-price periods, cluster 1).

Step 3: Responsive load model: economic viewpoint

The economic model is based on a previous work by Aalami [9], but modified, fixed in some details and, in general, has been improved with real data for prices, load and elasticities and with the use of PBLM response models. This model is based in classical optimization procedures and the objective is to maximize the customer's benefit. When the user is enrolled in Demand, Load, Capacity or other DR programs, the benefit B will be the income (economic and/or service) during hour i from the use of Di kWh. Indeed, there are additional incomes, for example incentives (IN, when response is effective) and penalties (PEN, when response fails over firm service level, FSL, agreed with ISO) for participating in some DR program available on modern energy/capacity markets. This is done through a change in customer demand (ΔDi). Mathematically, the global benefit GB is done by the formula:

$$GB_i = B(D_i) + \Delta D_i (P_i) + \Delta D_i IN_i - (FSL - \Delta D_i) PEN_i \quad (3)$$

The benefit function B is the quadratic benefit function proposed by Schweppe in [10]:

$$B(D_i) = B_0(D_{0i}) + P_{0i}\left[D_i - D_{0i}\right]\left\{1 + \frac{D_i - D_{0i}}{2E_{ii}D_{0i}}\right\} \quad (4)$$

where D_{0i} and D_i are demands before and after a response is cleared at time i. B_{0i} is the base benefit at time i, without any DR policy, i.e. the economic value of the service provided by load (heat, cool, processing, mass transport, etc).

By maximizing the above benefit B in the equation with respect to new demand at time i (D_i) if a demand policy is accomplished, we obtain:

$$P_i + I_i + PEN_i = P_{0i}\left\{1 + \frac{D_i - D_{0i}}{2E_{ii}D_{0i}}\right\} \quad (5)$$

It is important to take into account that IN and PEN values are a customer incentive and act like a price through elasticity, in the same way P_i does.

Moreover, the customer demand for Load-Response Programs (LRP) is evaluated with the expression:

$$D_i^{LRP} = D_{0i}^{LRP}\left[1 + E_{ii}\frac{\left(IN_i + PEN_i\right) - P_{0i}}{P_{0i}}\right] \quad (6)$$

.

And for Price-Response Programs (PRP):

$$D_i^{PRP} = D_{0i}^{PRP}\left[1 + E_{ii}\frac{P_i - P_{0i}}{P_{0i}}\right] \quad (7)$$

If a possible change of demand from on peak (time i) to off peak (time k) is available (depending on customer load capacity), the new customer demand should take into account the change of load from peak to off-peak hours. For example for PRP policies and considering the substitution elasticity $E_{i,}$ the load shifting to time k from time i (k←i) is:

$$D_{k\leftarrow i}^{PRP} = D_{0i}^{PRP}\left[1 + E_{ik}\frac{P_k - P_i}{P_i}\right]; k \neq i \quad (8)$$

And consequently the load reduction at time i due to load shifting to time k (k←i) is:

$$D_i^{PRP} = (D_{0i}^{PRP} - D_{k\leftarrow i}^{PRP}) \quad (9)$$

For example, by combining equations (6-10) for PRP, we will obtain the economic response model as following:

$$D_k^{PRP} = \left[D_{0k}^{PRP} + \sum_{k=1}^{24} D_{0k}^{PRP} E_{ik}\frac{P_k - P_i}{P_i}\right] - \sum_{i\neq k}^{24} LR_{eu} D_{i\leftarrow k}^{PRP}$$

Where $LR_{eu,}$ load recovery for a specific end-use is a real number [0, 1] characteristic for each end-use and DR response policy. If there is not any energy payback, LR=1.

Step 4: Load classification for Demand Response

The possibility of an electric load to participate in DR depends on the ability of the user to switch off, reduce partially or change the time of the load demand while maintaining a minimum level of service for such a load (comfort or process) [11]. Besides, if the load is being used for DRP, this demand is unable to be used for LRP, according to market rules and procedures. For instance, this restriction is applied in New England, see [12].

Several factors are relevant to classify load capability for DR: Final service supplied by the electric load (thermal, illumination, mechanical, electronic…), storage capacity (process, thermal or electrical), and the rate of load switching (ON-OFF times), dual energy supply (gas for HVAC, backup for electronic devices) and load dispatch facility.

The storage capacity is a critical factor because it drives the continuity of load service and consequently the possibilities of response (depth and duration of response). This factor is related to the ability of the whole process to store some kind of energy (electrical, thermal or in form of hydrogen) or some other "manufactured products" (process) that can be used in any other time. The higher the storage capability is, the higher the possibility of load re-scheduling over a broader time period is. For instance, conventional HVAC loads need energy payback to recovery the service (temperature) immediately after the response period. A heating or cooling load with storage (or with dual supply, i.e. gas/electricity) does not need the electricity to maintain service because they use the energy stored in the reservoir (or they change from electricity to gas supply). Moreover these loads can recovery their reservoir level some hours after the response (an example of substitution elasticity).

It is important to explain here that the general assumption (often assumed in the bibliography) that energy demand of end uses do not change when a load response is done is an important error [13] and it reduces the validity of results. For instance, we can consider the lighting end use. It has not sense the "recovery" of this demand in other periods (i.e. from night to daylight). They do not recover the energy saved in control periods. For other end-uses, savings from 5 to 20% have been reported during the response/payback period, ant this fact is often used by programmable thermostats to save energy.

Load demand behavior is also of interest. Load pattern of consumption can be discrete or continuous. A continuous demand to accomplish the service provided by the load may result in a continuous electricity consumption (this is the case of lighting loads or computers) or in a discontinuous consumption (for example in a refrigerator or in most of Air Conditioning devices where the operating state is thermostat controlled). From the previous considerations and the loads normally available in residential segments, a first classification according to their suitability for a flexible control is proposed in table I. This table also states the availability of loads for Forward Capacity Markets (FCM), and the possibility of response and payback (the forecast time of scheduled response is t=i).

Load	FCM	Elasticity		Energy Payback	
		Own(i→i)	Cross(i→k)	i+1	k
HVAC	Y	Y	Precooling Preheating	Y	N
Light.	Y	Y	N	N	N
Fridges	Y	Y	N	Y	N
Heat Storage	M	Y	Y	M	Y
Dual Loads	Y	Y	N	N	N
Water Heater	M	Y	Y	M	M
Dish Mach.	M	Y	Y	M	M

Table I. Demand Response Availability for different residential end-uses (Y: available, N: not available, M: indifferent)

Step 5. Modeling of Load Response

PBLM methodologies are the most promising approach for the load modeling problem applied to DR evaluation. A lot of models for HVAC, Water Heaters and ETS devices are described in the scientific bibliography [11] or are available from energy agencies, for example EnergyPlus or E_Quest (DoE-2,Dept. of Energy, USA [14]). The interest of these models is to forecast load behavior when external actions are considered –duty cycle modifications, voltage reduction- to achieve a targeted load curve. The modeling process for small customers has two steps: the first to achieve an individual, the second to aggregate these elemental models up to reach a minimum controllable demand size which allows the participation in the markets (the threshold is usually fixed around 100kW).

The proposed elemental model relies on information about physical load characteristics –heat transfer processes-, internal control mechanisms –thermostat-, usage and environmental parameters. The second step has consisted in aggregating the response of elemental loads. This problem consists on obtaining approximately the expected value of the total power demand due to the group [11]. To give an example, to be used in the next paragraph, we simulate the response of a set of HVAC 2kW loads. The internal temperature (thermostat setpoint) is 20.5ºC, and the outdoor temperature 6ºC. The average unforced duty cycle m(t) (the ratio of on time versus on+off times) obtained through simulation is 72%. With the software described in [11] we have performed some simulations to evaluate the performance of response. The results are shown in table II.

u(t) (%)	DR Period	Payback time	Peak Clipping (%)	Energy Savings	Comfort Temp (ºC)
25	i to i+4	i+5,i+6	65	19%	15
33	i to i+4	i+5,i+6	54	15%	15.9
50	i to i+4	i+5,i+6	22	8%	18
66	i to i+4	I+5	7.8	2.5%	18.8

Table II. Demand Response characteristics of HVAC end-use

The variable u(t) is the forced duty cycle during DR response. To evaluate the available load reduction in FCM auctions, we propose to use the following formula:

$$FCMB^{eu} = \sum_{k \in customers} RatedP_k^{eu} * (m(t) - u(t)) \qquad (11)$$

Where FCMB is the bid presented in FCM through a demand reduction of an specific end-use in group of customers. In our group and for HVAC loads, different levels of capacity are available. A higher level (i.e. a lower u(t) level) means a higher reduction in load service (comfort temperature), and this can produce a fail in the response and economic penalties imposed by ISO.

SIMULATION RESULTS

A simulation of residential response through an aggregator in energy and capacity markets has been performed and is described in this paragraph. This aggregator manages a number of residential users (see previous paragraph) high enough (up to 10 CT with loads very closed to the load shown in fig. 1) to obtain a minimum level of response of 100kW (a 20% of customer with the ability of respond to the aggregator is assumed).

The average price for 2007 winter is computed. At the same time, a forecast of high prices is obtained based on 2006 prices (structure of the model, step 2). When a high price period is forecasted during the previous day (see figure 3), the aggregator demands and manage a response from their customers sending a warning and price information.

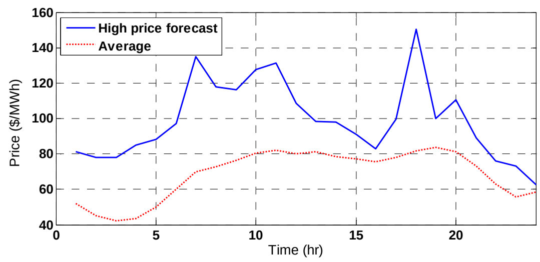

Figure 3. Average price and high price forecast

HVAC, Water Heater (WH), Dual Fuel (DF) and Heat Storage (HS) loads are divided into control groups, with similar size and the aggregator energy management system is programmed to apply different ON/OFF cycling control policies (HVAC), shifting of demand (WH, HS), change of supply (DF) during the high prices periods. The actual consumption for the customer with response ability is presented in figure 4 (curve "with DR"). "DR own" and "DR cross" curves represent the demand clipping (ΔD_i, equation (7)) and demand shifting and energy payback/recovery ($D_{i \leftarrow k}$).

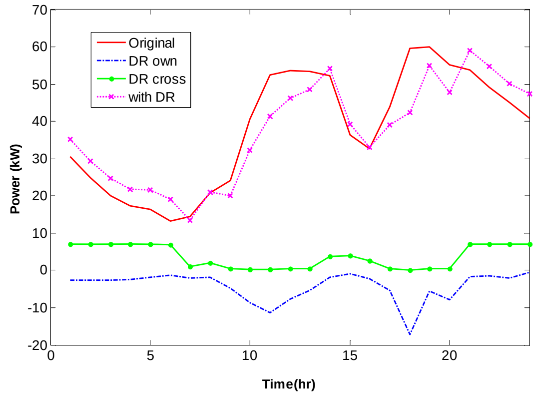

Figure 4. Original and modified demand due to PDR.

The overall consumption for a residential group CT is represented in figure 5 with the dotted line. A benefit of 9% in energy cost is achieved by this change in demand pattern.

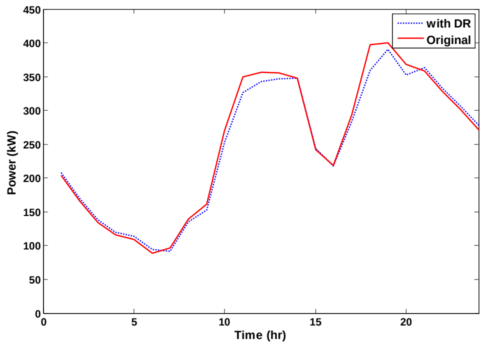

Figure 5. Change in the load. Level: Transformer Centre

CONCLUSIONS

The right operation of electricity markets is quite doubtful without the active participation of the demand-side. A methodology, suitable for small customers with an aggregator is presented in this work.

A discussion of the main elements of the model that drive and simulates DR participation is first presented in the paper. The methodology, well suited for the participation in energy and capacity markets, is presented afterwards, methodology that is based on the detailed knowledge of the load elements involved in the customer load mix (end-uses). The proposed methodology is applied to the case of a group of residential customers in Spain assuming the hypothesis that they have access to advanced DR policies (like the DR policies of PJM or NE-ISO markets). The simulations performed are oriented both to define the demand offers as well as to simulate the results of its implementation.

Acknowledgments

This work was supported by the Spanish Government (Mº de Ciencia e Innovación) under Research Projects ENE2010-20495-C02-02&ENE2007-67771-C02-01&02.

REFERENCES

[1] Reports of New England´s wholesale electricity markets (USA). Available on line: https://www.iso-ne.com/markets/mkt_anlys_rpts/

[2] Joint Research Centre, Energy and Transport Research. http://ec.europa.eu/dgs/jrc/index.cfm?id=2270.

[3] Staff report FERC, 2006, "Demand Response and Advanced Metering". Available on line: http://www.ferc.gov/legal/staff-reports/

[4] Piette, M.A., Watson D., Motegi N., Kiliccote S., 2006, (Lawrence Berkeley National Laboratory). "Automated Critical Peak Pricing Field Tests: 2006 Pilot Program Description and Results". CEC Commission, PIER Energy System Integration Program. CEC-500-03-026.

[5] C. Aubin et al., 1995, "Real-Time Pricing of Electricity for Residential Customers", *Journal of Applied Economics*, Vol.10.

[6] http://www.demandresponse.eu

[7] A. Conejo, J. Conteras, R. Espínola, & M. Plazas, 2005, Forecasting electricity prices for a day-ahead pool-based electric energy market, *International Journal of Forecasting*, vol 21, pp 435-462, 2005.

[8] A. Gabaldón, MC Ruiz, A. Guillamón et al., 2010, "Development of a methodology for clustering electricity-price series to improve customer response initiatives", *IET Generation, Transmission & Distribution*, vol. 4, nº 6.

[9] H.A. Aalami, M. Parsa, G.R. Yousefi, 2010, "Demand response modeling considering interruptible/curtailable loads and capacity markets programs", *Applied Energy*, vol. 87, nº 1, pp 243-250.

[10] F.C. Schweppe, M.C. Caramanis, R.D. Tabors et al. , 1898, « Spot Pricing of Electricity », Boston MA, Kluwer Ltd.,

[11] C. Alvarez, A. Gabaldón, 2004, "Assessment and Simulation of the Responsive Demand Potential in End-User Facilities: Application to a University" *IEEE Trans. On PWRS*, vol. 19, n 2, 1223-123.

[12] ISO New England Load Response Program Manual [Online], 2005.Available:http://www.isone.com/

[13] K. Sing, N.P.Padhy, J.D. Sharma, 2010, "Influence of Price Responsive Demand Shifting Bidding on Congestion and LMP in Pool-Based Day-Ahead Electricity Markets", *IEEE T. On PWRS*, vol. 25, nº4.

[14] http://doe2.com/equest/