

# DEVELOPMENT OF NEW TOOLS TO PROMOTE A MORE EFFECTIVE CONSUMER PARTICIPATION IN SHORT-TERM ELECTRICITY MARKETS

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**Abstract** – This paper summarizes the research work performed to show the capability of a combination of tools based on Self-Organizing Maps (SOM) and Physically Based Load Models (PBLM) to classify and extract patterns from distributor, aggregator and customer electrical demand databases (the objective known as data mining). This approach basically uses low cost information available for almost all supply side agents: historic load curves of several kinds of customers. The first objective is to find a correlation between demand and the evolution of energy prices in short-term energy markets. A SOM was trained that should allow to select the most suitable customer clusters whose demand modification would benefit customer and supply-side agents through, for example, energy efficiency, distributed generation or demand response. After a previous evaluation through PBLM of different possible strategies to reduce demand during consumption peaks, a SOM was trained to detect opportunities among users with high reduction capabilities during periods when day-ahead prices are lower than shorter-term prices. The results obtained clearly show the suitability of SOM approach to find easily coherent clusters between electrical users with high demand or available response capacity, and therefore a possible way to promote customer participation in electrical energy markets is opened.

**Keywords:** *Electrical Energy Markets, Self-Organizing Maps, Demand Pattern, Customer Segmentation, Demand Response, Load Modelling, Power System Operation*

## 1 INTRODUCTION

Deregulation of power markets has enhanced new business possibilities. Competition in retail markets and consumers option to participate in wholesale markets make commercializers, trading platforms operators and any other third part agent acting as interface between the consumers and their participation in the market to pay special attention to services and products to be offered to the customers. The complexity of the markets operation makes difficult for the consumers to decide in each situation if it is worthy to modify their load consumption curve in order to obtain some benefit from trading. For this reason, any product or service provided by other agents to ease the decision process will improve the participation of consumers in the market.

In this sense this paper presents an integrated tool to make easy the selection and identification of the potential customers interested in participating in Electric Markets and specifically in short-term products when some demand response or change can be offered.

Two different tools are used for this task: Self-Organizing Maps (SOM) and Physically Based Load Modeling (PBLM). The first methodology, developed by Teuvo Kohonen [1] is an unsupervised Artificial Neural Network that performs a transform from the original input space -n dimensional data vector- to an output space -two dimensional in this case-. These SOM tools have been previously used to classify electrical users on the basis of their electrical behavior. The uses of this classification were diverse: for example for short-term forecasting of anomalous load days [2], for improving the tariff offer of distributors and utilities [3] or to improve customer clustering through the previous filtering of anomalous demand pattern and anomalous load records [4]. The second tool, PBLM, has been broadly used to evaluate Demand Side Management policies in residential, commercial and industrial customers -intensively in regulated markets but also in liberalised environments- in order to analyse the possibilities of demand response and its effects [5], [6], [7].

In the research work presented in this paper a SOM tool is introduced and trained that allows -aggregators, platforms operators and customers- the identification of customers groups whose load curve follows short-term variations of markets prices. This would allow an economic benefit from customer demand contracted at day-ahead prices and in this way their participation in energy markets. The approach basically uses the load demand curves of each consumer. In our case, and for simplicity, we will study not only large size users but medium and small ones, because these customers usually are more reluctant to participate in energy markets. The results show the suitability of SOM approach to improve data management and to easily find coherent electrical users clusters.

The second objective of this paper is the identification of customers whose load curve modification -demand response- may produce the best economic results according to the difference between real-time and day-ahead prices. To perform this evaluation a new SOM network was trained with hourly customer de-

mand for time periods where the difference in prices was higher. Physically Based Load Models were applied to some end-uses of some of the customers -Space Conditioning, Water Heater, Refrigeration and Ventilation- to obtain and evaluate new load curves and feed SOM networks with them in an iterative way.

The paper does not tackle any estimation methods for short-term prices in electricity markets and, for this reason, historical day-ahead hourly prices are jointly used for the present study with historical real-time prices. Also, and for simplicity, only a limited Distributed Generation (DG) options -renewable sources- are considered to account for real participation of small and medium users, where conventional DG is not present.

## 2 OPPORTUNITIES FOR CUSTOMERS IN LIBERALISED MARKETS

The changes proposed during 90s by public authorities in main industrialised countries will face customer to a wide array of potential choices in energy markets. The old scenario where customers purchased electricity from a specific local utility supplier, the only alternative -for some industrial or commercial users, of course- being a substantial investment in co-generation equipments, is theoretically gone. In practice, alternatives are very limited for small and medium customers unless agents participating in markets perform some loads aggregation.

Aggregation supposes additional benefits for both the supply and the demand side of the market. From the customers point of view, aggregation allows the development of sufficient market power in comparison to the costs induced to serve them and manage their energy costs. From the supply point of view, commercializers and aggregators are able to offer a higher number of products and became more competitive when they aggregate customers. Aggregators, commercializers and other agents can optimise through customer aggregation the trading options of a complete portfolio of resources including distributed generation resources (self-generation) and demand resources (Demand Response, Energy Efficiency programs, DSM). Aggregation increases the flexibility for purchasing and buying energy therefore the trading of these portfolios may get profits from, for example, price changes in medium and short-term energy markets. Moreover they may have the option to provide some ancillary services to the market -i.e. spinning reserve, non-spinning reserve, interruptible load, replacement reserves, reactive and voltage control and black start capability- improving in that way their profit possibilities.

Therefore, aggregation is an instrument that improves customers' possibilities to participate in electricity markets. This customer participation is quite different from traditional forms of Demand Side Management in which participants -for example in energy efficiency policies- had been traditionally subsidised (a mechanism drive out by competition) by non-participants. These participants usually have had an appreciable loss

of service, a limited set of possibilities and benefits when load control policies have been exerted. Real-time pricing and new service options that would likely occur in new competitive markets could create greater incentives to predict market prices -for shorter or longer time periods- and to manage directly or indirectly their demand -customers and aggregators-. The incentive for the customer here is to share benefits for market participation with aggregators and commercializers.

The tool presented in this paper tries to ease two possible tasks of commercializers, or any other aggregator agent, when trading. For the case studies presented here, it was assumed that the aggregation agent make use of the necessary and tested tools to predict short-term market prices: day-ahead, hour-ahead and intra-daily markets prices [8] and a wide set of customers sectors. The tasks that can be tackled with the tool refer to classification and selection of customers for different trading options. This tasks are:

- Identification of customers that could be interested in demand response or self-generation for reducing consumption during periods of high differences of prices. The identification is based on the relation between demand curves and short term market prices (Section 3).
- Identification and classification of customers that are potentially interesting for trading demand modifications in energy or/and services markets. The identification is based on the potential capacity of the customer to provide changes in their demand when prices in day-ahead market are lower than in shorter time ones (Section 4).

One customer might be identified as interesting for both trading options. Perhaps both customers are the same in some cases. Due to this reason an independent method based in SOM tools and PBLM will be proposed for each case in next paragraphs.

## 3 POTENTIAL OF CUSTOMER CLASSES EVALUATION

### 3.1. Case Study: Aggregator Spectrum

The set of customers conforming the theoretical aggregator or commercializer spectrum has been selected in a way that guaranties a plausible real situation. Specifically, Spanish institutional, industrial, commercial and residential -in this case in the medium voltage side of a distribution transformer- daily load profiles were recorded from 2002 to 2003 in winter and summer periods.

The annual peak load varies from 50 kW for the smallest user to 10 MW for the largest customer demand -an industry and a university-. Besides customers were selected from two Spanish counties in the Mediterranean area to achieve a relative significance of results.

Winter demand profiles -96 data each day- have been used for the training of SOM. Table 1 shows the main customer sector, its economical activity, the label assigned to each customer and the number of daily load curves considered for each customer in each SOM.

Customer Sector	Activity	Label	N° of Records
Industry	Medium Industry	1,2	21
	Warehouses	3	21
	Large Industry	4 to 9	28
Institutional	Medium University	10,12,13	40
	Large University	11,19	28
Commercial	Small hotels	14,15	21
	Medium hotels	17	21
	Hospitals and Medical Centers	20 to 23	21
	Retailers	24,25	21
Residential	Small customers	26	40

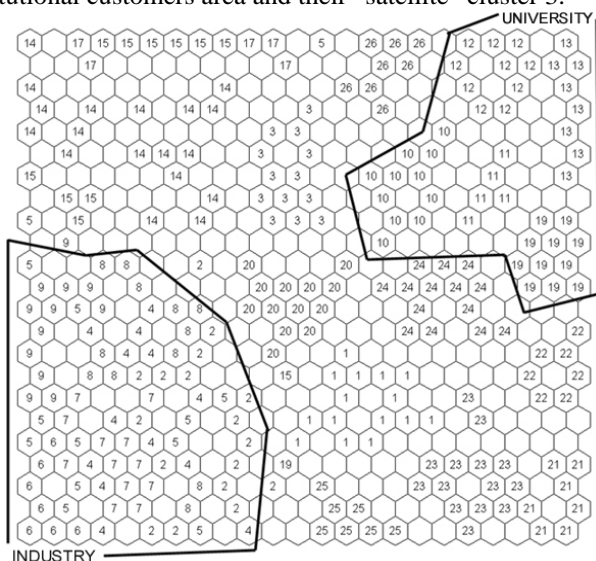
**Table 1:** Customer spectrum (winter 2002&2003 demand).

### 3.2. SOM Training.

Data used in the training of each neural network correspond to weekdays load curves -Sunday and Saturday are not considered for simplicity-. A previous filtering of anomalous daily loads was performed according to the methodology described in [4]. Customer load curves were supplied to SOM without any order -day or customer-.

Different possible configurations of SOM were tested. A map size of 23x23 cells and a number of 6000 and 2000 steps for primary and secondary training was finally applied because this configuration suited very well to achieve customer clustering -the number in the cell corresponds to a specific customer in table 1-.

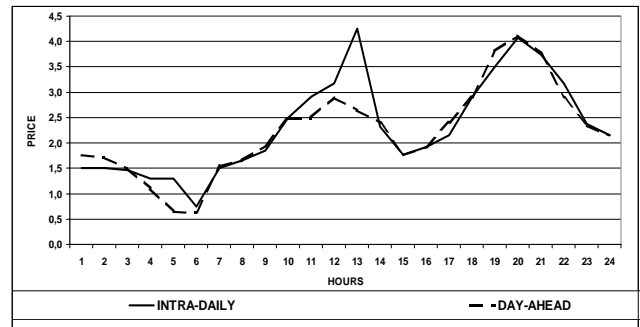
Figure 1 shows the final SOM. Notice the grouping induced by SOM for customers 10, 11, 12, 13 and 19 -right upper corner, marked as University- and for customer 2, 4, 5, 6, 7, 8 and 9 -left bottom corner, marked as Industry-. Also it is interesting to note here the neighborhood of residential customer -label 26- to institutional customers area and their "satellite" cluster 3.



**Figure 1:** Customer label map.

### 3.3. Short-term energy prices: finding customer potential

To find the customer interest in performing a demand offer -reduction of its forecasted demand in a time period where prices are high [7]- in short-term markets, the authors performed a comparison between day-ahead prices and hour-ahead prices (first session market) available in the Spanish Market Operator web [11]. A set of 15 days in January and February 2003, where the difference of prices in both markets was the higher in this winter period, has been selected. Figure 2 shows day-ahead and intra-daily prices for January 14<sup>th</sup>, 2003.



**Figure 2:** Short-term market prices (Jan 14th of 2003).

Through these prices, 15 difference of prices curves -such as the one presented in figure 3- have been presented to the SOM -previously trained with demand curves, see previous paragraph-. The objective here was to obtain the customer that suits better the evolution of the difference of prices -customer which could be interested in some change on its demand pattern if it was faced to real-time pricing-. Results for some representative days are shown in table 2. First 15 cells in the map that closely suit short-term market prices are presented in this table.

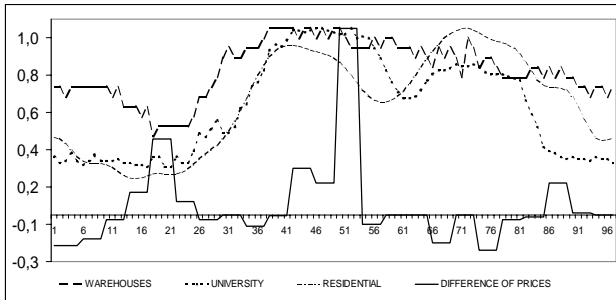
Cell order	Customer label				
	Jan. 14 <sup>th</sup>	Feb 4 <sup>th</sup>	Feb 5 <sup>th</sup>	Feb 12 <sup>th</sup>	Feb 20 <sup>th</sup>
1 <sup>st</sup> -5 <sup>th</sup>	12&13	12	12	12&13	26&12
6 <sup>th</sup> -10 <sup>th</sup>	12&13	12	12	12	26&12
10 <sup>th</sup> -15 <sup>th</sup>	12&13	12&3	3	3	26&3

**Table 2:** Cell customer ordering versus difference of prices.

From this preliminary result it can be seen that the more interested customers in joining some program to reduce peak -demand response, energy storage, self-generation- are medium university, residential households and some warehouses. In this way aggregators and commercializers should focus their effort in those customers.

The relation between the difference of prices and load demand for the customers selected in table 2 on January 14<sup>th</sup> is shown in figure 3. For example these customers should be very interested in a lot of demand policies: peak reduction through thermal energy storage

-change load from high prices to low ones-, direct load control -payback when low prices periods arise- or the installation of self-generation -for example, through photovoltaic panels-.



**Figure 3:** Comparison between prices and demand (pu)

Notice the residential customer is not selected by SOM for this day. This is due to customer load pattern: peak demand arises when intra-daily prices are lower, and valley demand follows the highest difference of prices period. On the other hand the University and warehouses follow the inverse pattern.

#### 4 EVALUATION OF ENERGY MARKET STRATEGIES THROUGH THE USE OF SOM AND PBLM

Those users for whom it would be profitable to change their demand following short-term prices market conditions can be identified through the joint use of SOM networks and PBLM methodologies.

In a first step the possibilities to change the customer demand are evaluated through PBLM. Different strategies are taken into account for this purpose. This step is done from the point of view of the customers, therefore it pays attention only to customer needs -peak shavings- without considering market prices.

In a second step, the aggregator agent scans the new demand curves -with Load Trading Strategies, LTS and DG policies- in order to identify the consumers with more possibilities in the trading according to the demand change stated in the previous step. The scanning is performed using SOM and considering the difference between day-ahead and intra-daily prices.

##### 4.1 PBLM

PBLM are physical-mathematical models that allow the description of different end-use loads behaviour. The models peculiarities are:

- They use real physical parameters of the load and its environment -such as devices rated power, climatic conditions,...- that allow to reproduce individual and aggregated behaviour of end-use loads with enough accuracy.
- Opposite to traditionally proposed methodologies, PBLM do not use historical data so they are suitable to describe transient phenomena, such as that occurred after a load control is carried out.

The PBML use analogies to reproduce real response of the end-use loads and its environment. For example, Space Heating model is based in an energy balance - thermal balance- that occurs between internal air, the dwelling constructive elements, energy storage capabilities, the external environment and the conditioner appliance [9], [10].

The following models for end-use loads have been used for the study shown in this paper: Photovoltaic Solar Panels, Space Heating, Electric Water Heater, Lighting and Electrical Energy Storage.

##### 4.2 Case Study

A customer identified by the SOM network in the previous section as suitable for participation in short-term market was chosen to evaluate the possible benefits a peak reduction response could contribute through different LTS and DG strategies.

The chosen customer was a University with a load peak of 650 kW and 500 kW in summer and winter respectively.

Dwelling	Area per unit (m <sup>2</sup> )	End-uses
42 classrooms	60-110	HVAC, Lighting
60 offices	16-20	HVAC, Lighting
40 student rooms	10	HVAC, Lighting, Water Heater
Sport facilities	----	HVAC, Lighting, Water Heater

**Table 3:** Identification of the types of rooms and end-uses of the customer.

This University has 4 schools and faculties -over 2000 students- with 5 buildings and sport facilities, including the rooms and end-uses described in table 3.

Winter time -January and February months- was used for the study purpose, corresponding the following end-uses share to that season:

HVAC	Lighting	Water Heater	Electronic Equipment	Others
40-45	35-40	10	5-10	< 5

**Table 4:** End-uses share for University customer (winter)

##### 4.3 Strategies Evaluated

The different strategies simulated are described in detail next:

- HVAC and Water Heater: duty-cycle limitation to a percentage of previous values -without control- in a defined control interval.
- Lighting control through electronic dimmable ballast regulation.
- Power generation by means of Photovoltaic Solar Panels directly connected to the grid or used to storage energy in batteries later discharged.

Specific strategies simulated were:

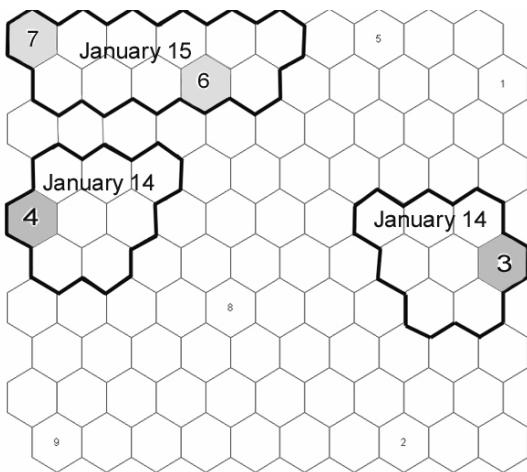
- Strategy 1: Dimming ballast of fluorescent lights to a 90% in a control period from 9 to 14 h.
- Strategy 2: for HVAC, reduction of the duty cycle up to 60% during 9 to 16 h. Progressive reduction of control from 14 to 15 h leading to a total interruption of the control from 15 to 16 h.
- Strategy 3: for electric water heater, the switch-off from 10 to 14 h and then the implementation of a progressive switch-on during the last hour -14 to 15 h-.
- Strategy 4: direct coupling of Photovoltaic Solar Panels.
- Strategies 5 and 6: Photovoltaic Solar Panels and Electrical Storage -with batteries discharging at different periods-.
- Strategies 7, 8 and 9: some combination of strategies 1, 2, 3 and 6.

#### 4.4 SOM application results

For developing the tool for the scanning of the modified customer demand -LTS and DG policies- through SOM, the results of the evaluations of the previous section where used jointly with historical data of Spanish day-ahead and intra-daily markets.

A training of a SOM network of 10x10 with 2000 and 1000 steps for primary and secondary training respectively was accomplished using as input the demand reduction curves due to each one of the previous described strategies.

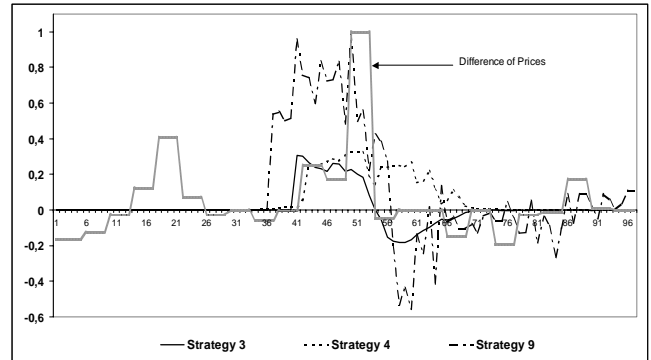
SOM network was tested with the curves obtained as difference between day-ahead prices and intra-daily prices for January 14<sup>th</sup> and 15<sup>th</sup>. As result a map was obtained that assigned those days the more suitable strategies -from the previously defined- under the exposed market conditions.



**Figure 4:** Difference of Prices SOM testing

Figure 4 shows how the SOM identifies strategies 3 and 4 as the more suitable for January 14<sup>th</sup> while strategies 6 and 7 were assigned for January 15<sup>th</sup>. Strategy 9 was selected by the network as the worst of them. Demand reductions obtained for strategies 3, 4 and 9 can

be observed in figure 5 with the corresponding difference of price curve on January 14<sup>th</sup>.



**Figure 5:** Difference of Prices vs. LTS-DG

## 5 RESULTS

Results from Section 3 show how SOM is able to classify customers whose demand follows difference of price peaks. This supposes the possibility to implement LTS resources and perhaps to use some DG options, - for example, back up generators whose operation price is higher than day-ahead price-.

To analyse results from section 4 it should be taken into account that SOM tool looks for policies that follow the difference of price: the overall reduction in demand is performed in positive price periods -energy sells- and payback, if necessary, is moved to negative price periods -energy purchases-. Notice SOM evaluates relative economic gains, but not an absolute value. In this way, strategies 3 and 4 would result in a lower economic profit that the strategy 9 -over a 60%-70% less of income- but strategies 3 and 4 suit better to price changes in time and amount.

An in deep analysis of demand reduction due to strategy 9 and difference price curves shows that customer is not using all the load control potential the strategy could offer. Control actions put into play an amount of energy that means demand reduction in some intervals and demand increments in others. If all energy not consumed is sold when the difference of prices in the markets is positive and all additional energy consumed is bought during periods of negative difference, the control strategy would be satisfactory. Moreover in the case of strategy 9, a great part of the reduction is made when the difference between prices is small while it would be more profitable to delay that reduction to a higher difference of price period. Thus it can be concluded that the strategy is not optimally designed. These two facts would cause economical losses if end-use demand reduction capability were limited -as it is expected to be-. On the other hand, strategy 3 is more efficient because reduction of demand available for control is performed during high and positive difference of price periods.

In an attempt to evaluate numerically the adequacy of each strategy to the corresponding difference of price curve, a Potential Profit Index (PPI, see table 5) was calculated as the percentage of energy sold or bought in

the appropriate period -sold during positive differences, bought during negative differences-:

Strategy	PPI
3	70.6 %
4	53.5 %
9	57.8 %

**Table 5:** Potential Profit Index evaluation.

For strategy 4 the index has not the same meaning. In fact, LTS strategies produce payback effect that supposes an increment of demand once the control is finished -with the subsequent economic cost- but DG strategies do not show this effect so the total modification over original curve is positive. But index can give information about if energy is being sold in a moment of maximum profit or if possible benefits would be better by modifying the strategy.

## 6 CONCLUSIONS

In conclusion, customers that find difficult to directly participate in the electricity market due to its complexity, and besides the time consuming task of deciding in every moment if they can obtain benefits from the energy trading, should benefit of this methodology. Through the mix of a tool such as SOM and PBML methodologies any third part agent can identify in each day the customers groups with better possibilities to obtain benefits of the energy trading within the day and therefore notify them and help them in the best way to manage demand to maximize benefits. In this way an integration of demand-side and supply-side options in the market will obtain a growing benefits and therefore the markets. Customers could have the possibility to manage better their cost through the help of aggregators and commercializers as a bridge to the effective participation in energy markets. Besides supply side agents should compete better through a wider product portfolio.

In future works LTS and DG strategies -short-term market and services oriented- will be studied individually in detail.

## REFERENCES

- [1] T. Kohonen, *Self-organisation and associative memory* (3rd ed.), (Springer-Verlag, Berlin, 1989).
- [2] R. Lamedica, A. Prudenzi, M. Sforna et al. "A Neural Network Base Short-Term Load Forecasting of Anomalous Load Periods", *IEEE Trans. on Power Systems*, Vol 11, n 4, Nov. 1996, pp 1749-1756.
- [3] G.Chicco, R.Napoli, P.Postolache, M.Scutariu and C.Toader, Customer Characterisation Options for Improving the Tariff Offer, *IEEE Transactions on Power Systems*. Vol.18, n° 1, Feb. 2003, 381-387.
- [4] S. Valero, M. Ortiz, Fco. García, A. Gabaldón et al., Application of Self-Organizing Maps for Classification and Filtering of Electrical Customer Load Patterns, 7th IASTED International Conference on Power and Energy Systems, Florida, USA, 2004.
- [5] C.O. Borjck, *Industrial Load Management-Theory, Practice and Simulation*, Amsterdam, Netherlands, Elsevier, 1989.
- [6] M. Orphelin and J. Adnot, "Improvements of methods for reconstructing water heating aggregated load curves and evaluating demand side control benefits", *IEEE Transactions on Power Systems*, Vol 9, May 1994, pp 957-964.
- [7] C. Alvarez, A. Gabaldon and A. Molina, "Assessment and Simulation of the Responsive Demand Potential in End User facilities: Application to a University Customer", *IEEE Transactions on Power Systems*, Vol 19, N 2, May 2004, pp 1223-1231.
- [8] F.J. Nogales, J. Contreras, A.J. Conejo and R. Espinola, "Forecasting next-day electricity prices by time series model", *IEEE Transactions on Power Systems*, Vol 17, N 2, May 2002, pp 342-348.
- [9] A. Molina, A. Gabaldon, J.A. Fuentes and C. Alvarez, "Implementation and Assessment of Physically Based Load Models: Application to Direct Load Control Residential Programmes", *IEEE Proceedings Transmission and Distribution*, Vol 150, N 1, Jan 2003, pp 2350-2360.
- [10] J.C. Laurent, R. Malhamé, "A physically-based computer model of aggregate electric water heating loads", *IEEE Transactions on Power Systems*, Vol 9, N 3, Jun 1994, pp 1209-16.
- [11] [www.omel.es](http://www.omel.es)