

PRICE RESPONSIVE CUSTOMER SCREENING USING LOAD CURVE WITH INVERTED PRICE TIER

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Abstract

A new methodology for customer prescreening of potential DSM participant is designed empowering the selectivity of a commercially used mass routine developed at Polytechnic University of Valencia (UPV), Spain. In this price responsive demand management program a normalized inverted price tier is used as a base line for this method. The list of preselected customers resulting from this screening process is compared with that generated from the UPV method which has been in use in some European countries for some time. A few of the customers who were found to be in different priority levels under each list were investigated to optimize both methods. The versatility of this method is examined to suit different DSM categorized customers. It is found to be a helpful cross check method to avoid blind judgment based on collected electricity consumption data. Final customer groups and ranking are performed after the on premises load survey was conducted.

Key Words

DSM, price tier, load shifting, demand reduction

1. Introduction

Customers screening through automated methods ease choosing right DSM schemes for right customers out of a numerically large pool. Automated prescreening of customers also helps to significantly reduce the work load for a subsequent electrical energy audit that should finalize the list for grouping and ranking. The prescreened data can be used for load forecasting which is important to select suitable DSM programs for each group. However load forecasting can be performed in Bulk from the feeder [1], but it is fairly acceptable for groups of residential customers under a certain feeder. Combining feeder data along with customers' hourly consumption data can strengthen load

forecasting for utility companies [2]. Recently, 15 minutes' interval data for 1 year of electrical energy consumption is considered fairly enough data to judge a customer's potential as a successful participant [3]. In case of small scale residential pilot price responsive load management program it is not surprising that the participants would be selected randomly from the billing information and then screened based on program equipment and billing system constraints. A technical analysis report published by Tampa Electric Company (TECO) in March 2007 on a residential price responsive DSM pilot program is an example of such prescreening process. Temperature correlation with everyday consumption data was seen as an important factor in the aforesaid report. At Polytechnic University of Valencia, enormous effort was made to study the segregation of groups based on their correlation with weather factors and every day activities [3]. At USF-PCUE lab the experience was utilized as a part of USF-UPV academic collaboration.

2. Objectives of the Load Analysis

Customers' periodic consumption data may appear huge and highly diverse in nature at the first step but after being filtered on the basis of required criteria, these data more likely and often shrink to one-third of its initial size on the average. Likewise our customer list shortened from 444 to 203 and further reduces to 150 after activity wise sifting procedure.

The prescreening process can be explained graphically from Fig. 1. Assume a three dimensional coordinate system where each axis represents the scaled parameters or criteria on which a potential customer will be justified. Each axis, say x for "relevance", y for "Improvement gap", and z is for load factor (100%) on each criteria. Similarly x_{\min} , y_{\min} , and z_{\min} is minimum requirement to be on the program. Any customer steps inside the pink pyramid shaped volume by its xyz property have been excluded from being considered for DSM program. The customers who fall entirely out of the pink volume are selected.

The cost effectiveness and benefits of DSM comes from choosing a goal on the criteria or parameters (x , y , and z in Fig. 1) that can yield rewarding financial returns not only from customers' side but also from utility operation,

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Recommended by Prof. A. Domijan
(10.2316/Journal.203.2011.1.203-4711)

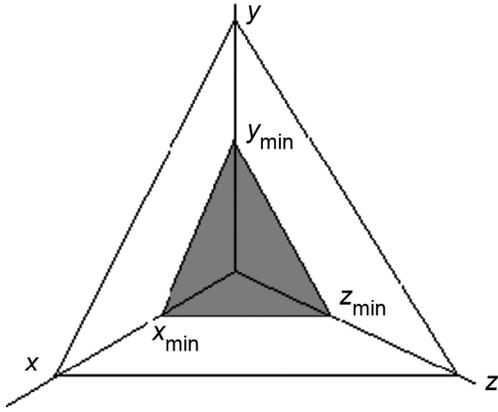


Figure 1. Customer screening based on xyz criteria.

system reliability and environmental regulation viewpoints. However the measurement of the savings may not be easy unless few real world benchmarks are set. In [4] some methods are proposed to observe the improvement and benefits of deployed DSM. Another important fact realized through years of experience from utility companies DSM pilot projects is that without spontaneous participation of customers the exercise is more likely to result in a dead end (unless it is enforced by state regulatory body). A successful DSM precedes more versatile and fruitful DSM as its follower [4].

The data analysis performed is primarily aimed at filtering those customers from the list who do not have any considerable flexibility on which they can be counted on for any price responsive demand management program. It also reduces the work load for the subsequent energy audit which is intended to finalize the list and classify potential DSM participant on basis of activities and hardware requirement. It is learned through long-term experience by many power industries that load analysis is crucial for a successful implementation of price responsive demand management. From the system reliability view point demand management is much cheaper than adding generators, transformers and improving transmission lines. In USA, the federal government assigned some committees under department of energy which are collectively working on designing demand response (DR) programs, market research, conduct survey or interview with load aggregators. The scope of analysis is vast considering highly diverse load aggregators under a utility. With very few differences the objectives of load analysis is to extract the viable customers for load management programs, forecast load demand for short term and rate design.

3. Data Analysis Environment

Most of the smart meters are designed to store periodic power consumption data in text file for research purpose beside the billing requirements. Some utility companies may be found using certain workstations to perform load analysis using the meter data. Historically few DOS-based IBM mainframe work stations were known to be in use by many utility companies for decades. The pressure of

extensive load data analysis within tighter project time lines persuaded some system developers to upgrade those systems to modern high speed microcomputers and related software with rich graphic interfaces. This effort is aimed at not only lessening the work load but also to enable programming of more powerful intelligence, with time, onto the analysis methods. The importance of this evolution was recognized by the Electric Power Research Institute (EPRI) in 1988 and they upgraded their research platforms to so called Load Data Analysis Workstation (LDAW) with few available configurations [5]. In recent days load data analysis is enriched by various powerful methods and can be performed very quickly on a personal computer.

The City of Tampa's local utility company (TECO) provided 444 customers' data to the Power Center for Utility Exploration (PCUE) lab at University of South Florida (USF) upon a non-disclosure agreement between them. The text data contains 15 minutes' interval data points for 2 years ($2 \times 35,040$ data points for each customer). The text data is converted to a numeric data file that can be fed into data processor spread sheets. At PCUE lab that data is used in MatLabTM to acquire more computational power and graphic user interface (GUI) capability. As a PCUE-UPV collaboration effort the data was analyzed independently using the method developed at UPV and the method developed at USF-PCUE to support and correct each other. The main goal of this strategy is to widen the viewing scope in the prescreening process. Finally the results came out with two sets designated as P and Q (three in case of UPV method) independent sets of customers sorted in order of priority. The two independent sets with different sorting order were compared. Disregarding the sorting order, since it is fairly trivial in the prescreening process, and focusing on priority groups, $P \cap Q (= R)$ results in a list of argued customers in priority groups. Set R is reexamined and both methods were tuned to agree 203 out of 444 customers who were picked as draft set B (see Section 1). The subset of draft B is filtered to yield final set B that takes into consideration the surveyed data to perform sifting based on intuition. In the following sections (4 and 5) these two methods are discussed.

4. Screening Method Developed at UPV

In this method few spread sheets were prepared to take input of the customers' data in serial fashion windowed in TECO suggested price tier for a complete year. Every customer data along with an encrypted ID number and consumption (KW) at every 15 minutes interval was input to a work sheet, which calculates the energy cost of a customer within each price tier and sums it up for the whole year. It also finds the percentile of total consumption in each price tier to the total consumption at all tiers during the whole year. In the next step it uses mass routine methodologies to sort customers taking into consideration each criterion independently. If $U \equiv (u_1, u_2, u_3, \dots, u_n)$ represent set of customers' usage pattern functions of independent criteria parameters called x , y , and z then a filter function $H(x_{\min}, y_{\min}, z_{\min})$ can be formed such that the process $S[U]$ will result in three identical sets of customers

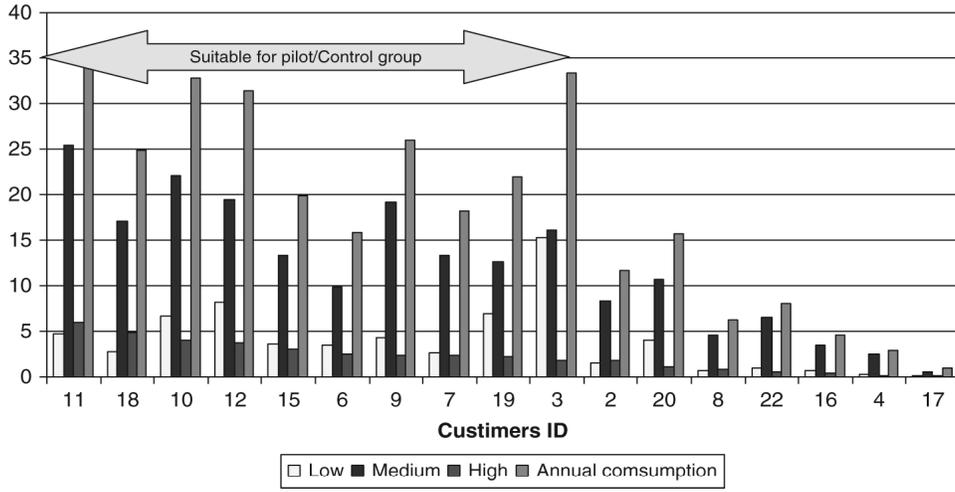


Figure 2. Customer screening through mass routine (UPV method).

of different dimensions. The customers who fall below an arbitrary threshold under each set are screened out from the possible offer of DSM. Mathematically we can express the process as shown below:

$$S[U] = [H] * [U] = \begin{bmatrix} u_{x1} & u_{x2} & u_{x3} & \dots & u_{xp} & 0 & 0 & \dots & 0 & (n-p \text{ zeros}) \\ u_{y1} & u_{y2} & u_{y3} & \dots & u_{yq} & 0 & 0 & \dots & 0 & (n-q \text{ zeros}) \\ u_{z1} & u_{z2} & u_{z3} & \dots & u_{zr} & 0 & 0 & \dots & 0 & (n-r \text{ zeros}) \end{bmatrix} \quad (1)$$

where p , q , and r are maximum non-zero terms in descending order at each row of the matrix. Each of the rows is assigned to a set namely P, Q, and R. Clearly those sets are the three subsets of set S.

Each criterion is then assigned a priority weight based on cost effectiveness and available hardware and all of the selected customers are sorted. The length of the list is equal to the minimum of p , q , and r . The mass routine rendered a data set ranked in priority order of 203 customers. It should be kept in mind that the aforesaid set is mandatorily a subset of the three original subsets. In other words the final subset includes only the customers who are the members of P, Q, and R. In set representation it can be expressed as:

$$S_F = P \cup Q \cup R \quad (2)$$

and $S_F \in S$

In Fig. 2 the customers with ID numbered 2, 4, 8, 16, 17, 20, and 22 are screened. Thus they are the members of the pink volume as shown in Fig. 1.

5. Screening Method Developed at PCUE

The focus of this paper is based on the method developed at USF-PCUE. At the Power Center for Utility Exploration (PCUE) lab more importance was given to the computational power since it was understood that customer characterization on the basis of an average over a year may

inherently introduce blind spots. The graphic interpretation is also important to show its trustworthiness. As a result, the data was read from a high level programming language and processed to plot load analysis results. The price tier suggested by TECO was used as a mean to justify a customer's flexibility to interact with the pricing signal. In other words the pricing signal was tested against a customer's ability to operate loads. For that, a function was also defined which reads customer data and returns an inverted price tier normalized by customer average maximum consumption. A measure of a customer's deviation from the inverted tier is a measure of significance of participating in the program. Conversely, a customer closely following the inverted price tier curve will not greatly benefit from such price responsive load management program.

For example, consider the above two monthly average load curves from two customers in the month of July 2007, with visibly close monthly maximum consumption level. Suppose that they have to be ranked on their suitability for this program based on the criteria known as *improvement gap* (to find if a customer is flexible to shift loads). Both of the customers in Fig. 3 consume similar amounts of average maximum level of power (≈ 0.65 KW) and an average minimum level (≈ 0.45 KW). Customer u 's monthly average daily load curve matched DSM suggested load curve or normalized inverted price tier more closely than the customer v did. For DSM v should place higher on the priority order than u since the customer can benefit more prominently from price responsive load management. However, this judgment is based on a certain criterion as mentioned before. Customers, having lower average maximum consumption than an assigned threshold (criterion – *relevance*), are screened out automatically due to possible long payback time. Another criterion termed *load factor* is considered as priority determining parameter. *Load factor* is a measure of a customer's load shifting capability in terms of overall load demand. At USF-PCUE lab the load consumption data was seen as time domain data signal which conveys the loads switching information. It was sought that in the frequency domain, load

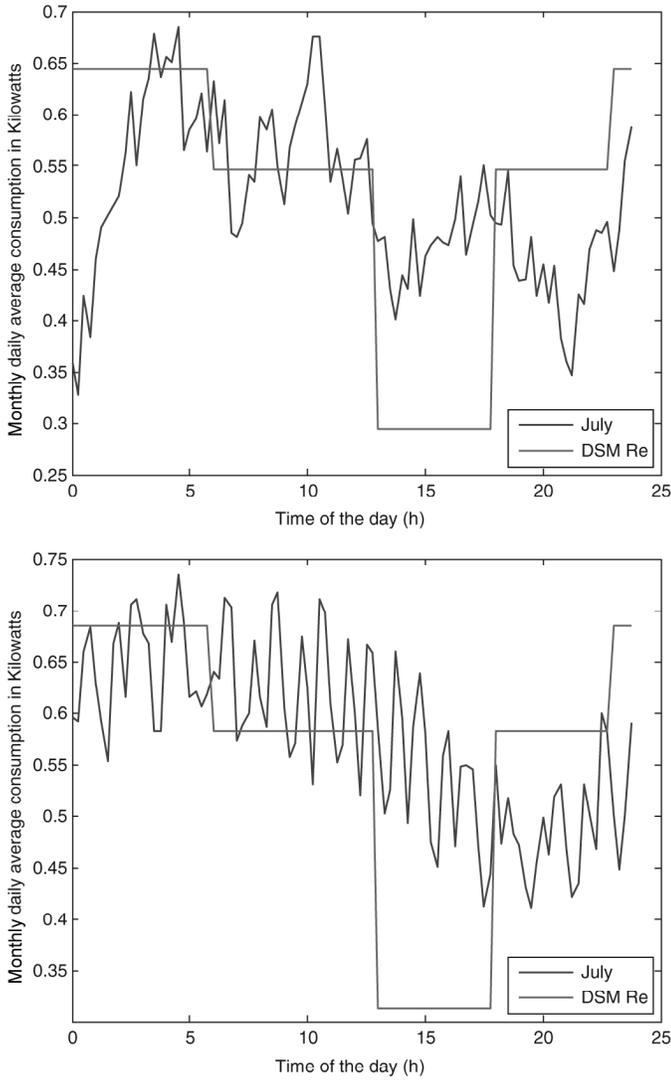


Figure 3. Monthly average load curve for customer u and v plotted for the month of July, 2007.

switching characteristics in this case, should carry the information about significant loads under operation. The plot of Fourier transform of monthly daily average data for customer u and v are shown in the following figure.

In Fig. 4 customer u and customer v have four significant sources shown by ellipses and the area of each ellipse is checked to indicate the level of significance. The position of the vertical axis of those ellipses also shows average turn-on and turn-off switching. This information can be easily modified to plug in the electrical load models deterministically instead of probabilistic methods. For example in [6] it will replace w for on and off switching. Another example can be found in [7], where a hybrid state stochastic differential equation is used as a sufficient model for a class of models. In that case it can replace $m(t)$. Similar kinds of mathematical load models can be found in [8]. Interested readers can grasp more knowledge on early stage mathematical load models described in [9] and [10]. Obviously weather condition might have a correlation with some of the loads' relative location on the load spectrum. That is to say, if the load data used span over different season

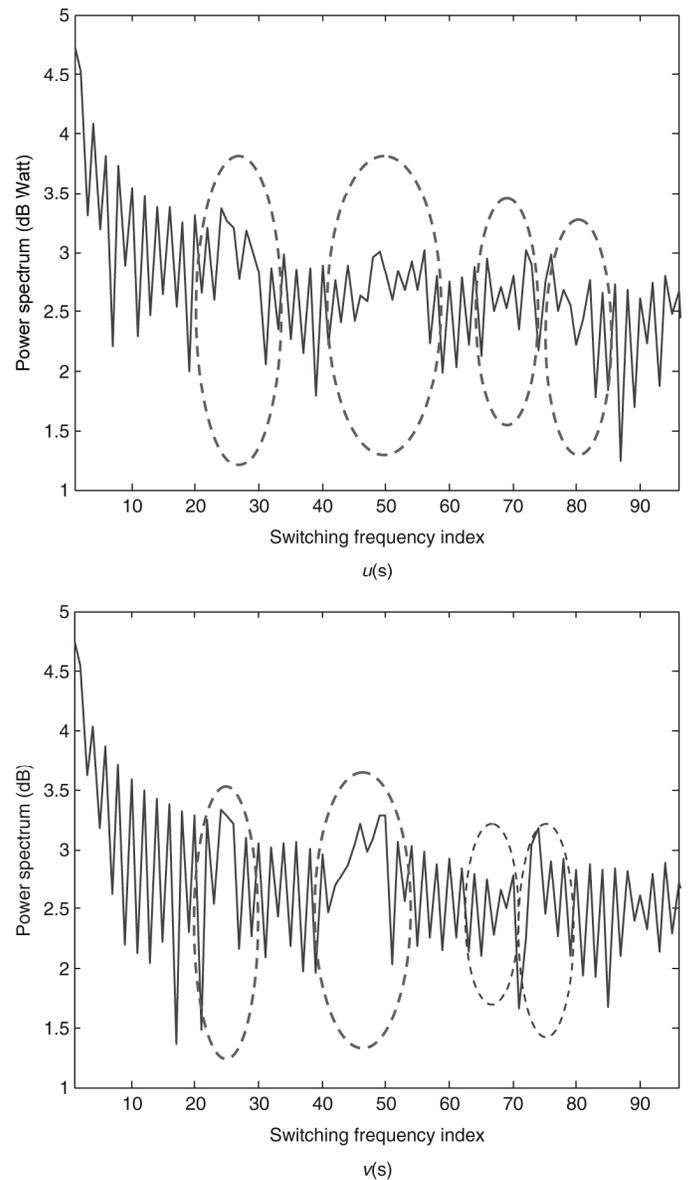


Figure 4. Fourier transform of monthly average consumption.

with distinguishable weather conditions, there are chances that the mutual overlaps of loads' switching spectrum may take the form of flat spectrum fading their distinguishable switching frequencies. In other words, care should be given on the time span of load aggregates.

6. How the Two Methods Compliments

Both methods are logically sound on searching customers' flexibility. However, observing the data in switching domain merges *load factor* and *relevance* criteria into single parameter that can be identified from switching characteristics, i.e., the energy under a specific loads' switching spectrum (Fig. 4). Moreover, a decision made on bulk algebraic computation may easily leave a chance of misjudgment that may come from similar numbers. On the other hand, the decision made through such computation may be questioned for insufficiency of intelligence programmed.

The PCUE developed method strengthens the computer routine to yield more realistic visually identifiable result. Also the design of GUI for accessing data file for MatLab™ and the plots was an attempt to mitigate the usual fatigue arising from analysis of very large data sets. As mentioned earlier, while both methods yield screened customers, eventually there are some discrepancies due to the unknown measure of the stiffness on the selection process or simply conflicts of viewpoints.

7. Conclusion

This is an interim research paper on the recent stage of TECO consolidated project named Advanced Commercial Energy (ACE)-DSM. In the next step some sifting methodologies are going to be used to complete finalizing the list of selected customers. On those sifting processes weather correlation, economic limitations and customer comfort indices will be emphasized. It is worth to mention that through long-term studies on practical price responsive DSM programs it came to clear view that customers played vital role on DSM and their spontaneous participation ensures the success of the technology deployed on premises.

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Other resources

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Biographies



Alex Domijan obtained his B.S.E.E. degree from the University of Miami, M.E. degree in electric power engineering from the Rensselaer Polytechnic Institute, Troy, N.Y. and Ph.D. degree in electrical engineering from the University of Texas at Arlington. He was a member of the electrical engineering faculty at the University of Florida and director of the Florida Power Affiliates and

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