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A Balancing Demand Response Clustering Approach of Domestic Electricity for Day-Ahead Markets

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Abstract—This paper introduces a new clustering approach for multi-customer intelligent demand response for customers living in the same or closer smart grid locations using real electricity consumption data from smart meters. Most of the demand side management or customer tariffs focused on a single customer to optimize their usage discarding the others connected to the same grid. The proposed balancing clustering focus on the customers connected to the same or closest grid to optimize the smooth operating of the energy producers. This approach offers a triple win-win-win model for peak and low consumption customers as well as the balancing for the producer/ distributor utility companies for planning the day ahead markets. This paper uses the most widely used clustering method of k-means for finding similar customers on the opposing side peak, low consumption profiles and combines the most distinguished customers forming more uniform consumption for day-ahead market. This customer balancing and grouping them provides a better way toaggregate residential load data for power buy and sell for all sides and results in better load scheduling.

Keywords-*clustering, balancing demand response, smart meters, smart customer profiles, smart meter analytics, intelligent dsm, day ahead markets*

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I. Introduction

Developments in information and computer technologies, imminent depletion of fossil-based natural resources are forcing humanity to act smart when generating and consuming its electricity needs. Renewable energy systems are the cleanest electricity generation method that is available today, but due to its randomness in availability factor, it requires a grid system which can compensate any drop due to renewable energy unavailability.[1] Electric consumption is the other important factor which is purely dependent on people. Therefore, it is influenced by many factors and events.[2, 3] Socio-economic parameters, geographic factors, education level, industrialization, urbanization and climate directly affect many parameters in electricity demand and has a strong impact on load curves. Conventional generation, distribution, and consumption of electricity was a brute force approach that had overall low efficiency, less management, and control over the system. Growing technology, population, and increase in overall human comfort are increasing electricity demand exponentially. [4-6]

Since electricity is very different from other economic commodities and goods with the following issues. Electricity cannot currently be stored in the commercial size for next day or next week efficiently. Delivery of the good requires the electricity grid which is different from fast moving consumer goods at any moment supply and demand must match almost exactly to avoid blackouts or other technical issues. The transmission capacity of the electricity grid also limits the amounts of goods delivered to residential. Therefore, for an electricity grid to function safely and efficiently, the configuration and physical limits of the grid and the locations of generation and consumption must be taken into account when making decisions about consumption and production.[7]

Supply and demand of electricity market as well as with pricing models in electricity markets is a very common issue in different studies in both prediction, modeling, and forecasting of customers. [8-11]

The common approach for managing electric grid will provide better usage of natural resources. Peak load reduction can only be done by changing customer behaviors by creating a demand response. Increasing and decreasing the prices of electricity for forcing people to manage their consumption during peak hours to incentivize shift able loads being used during off-peak hours will provide a more stable electric grid and decrease wholesale electric market price. Dynamic pricing can provide a significant decrease in peak loads.[12-16]

This increase, especially during peak hours, is requiring a high capacity electric grid that can provide customer needs if there is a distinct difference between peak load and base load that will make an optimum usage where most of the plants are running at full capacity during peak hours and becoming idle during base load periods. This is a highly undesired condition because of nature of plants that can go active during peak hours.

Electricity generation must match the demand at each instant, following seasonal patterns and instantaneous fluctuations. Thus, one of the biggest drivers of costs and capacity requirements is the electricity demand that occurs during peak periods.[17]

Plants that go active during peak load periods which is also known as peak hour plants must have a dynamic response to demand which is provided with natural gas burning stationary gas turbines. [18-20]

For many reasons, electric utilities and power network companies have been forced to restructure their operations from vertically integrated mechanisms to open market systems with the restructuring and deregulation of the electricity supply industry, the philosophy of operating the system was also changed. The traditional approach was to supply all power demands whenever they occurred. However, the new philosophy states that the system will be most efficient if fluctuations in demand are kept as small as possible.[21]

II. Demand Side Management, Demand Response And Customer Response

Demand Side Management, DSM refers to only energy and load-shape modifying activities such as planning, implementing, and monitoring activities of electric utilities that are undertaken in response to utility-administered programs improve the energy system at the side of consumption. It ranges from improving energy efficiency by using better materials, over smart energy tariffs with incentives for certain consumption patterns, up to sophisticated real-time control of distributed energy resources. [22]

In the past, the primary objective of most DSM programs was to provide cost-effective energy and capacity resources to help defer the need for new sources of power, including generating facilities, power purchases, and transmission and distribution capacity additions. However, due to changes that are occurring within the industry, electric utilities are also using DSM to enhance customer service.[23-25]

DSM does not refer to energy and load-shape changes arising from the normal operation of the marketplace or government-mandated energy-efficiency standards.

Demand Response, DR can be defined as the wide range of actions and changes in electricity usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time as well as the incentive payments designed to induce lower electricity use at times of high wholesale market prices. Different than DSM, DR includes all intentional electricity consumption pattern modifications by end-use customers that are intended to alter the timing, level of instantaneous demand, or total electricity consumption.

In principle DR initiatives can bring about significant reductions in electricity prices, as shifts of demand during peaks could reduce the need for higher marginal cost generation, offer lower cost system balancing and decrease grid reinforcement investment.[26]

Customer Response can be defined as the response of the customer for demand response actions. In general, three types of common responses obtained from the customer. First, customers can reduce their electricity usage avoiding consumption during based on critical peak periods when prices are highest without changing their consumption pattern during other periods. Most of the time this option involves changing behavior, conditions, and comfort. This customer response is achieved, for instance, when thermostat settings of heaters or air conditioners are temporarily changed on peak hours. This type of customer response does not make any shifts to other hours. Secondly, customers may respond to high electricity prices by shifting some of their peak demand operations to off-peak periods, as an example, they shift some household activities like cleaning, the instant user of hot water for shower, use of dishwashers, pool pumps, vacuum cleaners, ironing to off-peak periods. The residential customer, in this case, will bear no loss and will incur no cost. The third type of customer response is by using onsite micro-generation from renewables, heat pumps and other customer-owned distributed generation. Customers who generate their power may experience no or very little change in their electricity usage pattern; however, from utility perspective, electricity use patterns will change significantly, and demand will appear to be smaller.[27]

III. Residential Consumption And Pricing Models

Electricity market tariff can be defined as the rate customers receive the electricity service from their provider. Another definition can be made as the pricing of demand response and customer response on the utility and market side.

Because of an increase in electrification in all aspects of daily life, electricity demand has risen rapidly, especially during peak hours. Suppliers must have adequate capacity to meet peak load requirements of the grid. Different approaches to managing peak load is possible such as peak hour power plants, pumped hydropower plants, large-scale stationary battery systems, etc. where results will vary depending on country's fuel prices and technological advancement. [28]

A different approach is to manipulate customer behavior as defined the customer response so investments for peak hour power plants(which uses more expensive fuels or has less efficiency) are not required which will result in a decrease in wholesale electricity prices. One of the main reasons why dynamic pricing programs are found in the first place is the need to reduce peak load magnitude and duration. Dynamic pricing methods can be implemented to directly prevent that load from ever happening or create incentivize for shifting it to off-peak periods.

A good tariff policy would have a rate which is high enough for suppliers, so they will earn some profit for their capital investment after their generation and maintenance cost is covered. At the same time prices should be low enough so the customers will be incentivized to consume electricity if suppliers can provide it.

Traditional methods of tariffs could be counted as the simple tariff, flat-rate tariff, block rate tariff, two-part tariff, maximum demand tariff and power factor tariff. [21, 29, 30]But due to increasing technology, grid system priorities and environmental concerns changes in tariff approach have to be made. Modern pricing methods exploit technological advancements such as smart grid metering and intelligent appliances.

Most popular dynamic pricing methods in the market are:

- Time-of-Use(TOU): Where there is a fixed amount of price increase during peak hour. Peak time prices are relatively higher when compared to off-peak time. Application of TOU levels and duration may differ between providing companies. The main goal in this price increase is to make people shift their peak time consumption to off-peak time. TOU applications may vary during a year as well. Extreme weather conditions may increase consumption in the morning and evening during winter while during summer peak consumption is generally during theafternoon as most buildings operate their air conditioning systems which will boost their consumption greatly.[31-34]
- Critical Peak Pricing(CPP): A specialized version of TOU, CPP aims to reduce highly critical values. After a load forecasting, if following day is classified as critical day, CPP is declared. Generally declared at least one day before the action. CPP can be declared for many consecutive days. CPP can be managed to handle extreme cases as well, i.e. Maintenance of some big scale power plants, hydropower plants not operating due to drought, etc. Manipulating customers to shift their loads to off-peak periods, peak loads can be managed while not operating peak hour power plants. [35-37]
- Peak Time Rebates(PTR): Customers are paid back for energy saving they did during peak demand.[38-40]

- Real-Time Pricing(RTP): Real-time pricing requires IED infrastructure which is generally done by smart metering devices. Real-time pricing can be implemented beforehand or can be updated hourly during the day. Reflecting wholescale market price(as peak hour plants go active during peak demand, the overall costforelectrical energy increases, therefore wholesale electricity price increases greatly). Customer behavior and participation is a key element in RTP where customers can evaluate wholesale market prices. RTP is the most sophisticated pricing program with highest possible reward whereas TOU is regarded as the simplest one with lowest possible reward and risk.[41]

IV. Machine Learning and Clustering

Machine learning is the science of getting computers to act without being explicitly programmed. Machine learning can be divided into three main learning patterns such as supervised, unsupervised and reinforced learning. [42-44] Most of the people confuses the machine learning is some making and programming intelligent robots which learn and acts. In fact, it is not wrong however machine learning uses the theory of statistics in building mathematical models because the core task is making an inference from a sample. [45]. Depending on the type of mathematical input and output; machine learning can be divided into three methods. Predicting continuous values by learning the relations between the input and the output from a sample provided by the supervisor is called regression. A good example for this is predicting the peak hour demand for the customers for the future. The second method is predicting the discrete value or namely the class again learning from a sample input given by the supervisor, like predicting the tomorrow's weather like sunny, cloudy or rainy without proving continuous values. On the other hand, the third method is unsupervised learning. Like classification without the lack of discrete outputs, just the input data. Like the hourly electricity consumption of customers. In other words, clustering is the process of grouping the data into classes or clusters so that objects within a cluster have high similarity in comparison to one another, but are very dissimilar to objects in other clusters. Classification is supervised learning algorithms in contrasts with clustering, which are unsupervised learning algorithm [46] The most common classification data mining techniques are Case-Based Reasoning, Decision tree, Backpropagation neural network, Radial basis neural network, Bayesian classification, Rough set Approach, Fuzzy Set Approaches, K-nearest Neighbor classifiers. [47]

These methods are widely used in nowadays different data mining and big data analytics problems. There are also various studies based on the customer clustering based on the electricity consumptions. [7, 48-52] Most of the papers used and found that the k-means clustering works well on customer clustering based on hourly consumption values. However, all these studies focus on the customers as individuals and customer response policies.

V. Customer Data Structure

The electricity consumption for various customer data taken from smart metering trial carried out by Ireland Commission for Energy Regulation(CER). The data includes a detailed questionnaire which provides customer information[53]. The trial was conducted between 2009 and 2010 and consisted of installing smart meters in over 4000 residential houses collecting consumption data at half hourly intervals. Data also has dimensions like occupant and appliance characteristics for a representative sample of residential houses in Ireland was recorded. The data provided was in the anonymized formatto protect personnel and confidential information relating to the customer.[51] This data has also been used in various clustering and energy policy research papers. [54-57]

The idea behind the paper is based on different customers with different income, house formation, electricity consumption of various devices in the house and more over the customer response behaviors of the customers for demand-side management programs and willingness to change their living styles and consumption pattern as well as replacement of some equipment’s in the house to energy saving devices. The following consumption figures are plotted for different profile customers selected by sampling according to their answers to the questions. The data plotted weekdays and weekends also for different months to observe usage on the electricity consumption. As can be seen from the figures all customers have different profiles living in similar areas.

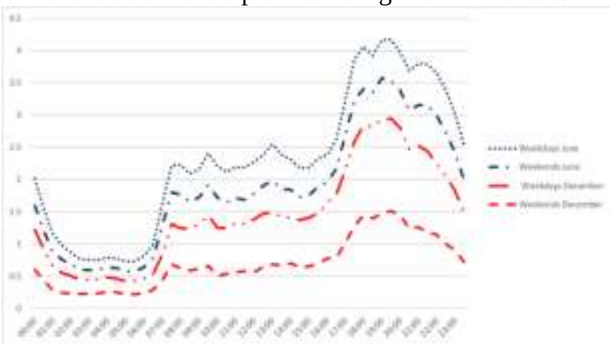

Figure 1. Average Electricity Consumption of Selected Customers

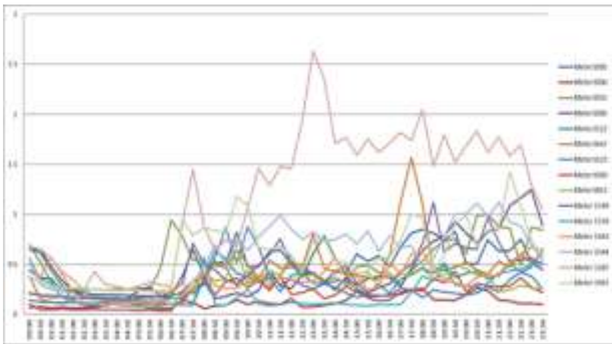

Figure 2. Average Electricity Consumptionfor June 2010 Weekdays

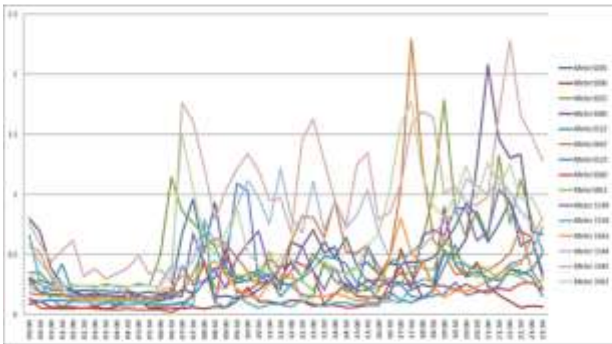

Figure 3. Average Electricity Consumptionfor June 2010 Weekends

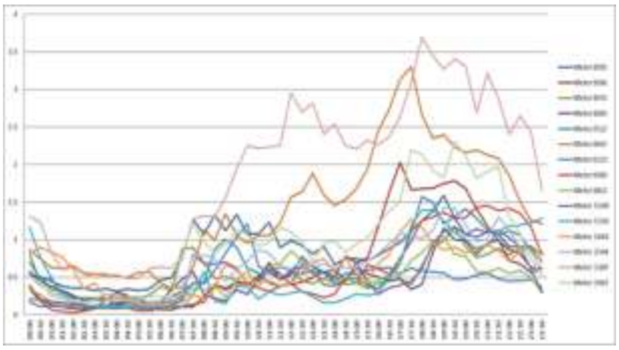

Figure 4. Average Electricity Consumptionfor December 2009 Weekdays

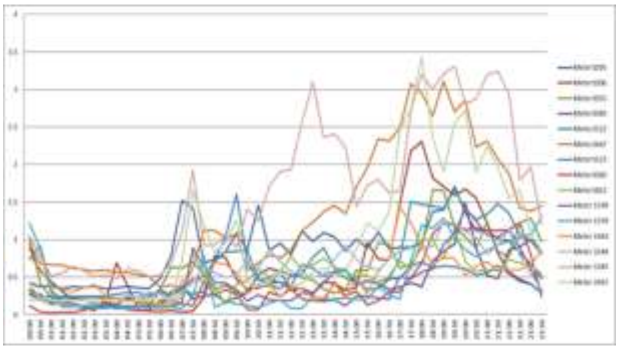

Figure 5. Average Electricity Consumptionfor December 2009 Weekends

As can be seen from the figures average consumption of different customers forms a similar trend with a different magnitude in June and December where HVAC, lightningand other consumptions mostly affects the consumption. On the other hand, looking by customer by customer consumptions are not similar even for the same house for weekend and weekdays. The main idea behind the paper is due to the changes in the customer types they cannot be fitted into standard tariffs based on individual consumption profiles.

Since the study includes the profile questions as follows a pre-clustering can be done by looking at their answers to selected questions like;

- know enough about how much electricity different appliances use in order to reduce my usage,
- have enough time to reduce my electricity usage,
- reducing usage would not make enough of a difference to bill,
- heating water equipment,
- heating home equipment,
- prefer cool/warm inside,
- electrical devices and appliances,
- willing to switch electricity suppliers in the market

VI. CLUSTERING MODEL AND ALGORITHM

The main aim of the clustering model and algorithm is to provide a better prediction to electricity producers for the day ahead market as well as to provide a uniform customer behavior at the total of demand one different timing.

The data cleaned, normalized and prepared for clustering with WEKA software packet k-means clustering with automatic selection of k. So, the algorithm restarts k-means and selects the best k using the Calinski and Harabasz criterion, without cross-validation. As a result of the clustering similar customers with similar consumptions obtained. [58]

This is not different than most of the other studies except the data is also enriched with profile questions and inputs. So, the input matrix includes both the consumption and the profile properties.

The individual clusters formed by WEKA and created as profiles for the customer database system can be seen from Table 1.

The algorithm that works for the calculation for the day ahead market biddings and sells first look at the clusters for the average for the customers from the previous year's smart metering data.

Clustering obtained for the next day assumptions also created for daily, weekly and monthly for the day ahead and based on general customer agreements for the electricity utility company.

From the utility company a general optimization based on the possible usage also with clustering the customers and joining different ones also the similar ones into one aim to maximize the profit by increasing the sales with decreasing the amount of money paidby the customers. In this model, the less consumption profile customers even pay less, and the peak consumption profile customers peak less than normal payments due to the overall bargain and pricing mechanism. From the utility company side, the information is the power and stability of the power line increases the purchase power and bargaining with other energy producers in the area or the company.

TABLE I. SAMPLE CUSTOMERS CLUSTERING

Customer	**3697**	**1005**	**1006**	**3344**
Clusters	010(15%)	010(15%)	05(8%)	06(9%)
	15(8%)	15(8%)	11(2%)	16(9%)
	23(5%)	23(5%)	22(3%)	28(12%)
	34(6%)	34(6%)	36(9%)	38(12%)
	44(6%)	44(6%)	43(5%)	411(17%)
	55(8%)	55(8%)	57(11%)	58(12%)
	619(29%)	619(29%)	616(24%)	66(9%)
	71(2%)	71(2%)	77(11%)	76(9%)
	88(12%)	88(12%)	811(17%)	84(6%)
	97(11%)	97(11%)	98(12%)	93(5%)
Customer	**1055**	**1083**	**2522**	**2667**
Clusters	010(15%)	013(20%)	02(3%)	027(41%)
	116(24%)	113(20%)	15(8%)	113(20%)
	231(47%)	225(38%)	26(9%)	25(8%)
	34(6%)	32(3%)	35(8%)	321(32%)
	44(6%)	41(2%)	45(8%)	
	51(2%)	512(18%)	54(6%)	
			617(26%)	
			714(21%)	
			88(12%)	

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