A NOVEL APPROACH TO TARIFF DESIGN AND CUSTOMER CLASSIFICATION IN DEMAND SIDE MANAGEMENT APPLICATIONS

Burak Işık
[1]Mechatronics Engineering Department, Istanbul Commerce University, Istanbul, Turkey
Corresponding author: Burak Işık, e-mail: burakisik@ticaret.edu.tr

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ABSTRACT

Developing energy policies to satisfy current demand while providing a sustainable development is one of the most important topics in current energy research areas. As more and cheaper Information Communication Technology (ICT) products are developed, penetration of those products in households and their total consumption is also increasing. Due to semi-random nature of household consumption behavior, residental customers are cause of peak loads which effects green house gasses, grid reliability and wholesale market prices.

In this study, a new method for customer pricing is proposed as customer group day ahead power buy. Aim is to cluster customers to provide a much stable load profiles which can be incentivized by offering certain discounts. k means clustering is performed on normalized monthly average load profiles also effects of certain parameters like customer characteristics, weekday/weekend variation and seasonal effects are investigated.

1. INTRODUCTION

Sustainable development is a hot topic to find effective methods to improve and prolong comfort for humanity. As most of the fossil based fuel resources are expected to be depleted in next two centuries, renewable energy sources are emerging as a possible candidate to replace most fossil based systems that are in use today. However, randomness of renewable energy sources (weather conditions) are reducing their current effectiveness. Therefore an adequate use of system resources holds great importance. With increasing technology, cheaper and more Information and Communication Technology(ICT) products are being used by residental consumers.[1] Currently, residental total final electricity consumption has reached more than a quarter of final electricity consumption(IEA).

Daily variations in grid demand requires control effort through management of generating power plants. Plants that have the capability to have dynamic response for load changes require additional investment and contibutes to 20% of total electricity generation capacity only to have 5% uptime.[2]

Another method to shift or reduce peak loads is through demand side response. Demand side response method uses dynamic pricing to incentivize customers to shift their load to gain economic benefit.[3] Dynamic pricing programs are being tested in various case studies and local optional programs.[4] Most commonly used dynamic pricing methods are:

- Time-of-Use (TOU): Pricing levels may be divided into 2 or more levels depending on grid demand.
- Critical Peak Pricing (CPP): Generally performed on extreme conditions, CPP may reach varying amounts to prevent system catastrophes
- Real Time Pricing (RTP): Daily price is directly effected by wholesale market prices.

Currently Turkey electricity pricing is regulated by EPDK providing a constant pricing throughout the day and an optional TOU pricing with day time tariff, night time tariff and peak time tariff. Peak time lasts 5 hours and priced according to peak load, day time lasts 11 hours priced according to mid-peak time night time lasts 8 hours and priced according to off-peak time.

Due to nature of human behaviour, electricity consumption has a semi-random consumption effected by 3 major factors:

- Physical properties: Climate, residence age and insulation.
- Appliances and their usage pattern:
- Household characteristics: Household demographics and active consumers during day.

Increasing technology has provided new methods to measure collect and store electricity customers consumption data in certain intervals through smart metering. Customer classification is a key element for forming an effective dynamic pricing program. Clustering customers depending on their load profiles allows predicting possible customers which can perform load shifting to pay less [5]. Various methods and their performances have been reviewed by G. Chicco[6].

2. METHODOLOGY

In this study, smart meter readings of various households are combined with their detailed household consumption survey. Combining smart meters and survey information is a key factor for customer classification and predicting expected customer of new customers enrolling for utility companies.[7] By applying consumption survey, new customers can be offered certain billing systems or can be advised for methods to reduce their electricity usage.

Ireland electricity and natural gas sectors are regulated by the CER. A pilot project conducted includes more than 5000 households and small-medium enterprizes during 2009 and 2010. Main purpose of "The Smart Metering Electricity Customer Behaviour Trials was to gather important parameters that effect different consumption of individual customers. Smart meter data is also supported with consumption surveys that includes great details about characteristics of building, household, appliances and their usage. Data is anonymized to provide customer privacy.

Smart meter consumption data is provided in ".txt" format seperated into 6 different ".txt" files. First 3 columns of data corresponds to MeterID, five digit code that represent time and electricity consumption during 30 min interval in kWh unit respectively. MeterID for File1.txt represent customers coded 1000-1999 as MeterID, File2.txt represent customers coded 2000-2999 as MeterID, File3.txt represent customers coded 3000-3999 as MeterID, File4.txt represent customers coded 4000-4999 as MeterID, File5.txt represent customers coded 5000-5999 as MeterID. 1st 3 digits of five digit code represents date (day1= 1st January 2009) remaining 4th and 5th digit representing time from 1 to 48 each increase resulting in 30min increase in time(1 = 00:00:00-00:29:59).

2.1. Preparing Data

".txt" files are imported into Matlab to provide time efficient seperation for desired data. Later 2nd column of raw data has been seperated to provide appropriate representation of day and time codes. For each customer there are 25728 rows of 30min interval consumption data.

A group of consumers having different survey information have been chosen to investigate some of the most anticipated factors in household consumption. Total number of appliances, electricity usage of certain tasks, age of the building, number of people living in the house and number of active consumers during day are investigated parameters.

MeterID have been filtered to get daily load data for specific customers. Some characteristic seasons have been chosen to investigate daily, weekly average and monthly average data for consumption. Seasons chosen are autmn, winter and summer.

2.2. Forming load profiles

For each customer monthly average load profiles are formed by using excel features. This load profiles allow us to gather certain differences for weekday and weekends, seasonal consumption changes etc.

Survey data provided by CER allows mapping of household characteristics and load profiles. When provided with both survey data and load profiles, it is possible to get more accurate forecasting and even implementing machine learning techniques for better planning.

Table 1. provides generalized information that is relevant to electricity usage. As reviewed before, residental electricity consumption is directly effected by physical conditions, electrical appliances with their usage information and resident behaviour.

Table 1. Some of the consumption parameters for chosen group of customers.

MeterID	#of people living	#of active consumers during day	Total # of appliances
1005	2	0	10
1055	2	0	8
1060	2	2	7
1083	2	0	13
1123	2	0	8
1549	4	0	15
1559	1	0	6
1663	6	6	12
1812	4	0	16
2522	2	2	10
2667	2	2	7
3344	6	1	12
3387	6	0	13
3967	6	5	16

Climate and season is directly effective on electricity consumption instensity and shape of the load profiles. For Comparison group 1, during 2009 December it has been observed that averaged peak values can reach up to 8 times base load of December consumption both in weekends and weekdays. As can be seen on Fig1. Obvious factors like insulation of the building and heating type is directly effective on building electricity consumption.

Table 2. “Comparison group 1” key characteristics.

MeterID	Water heating	Total number of appliances	Has electric shower ?
1005	Oil	10	Yes
1055	Oil	7	No
1083	Electric immersion	11	Yes
1123	Electric immersion	8	Yes

Comparison group 3 analyzes consumption characteristics provided on Table3. for two residents having 4 people above 15 years old and none of them are active consumers during day. Surveys point out there is significant difference in household appliance usage patterns, building physical properties and water heating method

Properties provided on Table 2, comparison group 2 studies a similar case to group 1 but this time residents are active consumers during day. Comparison group 2 focused on appliance usage differences’ effect on consumption. Tumble dryer is one of the most power consuming appliances that is present in the survey. Most of the household demographics and residence physical properties are similar. Difference of appliance usage frequency provides a significant change to load profiles

Table 3. “Comparison group 2” key characteristics.

MeterID	Washing machine frequency	Tumble dryer frequency	Electric shower
1060	Less than 1 load daily	Less than 1 load daily	10-20 mins
2522	Less than 1 load daily	Less than 1 load daily	5-10 mins
2667	1 load daily	1 load daily	10-20 mins

This comparison is a perfect example for checking the difference between weekdays and weekends aswell. Weekdays monthly average for June shas two local peaks which are mainly when household wakes up and gets ready for their job/school and when they come back to the household and perform their evening activities like cell phone charging, cooking, watching TV etc. until they sleep. Between 01:00 and 06:00 it is expected that only consumption in household is due to continuous appliances such as fridge, burglar alarm, internet router and standby and off-mode consumption of appliances such as TV, computer. Weekend monthly average consumption profiles for both June and December differs greatly from their weekday counterparts. During weekend vacancy and day-time consumption is totally randomized and weekend consumption allows more flexibility for load shifting as there is no large gap during work/school time, residents can perform indoor activities as they want. June and December differences are heaily effected by residence physical properties. Old building with poor insulation causes customer 1812 to consume more during off-peak hours. There is around 50% increased consumption in day-time off peak hours and around 100% increase for peak hours. December weekdays average of customer 1549 is just a magnified version of their June consumption as they have relatively new building with proper insulation however their energy intensive consumption still proves to be greater than customer 1812 during peak hours.

Table 4. “Comparison group 3” key characteristics.

MeterID	Electric cooker	Electric convector heater	Gaming console
1549	30-60 minutes	30-60 minutes	1 – 3 hours daily
1812	No electric cooker	No electric convector	No gaming console

Comparison 4 reflects effect of appliance usage intensity and ownership of different appliances. Both residents houses 2 adult and 4 kids while having similar physical properties. According to survey information, apart from white goods, customer 3387 owns more ICT products and have intense usage Even though customer 3344 owns a stand alone freezer and water pump, intense usage of white goods and ICT products causes customer 3387 monthly average consumption to be greater.

Table 5. “Comparison group 4” key characteristics.

MeterID	Washing machine usage	Tumble dryer usage	Dishwasher usage	Gaming console usage
3344	Less than 1 load daily	Less than 1 load daily	Less than 1 load daily	Doesn’t have
3387	2 to 3 loads daily	1 Load daily	2 to 3 loads daily	3-5 hours per day

Comparison 5 focuses on effect of electrical space heating on monthly average consumption and its results on June-December comparisons. Customer 1559 is living alone and an employee whereas customer 1663 survey information claims that household is consisting of 2 adults and 4 kids which are all active consumers during day. Customer 1559’s residency has poor insulation when combined with electrical space heating is expected to increase electricity consumption especially during winter. Having less electrical appliance than customer 1663 and being absent during day during off-peak hours customer 1559 should have less monthly average weekday consumption than customer 1663.

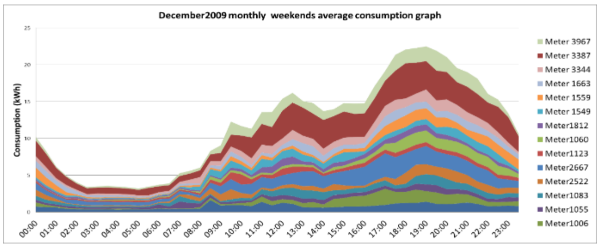

Fig1. December 2009 monthly weekends average consumption data accumulated.

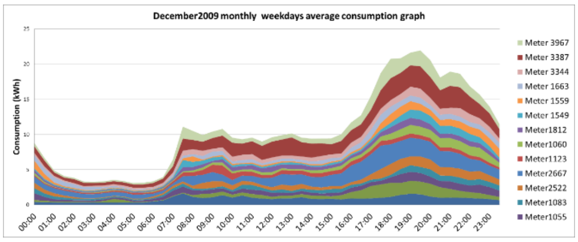

Fig2. December 2009 monthly weekdays average consumption data accumulated.

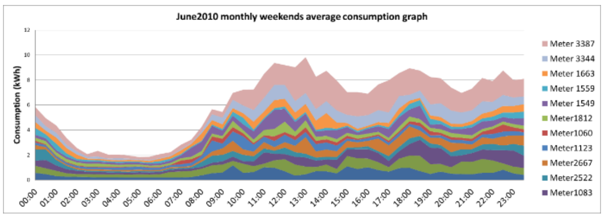

Fig3. June 2010 monthly weekends average consumption data accumulated.

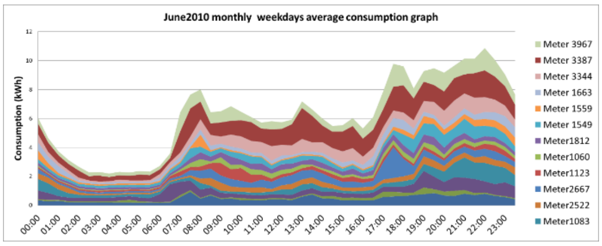

Fig4. June 2010 monthly weekdays average consumption data accumulated.

Table 6. provides general physical properties of examined households while providing effect of seasonal changes on monthly average consumption changes.

Table 6. Survey data regarding June-December consumption change.

ID	Building age	Convector heater	Overall Insulation	Summer-winter consumption change
1005	Very old	Yes	Moderate	Moderate increase
1055	Moderate	No	Proper	No change
1060	Old	Yes	Proper	Dramatic increase
1083	Moderate	No	Moderate	No change
1123	Moderate	No	Inferior	Moderate increase
1549	Moderate	Yes	Proper	No change
1559	Very old	No	Moderate	Dramatic increase
1663	New	No	Proper	Moderate increase
1812	Very old	No	Moderate	Moderate increase
2522	Very old	No	Proper	Moderate increase
2667	Very old	No	Moderate	Dramatic increase
3344	New	No	Proper	Moderate increase
3387	New	No	Proper	Moderate increase

3. CONCLUSIONS

k means clustering through WEKA software has been performed. Cleaned and normalized k means clustering allows automatic selection of k. By using the Calinski and Harabasz criterion, automaticly the best k values are achieved without cross-validation. Customers having similar consumption are gathered through clustering to form a valid customer grouping and customer selection.[8] Table 7. provides the result of WEKA results of k means clustering.

Table 7. Consumption parameters for chosen group of customers.

Customer	3697	1005	1006	3344
Clusters	0 10 (15%)	0 10 (15%)	0 5 (8%)	0 6 (9%)
	1 5 (8%)	1 5 (8%)	1 1 (2%)	1 6 (9%)
	2 3 (5%)	2 3 (5%)	2 2 (3%)	2 8 (12%)
	3 4 (6%)	3 4 (6%)	3 6 (9%)	3 8 (12%)
	4 4 (6%)	4 4 (6%)	4 3 (5%)	4 11 (17%)
	5 5 (8%)	5 5 (8%)	5 7 (11%)	5 8 (12%)
	6 19 (29%)	6 19 (29%)	6 16 (24%)	6 6 (9%)
	7 1 (2%)	7 1 (2%)	7 7 (11%)	7 6 (9%)
	8 8 (12%)	8 8 (12%)	8 11 (17%)	8 4 (6%)
	9 7 (11%)	9 7 (11%)	9 8 (12%)	9 3 (5%)
Customer	**1055**	**1083**	**2522**	**2667**
Clusters	0 10 (15%)	0 13 (20%)	0 2 (3%)	0 27 (41%)
	1 16 (24%)	1 13 (20%)	1 5 (8%)	1 13 (20%)
	2 31 (47%)	2 25 (38%)	2 6 (9%)	2 5 (8%)
	3 4 (6%)	3 2 (3%)	3 5 (8%)	3 21 (32%)
	4 4 (6%)	4 1 (2%)	4 5 (8%)	
	5 1 (2%)	5 12 (18%)	5 4 (6%)	
			6 17 (26%)	
			7 14 (21%)	
			8 8 (12%)	

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