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GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

TARIFF DESIGN FOR ENERGY PRODUCTION AND DISTRIBUTION WITH MACHINE LEARNING

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ACCEPTANCE AND APPROVAL PAGE

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MAKİNE ÖĞRENMESİ KULLANILARAK ENERJİ ÜRETİM VE DAĞITIMINDA TARİFE MODELLENMESİ

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Danışman: Yrd. Doç. Dr. Alper ÖZPINAR

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Bu çalışmada,
Aynı veya daha yakın akıllı şebeke konumlarında yaşayan elektrik müşterilerinin akıllı talep tarafı yönetimi için yeni bir kümeleme yaklaşımı önerilmiştir. Literatürdeki çalışmaların çoğu, her bir müşterinin bireysel tüketim davranışlarına odaklanırken, bu çalışma, enerji üreticilerinin düzgün çalışması için aynı veya en yakın şebekede gruplanmış müşterilerin kümelenmesini optimize etmektedir. Bu yaklaşımın sağladığı en büyük avantaj, puant ve baz tüketimli müşterileri dengeleyerek elektrik şirketlerinin gün öncesi planlamasına fayda sağlamaktır. K-ortalamalar kümesi yöntemi, günlük boyunca daha üniform bir yapı sağlamak üzere birbirlerini dengeleyecek baz ve puant tüketiciler için benzer tüketicileri bulma imkanı sağlar ve mesken müşteriler için yük çizelgeleme ve güç satın alımı için daha iyi bir çözüm sunar.

Anahtar Kelimeler: Akıllı müşteri profilleri, kümeleme, akıllı sayaçlar, akıllı sayaç analitiği, dengeleyici talep tepkisi, sonraki gün piyasası.

ABSTRACT

M.Sc. Thesis

TARIFF DESIGN FOR ENERGY PRODUCTION AND DISTRIBUTION WITH MACHINE LEARNING

Burak IŞIK

İstanbul Commerce University
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Department of Mechatronics Engineering

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In this study,

A new approach have been proposed for intelligent demand side management in clustering of electricity customers living in the same or closer smart grid locations. While most of the studies in literature focuses on individual consumption behavior of each customer, this study optimizes clustering of grouped customers in the same or closest grid for smooth operation of the energy producers. Greatest advantage provided by this approach is its capability to provide benefits to utility companies' day ahead planning by balancing peak and low consumption customers. K-means clustering method provides finding similar customers for low and peak consumers that balances each others load to provide a more uniform throughout a day provides a better solution for load scheduling and power buy for residental customers.

Keywords: Balancing demand response, clustering, day ahead markets, smart customer profiles, smart meters, smart meter analytics.

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İSTANBUL, 2018

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SYMBOLS AND ABBREVIATIONS

ANN	Artificial Neural Network
BESS	Battery Energy Storage Systems
CER	Commission for Energy Regulation
CPP	Critical Peak Pricing
DP	Dynamic Pricing
DR	Demand Response
DSM	Demand Side Management
DoD	Depth of Discharge
GHG	Greenhouse Gas
HEMS	Home Energy Management Systems
ICT	Information and Communication Technologies
IoE	Internet of Energy
IoT	Internet of Things
IEA	International Energy Agency
MENR	Ministry of Energy and Natural Resources
NIST	National Institute of Standarts and Technology
OECD	Organization for Economic Co-operation and Development
PAR	Peak to Average Ratio
PHEV	Plug-in Hybrid Electrical Vehicles
PV	Photovoltaic
RES	Renewable Energy Systems
RTP	Real Time Pricing
SoC	State of Charge
SVM	Support Vector Machine
ToU	Time of Use
V2G	Vehicle-to-Grid

1 INTRODUCTION

Dynamic electricity pricing is an indirect method for managing peak loads in electricity grids. Main purpose is to develop a tariff policy to give customers incentive to shift their electricity consuming habbits to off-peak periods. Through smart programmable home appliances such as dishwasher, dryer etc. most appliances can be programmed to operate during off-peak periods.

Overall economic growth, rapid increase in technology and cheaper appliances and product having more penetration in daily use is increasing electricity demand across the globe. Residental energy demand has a considerable share in total energy consumption and its share is increasing over decades as can be seen on Figure 1.1. World gross electricity total final consumption from 1971 to 2015 by sector.

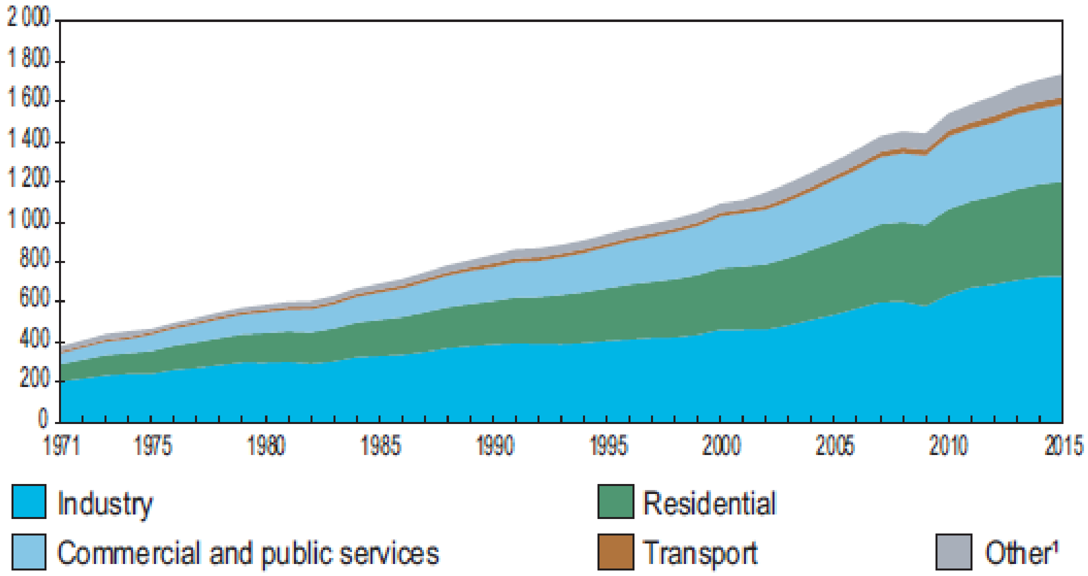


Figure 1.1. World gross electricity total final consumption from 1971 to 2015 by sector.

Conventional power system is over-achieving peak demand requirements to provide some spare capacity for emergency cases (decreases in renewable energy availibility, unexpected increase in demand, maintenance and malfunctioning of active power plants). Generally 20% of the instaled capacity only goes active during peak demands which happens to be happening for approximately 5% of the time. This is why an alternate approach is required to provide better solution for electricity market management. Rather than building electricity grid to reflect consumer parameters, incentivizing customers to manage their load according to optimum management of resources which is called demand side management (DSM). Currently energy consumption of the residental sector accounts for around 30-40% of total energy use. According to International Energy Agency (IEA) statistics (IEA, 2017), world gross electricity consumption in residental sector has a share of 27,1% while this share is 31,1% and 23% in Organization for Economic Co-operation and Development (OECD) and non-OECD countries respectively.

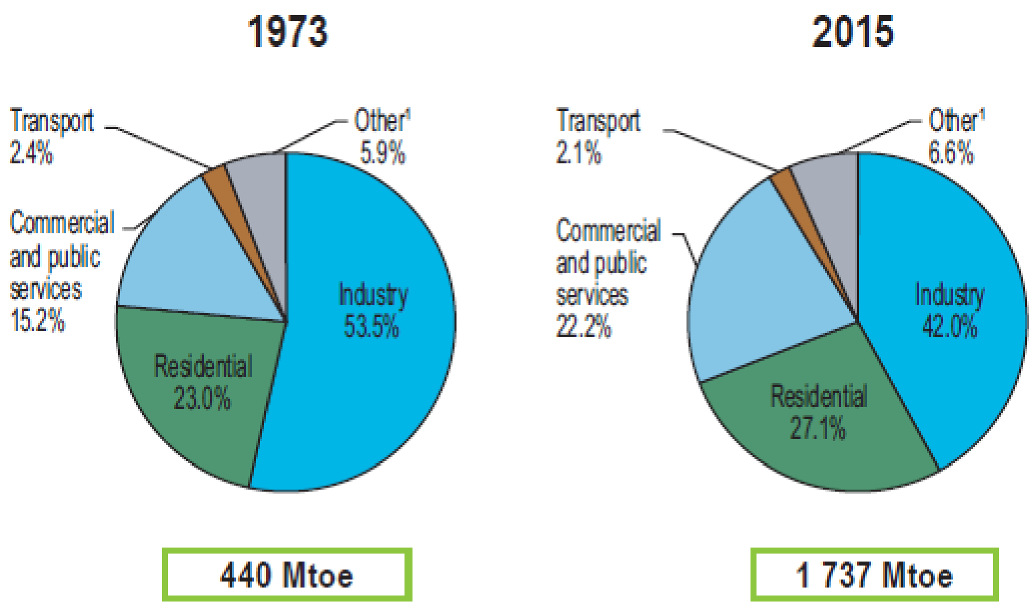


Figure 1.2. Share of electricity total final electricity consumption from 1971 to 2015 by sector.

Final electricity consumption of non-OECD countries in 2015 was 10 803 TWh. OECD consumption 9 397TWh which can be seen on (Figure 1.3).

Residental consumers are key contributor to seasonal and daily peak demand. Shifting residental electricity consumption by means of DSM is one of the main focuses in modernized electrical energy structure.

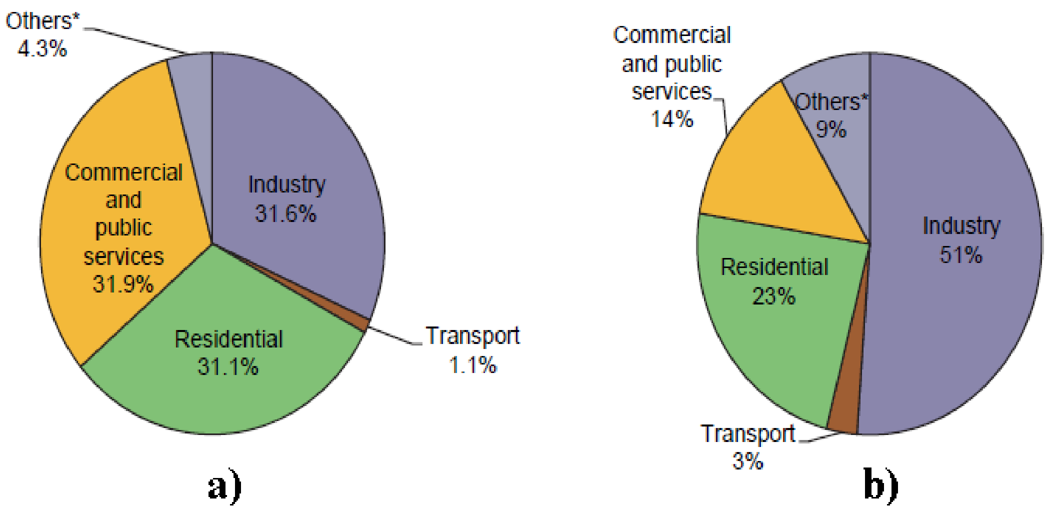


Figure 1.3. a) OECD, b) non-OECD countries final electricity consumption.

Conventional grid system was designed around customer characteristics. For a sustainable growth, this was a non-optimum solution as most of the plants that is used in managing peak loads having required perks such as fast response, dynamic load shifting and relatively small capacity but having major drawbacks like using fossil based and expensive fuels, Greenhouse Gas (GHG) release into atmosphere and required initial investments (plant, pipeline or infrastructure to provide required fuel logistics etc.) Even though new methods for peak load managements are proposed in terms of Battery energy storage systems (BESS), Vehicle-to-Grid (V2G) and Plug-in Hybrid Electrical Vehicles (PHEV), high peak to average ratio (PAR) is problematic for grid health. Smart grid systems are expected to overcome all conventional grid shortcomings. By promoting utility-customer information sharing, distributed generation, microgeneration, efficient energy storage systems, smart grid forms foundations on which dynamic pricing (DP) methods can be implemented for a healthy demand response (DR) system.

With increasing focus on global warming, GHG and climate change there is observation of behavioral changes to adopt energy efficient, low carbon lifestyles in various countries. However this change alone isn’t considered sufficient for adequate use of system resources.

Mechanical work has been an important factor in development of civilization since before recorded history. Mechanical work provided by human and animals played an important role in providing food, shelter and clothing for growing society. After having a better understanding of nature and its sources; wind, tidal and river flow has been exploited to provide additional mechanical work for transportation, grain milling, timber and marble sawing. Starting with industrial revolution, steam engines provided immense amount of mechanical work originating from fossil fuels. Developing technology resulted in discovery of steam turbines, diesel and gasoline engines etc. All these cummulative developments resulted in increase in overall human comfort, wealth and life standarts. After discovery of electric, due to its varied usage such as lighting, heating, cooling etc. and distribution it is one of the main source of energy used in modern era. Conventional sources of mechanical works are exploited to provide electrical power in various plants like wind turbines, using solar photons on photovoltaic (PV) cells, geothermal plants, hydro power plants, nuclear power plants, natural gas powered gas turbines or coal fired steam power plants using an alternator or generator. Transmission is provided by high-voltage transmission lines then distributed from certain hubs in low voltage to various users around a vicinity. There are some methods of using generated mechanical or electric energy for later use. Those methods are generally converting electrical or mechanical energy into mechanical or chemical energy. Some of the energy storage systems are; pumped hydro power plants, Li-ion batteries, fuel cell and flywheel.

Main differences between capacity and generation are: capacity is maximum power of a plant wheras generation is total electrical energy generated over a certain period.

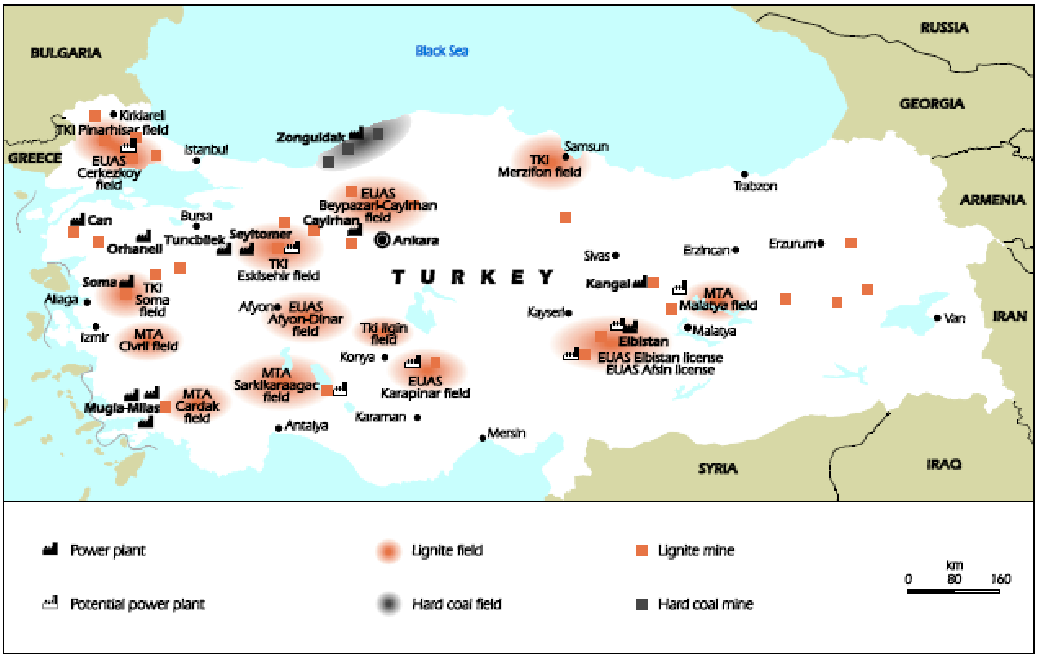
Electricity can be divided into 3 main groups such as:

- Generation: Electricity generation is accomplished by generating mechanical work and using that mechanical work to generate electricity in required quality. Getting mechanical work from a source is generally affiliated with laws of nature in thermodyanics, fluid mechanics, combustion, nuclear physics. Power plants can be classified into different groups based on their source to provide rather easier approach and this approach also provides a generalized pros and cons for each type. Prevalent electricity plants can be classified as:

- Fossil-Fueled Power Plants
  - Coal-fired power plants: Coal fired power plants uses coal as main source of energy. Using water steam as working fluid, coal-fired power plants works under the principle of Rankine cycle. Coal preparation is a key factor in overall plant efficiency as well as GHG and other contaminating particles it produces. Some of their key equipments are: burner, boiler, steam turbine, condenser, cooling tower and generator.
  - Natural gas fired power plants: Natural gas power plants which is also known as gas turbines uses burned fuel-air mixture as working fluid. Working under the principle of Brayton cycle, they can easily reach their optimum work parameters after a cold start and adjust their load more dynamically when compared to coal-fired plants.
- Nuclear-Fueled Power Plants: Using energy radioactive elements emmit when they are bombarded with neutrons, nuclear power plants controls control rods to sustain adequate free neutrons required for a chain reaction. Depending on plant type, energy generated is transferred directly into working fluid or a pressured fluid to transfer its energy to a working fluid by a heat exchanger, rest of the process is typical Rankine cycle. While nuclear power plants provide energy with no GHGs, plant security and stability due to Fukushima, Three Mile Island and Chernobyl disasters as well as final product handling remains as concerning issues.
- Renewable Energy
  - Hydropower: Using water potential energy at dam or by transferring momentum of water flowing along a river to mechanical energy and eventually to electricity they provide electricity as long as they have a continuous water supply. They generally require local topographical and water supply

therefore heavily dependant on local region to provide electricity at a constant rate.

- Biomass: They are available as remains of local fauna and flora.
- Geothermal: Using the lava heated underwater sources that are around tectonic plates of the Earth, geothermal sources can be used to generate electricity. They require certain characteristics to be able to provide electricity but they can provide local heating even if they can't produce electricity. They are rare and only contains a small fraction of total power capacity.
- Solar: Using the solar irradiation on Earth, they can provide electricity by PV cells or collector plate power plants. Turkey solar potential map provided by Turkish Ministry of Energy and Natural Resources (MENR)
- Wind: By transferring momentum of passing wind bulk, wind turbines can produce electricity and their generation is limited by Betz's Law.



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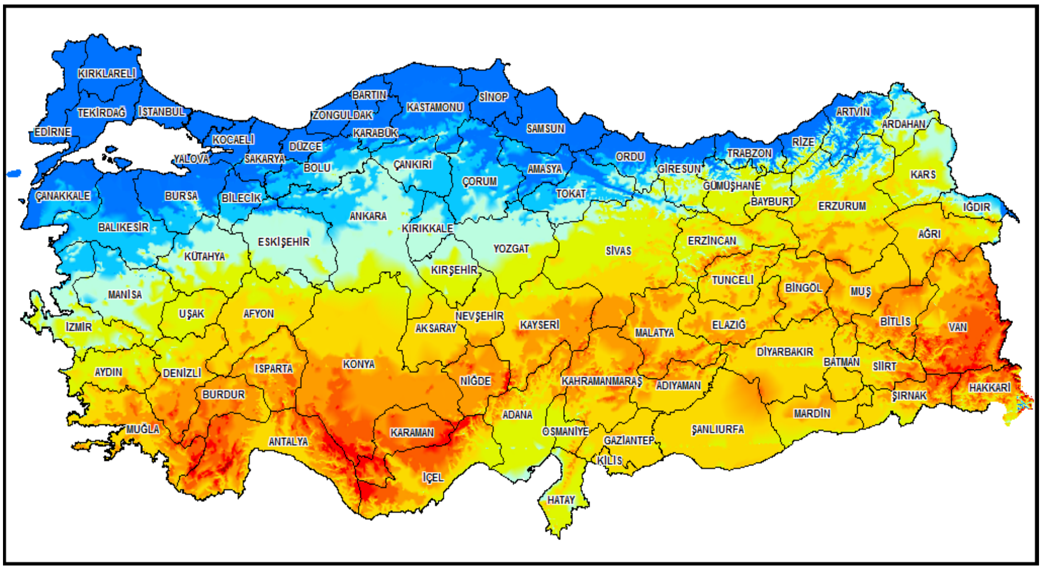

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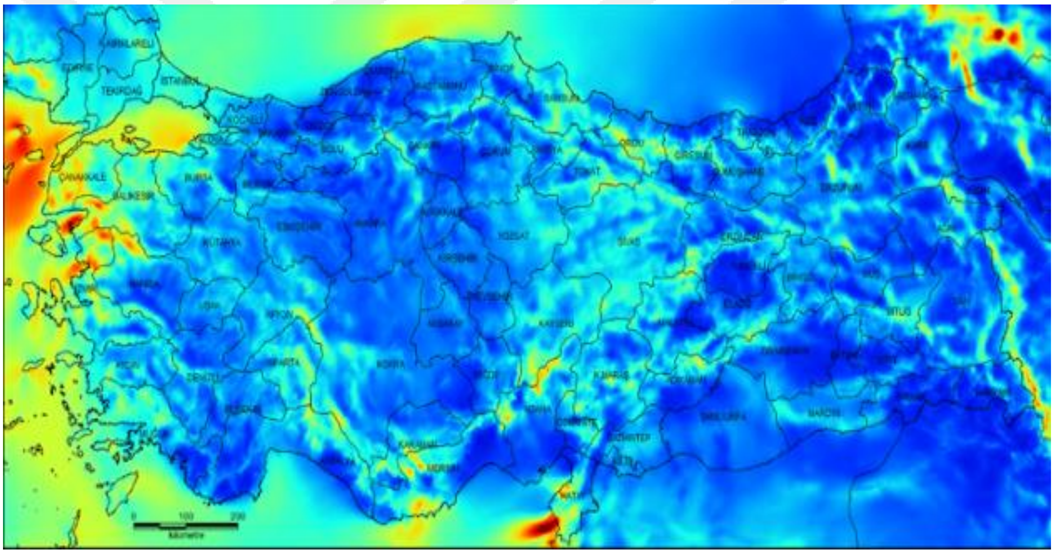

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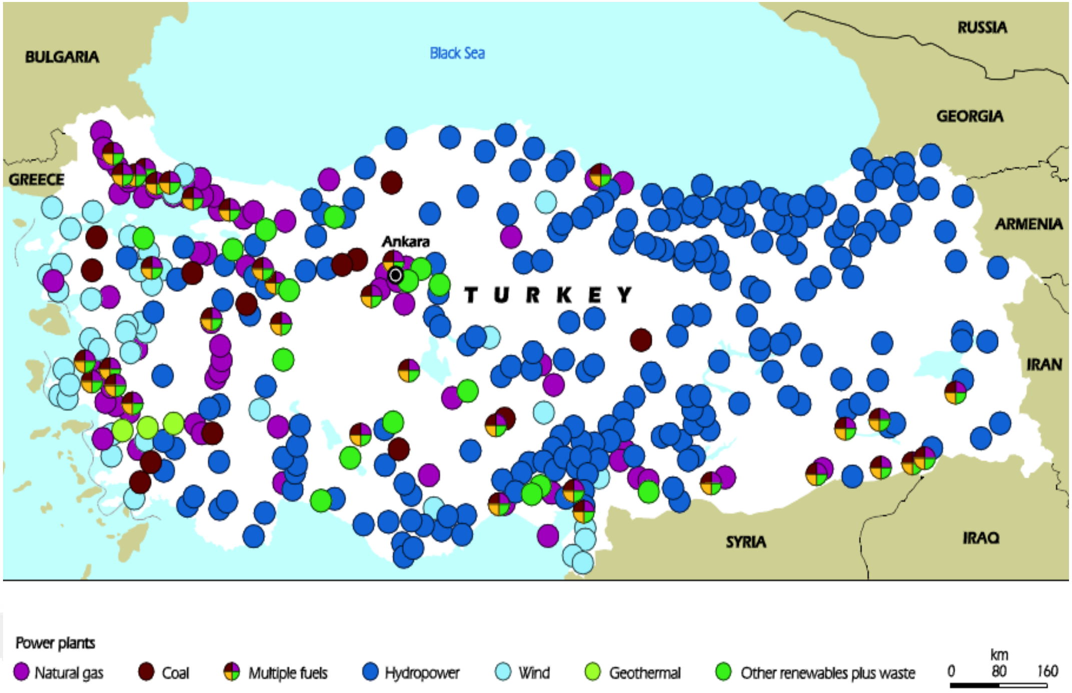

Figure 1.9. Turkey generation map (International Energy Agency)

- Transmission: One of the perks of electricity is its ease of transportation between centralized generation to distributed consumption. While there is some amount of transmissional losses through the grid, having an infrastructure with adequate maintenance would prove a rather easy method of energy transportation when compared to fossil sources. Electric energy produced by power plants provides emergy to transmission line after having its voltage increased in step-up transformers, main reason why electricity is transferred in high voltage is to reduce transmissional losses due to wire resistance. After transferring electricity to local consumption hubs, voltage is decreased at step-down transformers to provide consumers with needed electricity.

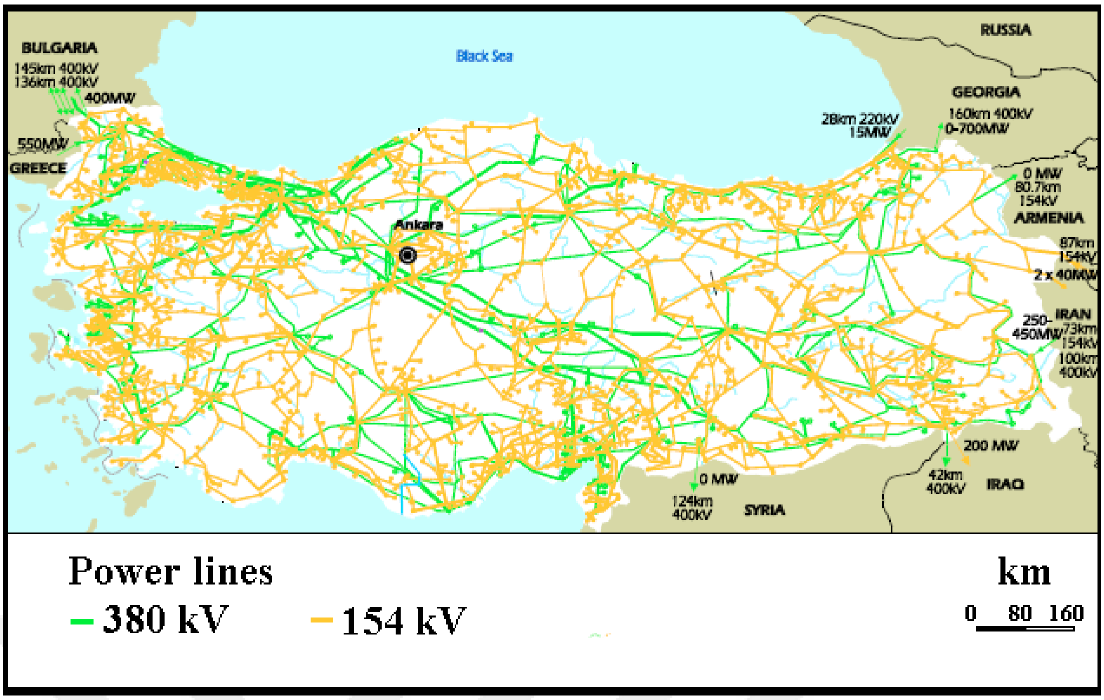

Figure 1.10. Turkey transmision grid (International Energy Agency)

- Consumption: Consumption of electrical energy can be dependant on many variables. In a focus area parameters such as socio-economic development, industrialization, urbanization, climate and geographic characteristics can effect consumption amount and patterns greatly. Some events such as holidays, unexpected natural events, immigrations can provide additional complexity aswell. due to this complexities and variations. Amount of electric required by the end user changes during day aswell. This variation forms a load curve depending on location's electricity needs. Generally a curve with minimum load requirement during morning, increasing during morning and afternoon and reaching its peak value during or before early evening hours and decreasing until next morning is formed due to daily usage of electricity. Lowest value of the curve is named as base load, which is the base electricity load that needs to be supplied to grid. Peak load is the maximum required electricity need. Power plants that supply electricity need to run continuously to provide base load. This power plants are regarded as base load power plants which use cheap or relatively efficient methods when producing its electricity. Hydro power plants, coal-fired power plants, geothermal power plants and nuclear power plants can be counted amongs base load plants. Base load power plants are generally has great capacity, high availability high initial investment costs but lower fuel and maintenance price. Plants that provide electricity during peak hours when energy demand is increased for 1-6 hours are called peaker plants. Peaker plants requires fast response to varying loads during peak hours. Gas turbines are an effective tool in satisfying peaker plant requirements and widely used for managing peak loads. Its relatively high cost fuel makes it undesirable for base load requirements. Renewable energy sources due to their randomness in availibility must be used whenever possible or store their energy in some other form to use it more reliable when desired but such methods would increase overall energy cost.

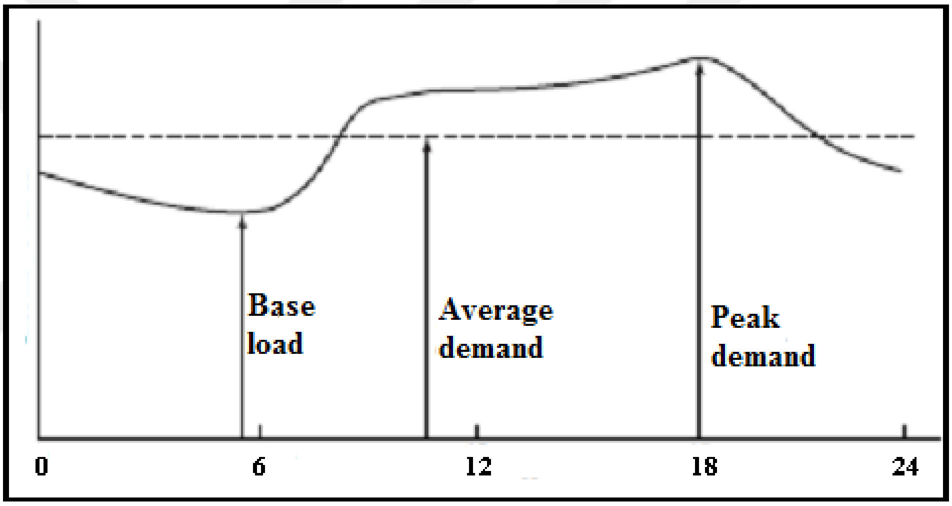

Figure 1.11. Representative load data

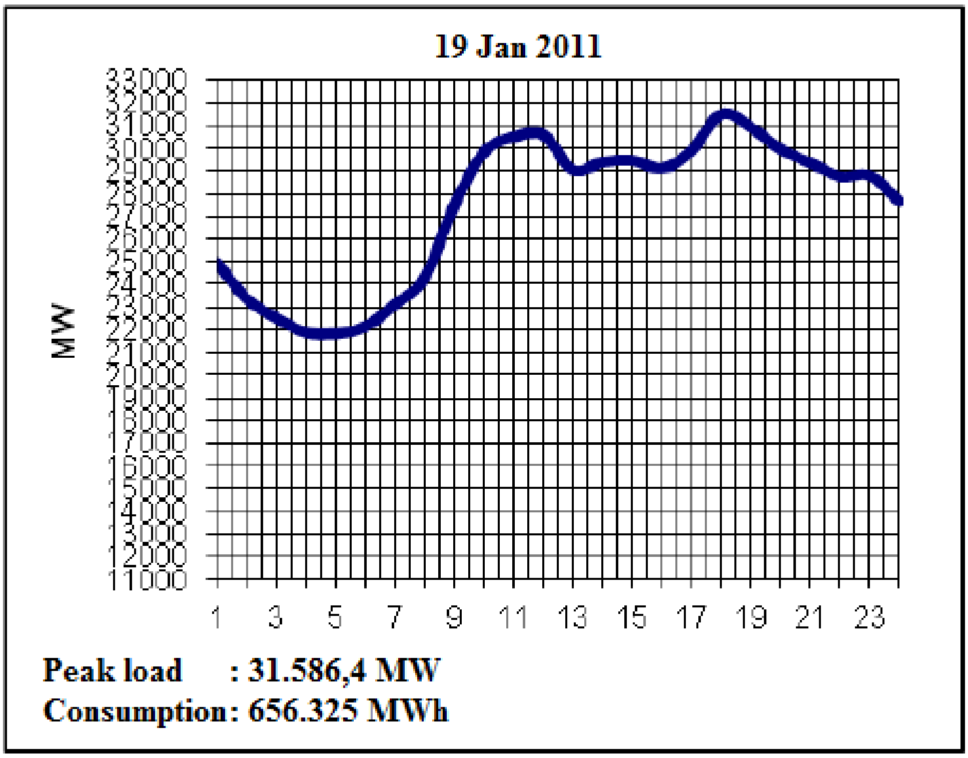

Figure 1.12. Turkey load data for 19 Jan 2011

There are 3 types ofmajor electricity consumers:

- Residental
- Commercial
- Industrial

One of the parameters defining a nation’s development is total energy consumption per capita. It has been observed that more developed countries spend more energy per capita when compared to less developed countries. A growing economy will require more energy to cope with their growing energy needs in residental, commercial and industrial facilities. Therefore it is an observable relation between economic growth and electricity demand. Growing economies must find sustainable methods to manage their growing energy needs and must build new power plants or manage their grid usage. A study made in Russia compares different conventional methods of managind peak loads with PHEV used in grid to provide energy storage in off-peak hours and provide their energy to grid during peak hours, forming a peak reduction for short periods of time. An economic analysis ignoring vehicle initial investments and battery life decrease due to charge/discharge cycles suggests that PHEV is the most effective method for peak loads lasting less than 1 hour but for peak loads exceeding 1 hour, conventional methods are better (Zhuk et al. 2016).

Growing energy needs and slowly depleting natural resources are forming the need for a method to manage available resources adequately rather than using brute force to provide energy needs. DSM is a method to increase grid resillience by regulating energy policies to manage customer consumption behaviors resulting in desired demand conditions matching grid features. Smarter, more efficient technologies provide better or same outcome using less resource/effort.

One of the main focuses on energy sector is managing the consumption. Consumption is dependant on too many parameters such as demographic and socio economic characteristics of the region, customer type, customer behavior, Daily, weekly, monthly or seasonal events, fuel prices. Different customer types such as industrial, commericial, residental has different magnitude and time varying electric consumption depending on their characteristics. Two residental consumers can have totally different consumption patterns depending on their socio-economic properties, yearly earnings, building type, home appliances and even car type(i.e. PHEV, EV). Smart metering is method of logging electric energy consumption of a building and using that data to get customer’s consumption behavior. Modelling of consumption pattern may be performed using surveys regarding characteristics of building, household, appliances etc.

Turkey is an emerging country which has been a founding member of the OECD and IEA. As an emerging country Turkey’s energy policies must cope with its needs of growing population, economy while mitigating its import dependance.

Growing economy and population resulted in increasing energy demand. Over a decade (2004 to 2014) electricity demand has grown from 121 terrawatt-hours(TWh) to 207 TWh while its gas demand increased even more, rising from 207 billion cubic meters (bcm) to 49 bcm. Turkey reformed its electricity market with Electricity Market Law (No.6446) in 2013 which is revised a few times and still active.

According to annual electricity report provided by TEİAŞ, by the end of 2016 Turkey has total electricity capacity of 78497,4MW. As it can be inferred from the data that Turkey's current energy policy is highly dependant on imported fuel. Total electricity generation during 2016 is 273,4GWh.

Prior to 1993 electricity generation, transmission and distribution was being organized by "TEK" a State Economic Enterprise whose name means "single or unique" in Turkish marking its name as only institution in Turkey that has the authority on electricity. After 1993 TEK was dismantled into 2 different institutions. TEİAŞ and TEDAŞ where TEİAŞ managed generation and transmission while TEDAŞ handled distribution. Privatization of state-owned plants and new investments from private sector is one of the most important events after dismantling of TEK, providing a competitive energy sector for Turkey. Further reforms resulted in TEİAŞ activities divided into 3 companies; EÜAŞ managing remaining state-owned generation plants, TETAŞ organizing wholescale market and TEİAŞ only responsible for transmission. TEDAŞ also divided its authority to 21 regionally active distribution companies.

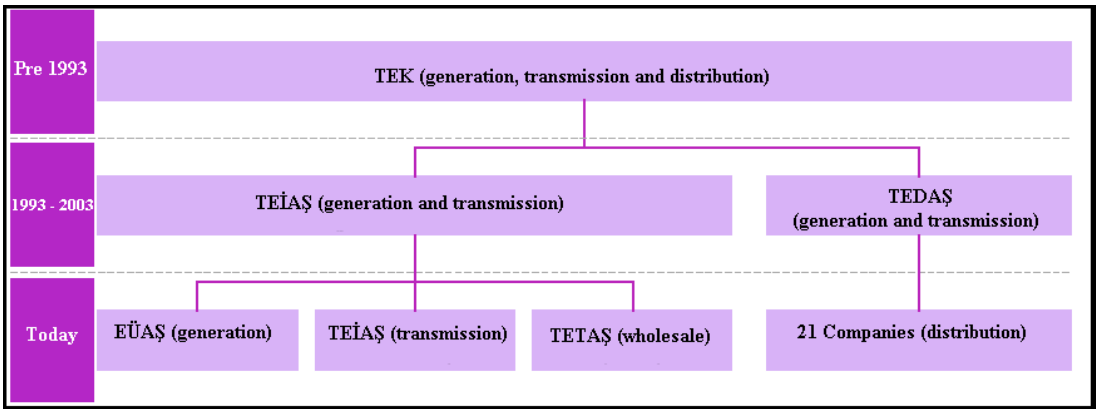

Figure 1.13. Historical development of modern Turkey electricity market structure. (International Energy Agency)

Currently most electricity generation elements in the sector are being converted to private sector (except some of the high capacity coal and hydro plants). New day-ahead market, intra-day market and balancing power market are managed by EPİAŞ. These revisions provided a competitive energy market.

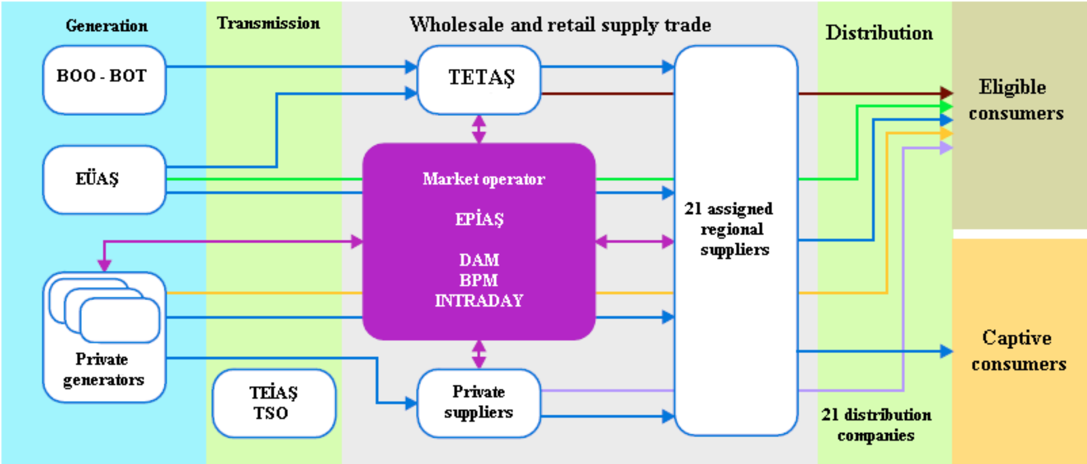

Figure 1.14. Turkey electricity sector industry structure (International Energy Agency)

2 LITERATURE REVIEW

2.1 Household Consumption

Electricity consumption is residental sector is directly effected by 3 parameters which are quantity and quality electrical appliances, pyhsical factors such as building type, age, floor area, climate and occupant/consumer behavior in using them. While electrical appliances have some definitive characteristics in terms of consumption, semi-randomness of human habbits is making cummulative effect of appliance consumption highly stochastic. Studies and surveys provide the infomation that other than appliances such as usage patterns, total floor area, socio economic and socio demographic characteristics of individual households are also in effect and making consumption predictable.

Examining household energy consumption can be done in different ways. Two of the most common methods are; on-site measurements and detailed house surveys. On site survey requires technical equipment to measure consumption of appliances one-by one or a collection of them. Surveys provide general information about physical characteristics of surveyed home and consumer behavior. Which provides important parameters such as buiding age, floor area, number of rooms, number of individual electrical appliances and household charactersitics such as number of people living in the house, their age group, general usage frequency of electrical appliances.

Appliances can be divided into 4 groups depending on their consumption characteristics:

- Continous appliances: Appliances that are expected to be active all day therefore they consume electricity all day long. Burglar alarms, clocks etc.
- Standby appliances: Appliances can be used actively then turn to standby or sleep mode by use of remote control. They have 3 stages of work; active when they are operational for their primary use, off mode when they are shut down completely and requires activation through an on/off switch to operate and standby mode when appliance is not performing its primary duty but can respond to remote control or scheduled operation cycles. Fundamentally TV,

sattelite recievers etc. fall into this category however as more smart appliances that allow programmable schedules are being produced such as washing machines, diswasher, oven, microwave etc. such appliances also consume electricity during their idle/sleep mode.

- Cold appliances: Cold appliances works in a cycle, their power consumption is active between a certain treshold. When temperature inside is between desired values, they don't perform their primary duty. Fridge and freezers etc.
- Active appliances: Appliances that don't have any standby mode. They are generally controlled by a switch, operate when needed and don't consume electricity when they are idle. Kettles, hair dryers, lighting etc.

Household consumption is around 15-25% of total electrical energy consumption depending on development and socio-economic characteristics of a country. Even though there has been increasing development in overall appliance efficiencies, increasing developments on Information and Communication Technologies (ICT) and Consumer Electronics resulted in greater penetration of new products into household consumption. Increase in daily comfort standarts are also boosting this increase.

REMODECE Project was conducted on 12 European countries to get a better understanding of European Union household consumption patterns and behaviors.(A. de Almeida, et al., 2011) Project aims to propose policies and strategies to change consumer behaviors to reduce standby consumption while evaluating potential savings by replacing appliances with more efficient ones. Due to budget limitations, large-scale monitoring campaign was limited to 1300households. Each household was monitored for 2 weeks using serial data loggers and watt meters with 10minutes integration period. Project provided a detailed dataset containing data for most Eastern, Central and Western European countries. One of the most important finding is usage pattern and technology diversities caused some significant difference in minimum and maximum values. Switching to best technology possible will result in around 1300kWh annual electricity saving for an average household monitored during project.

Some modern Home Energy Management Systems (HEMS) are able to manage household consumption using smart meter data and interacting with the customer. A study conducted in cold region of Japan proves that smart meters providing consumption information to customer is capable of providing peak load reductions and load shifting (Matsui, Ochiai and Yamagata, 2014). Smart meter capable of using IEEE1888 communication protocol collecting data each minute and transfer this data to a database using the internet. Communicating with the customer using a web browser based User Interface, system gives general information of daily electricity usage and give tips to reduce current usage. Study is made on 4 households where 3 of the households had access to the web system and could react according to their consumption, 1 household was left as control group to check how much effect did DR had. All 4 households shown different results during winter season mainly because of their lifestyle and characteristics of their home (i.e. one of the residents not working and house providing all its all heating requirements from electrical appliances).

Another study made in Japan containing more than 1600 households using HEMS also analyzed consumers' capabilities of changing their consumption during winter of 2015 and 2016 also summer of 2015. Using HEMS, study was able to monitor electric usage of individual purposes like space heating, space cooling and other appliances. Using such data and data provided by customers like floor area, household size, monthly average temperatures, availibility of central or floor heating, source of water heating system; study was able to provide more insight into customers load shifting/reducing capabilities. As a result overall electric consumption was reduces. However its effect have been completely different in large and small households.

Green button initiative: As a result of call-to-action from USA government, starting from 2012 ultility providers led project to provide their customers energy usage data with easy internet based computer data.

Consumer loads can be divided into 2 sub-groups as interruptible/movable loads (plugging of EVs, washing machine, dishwasher, iron) and uninterruptible/immovable loads (TV, PC, fridge, internet router, security system).

Standby power consumption is power an appliance draws from the house while plugged to power but not performing its primary function. As more advanced appliances are developed which providde different eases like display clock, programmable operating schedules, memory, remote control etc. such extra features will require appliance to draw continuous energy which will result in standby consumption. Different studies has been done on standby power consumption modelling, metering with help of on-site metering, surveys or both combined. Measuring of stanby power requires appliance to be connected to power grid of home while it is not performing its main duty. Standby power is heavily dependant on appliance type while different products of same appliances have been found to have different amounts of standby power (Guan et al. 2011). While some studies focused on potential load reductions/energy savings by modelling mathematically, other studies propose solutions by installing equipment to prevent energy loss. Whole House Switch is consisting of 2 main components which are plug type disconnect and a controller which manages disconnect usage. Study suggest that at current market prices whole house switch would pay back in around 7 years (Burgett, 2015). Different studies and their results can be found in Table 2.1.

Various studies prove that with increasing population and advanced ICT products, standby power is reaching magnitudes that needs to be mitigated as much as possible. A metering study made in Taiwan covered 100 households that represent various regions with varying total consumption amounts. After having measurements, standby power loss and total consumption is found to be directly related. Expanding standby consumption data of 100 households, researchers has made the estimation on total standby consumption of Taiwan households to be around 1390,650 GWh (Lu et al. 2011).

Study made in Ankara which is the capital and 2nd most populated city of Turkey, covers 260 household measurements on 1746 appliances. Surveyed homes are picked to represent a variety of users to reflect miniature portion of Turkey household electricity users. Study claims to be the first work on Turkey which includes standby consumption measurements in the country and an extensive comparison is made between countries that includes whole-house measurement data on the literature. According to the data, Turkey has one of the least average standby power(22W) and average annual standby consumption (95kWh/yr) values when compared to major EU countries, USA, Taiwan and China (Sahin and Koksal, 2014).

Focus is to be able to reach less than 1W standby consumption per appliance regardless of its type. A study made on 10 households in California measured a total of 190 appliances which fit into different categories such as entertainment, communications and computer hardware. Measurements made finds that 5-26% of annual electricity consumption is due to standby consumption. If all the appliances were designed to have at most 1W standby power that would reduce annual stand by electricity consumption and total household consumption by 70% and 9% respectively (Ross and Meier, 2002).

Another study in Canada analyzes total standby consumption by measuring and recording 75 different household’s appliances and their usage patterns, then performing standby power measurements in 1 PC store and 3 electronic retail superstore at Halifax. They compare appliances and see whether 1W maximum standby power is realistic or not. Their findings prove that 1W limit for standby power is achieveable and it would provide 59% annual reduction in standby consumption (Fung et al. 2003).

Table 2.1. Various studies on Standby consumption amounts.

Study	Country	Method	Potential Saving	Test extend
(Burgett, 2015)	USA	survey, test homes, WHS installment	282kWh/year on 5 appliance	+12000 survey
(Guan et al., 2011)	Australia	field measurements, appliance change	170kWh/year for home theater	
(Sahin and Koksal, 2014)	Turkey	survey, household measurements	95kWh/year for average household	260households

2.2 Tariff, Dynamic Pricing and Demand Side Management

2.2.1 Tariff

Tariff can be defined as the rate customers recieve the electricity service from their provider. As a result of 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 manage peak load is possible such as peaker power plants, pumped hydro power plants, large scale stationary battery systems etc. where results will vary depending on country's fuel prices and technological advancement. A different approach is to manipulate customer behavior so investments for peaker power plants (which generally uses more expensive fuels or has less efficiency) are not required which will result in a decrease in wholescale electricity prices. One of the main reasons why DP programs are found in the first place is the need to reduce peak load magnitude and duration. DP 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 an optimized rate which provides supplier enough income so they will earn some profit for their capital investment after their generation and maintenance cost is covered while prices should be fair for customers that they will consume their needs without having too much penalty.

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

After developments in computational power and advancements in Information Communication Technologies, DSM is showing great promise to provide system stability and reliability. Various types of DSM strategies are possible but segmentation of customers are required in order to provide a fair and effective DSM.

Customer segmentation:

- Residental
- Commercial
- Industrial

Main techniques:

- Load Forecasting
- Appliance scheduling
- DP scheme

2.2.2 Demand response techniques:

2.2.2.1 Incentivize-based

Customers are encouraged to reduce energy consumption by signing a contract between utility company and customer. administrator can manage customer load by scheduling, reducing or disconnecting customer to save cost. Direct load control, interruptible tariffs, demand-bidding programs and emergency programs. Low customer privacy system scalability are major brawbacks.

2.2.2.2 Price-based

Customers are subject to time-varying rates of electricity prices that reflect wholesale market prices. Customers can directly effect their electricity bill by reducing or shifting their energy consumption from peak hours to off-peak hours to provide load balancing. Some of the main applications of price-based DR techniques are Time of Use (ToU), Critical Peak Pricing (CPP), Real Time Pricing (RTP). System scalability and customer privacy are not problematic issues in price-based programs but offering same prices to all customers is totally unfair especially for customers who has uniform and low consumption rates. Even customers in the same consumer category (residental, industrial, commercial) may have differences in load profiles and different load shifting capabilities, for an effective and fair DR, customer classification/segmentation and corresponding tariff rates must be provided by utility companies for each customer.

DR can manage customers to be reactive to price changes and emergency cases when system reliability is threatened. By shifting or reducing peak loads, peak energy prices, air pollution and new generation capacity for future demand can be reduced.

2.2.2.2.1 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. 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 aswell. Extreme weather conditions may increase consumption in the morning and evening during winter while during summer peak consumption is generally during afternoon as most buildings operate their air conditioning systems which will boost their consumption greatly.

2.2.2.2.2 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 a number of consecutive days. CPP can be managed to handle extreme cases aswell 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 peaker power plants.

2.2.2.2.3 Peak time rebates (PTR)

Customers are paid back for energy saving they did during peak demand.

2.2.2.2.4 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 peaker plants go active during peak demand, overall cost for uni electricity energy increases, therefore wholescale electricity price increases greatly). Customer behavior and participation is a key element in RTP where customers can evaluate wholescale market prices. RTP is the most sophisticated pricing programwith highest possible reward whereas TOU is regarded as the simplest one with lowest possible reward and risk.

Different case studies have been conducted on DP and its focuses mainly on:

- Risk and rewards
- Enabling Technologies
- Types of DP programs
- Lower-income groups
- Customer types
- Temperature

According to regulations of EPDK, current household pricing model for Tukey is TOU divided into 3 parts. These time is seperated as 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.

For a reliable and resillient grid structure, peak loads must be reduced or shifted to off-peak periods. To prevent peak capacity increases, to mitigate new investments on new power plants which would increase overall electricity prices peak load must be reduced by means of load shifting or load reduction. DR is an effective and cost efficient method for changing customer consuming behaviors.

As a result of increase in electrification in all aspects of daily life, electricity demand has risen rapidly, especially during peak hours. One of the main reasons why DP programs are found in the first place is the need to reduce peak load magnitude and duration. DP methods can be implemented to directly prevent that load from ever happening or create incentivize for shifting it to off-peak periods.

Dynamic electricity pricing is an indirect method for managing peak loads in electricity grids. Main purpose is to develop a tariff policy to give customers incentive to shift their electricity consuming habbits to off-peak periods. Through smart programmable home appliances such as dishwasher, dryer etc. most appliances can be programmed to operate during off-peak periods.

Main benefits of DP:

- Manages system reliability
- Ability to lower wholesale market prices
- Mitigating market power
- An effective tool to maintain system resource adequacy

Regional work focuses:

- America: DR resulting in decrease in peak to off-peak ratio
- EU: smart meter rollouts
- Japan: DP to improve grid management.

Main challanges for DR is establishing a systems where utility companies and customers are in a win-win situation, customers performing load scheduling to balance energy consumption with optimum usage of supplies. An effective communication system to provide continous DR interaction is also vital for long term health of DR system.

One of the main challanges in DR system is balancing energy and optimizing costs for customers and utility. A system where utility provides required energy with optimal use of system resources and customers are not crippled by heavy bills provides a mutualistic relationship between two parties.

Customer awareness is a key element to DR success. Customers can be motivated to shift their load by knowing that it will cause some outcomes that directly effects themselves like cost saving and blackout prevention.

Case studies in DR systems:

DP experiment made in Kitakyushu, Japan. İncluding 200 households using hourly load data collected from smart meter. Peak demand reduction proves that residental customers have the ability to respond DP and shift their movable loads to off-peak periods. There is a greater load reduction in extreme temperatures.

Aim of DP study in Kitakyushu was to give consumers incentives to reduce their consumption when grid is highly stressed and wholesale prices are high. DR method requiring participation from customers and power suppliers. Study shows that with extreme temperatures (too cold winter days or too hot summer days) electricity consumption also increases. After implementing 40 days of summer and 43 days of winter critical peak pricing, study shows that there is 6-14% peak demand reduction ratio change (Zhang et al. 2016).

2.3 Enabling Technologies

An effective DP is only possible with evolution of conevtional grid into a modern grid system. Conventional grid is a result of massive urbanization and forming an infrastructure capable of carrying its needs. Due to its forming era, conventional grid and its elements are mostly composed of electromechanical components and hierarchical structure led by centralized generation.

Smart grid is an electrical and informational network which intelligently integrates actions of all active contributors such as generators, consumers and those that do both to provide sustainable, economic and secure electricity supplies.

Smart grid aims to integrate renewable energy sources into modern grids as well as optimizing energy consumption and resource management. Manage electricity grid to minimize carbon emissions, peak to base load ratio, wholesale market prices.

Smart grid is often regarded as a viable solution for renewable energy integration into modern grid systems. Due to unpredictable nature of renewable energy systems (RES), it is risky to plan day ahead pricing in conventional grids. With increases in modern day renewable energy forecasting accuracy, it is much safer to manage electricity generation facilities via smart grid.

Conventional grid measured electric consumption by electro-mechanical energy meters which performed their task by rotating an aluminum disk therefore recording active energy. Later technological advances in microprocessor units and better analog-to-digital converters allowed more electronic based meters to be produces which were more accurate and provided better information such as reactive power, apparent power, voltage and current Root Mean Square values.

Developments in ICT and improved measurement accuracy has provided researchers and utility companies with new sets of data previously unavailable. Implementing buildings with sub-metering devices and home surveys provided better information of consumption patterns. HEMS monitor ongoing consumption provide its data to both customer and utility company, cluster energy management system(CEMS) collects data from various houses connected in a region/district, forecast next day electricity demand predictions and send billing information to consumers through their HEMS. Therefore they can do planning for next day loading. This is also known as day-ahead pricing and it is one of DP schemes.

Some of the most anticipated challanges for smart grid are as following:

- Providing an effective EV infrastructure

- Implementing DP schemes that reflects wholesale electricity price.
- Providing enough incentives and education for customer participation.
- Providing security of customer information and data.

Inclusion of sub-metering devices provide more detailed information of building energy consumption. Having information of building characteristics, resident quantity, occupant behavior and as a result load profiles are providing large scale supervised data which can be learned thorugh machine learning and provide accurate predictions for classification of individual consumers and future load predictions.

National Institute of Standarts and Technology (NIST) is providing some standardization to smart grid elements as well as smart grid intergration to conventional grid systems.

A smart grid is highly dependant on enabling technologies that provide vital functions of smart meters such as renewable energy integration, automated distribution, self healing, DP, accurate forecasting etc. Enabling technologies that provide required infrastructure for smart grid are battery storage systems, EVs, PHEVs, V2G systems, cloud computing, vast control and communication infrastructure which can be summed as enabling technologies.

Enabling technologies can be divided into sub groups such as:

2.3.1 Submetering systems and smart meters

Smart meters logs customer's consumption data in certain intervals and provide it to both utility company and customer. Smart meter allows customers to adapt their consumption to be able to minimize their electricity bill. Even though real time pricing is not a widespead used billing method, peak load reduction in TOU and CPP based pricing will allow customers to adapt varying hourly price. Utility companies use vast amount of smart meter data collected from customers to plan next day generation and forecast pricing of next day electricity usage. Smart meter data provides insight for day-ahead pricing as well as long term planning of district/nationwide grid.

A study made by J.P Gouveia et al. in Portugal combines smart meter data with door-to door surveys. Survey covers 389 households around Evora municipality with 37% of them being in rural areas and the rest in the urban areas. Their smart meter dataset contains electricity consumption data of 31000 households in 15min intervals since 2010, but to have a more complete dataset, only 3 years (2011 to 2014) of data has been used. They also linked surveyed houses with their smart meter database using household smart meter number (Gouveia and Seixas, 2016). During this process only 64% of the surveys can be linked to their smart meter data. Study consisted of clustering analysis,... During clustering analysis, daily means of electric usage per household has been used 2011-2014 for each day. They completed iterative clustering process which segmentated customers into clusters starting from 3 to 12. As a result 10 clusters are chosen depending on mean and standart deviations. Matching the survey data to clustered groups, they found dominant physical variables of households as: location (urban and rural), dwelling type, dwelling age, dwelling floor area, type of glazing and window framing, bearing structure and type of outer walls. While socio-economic variables were: number of occupants, education of household members. On appliance level, heating and cooling appliances, white electrical appliances, type of tariff and contracted power were defining variables. In conclusion, they were able to comment on various factor effecting building energy consumption by matching clustered smart meter data with surveys.

2.3.2 Renewable energy systems

Renewable energy is a main focus in energy systems research as imminent issues such as depletion of fossil based resources, global warming, climate change, carbon and NOx emissions merge as huge problems. For a sustainable development, future grid systems is expected to have a large portion energy produced from renewable sources. Due to their working principles, RES are heavily dependant on weather conditions and climate which can be forecast but contains a heavy element of randomness in its nature.

RES especially in form of PV and wind micro generation is expected to provide demand reduction in microgrids and overall grid system. Rather than having centralized generation supported by sufficient transmisison infrastructure which causes transmissional losses, on-site generation and consumption provides more sustainable solutions. RES penetration is vital for a resillient smart grid structure. When supported by energy storage systems, RES may overcome some of its greatest disadvantages such as randomness and fluctuations.

Many of the studies made on renewable integrated storage system indicates that PV+battery systems alone is not viable to become totally independant from the grid but it is good as a suplementary to reduce bills and carbon footprint. PV battery systems without being connected to grid is only viable when high battery capacity is available which increases battery storage requirements that increases initial investment therefore crippling economic benefit of the system (Hanser et al., 2017).

2.3.3 Energy storage systems

Energy storage systems are vital to long term health of a smart grid and reducing carbon emissions and GHGs effectively. Due to randomness in renewable energy sources' nature, fluctuating and surplus energy can be storaged as well as generation during off-peak periods. This would prevent energy generated from wasting. Other possible economic benefit of having a battery storage unit is, charging it during times when tariff price is low to use stored energy during peak times to use it during high price times which is also referred as peak shaving. Energy storage systems can provide peak shaving and load shifting to reduce PAR values and provide a more stable grid.

Depending on their goal, energy storage systems can be integrated with various renewable energy storage. For energy storage systems to be widespread they also need to be economically viable. Energy storage systems' lifetime, initial investment and maintenance cost are heavily effected by 2 parameters State of Charge (SoC) and Depth of Discharge (DoD). Battery operation strategy effects SoC and DoD directly. As a result of that. Battery systems must perform their task while having an optimum solution to have maximized economic and environmental goals.

Distributed energy storage systems provide managing home/building level energy storage and consumption during peak loads. In a scenario where most of the customers have access to energy storage appropriate for their total consumption amount, PAR values reduce greatly due to peak clipping and valley filling operations provided by each storage unit.

A case study for New York under TOU tariff conditions proves effectiveness of distributed energy storage systems and their ability to provide economic benefits and emission reductions. In a case of 15% state level participation by replacing electricity generation in peak hours, it is possible to mitigate about annual 128 tons of SO_2, 60 tons of NO_x, 9 tons of CO_2 while maintaining economic benefits(Zheng et al., 2017). A study in Sweden studies task optimized battery sizing in a PV-battery system. They optimized Self Sufficiency Ratio and Net Present Value for a rental multi-apartment building in Gothenburg. Self Sufficiency Ratio and Net Present Value represent economic and environemntal goals respectively. Optimization for Gothenburg is especially challanging due to consumption increase and PV generation reduction during winter period (Zhang et al. 2017). Their simulation results proves that for battery capacities up to 72kWh Self Sufficiency Ratio and Net Present Value increases but after 72kWh, there is a trade-off between Self Sufficiency Ratio and Net Present Value.

Due to their currently non-profitable market of energy efficiency investments, some governments are incentivizing home owners to install systems to reduce their electricity consumption. Green Deal provided by the UK government providing repayment for customers who reduce their overall consumption especially during peak load times. A study analyzing viability of household battery system when household charges its battery system during base load hours when electricity prices are low and providing its energy to home during peak times to prevent usage of high price electricity from grid.

2.3.4 Vehicle to grid (V2G)

With increasing concern on GHG and carbon emissions, electric vehicles are becoming a much more environmentally friendly alternative in future transportation system. While some challanges such as sufficient grid infrastructure and vehicle battery life span needed to be solved, electrical vehicles serving as an energy storage unit is one of the possible solutions to manage a smart grid system. V2G technology can provide viable solution to peak loads as most of the time that EVs are idle and needs recharging is during base load times when electrical grid system is less strained. Idle and recharged EVs can provide needed electrical power during peak load times and customer can be reimbursed for power they provided or some type of discount can be offered for EV battery charging.

Ken Darcovich et al. İnvestigated various V2G conditions in Canadian residental electrical demand scenario. Physics-based models simulated to provide results for possible V2G scenarios impact on battery life, as well as real life condition such as V2G impact with daily driving patterns. Their simulations result in different rates of V2G discharge, driving style and daily V2G activation durations have a direct impact on battery life. They also examine battery life changes on batteries having different capacity (Darcovich et al. 2017).

2.3.5 IoT and big data

Internet of Things (IoT) technology is a network of embedded devices that can be monitored on the internet. Its varied usage in energy related applications even formed a new term “Internet of Energy” (IoE). It enhances monitoring and control of everyday devices such as home appliances, health care systems, security and surveillance systems, industrial systems, electrical systems, energy systems, transportation systems, military systems etc. To provide fully automated systems, this devices must be provided with micro controllers, transceivers and protocols to operate and standardize their communication with each other. IoT systems consists of 3 main layers; perception layer, network layer and application layer. Perception layer is providing sensing ability of IoT systems. It consists of sensors, GPS systems, cameras, RFID devices. Network layer serves as a bridge between perception layer and application layer, it provides information of collected data to be transferred into application layer. Its capabilities are heavily dependant on used communication technology and network constraints. Bluetooth, ZigBee, WiFi, 2G, 3G, 4G and Power Line Communication are some of the most used communication types. Application layer provides end-use applications like RES integration, management of smart homes, electrical vehicle integration and demand-side energy management. (Jaradat et al. 2015)

In a smart city environment, IoT is network of various devices providing immense continuous data transfer. Since individual power consumption optimization of each IoT element is a major concern in a sustainable development point of view, each sensor must perform on desired technology. For example bluetooth technology can provide effective short range data transfer in low rates which can provide connection between smart phone and car. Another example is car/phone GPS data which needs to be responsive and accurate therefore requiring a greater data transfer rate at further range such as 4G.

Some of the biggest challanges that yet to be overcome is stated by Iman Khajebsairi et al. as reliability is providing accurate and continuous data transfer across the system, interoperability across different devices that operate on different communication protocols, scalability to provide new or extended services without jeopardizing their current capabilities, availability as capability of providing services anytime and anywhere, security to provide device security to prevent data theft and software attacks that can effect hardware, big data analytics and cloud services to provide big data collected from IoT elements to be processed/stored effectively, low-power and modular sensor nodes design to provide devices with enough battery to prevent frequent maintenance or implement them with energy harvesting techniques to enable permanent service. (Khajenasiri et al. 2017)

Big Data management is expected to provide solutions to nowadays energy sector challanges such as: operational efficiency and cost control, stability and reliability issues in overall system, renewable energy integration and management, energy efficiency and sustainable development. Most of the modern smart meters logtheir data in 15 minutes of intervals. Some reports suggests that by the year 2020, at least 800 millions of smart meters are going to be operating. With 15 minutes of data collection intervals it results in around 77 billions of daily reading data that needs to be processed. Apart from that on-line monitoring of power line conditions, load demand, energy consumption scheduling, collection and processing of forecasting inputs and advanced metering data history makes Big Data management and smart grids inseperable. Big Data is defined as 5V which referres to volume, velocity, verecity, value and variety. There is immense amount of data collected in smart grid systems which is related to volume. Value of the vast amount of data is only meaningful after appropriate segmentation and classification. Data source such as various sensors, smart meters and customer inputs provides variety. Data collection and processing speed needs Big Data velocity to operate (Zhou et al. 2016). Supervisory Control and Data Acquisition systems are providing core decision making, real-time monitoring and control in smart grid systems. With increasing efficiency and global usage cloud computing systems provide a possible solution to usage of Big Data in Supervisory Control and Data Acquisition systems. This integration however is heavily dependant on network, storage and server capabilities.

Madeline et al. Proposed a big data analysis of smart meter data of customers (Martinez-Pabon et al. 2017). Their dataset is provided by a smart metering pilot project conducted by Irish Commission for Energy Regulation (CER) containing a total of 6429 data spanning a total of 535 days, 22 hours and 30 minutes. They proposed a method having 5 stages in clustering followed by 4 different machine learning algorithms to predict enrollment for DR programs. 5 stages for clustering: data processing, examination of dataset, applying hierarchical clustering, choosing best combination of clusters, predicting eligibility. Compared algorithms are k-nearest neighbor, decision tree, Artificial Neural Network(ANN) and random forest.

Their findings result in random forest being best performing method followed by k-nearest neighbor, ANN and decision tree.

2.3.6 HAN-NAN-WAN

HAN: Home Area Networks (HANs) are every appliance used by home owner aswell as all the sensors and metering devices that are connected

NAN: Neighbour Area Networks provides connection of multiple HANs to manage a district or municipality. They may include automation and management of local generation facilities such as combined heat power plants to optimize system's heating and electricity needs.

WAN: Wide Area Network manages nation/region-wide grid consisting of multiple HANs and providing control of distributed energy storage units and power plants.

2.3.7 Computing network structure

Computing Network Structure allows immense data collected from advanced metering infrastructure(smart meters and sub-metering devices) , distributed sensor networks, online monitoring data of electricity distribution system to be stored and processed more efficiently and rapidly. Cloud computing is one phenomena that allows hosting of processing power and data storage services online via the internet. This online access to storage and processing service is highly dependant on network infrastructure capabilities. Wide usage of cloud computing will provide economic benefits to user aswell as it will mitigate their IT service share on their budget. Rather than having specialized data centers, sofware application and development platforms invested and continuously maintained companies can have agreements for cloud usage. While most common usage of cloud term is public clouds where data and access to that data is available from anywhere that user sees fit, security issues can be ovecome by having a private cloud which can be accessed from certain networks that customer specifies. Due to its capabilities, cloud computing is a strong candidate in satisfying big data processing. Some of the privacy issues must be overcome to provide customer anonymity to protect electricity customer’s private data by using stenagrophy or other means. For smart grid applications, 3 cloud service models; IaaS, PaaS and SaaS are the most common ones.

3 LOAD AND TARIFF FORECASTING

Forecasting holds a great importance in modern and future grid system. Judging from meteorological data, load forecasting can determine the availibility of RES such as wind, solar and hydro. Therefore they are crucial in initial planning of electricity grid. Forecasting can be short term, medium term and long term. Depending on requirements and available data, load forecasting can accomplish day-ahead utility planning, power plant maintenance planning and even 20 to 50 years long long term energy planning on local, regional or global scales.

3.1 Top-Down Methods

Using characteristics of entire district, obtains load profiles for individual buildings. Two main modeling techniques:

3.1.1 Econometric model

District consumption modelled using independant variables. like price indices, GDP, income, population, socio-demographic, socio-economic and environemntal characteristics. Earlier econometric models were started with development of simple models. In 1978, Chessire and Surrey’s forecasting model was connecting growth with consumption using gross national product (GNP), gross domestic product (GDP) parameters. Another later study used a time-serier data of historical electricity consumption, GDP, GDP per capita and population data over 37 years. Analyzing main driving parameters behind electricity consumption.

3.1.2 Technological model

Uses physical realities of the consumption process like appliance ownership, daily usage patterns, building characteristics, seasonal and event based consumption patterns. Technological models generally require in-site measurements like appliance level and house level measurement of energy consumption.

3.2 Bottom-Up Methods

Uses individual building characteristics to obtain district-wide load. Founded on the basis of individual building's effects cummulating on district level. Main features of bottom-up methods approach are building based relevent parameters on building level and thermal and electricity final use data as hourly or daily data. Some of the main advantages of bottom-up methods are their capability to model under different scenarios and ability to predict total residental energy consumption without historical data. To have a more model based categorization of bottom-up methdos, they can be divided as:

3.2.1 Empirical models

Based on previous experience, inherited models like engineering handbooks can be used for quick and cheap load prediction in building level. They can easily provide useful information during design or decision making period. Empirical methods are effective in initial planning and scheduling period but can't reflect every aspect of the consumption if conditions are diverging from empirical data conditions.

3.2.2 Engineering models

Models that can also be referred as white box models or physical models, model the buildings or districts based on true physical realities of the system in terms of thermodynamics, heat transfer etc. They offer perfect solution for given model parameters and due to their accuracy, have been conducted and studied for a long time. Engineering models can be classified as simple and true approach. True approach implements every single parameter that is effecting the buliding electricity consumption based upon conservation of energy. Deploying highly detailed and complex method requires computer aided simulations where appliance usage, environmental and building characteristics can be implemented to get accurate results. Simple approach neglects the effect of some parameters to provide faster/easier solutions for load prediction and can be accurate enough to use on district based load forecasting. It can also be simplified by classifying buildings into different categories based on parameters such as age, size, technologies involved, type etc. Depending on developed simulation tool, simulations can be done to forecast electricity load on single-building or district/city/nation wide.

3.2.3 Statistical models

Known as black box data driven models, they are founded on the basis of predicting future data using large number of historical data. Statistical analysis allows establishing of new forecast models.

3.2.3.1 Regression-based models

Determines the coefficients of load forecasting model based on regression analysis. Used commonly especially electricity load on a district basis.

3.2.3.2 Time series models

Time series models current and past loads based on past data including appliance use, heating and cooling. Time series models can be divided into two groups such as time-domain and frequency domain. Time domain models contain Exponential smoothing(ES), multiplicative autoregressive models (AR), autoregressive moving average(ARMA), autoregressive integrated moving average(ARIMA), autoregressive moving average with exogenous input model (ARIMAX). Frequency domain models are generally used for on-line load forecasting which includes Kalman filtering, Fourier series model, wavelet theory and spectral analysis.

3.2.3.3 Intelligent models

Intelligent models are founded on the basis of machine learning techniques which don't require extensive programming but able to predict load data by learning. Machine learning approaches include support vector machine(SVM), ANN, fuzzy logic(FL), expert system(EP), genetic algorithms (GO) and particle swarm optimization (PSO). SVMs are supervised machine learning techniques that allow classification and regression analysis. ANN are connecting inputs and outputs in layers of neuron-like system defining weights by intelligently computing their effecting weights. Their perks of acceptable accuracy with easily developed modes and non-linear problem solving. Fuzzy logic attempts to solve multi-value logic having nonlinear and uncertain conditions by assigning values of variables real numbers between 0 and 1. Genetic Algorithm(GA) uses inspired by bio operations like selection, crossover and mutation to solve search and optimization problems. GA finds appropriate forecasting model when given enough historical data. Expert system(EP) is acting as an advisor rather than giving exact forecast for load. It can be supplementary to other forecasting methods especially in defining which method is better for different cases. Particle swarm optimization is used for optimal design of load forecasting model by iteratively trying out diffrent solutions. Can be integrated with other statistical methods

3.2.3.4 Hybrid statistical models

Hybrid statistical methods merges statistical models with emerging machine learning models such as neural network, fuzzy logic, SVM and time series.

3.2.4 Physical-statistical hybrid models

Some efforts aim to overcome shortcomings of both physical and statistical models. There is a variety of buildings inside a district which may have some modelling errors when taken as identical, also randomness nature of meteorological conditions (irradiation due to cloudy weather, temperature, humidity, wind speed etc.) are difficult to forecast. Statistical data uses historical data to overcome load uncertainties but their prediction accuracies are relatively low. Dominant feature in hybrid models has different success in different forecast tasks. For example statistically dominated models performs better electricity load predictions while physics dominated models have better heating and cooling forecast.

Katarina et al. used sensor-based data to predict electricity demands during event venues exploring ANN with SVR and data collection interval effects on prediction accuracy. Model accuracy comparison used two metrics mean absolute percentage of error(MAPE) and the coefficient of variance(CV). Duraing acquisition of data group used the Green Button Program which provided deatiled data of electricity consumption to their customers. A total of 4 different models were considered and each model was examined for daily, hourly and 15min data. Simulation results showed that Neural network performed best and outperformed SVR in daily load models. However hourly and 15-min interval prediction errors are higher for both methods, on some models SVR achieved less MAPE than NN (Grolinger, 2016).

A study made by Yangyang Fu et al. Is on formring a SVM based model to predict loads at system level. 24 seperate models (seperated for each hour) predicting hourly load for each sub systemusing weather conditions and data from previous 2 days study also compared SVM based method to other data mining methods such as ARIMAX, Decision Tree and ANN (Fu et al. 2015).

Study made by A. Ghasemi et al. proposes a novel hybrid algorithm for simulteneous price and load forecasting. algorithm is tested on reveral real and well-known marketsresulting in high accuracy and simulitenous forecast. literature review provided by the group suggests that high accuracy models for simultenous price and load predictions are scarce and in their study they are proposing a novel hybrid algorithm to perform more accurate forecast. They divided their approach into 3 main parts as preprocessing, forecasting engine and tuned algorithm. Their model is based on FWPT in decomposing and reconstructing input signals in different frequencies then implementing low and high pass filters. Later they developed a MIMO model based on and NLSSVM and ARIMA to form a linear and nonlinear correlation between load and prices. Final component deploys a modified Artificial Bee Colony(ABC) to form an optimized learning. simulations made on 3 electricity markets; PJM which covers 13 states in USA, NYISO which covers New York State and NSW which is operating in Australia. their algorithm shows less MAPE (%) when compared to ANN-MIMO and LSSVM-MIMO based methods that are available in the literature (Ghasemi et al. 2016).

Another study made during 2014 on the same markets proposes its model in 4 stages. 1st stage uses historical price and load data as input signals and uses WPT to transform signals and uses GMI to select best input data. Then they start training input data in a MIMO fashion to perform learning. Stage 3 tries to form/predict price and load signals. Stage 4 performs adjustments of MIMO-LSSVM parameters using forecasted and actual values to minimize prediction errors (Shayeghi et al. 2015).

Emmanouil Malliotakis et al. Presented a district based energy balance which is connected as a thermal and electrical micro grid. Model proposes a fictional semi-autonomous district which provides its own electricity and heating needs while has the ability to export to market. Main advantage of μ-Combined Heat Power systems is their ability to provide thermal or electrical energy needs based on demand and reduce overall emissions by using its waste heat for thermal usage in households that are connected to district. Neural Network based electrical demand prediction is calculated using historical demand data, historical weather data, calender data and weather forecast. Thermal demand predictions are done using hourly simulation data (Malliotakis and Founti, 2017) .

4 RESEARCH FINDINGS AND DISCUSSIONS

4.1 Pre Model Analysis

Clustering of customer groups is vital in forming a modern electricity infrastructure capable of implementing dynamic pricing. Evaluating large scale data through machine learning, utility companies are able to classify different customer groups analyzing their average daily consumption and load profiles. Customer clustering is vital to implement a fair pricing policy which offers incentives and discounts for certain customer groups and profiles while providing utility companies with better control over their distribution management and day-ahead electricity pricing. Some of the recent methods overviewed by (Chicco, 2012) includes Adaptive vector quantization, Entropy-based, Follow-the leader- Fuzzy logic, Fuzzy and ARIMA, Fuzzy k-means, Hierarchical clustering, Iterative refinement clustering, k-means, Min-max neuro fuzzy, Multivariate statistics, Probabilistic neural networks, Self organizing map, Support vector clustering and Weighted evidence accumulation clustering.

A study made in Spain, uses power index data such as mean daily power, mean valley hour power, mean shoulder hour power and mean peak hour power to classify a group of administrative, industrial and residental customers. Clustering is performed by two-stage hybrid algorithm a recurrent Hopfield’s neural network followed by k-means which refines the solution of initial neural network stage (Lopez et al. 2011).

Another study consisting of a total of 219 dwelling data set from mixed nationality between 30/03/2010 and 24/11/2010 providing load data and features of dwellings such as number of occupants, number of bedrooms and type of dwelling performed clustering using Dirichlet process mixture model. One unique advantage propsed by this clustering method was its ability to provide number of clusters without needing predetermined number of clusters at the expense of overall execution time (Granell et al. 2015).

Hourly (or more frequent) household consumption data for Turkey is unavailable to us. When contacted utility providing companies they either stated that they don't have such data or they can't share due to trade secret. Modelling of household consumption through surveys have been reviewed in previous chapters. Having Ireland CER smart meter pilot project data containing household consumption in 30 min intervals and survey corresponding to each customer covering dates July 2009 to end of December 2010, we are able to model Turkey household consumption profiles for a given survey data.

4.2 CER Pilot Project

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).

4.2.1 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.

4.2.2 Forming load profiles

For each customer daily, weekly average and 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.

4.2.2.1 Daily load profiles

Daily load profiles are directly effected by consumer behavior specific to that date. Daily consumption profiles are highly susceptible to be date specific data like house occupancy, extreme events etc.

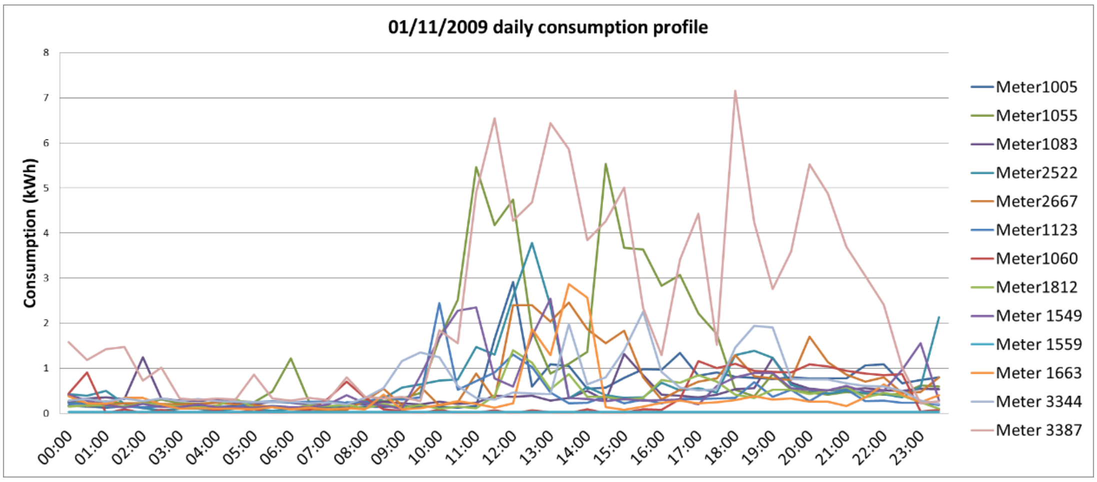

Figure 4.1. 01/11/2009 load profiles for given customers

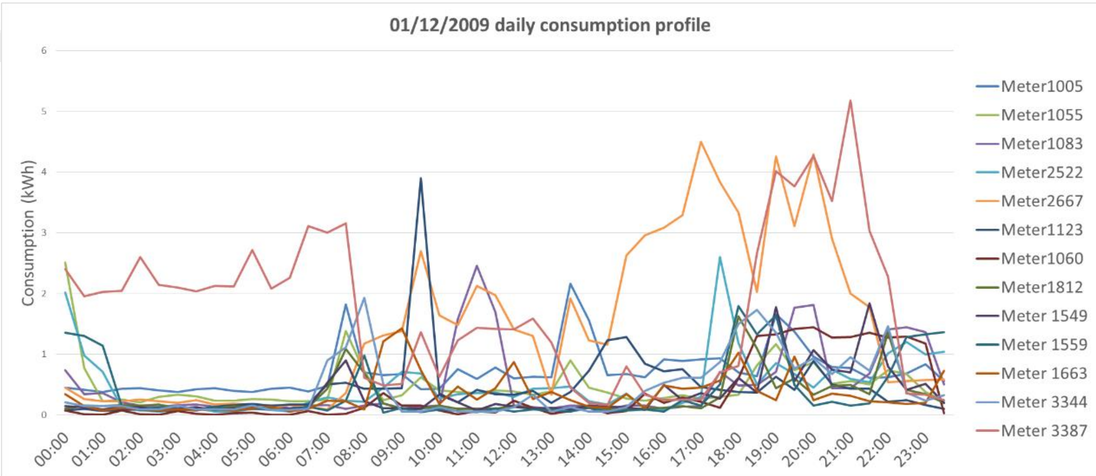

Figure 4.2. 01/12/2009 load profiles for given customers

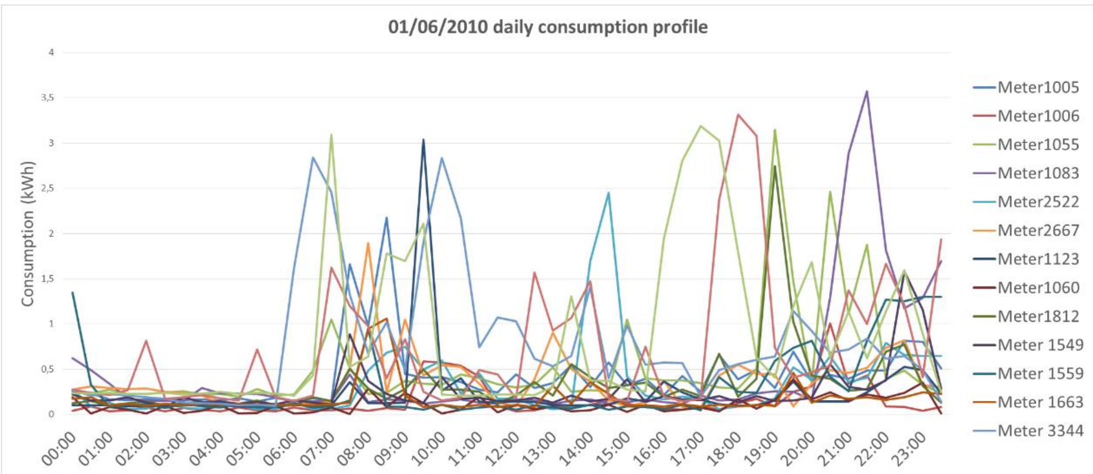

Figure 4.3. 01/06/2010 load profiles for given customers

4.2.2.2 Weekly average load profiles

Weekly load profiles reflect overall consumer behavior better than daily usage but it still gets heavily effected by extreme daily actions. A day of absence or extreme usage may have effects on weekly average load profiles.

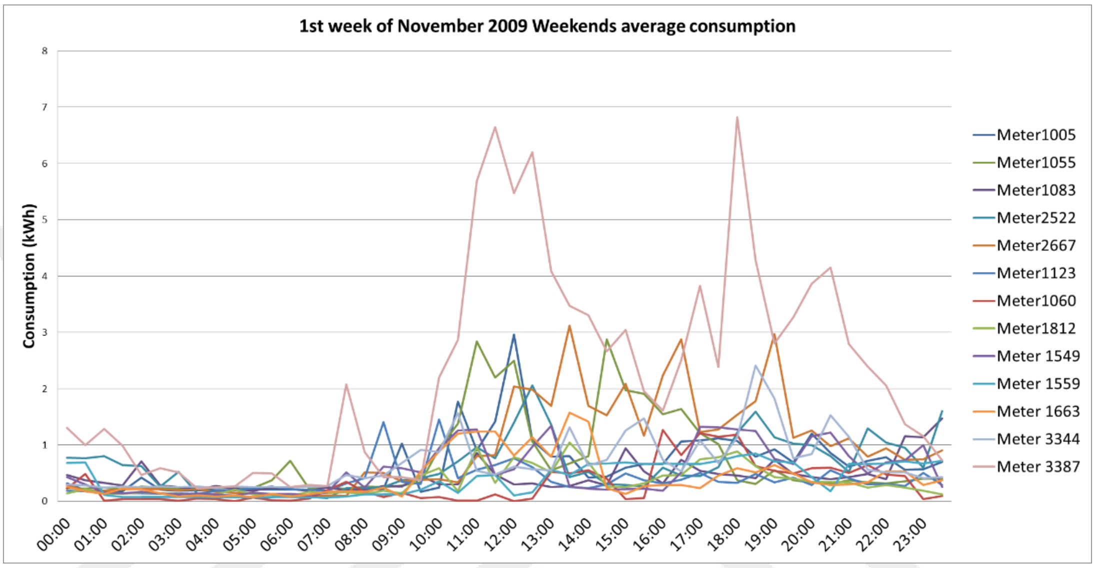

Figure 4.4. 1st week of November 2009 weekends average consumption for given customers

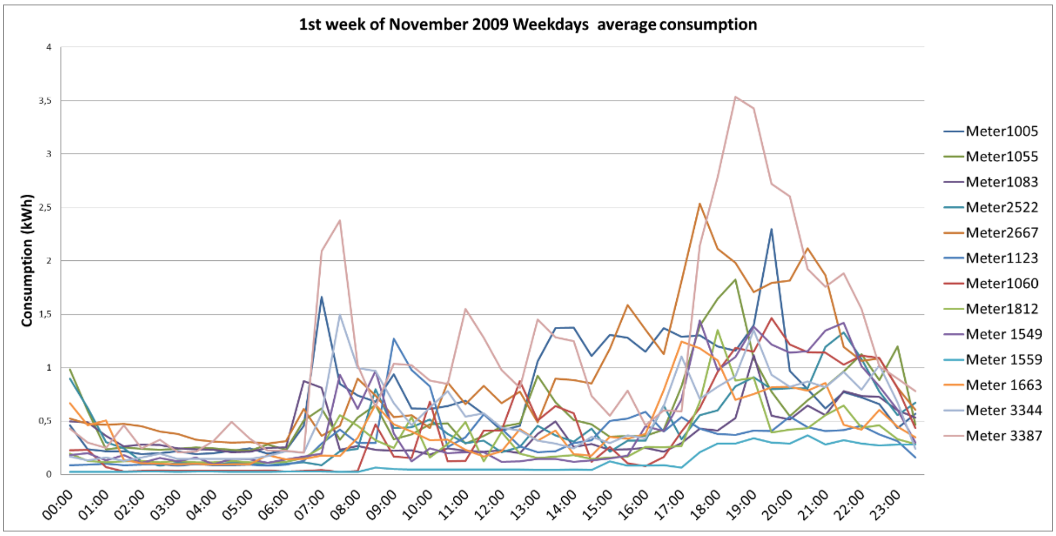

Figure 4.5. 1st week of November 2009 weekdays average consumption for given customers

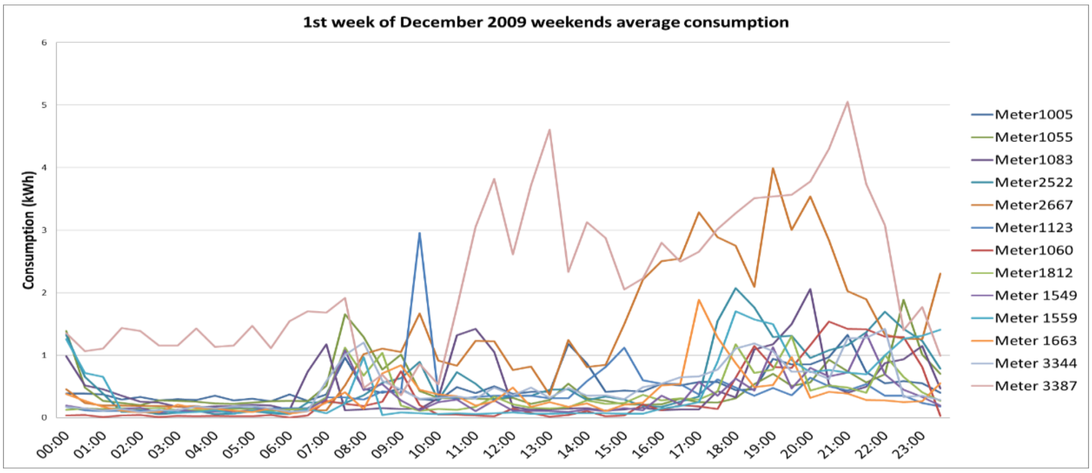

Figure 4.6. 1st week of December 2009 weekends average consumption for given customers

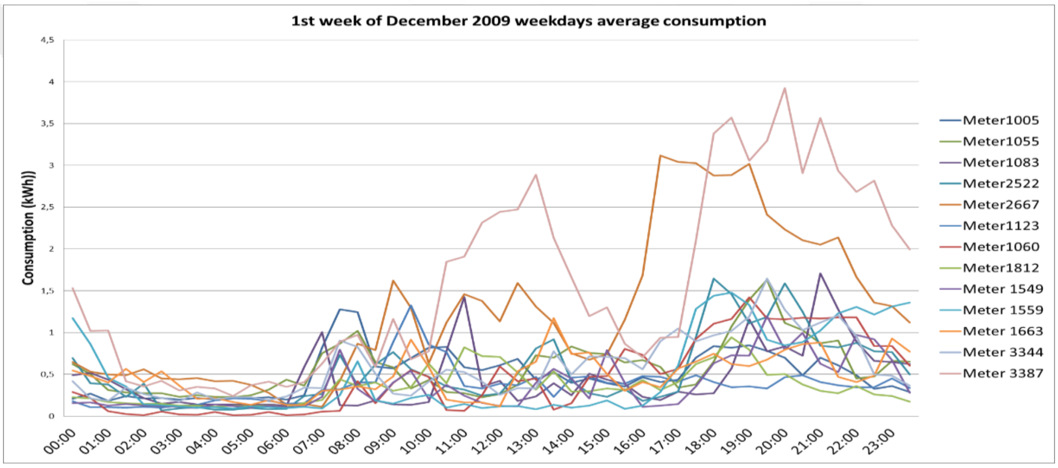

Figure 4.7. 1st week of December 2009 weekdays average consumption for given customers

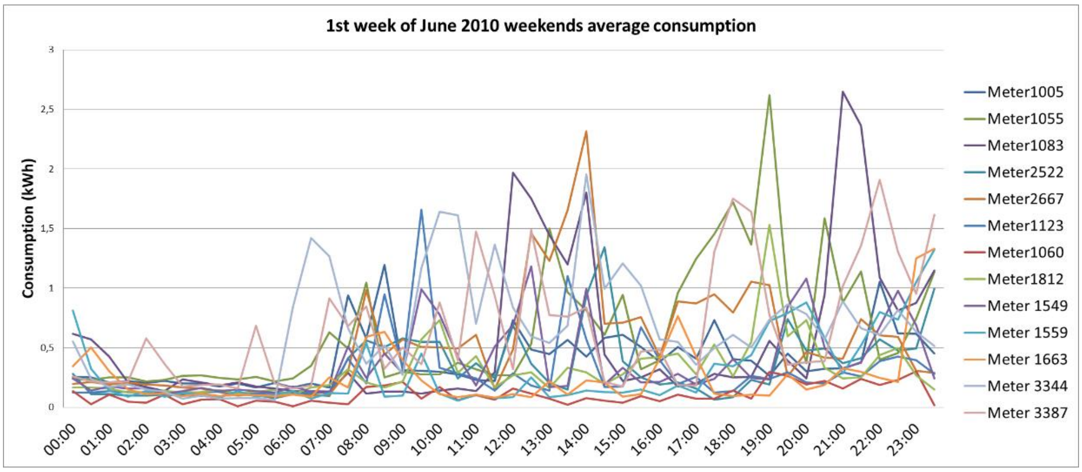

Figure 4.8. 1st week of June 2010 weekends average consumption for given customers

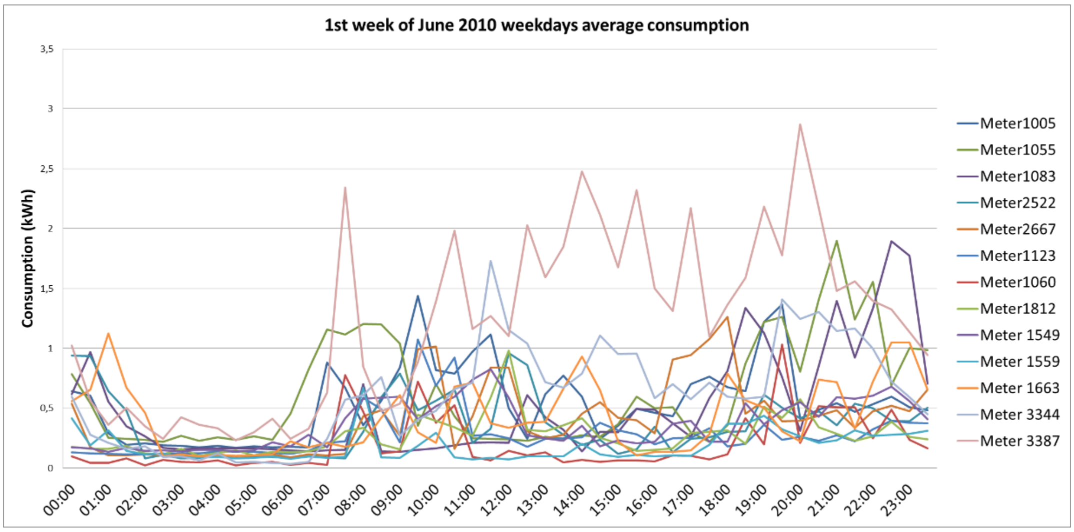

Figure 4.9. 1st week of June 2010 weekdays average consumption for given customers

4.2.2.3 Monthly average load profiles

Monthly average load profiles reflects seasonal characteristics of consumer load profiles best as all distinct behaviors and abnormalities are leveled down by general usage of electricity along the month.

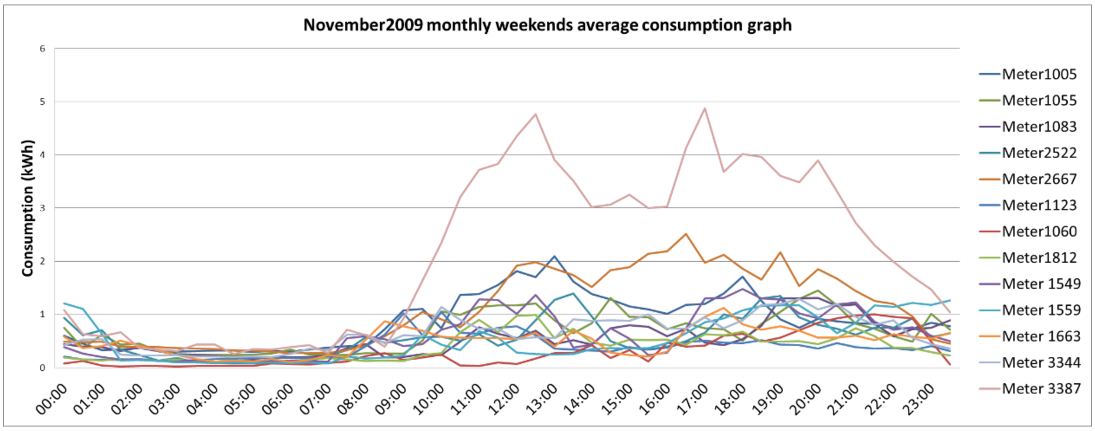

Figure 4.10. December 2009 monthly average weekends consumption for given customers

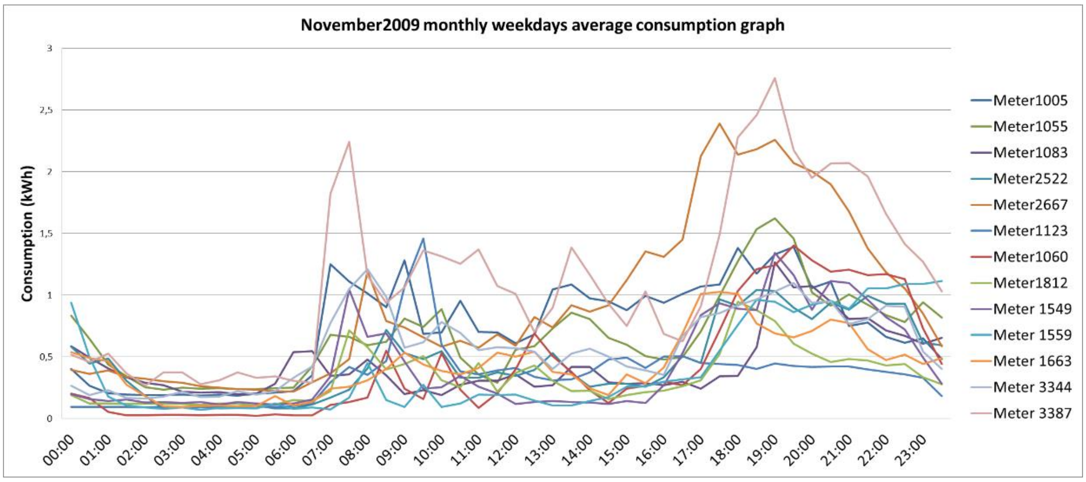

Figure 4.11. November 2009 monthly average weekdays consumption for given customers

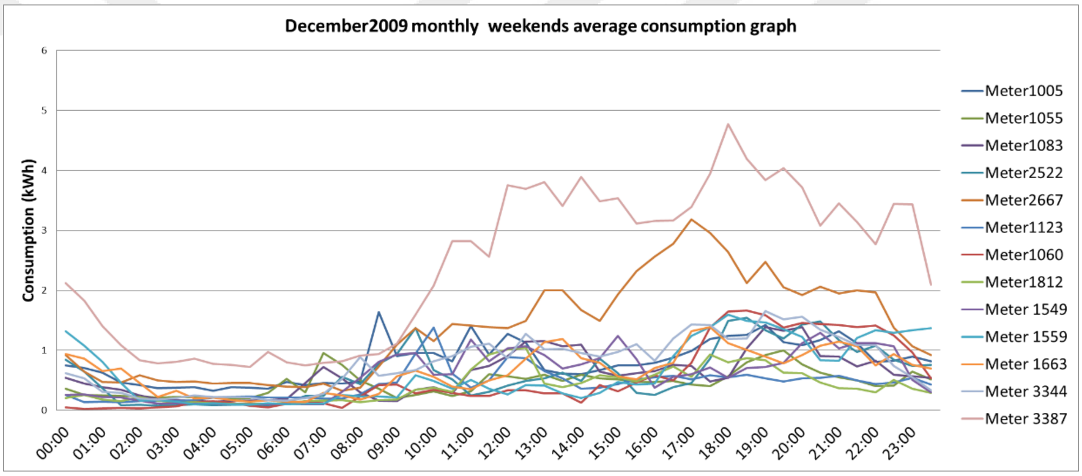

Figure 4.12. December 2009 monthly average weekdays consumption for given customers

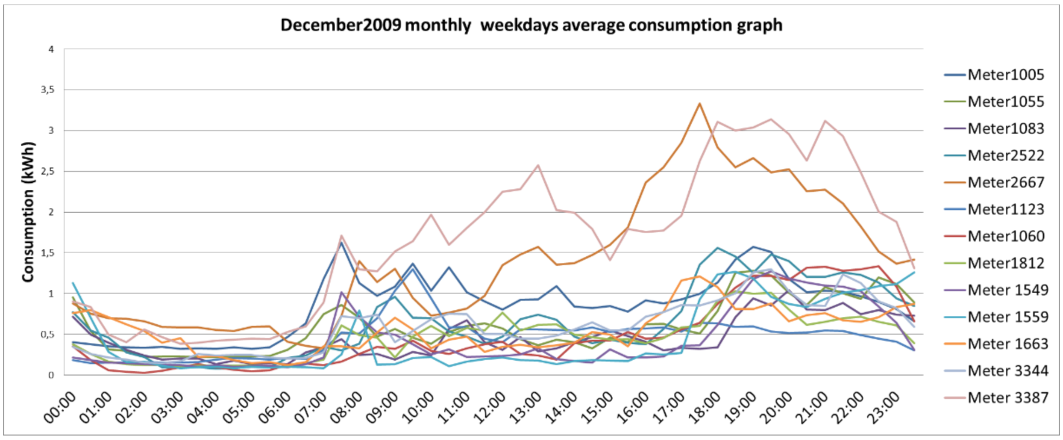

Figure 4.13. December 2009 monthly average weekdays consumption for given customers

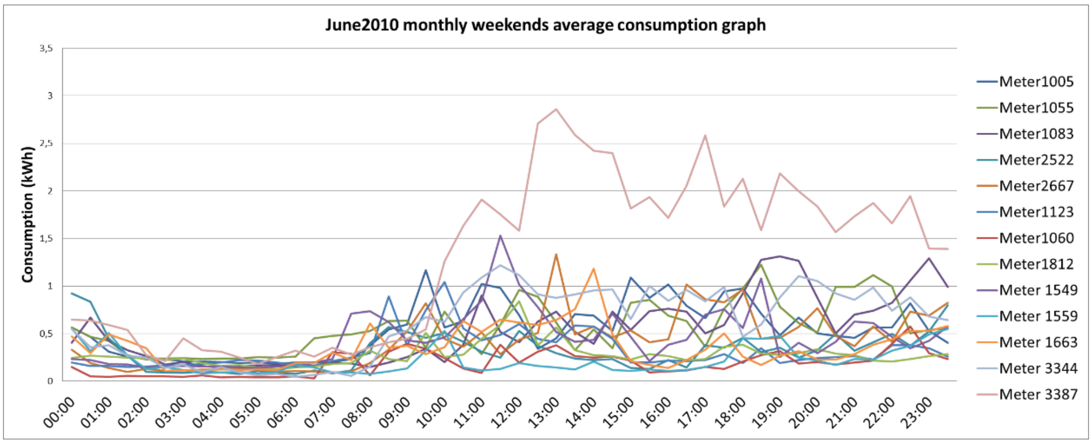

Figure 4.14. June 2010 monthly average weekends consumption for given customers

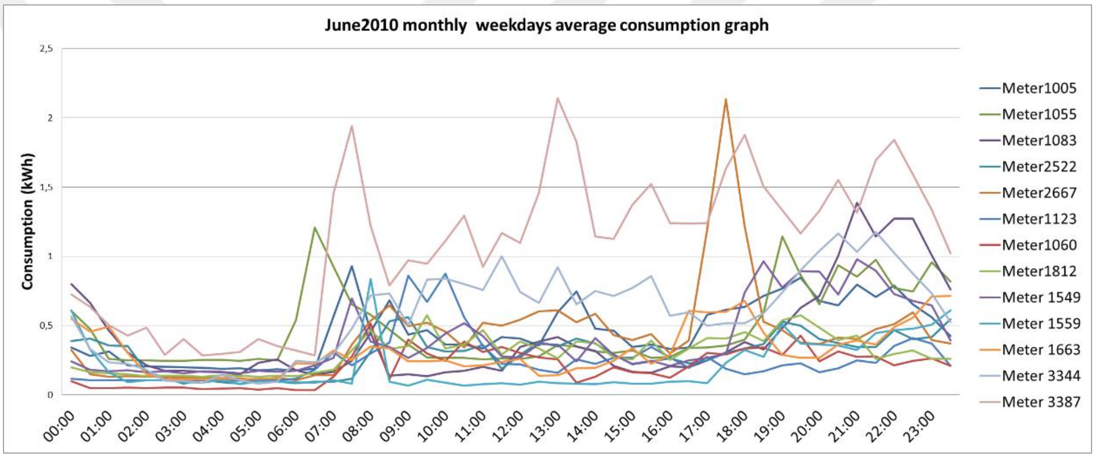

Figure 4.15. June 2010 monthly average weekdays consumption for given customers

4.2.3 Relations between survey and load profiles

Survey data is also provided in excel format. For 4233 residental customers, 144 columns of survey answer data are provided. Survey questions include household specific data such as number of child and adult residents of the household and their vacancy status, household type and its physical properties such as age, floor area, room count and insulation, space and water heating characteristics of household, quantity of each individual electrical appliance and their usage info.

4.3 Consumption Parameters Survey

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 to plan daily, weekly, monthly, yearly and 10 year electricity planning.

Table 4.1. Consumption parameters for chosen group of customers.

Meter ID	#of people living	Active consumer during day	Space heating use electricity?	Water heating use electricity?	#of rooms	Building age	Cooking use electricity?	Total # of appliances
1005	2	0	No	No	3	79	Yes	10
1055	2	0	No	No	4	15	Yes	8
1060	2	2	No	No	3	35	No	7
1083	2	0	No	Yes	4	11	Yes	13
1123	2	0	No	Yes	3	25	Yes	8
1549	4	0	No	No	4	29	Yes	15
1559	1	0	Yes	No	3	62	Yes	6
1663	6	6	No	No	3	5	Yes	12
1812	4	0	No	Yes	3	86	No	16
2522	2	2	No	Yes	4	114	Yes	10
2667	2	2	No	No	3	85	No	7
3344	6	1	No	No	4	2	Yes	12
3387	6	0	No	Yes	4	3	Yes	13
3967	6	5	No	No	5	14	Yes	16

4.3.1 Load profiles and survey data combination

CER survey data provides useful information such as household demographics, household physical properties(type, floor area, number of bedrooms, insulation etc.), space and water heating source also inculdes electrical appliances owned by household and their appliance usage routines. REMODECE project uses active, standby and off-mode consumption data which is provided by Schlomann et al. from Fraunhofer ISI for most of the appliances and white goods. Using CER survey and consumption data while providing them with REMODECE data provides a relation between survey and load data.

To examine relations between surveys and consumption data, customers that have been chosen have been divided into 6 different comparison groups.

Table 4.2. Comparison groups

Comparison1	Comparison2	Comparison3	Comparison4	Comparison5
1005	1060	1549	3387	1559
1055	2522	1812	3344	1663
1083	2667			
1123				

Comparison group 1

Comparison group 1 analyzes effects of household physical properties, HVAC and electrical appliances on consumption profiles for households having same amount of consumers. All households have 2 adults which aren’t active consumer during day.

Table 4.3. “Comparison group 1” key characteristics.

MeterID	Space heating	Water heating	Insulation	Total number of appliances	Unique appliance among group	Has electric shower?
1005	Oil	Oil	Moderate	10	Electric convector heater, stand	Yes
1055	Oil	Oil	Proper	7	Desktop computer	No
1083	Oil	Electric immersion	Moderate	11		Yes
1123	Gas	Electric immersion	inferior	8		Yes

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 Figure 4.19. Obvious factors like insulation of the building and heating type is directly effective on building electricity consumption.

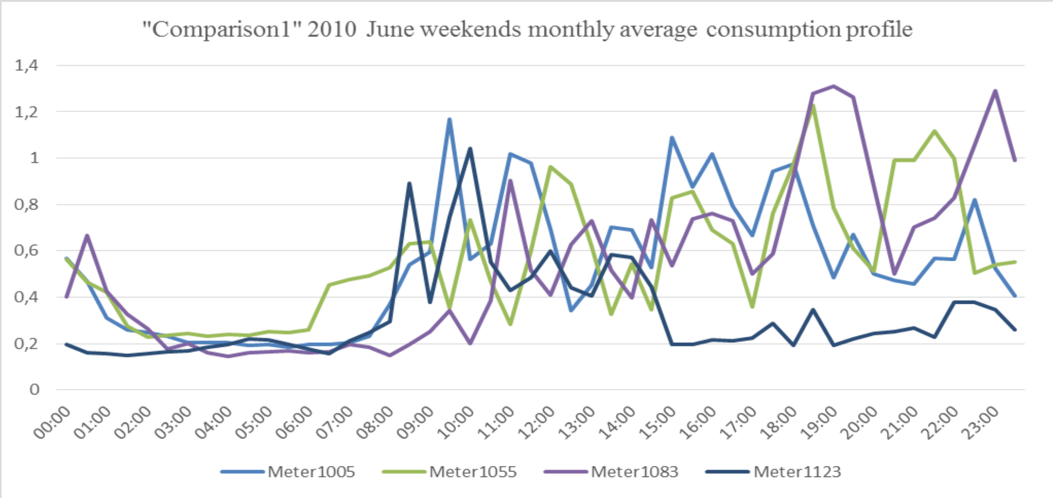

Figure 4.16. "Comparison group 1" 2010 June weekends monthly average consumption profile

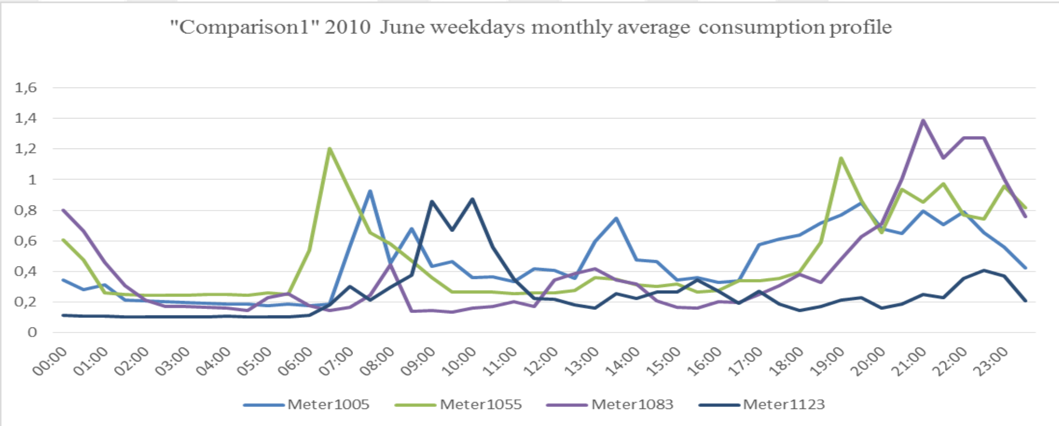

Figure 4.17. "Comparison group 1" 2010 June weekdays monthly average consumption profile

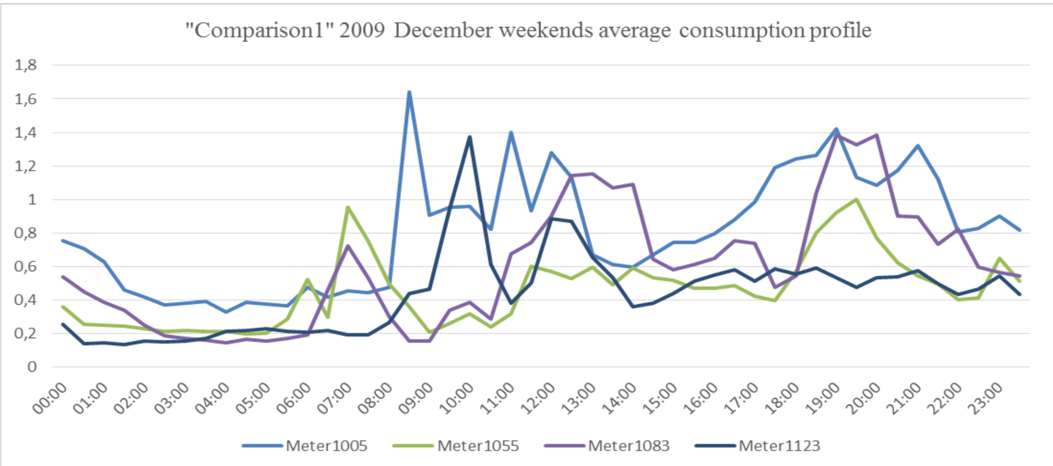

Figure 4.18. "Comparison group 1" 2009 December weekends monthly average consumption profile

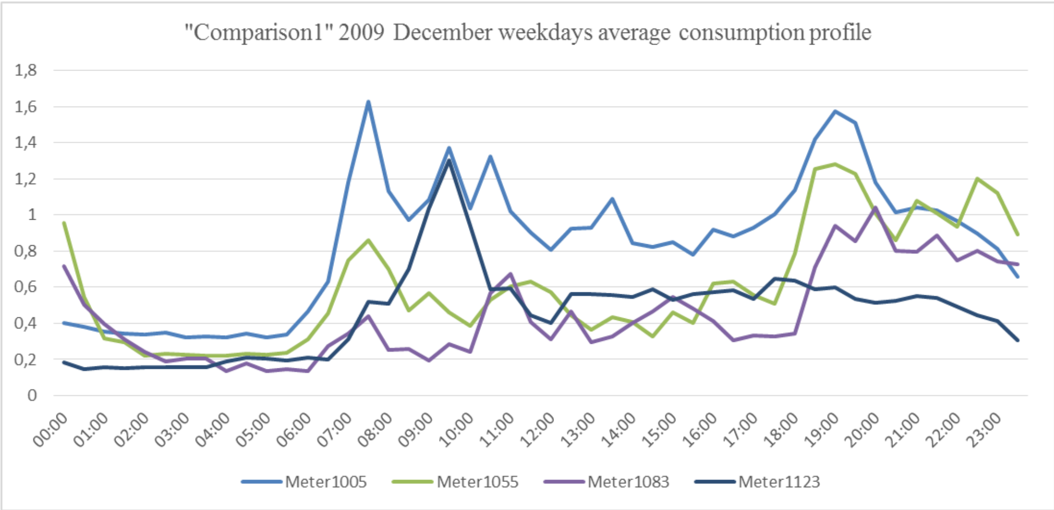

Figure 4.19. “Comparison group 1” 2009 December weekdays monthly average consumption profile

Comparison group 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 4.4. “Comparison group 2” key characteristics.

MeterID	Washing machine frequency	Tumble dryer frequency	Total number of appliances	Electric shower
1060	Less than 1 load daily	Less than 1 load daily	6	10-20 mins
2522	Less than 1 load daily	Less than 1 load daily	10	5-10 mins
2667	1 load daily	1 load daily	7	10-20 mins

As it can be seen on Figure 4.22. and Figure 4.23. usage frequency of certain appliances has an overall effect on consumption intensity. During June, customer 2667 already has the most average consumption due to using washing machine and electric shower more frequently and for longer time respectively. Assuming that residents don’t use their tumble dryer during summer, it is possible that rise during

December is heavily influenced by usage of tumble dryer since none of the residents use electric heaters in their home.

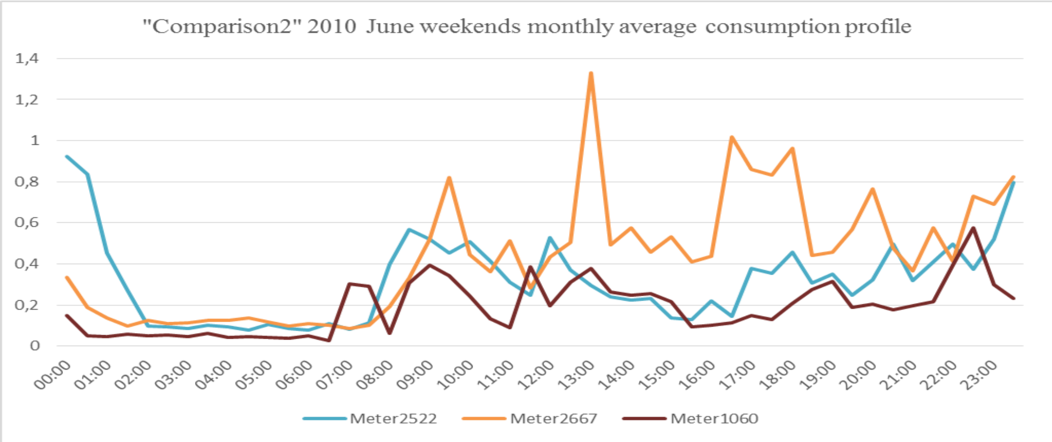

Figure 4.20. "Comparison group 2" 2010 June weekends monthly average consumption profile.

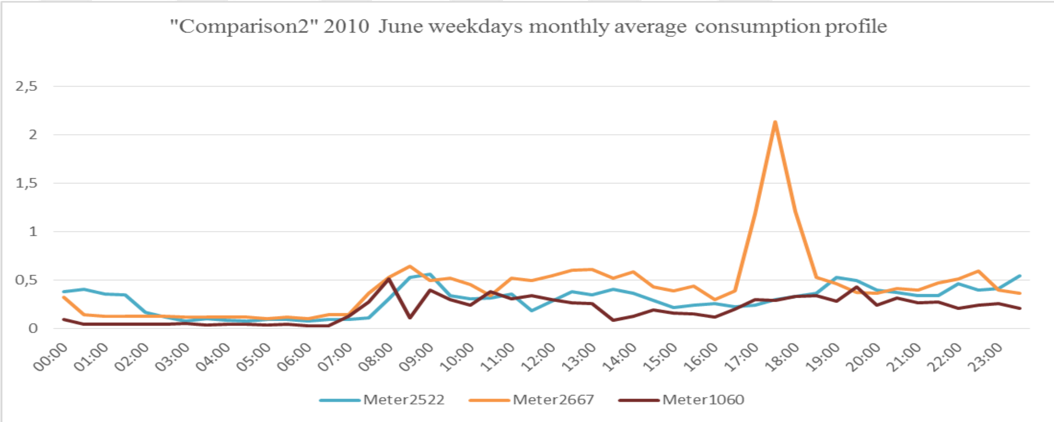

Figure 4.21. "Comparison group 2" 2010 June weekdays monthly average consumption profile

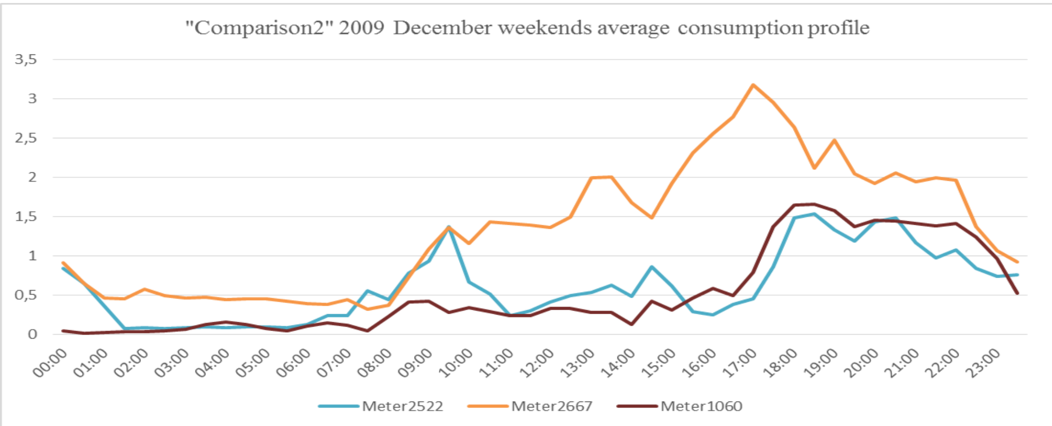

Figure 4.22. "Comparison group 2" 2009 December weekends monthly average consumption profile

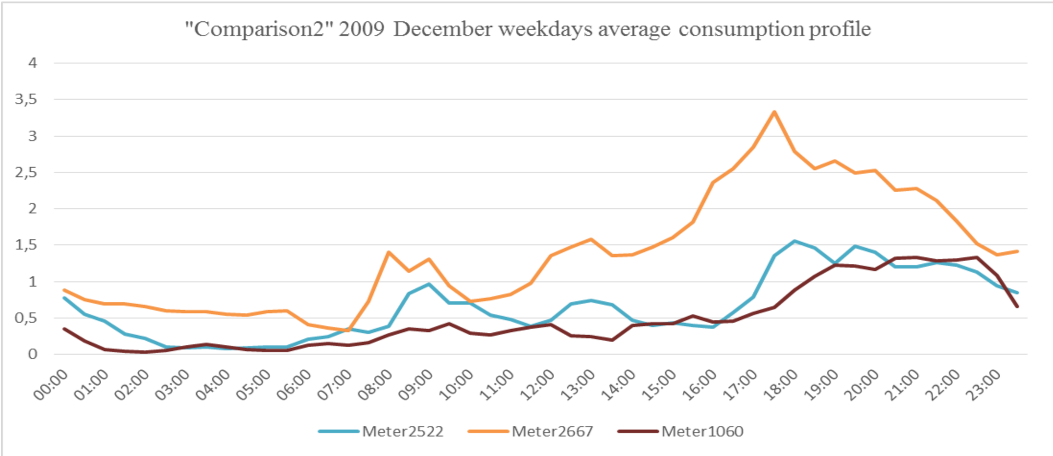

Figure 4.23. "Comparison group 2" 2009 December weekdays monthly average consumption profile.

Comparison 3

Comparison group 3 analyzes consumption differences 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.

Table 4.5. "Comparison group 3" key characteristics.

MeterID	Building constructed during	Insulation	Washing machine	Dishwasher	Electric shower	Electric cooker	Electric convector heater	Gaming console
1549	1980	Proper	1 load daily	1 load daily	Less than 5 minutes	30-60 minutes	30-60 minutes	1 – 3 hours daily
1812	1923	Poor	Less than 1 load daily	Less than 1 load daily	10-20 minutes	No electric cooker	No electric convector	No gaming console

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.

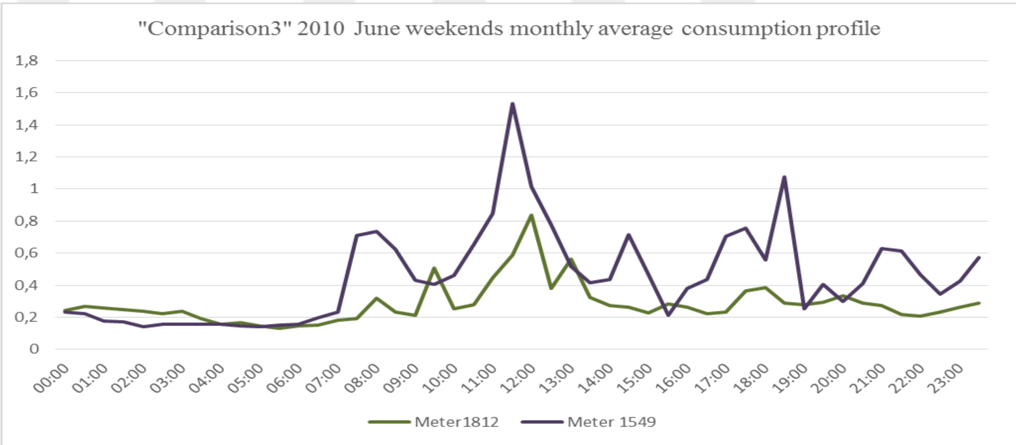

Figure 4.24. “Comparison group 3” 2010 June weekends monthly average consumption profile.

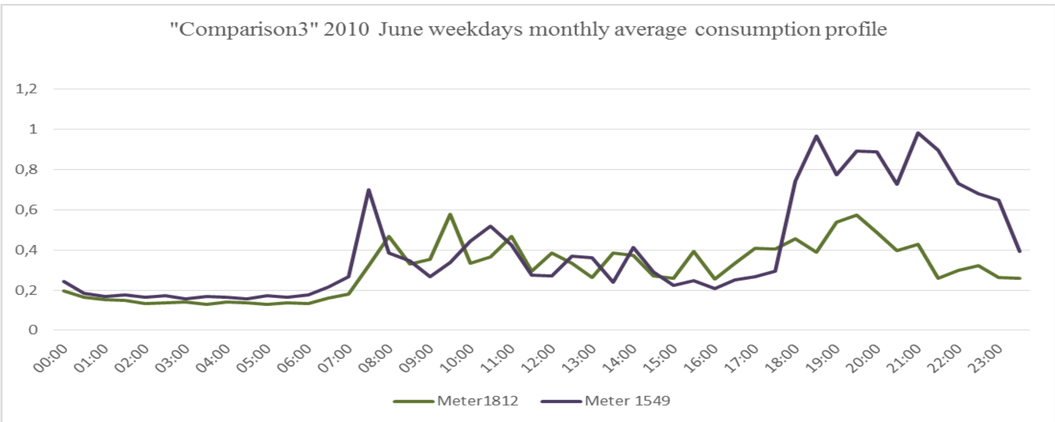

Figure 4.25. “Comparison group 3” 2010 June weekdays monthly average consumption profile.

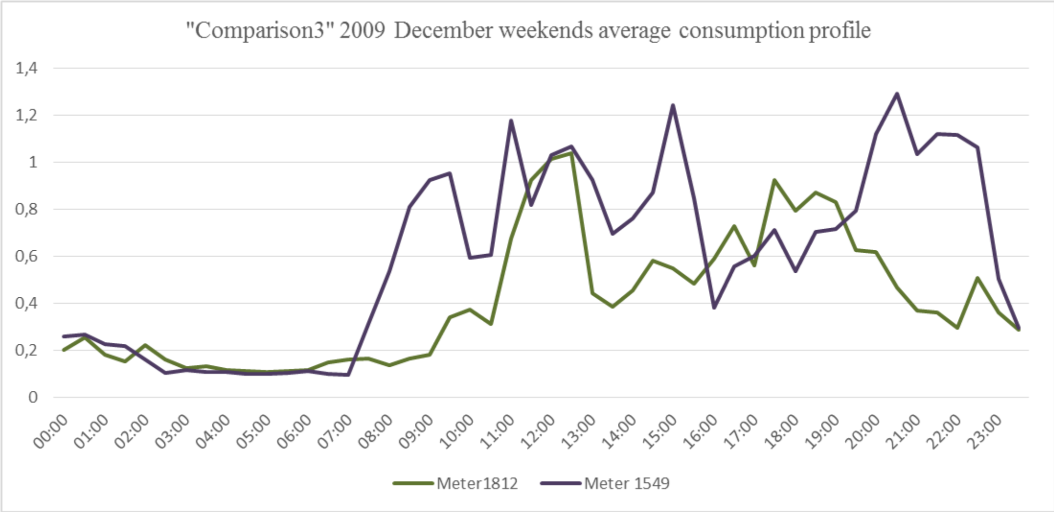

Figure 4.26. “Comparison group 3” 2009 December weekends monthly average consumption profile.

Figure 4.27. “Comparison group 3” 2009 December weekdays monthly average consumption profile.

Comparison 4

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 4.6. “Comparison group 4” key characteristics.

MeterID	Washing machine usage	Tumble dryer usage	Dishwasher usage	Electric shower usage	TV usage	Desktop computer usage	Gaming console usage
3344	Less than 1 load daily	Less than 1 load daily	Less than 1 load daily	10-20 minutes	1 – 3 hours per day	Less than 1 hour daily	Doesn’t have
3387	2 to 3 loads daily	1 Load daily	2 to 3 loads daily	Over 20 minutes	More than 5 hours per day	3-5 hours per day	3-5 hours per day

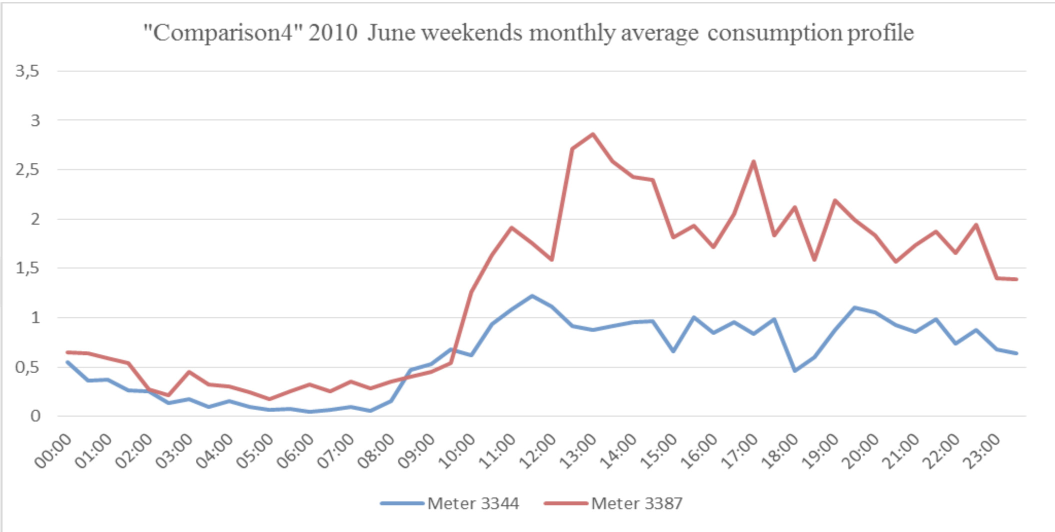

Figure 4.28. “Comparison group 4” 2010 June weekends monthly average consumption profile.

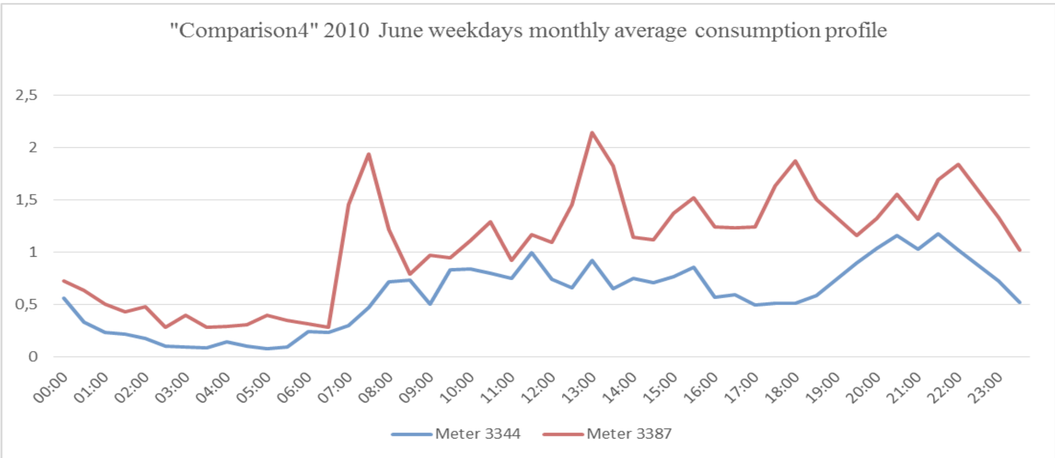

Figure 4.29. “Comparison group 4” 2010 June weekdays monthly average consumption profile.

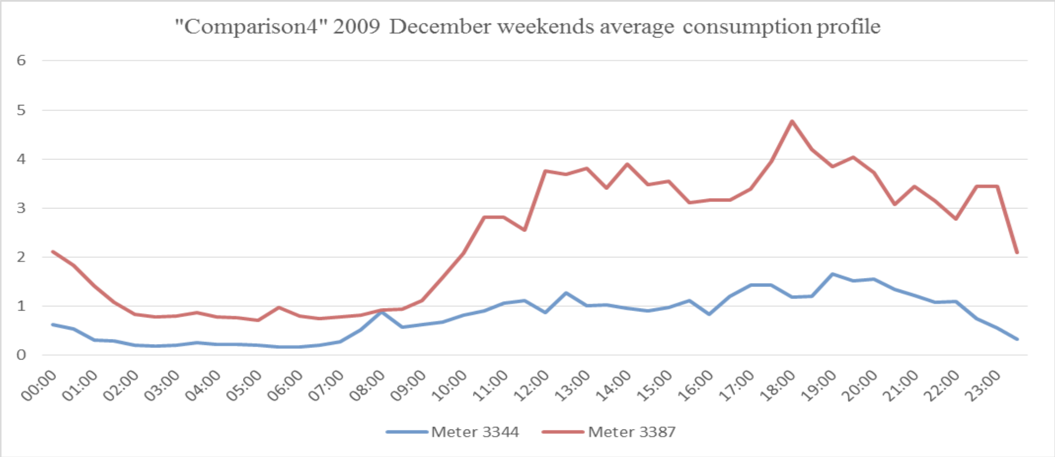

Figure 4.30. “Comparison group 4” 2009 December weekends monthly average consumption profile.

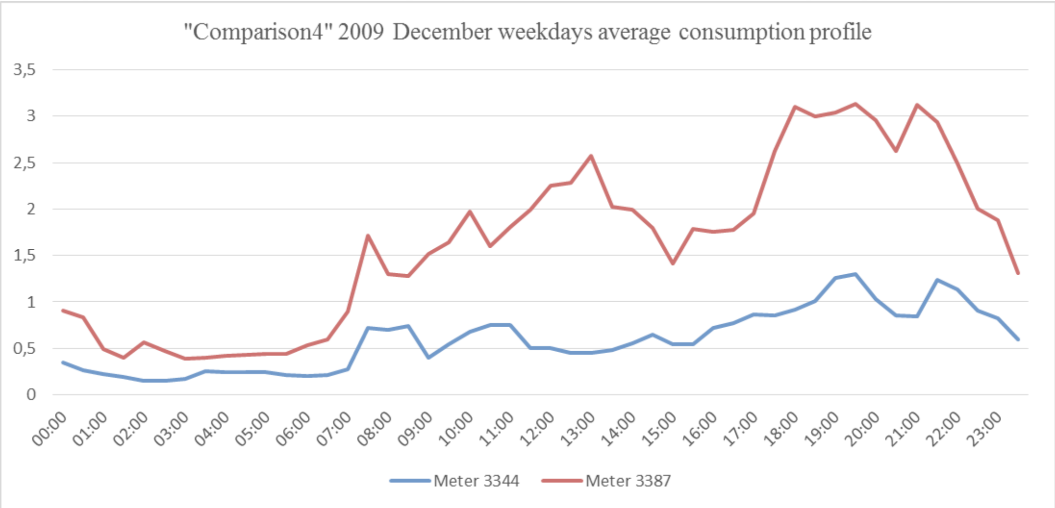

Figure 4.31. “Comparison group 4” 2009 December weekdays monthly average consumption profile.

Comparison 5

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

Table 4.7. “Comparison group 5” key characteristics.

MeterID	Household	Active Consumers	Insulation	Space heating	Number of TV	Total number of appliances	TV usage
1559	1	0	Poor	Electric, Gas	1	6	3-5 hours daily
1663	6	6	Proper	Solid fuel	2	11	More than 5 hours daily

Customer 1559 June weekend average consumption profile is relatively low as household doesn’t require heating and a single person residency with few electrical appliances. During weekdays, only 2 peaks are observable 1 in the morning most probably getting prepared for work and the other one during evening when resident is an active consumer. Customer 1663 June weekends have relatively more average consumption due to having more people in residency. During weekdays, while most of the other customers show consumption amounts close to base load, they have active consumption during day-time due to having active consumers.

During December weekends, customer 1559 is having increased early day and late evening/night consumption due to having electrical space heating in a poor insulated house. Also being an active consumer, there is a signifact difference between average consumption between customer 1559 and customer 1663. Until late evenings customer 1663’s average consumption is higher than customer 1559 but it changes at late hours due to customer 1559 has to consume electricity for space heating purposes. During December weekdays, customer 1559 early day consumption is identical to June consumption but during and after evening peak time consumption average reaches around 3 times of June consumption.

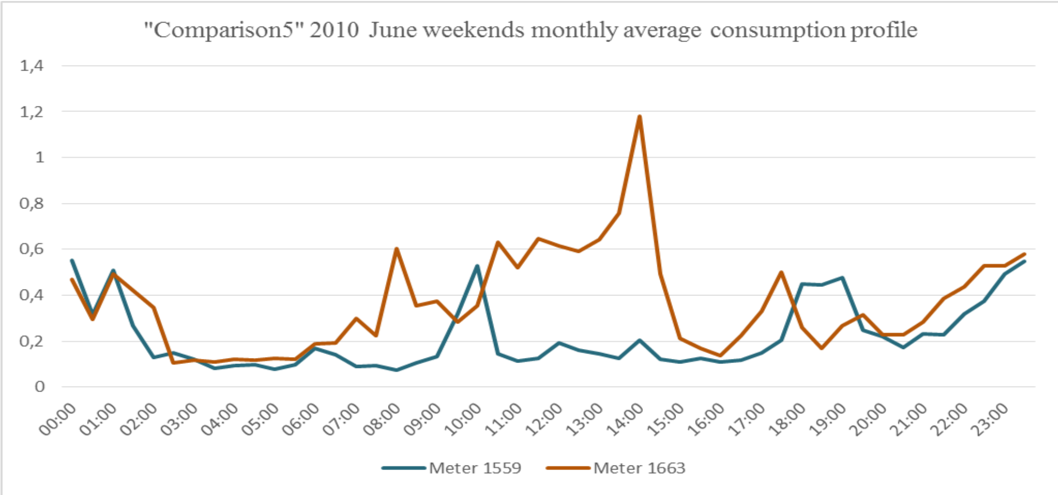

Figure 4.32. “Comparison group 5” 2010 June weekends monthly average consumption profile.

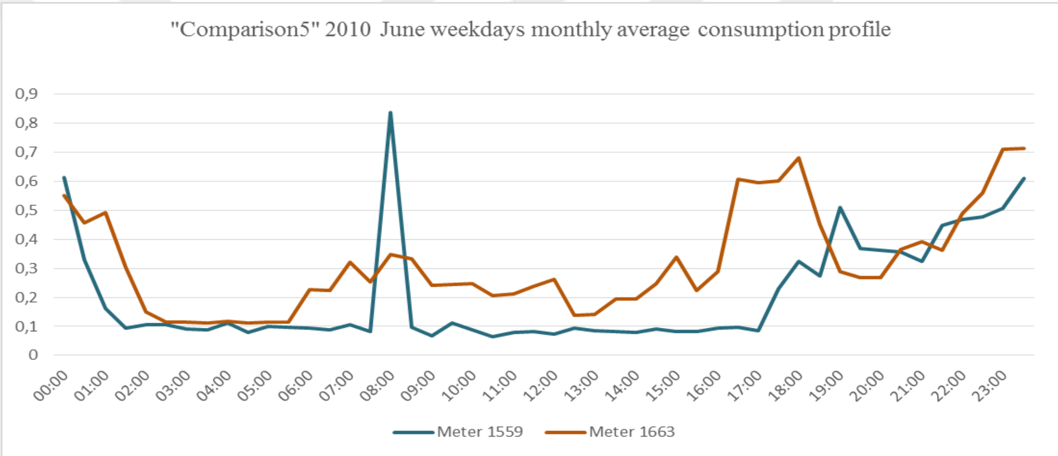

Figure 4.33. “Comparison group 5” 2010 June weekdays monthly average consumption profile.

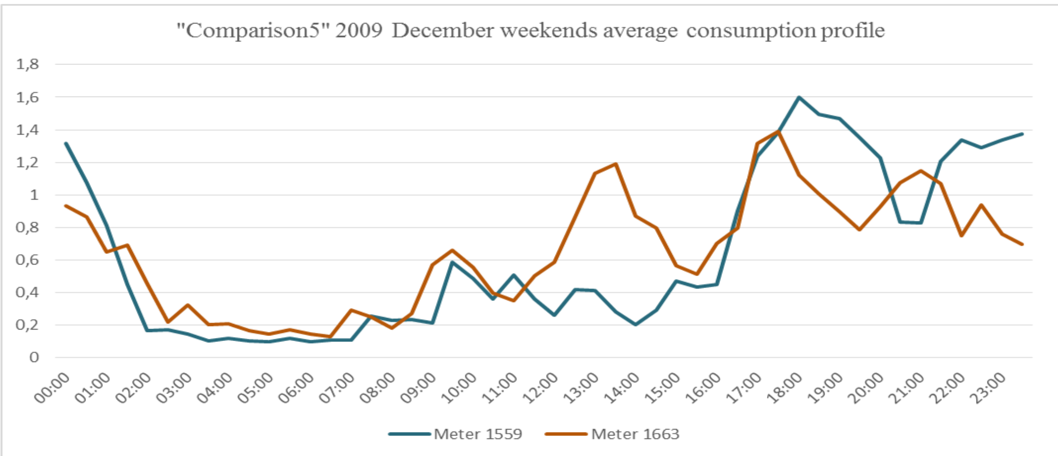

Figure 4.34. “Comparison group 5” 2009 December weekends monthly average consumption profile.

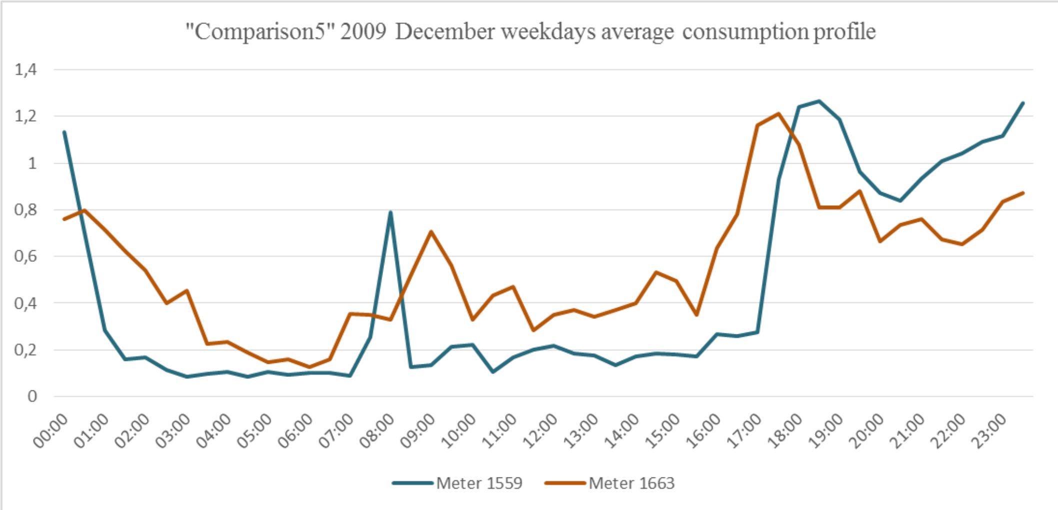

Figure 4.35. “Comparison group 5” 2009 December weekdays monthly average consumption profile.

Table 4.8. Calculated monthly average daily consumption amounts of June and December for investigated customers seperated by weekend and weekdays using smart meter data.

Meter ID	December 2009		June 2010	
	Weekends	Weekdays	Weekends	Weekdays
1005	38,85kWh	40,91kWh	25,93kWh	21,92kWh
1055	21,995kWh	29,07kWh	27,18kWh	23,12kWh
1083	28,63kWh	21,505kWh	25,97kWh	19,76kWh
1123	21,02kWh	22,23kWh	15,48kWh	12,1kWh
1060	25,66kWh	23,24kWh	9,06kWh	9,65kWh
2522	29,41kWh	31,38kWh	15,4kWh	14,3kWh
2667	65,14kWh	66,56kWh	20,75kWh	20,76kWh
1549	28,94kWh	20,62kWh	21,9kWh	19,17kWh
1812	19,77kWh	22,30kWh	13,63kWh	14,46kWh
3387	115,25kWh	78,9kWh	62,01kWh	52,13kWh
3344	37,69kWh	28,5kWh	29,43kWh	28,27kWh
1559	30,31kWh	21,6kWh	10,52kWh	9,97kWh
1663	31,22kWh	26,37kWh	17,6kWh	15,22kWh
Total	493,885kWh	433,185kWh	294,86kWh	260,81kWh

Calculations regarding monthly average daily consumptions are calculated through summing 48 half-hourly average consumption data for corresponding month. Apart from some minor deviations, winter consumption is proven greater than summer as most studies have found out previously. Apart from seasonal changes, amount of electrical appliances and their usage frequency is a key factor in total electricity consumption of households.

Data provided by Table 4.8. shows varying consumption increases between June and December months. analyzing data provided with pre-trial survey, main driving factors behind seasonal changes between June and December is expected to be related to building physical properties.

Table 4.9. Survey data regarding June-December consumption change

ID	Building age	Convector heater	Overall Insulation	Age of homeowner	Summer-winter consumption change
1005	Very old	Yes	Moderate	36-45	Moderate increase
1055	Moderate	No	Proper	36-45	No change
1060	Old	Yes	Proper	56-65	Dramatic increase
1083	Moderate	No	Moderate	26-35	No change
1123	Moderate	No	Inferior	65+	Moderate increase
1549	Moderate	Yes	Proper	56-65	No change
1559	Very old	No	Moderate	46-55	Dramatic increase
1663	New	No	Proper	26-35	Moderate increase
1812	Very old	No	Moderate	46-55	Moderate increase
2522	Very old	No	Proper	65+	Moderate increase
2667	Very old	No	Moderate	65+	Dramatic increase
3344	New	No	Proper	36-45	Moderate increase
3387	New	No	Proper	26-35	Moderate increase

It has been observed that drastic increases in electric consumption between June and December is due to old building with almost no insulation increasing electricity consumption for space and water heating. Elder homeowners can also be related to increase in consumption as they probably have older inefficient heating appliances.

Table 4.10. Daily average consumption of selected households through survey data calculations.

MeterID	December	June
1005	20,3328 kWh	18,3328 kWh
1055	7,4098 kWh	7,4098 kWh
1083	11,3208 kWh	11,3208 kWh
1123	10,0168 kWh	10,0168 kWh
1060	21,4388 kWh	19,4388 kWh
2522	20,4038 kWh	20,4038 kWh
2667	20,8908 kWh	20,8908 kWh
1549	30,2348 kWh	26,2348 kWh
1812	11,2218 kWh	11,2218 kWh
3387	32,2758 kWh	32,2758 kWh
3344	22,5918 kWh	22,5918 kWh
1559	4,3228 kWh	4,3228 kWh
1663	12,5648 kWh	12,5648 kWh

Using pre trial survey data acquired from Irish CER and combining it with REMODECE pilot project appliance data for ICT products and white goods while gathering other appliances consumption data from retailers, calculation of daily average consumption is performed. While survey is extensive and provides detailed information, it overlooks some factors like lighting.

Appliance consumption patterns may also show variance between survey and actual consumption measured by smart meter while REMODECE appliance consumption data may not fully reflect modern appliances that are being used in residences. Survey based consumption calculation is modelling an ordered case disregarding any other factor like vacant residence, intense consumption due to an event or routines that are not stated in surveys. However survey can provide important information to compare and contrast different consumption profiles and get effecting factors. Another possibility is due to elder residents living in old houses using outdated appliances. According to a report made by (Dickert and Schegner, 2015) outdated appliances greatly increases electricity consumption. Data provided by their report which can be seen on Table 4.11, emphasizes the effect of using appliances that reflect technological advancements of the modern era. When values of 1977 are used for consumption calculation using survey data, it matches with Table 4.8. December data.

Table 4.11. Developments in appliance consumption

Appliances	1977 consumption per cycle (Wh)	1999 consumption per cycle (Wh)	2015 consumption per cycle (Wh)
Fridge	900	480	60
Freezer	1100	480	120
Dishwasher	210	100	60
Washing machine	420	190	70
Tumble dryer	900	640	140
Baking oven	1500	1100	630

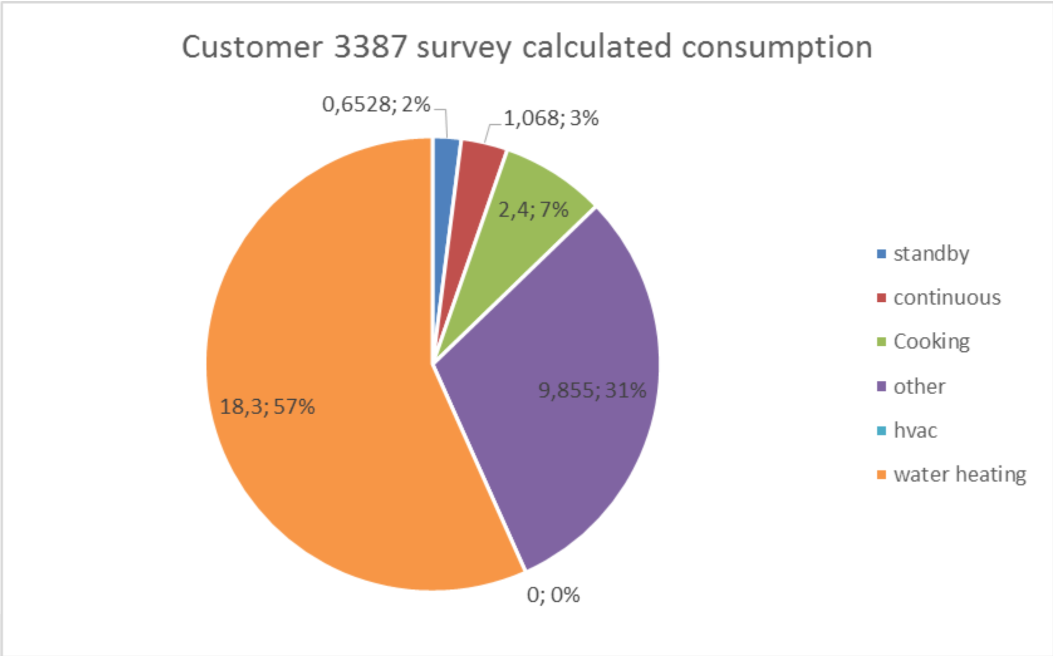

Figure 4.36. Calculated energy consumption mapping of resident 3387 using survey data.

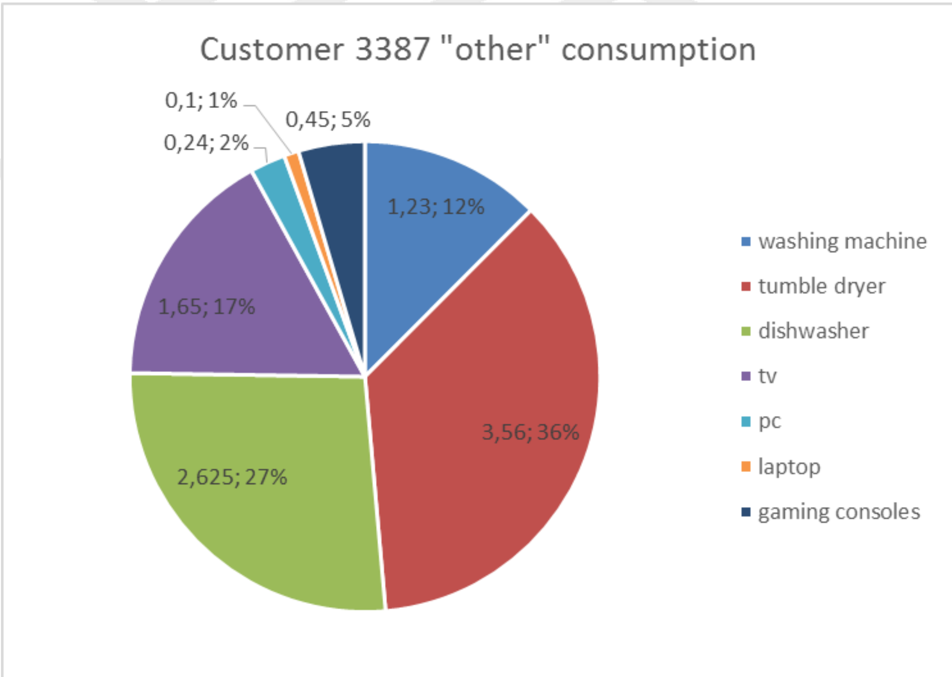

Figure 4.37. Contents of “other” section for resident 3387 survey data calculation.

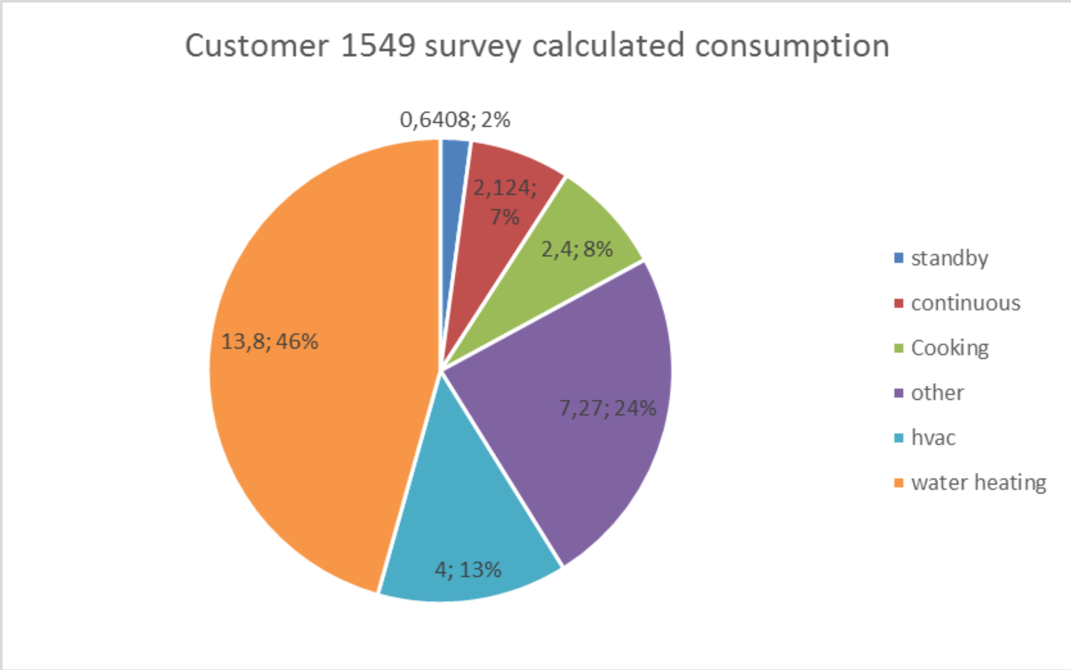

Figure 4.38. Calculated energy consumption mapping of resident 1549 using survey data.

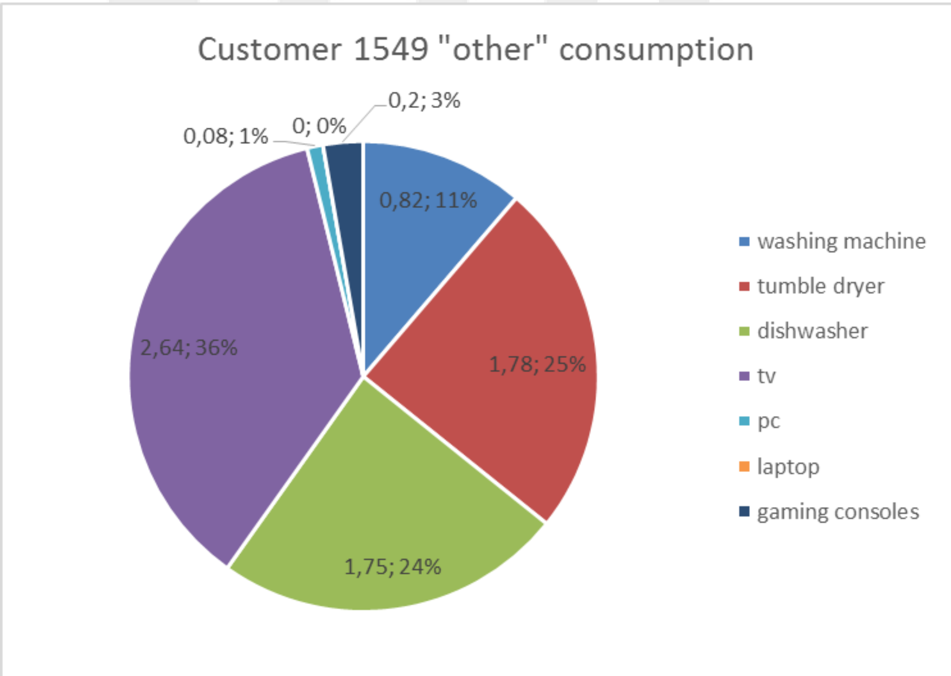

Figure 4.39. Contents of “other” section for resident 1549 survey data calculation.

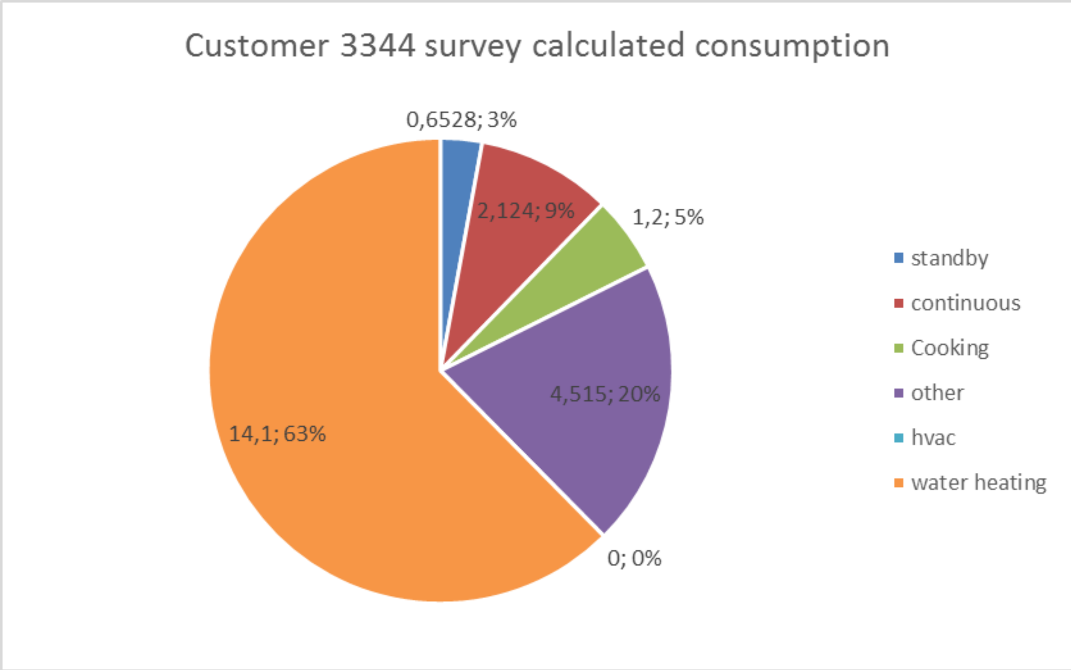

Figure 4.40. Calculated energy consumption mapping of resident 3344 using survey data.

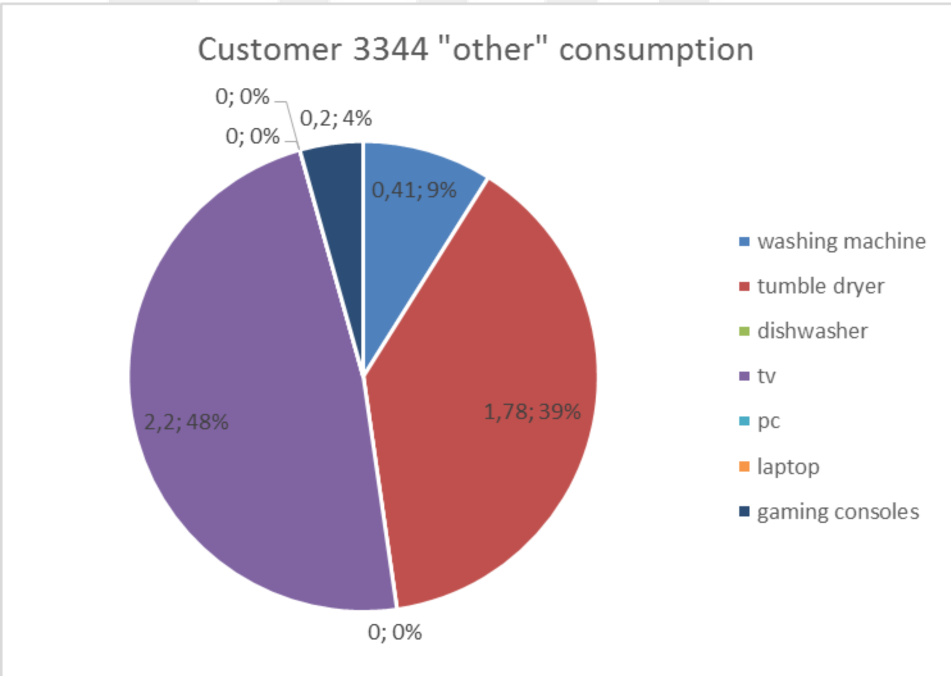

Figure 4.41. Contents of “other” section for resident 3344 survey data calculation.

Figure 4.42, Figure 4.43, Figure 4.44, Figure 4.45 provides accumulated consumption data measured by smart meters. Survey calculated consumption on Figure 4.46 and Figure 4.47 provides expected proportions of certain tasks in accumulated consumption. According to survey data based calculations, energy intensive white goods such as tumble dryers, dishwashers and washing machines contributes to 10,4%, 4% and 3,6% of total consumption respectively.

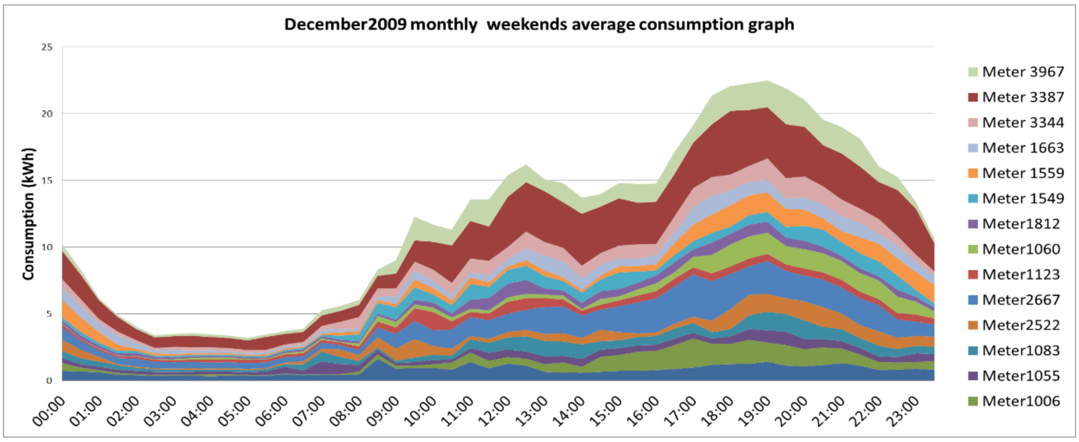

Figure 4.42. All selected customers December 2009 monthly weekends average consumption data accumulated.

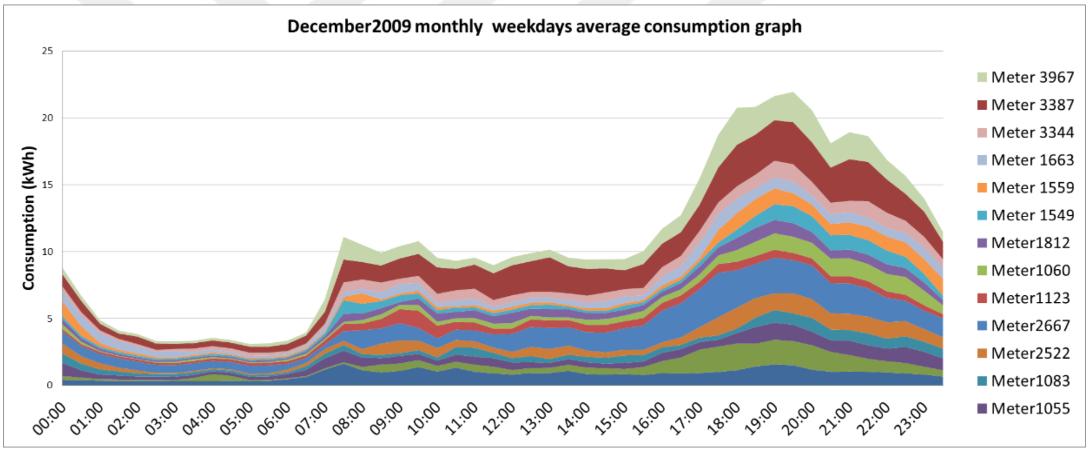

Figure 4.43. All selected customers December 2009 monthly weekdays average consumption data accumulated.

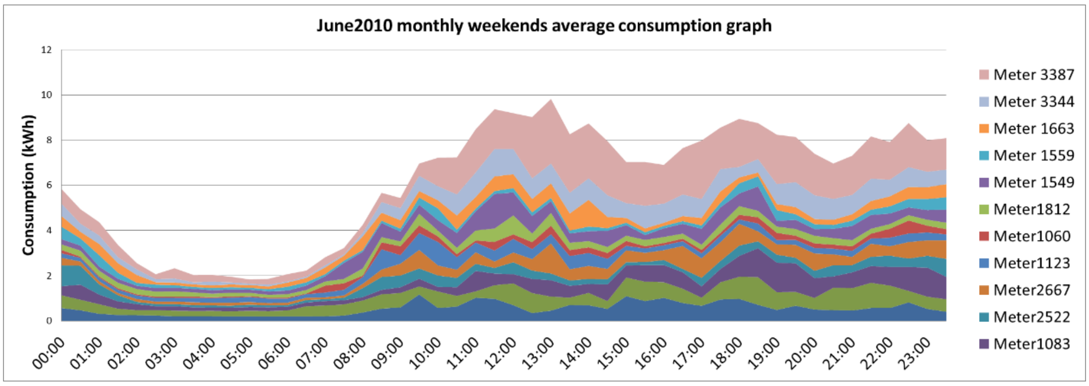

Figure 4.44. All selected customers June 2010 monthly weekends average consumption data accumulated.

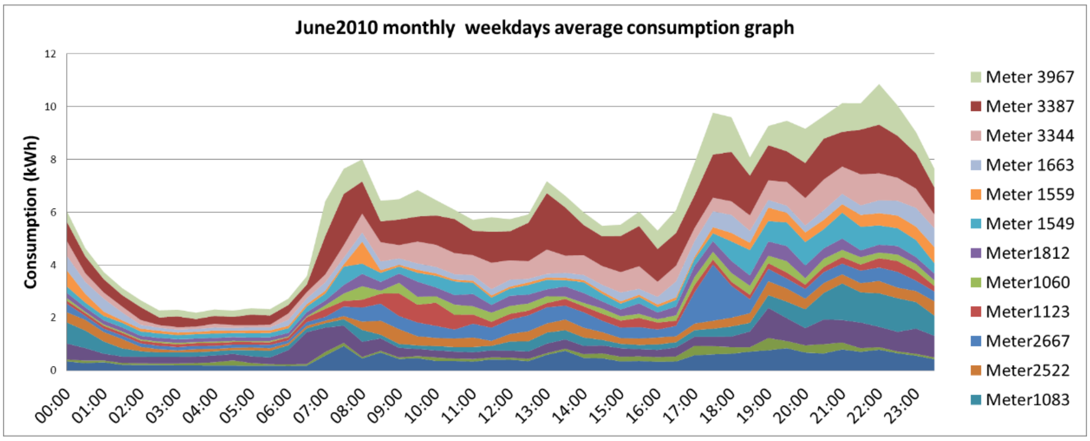

Figure 4.45. All selected customers June 2010 monthly weekdays average consumption data accumulated.

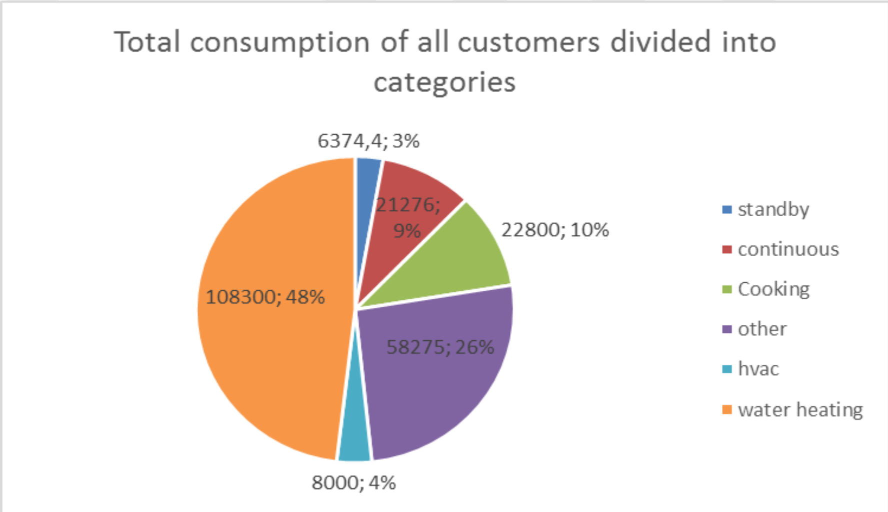

Figure 4.46. Survey calculated segmentation of accumulated consumption

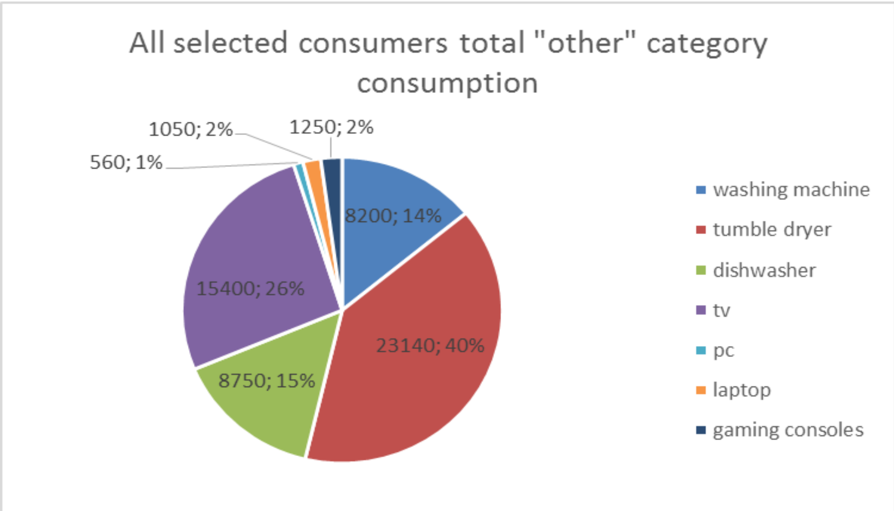

Figure 4.47. Survey calculated “other” content of accumulated consumption

4.4 Forming Consumption Data/profiles From Survey Data

Survey is conducted on a group of students from varying departments of engineering faculty regarding their household demographics, residence physical conditions, HVAC and water heating system and appliances owned by household and their usage frequency. From a total of 190 surveys, 148 of them are selected to be able to provide reliable information regarding household consumption characteristics. After mapping Ireland residental smart meter data to surveys conducted on corresponding customers, main goal of this study is to use this relation to use Turkey survey data to map them into possible consumption profiles.

This method is only viable if parameters that are effective on electricity consumption show similarities. Main factors effecting residental consumption have been investigated in this thesis work. Main factors can be summerized as physical properties of residence (including external weather), consumer demographics, appliances and their usage patterns. Climate of Ireland show some similarities to northern shores including coastal areas of Black Sea region and Marmara region which don’t reach too extreme seasonal temperatures (too hot summer or too cold winters). Even though June average temperatures of Istanbul is around 8 degrees higher than Cork, which is a coastal city in south section of Ireland. Only expected difference would be inclusion of HVAC consumption for Istanbul if residence included one. For mapping of survey data into consumption profile, household demographics, appliance and its usage data will provide monthly average of daily total consumption. while people being active consumer during day effects profile’s shape. Insulation level will determine seasonal shape and intensity change on profile.

SurveyID 248’s household characteristics are provided in Table 4.12. Which includes household demographics, residence physical properties, appliance usage and key appliances. Using survey data and appliance electricity consumption data, Monthly average daily consumption has been calculated for June and December as.

Table 4.12. Major household characteristics for survey 248.

Total number of residents	Total number of appliances	Area	How old is building	Water heating uses electricity?	Insulation	Active consumers during day
4	12	90	New	Yes	Poor	2

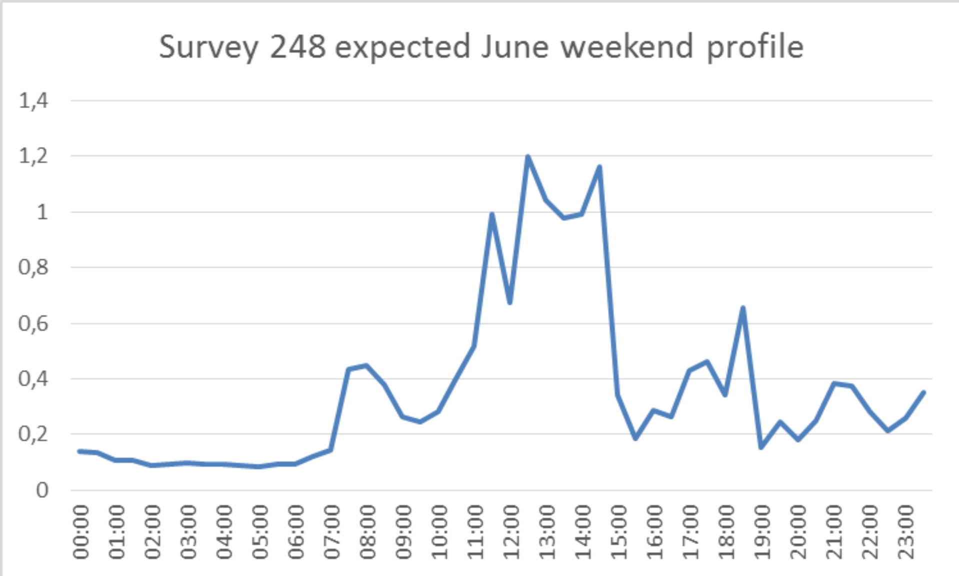

Figure 4.48. Survey 248 expected June weekend consumption profile.

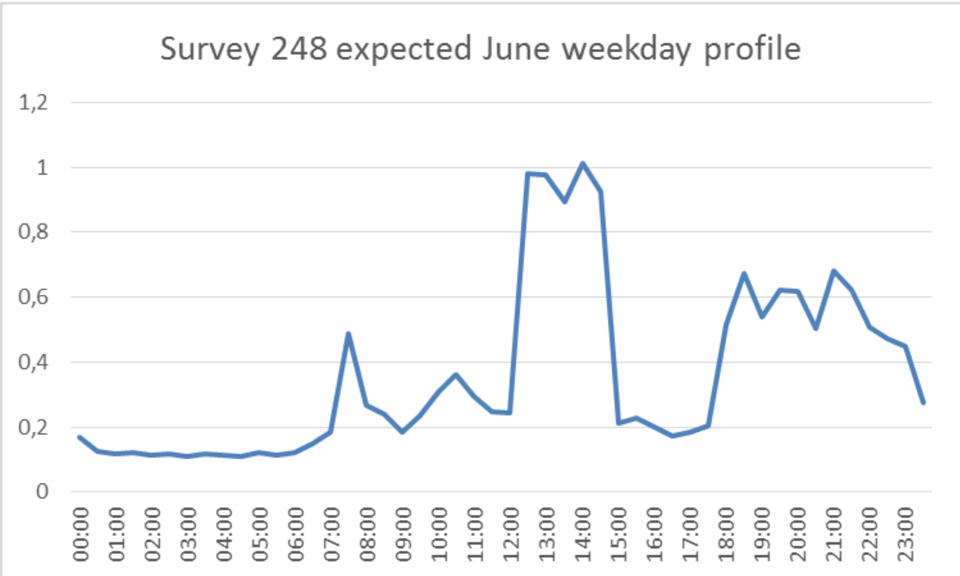

Figure 4.49. Survey 248 expected June weekday consumption profile

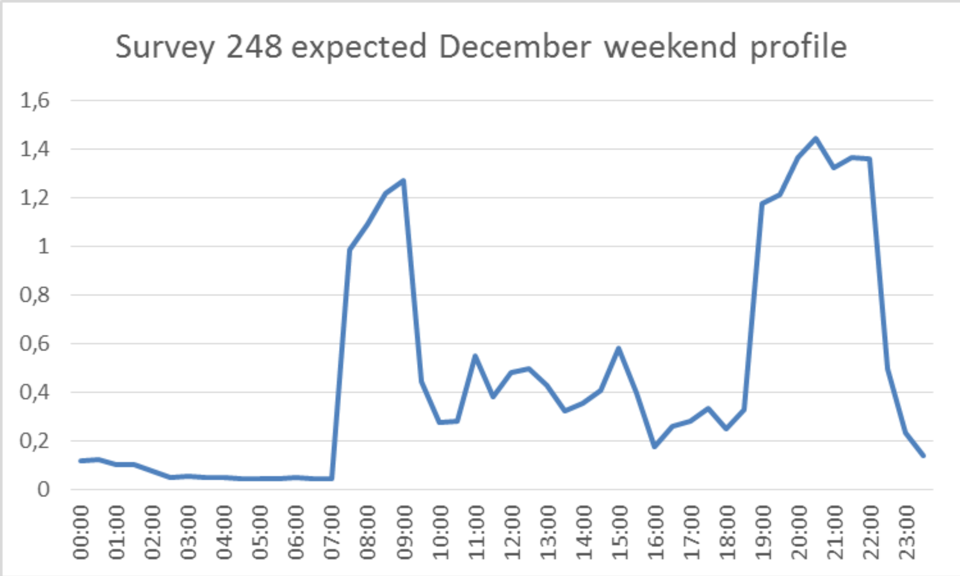

Figure 4.50. Survey 248 expected December weekend consumption profile

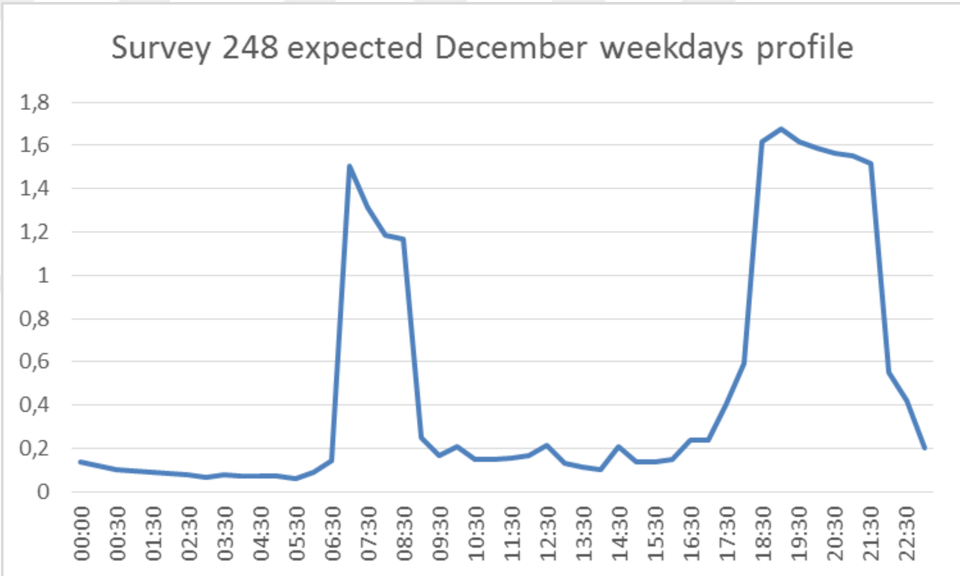

Figure 4.51. Survey 248 expected December weekday consumption profile

5 CONCLUSIONS AND IMPLICATIONS

Power buy is a pre-paid method for a group of customers to buy their electricity consumption before-hand and consume according to their weekly/monthly planning. Aim of this method is to provide a uniform-like loading for a group of customers which will reduce PAR greatly. Rather than charging customers for their individual consumption, group power buy model aims to have consumption of a customer group with least PAR value. This allows customers with high peak consumption who can't reduce peak usage in a meaningful way to be balanced by other customers in their power buy group.

Cleaned and normalized data has been prepared for clustering with WEKA k-means clustering software packet provided automatic selection of k by restarting k-means using the Calinski and Harabasz criterion, without cross-validation to cluster group of customers having similar consumption.

This method holds similarities with most of the other studies in the literature but having a dataset enriched with profile questions and inputs provided input matrix to include both the consumption and the profile characteristics makes a difference.

WEKA formed individual clusters and created as profiles for the customer database system can be seen from Table 5.1.

Day ahead market biddings operation is provided by the algorithm that sells to the customers that belong to clusters from the previous year's smart metering data for lower price.

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.

Table 5.1. Weka results for customer clusters

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

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 paid by 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.

Accurately predicting consumption through survey data without on site measurements would provide great insight to utility companies while decreasing their expenses. This study is providing a mapping between smart meter and survey data, investigating parameters that influence load profiles and maps new survey data that is similar to previously mapped survey-smart meter relations to provide consumption profiles from new survey data.

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