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Using Big Data Analytics for Measuring Energy Consumption Patterns:

Applying big data for energy efficiency

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ABSTRACT OF
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<p>Global energy requirements are continuously increasing. Conventional methods of producing more energy to meet this growth pose a great threat to environment. CO2 emissions and other bi-products of the energy production and distribution processes have dire consequences for the environment. Efficient use of energy is one of the main tools to restrain the energy consumption growth without compromising on the customer requirements. Improving energy efficiency requires understanding the usage patterns and practices. Smart energy grids, pervasive computing, and communication technologies have enabled the stakeholders in energy industry to collect large amounts of useful and highly granular energy usage data. This data is generated in large volumes and in a variety of different formats depending on its purpose and systems used to collect it. The volume and diversity of data also increase with time. All these data characteristics refer to the application of Big Data.</p> <p>This thesis focuses on harnessing the power of Big Data tools and techniques like MapReduce and Apache Hadoop ecosystem tools to collect, process and analyse energy data and generate insights that can be useful to improve energy efficiency. Furthermore, it also includes studying the energy efficiency to formulate use cases, studying Big Data technologies to present a conceptual model for an end-to-end Big Data analytics platform , implementation of a part of the conceptual model with capacity to handle energy efficiency use cases and performing data analysis to generate useful insights.</p> <p>The analysis was performed on two data sets. The first data set contained hourly consumption of electricity consumed by a set of different buildings. The data was analysed to discover the seasonal and daily usage trends. The analysis also includes the classification of buildings on basis of energy efficiency while observing the seasonal impacts on this classification. The analysis was used to build a model for segregating the energy inefficient buildings from energy efficient buildings. The second data set contained device level electricity consumption of various home appliances used in an apartment. This data was used to evaluate different prediction models to forecast future consumption on basis of previous usage.</p> <p>The main purpose of this research was to provide basis for enabling data driven decision making in organizations working to improve energy efficiency.</p>			
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Espoo, June, 2014

Hussnain Ahmed

Abbreviations and Acronyms

ICT	Information and communication technology
CIVIS	Cities as drivers of social change
VTT	Valtion Teknillinen Tutkimuskeskus (State Technical Research Center of Finland).
MPP	Massively Parallel Processing
SN	Share Nothing
HDFS	Hadoop File System
SQL	Structured Query Language
ETL	Extract Transform and Load
RAM	Random Access Memory
HDD	Hard Disk Drive
VizQL	Visual Query Language
CDH	Cloudera Distribution including Apache Hadoop
VM	Virtual Machine
CPU	Central Processing Unit
VMDK	Virtual Machine DISK (format)
CSV	Comma separated values
FTP	File Transfer Protocol
API	Application programming interface
ANN	Artificial neural network
MAE	Mean absolute error

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Chapter 1

Introduction

In modern era, we have seen phenomenal increase in human dependency on information and communication technology (ICT). ICT-enabled products and services have transformed the way of life on the planet. We need and depend on ICT to fulfil our needs from basic physiological level to the human desire of being effective part of society. There are many research areas and opportunities that are emerging as bi-products of this continuous transformation. One of them is the availability of digital traces of human activities. Every time we use these services, we produce digital traces that can be recorded and analysed. Big Data refers to these digital traces of human activity. Ubiquity of computing resources, fast and highly mobile connectivity and advent of social media usage has caused a great surge in volumes of data. Realizing the true potentials of data, businesses are not only utilizing it as source of decision making, but as a new revenue stream. Emerging large scale opportunities are reshaping the business models of many companies around the globe.

To support this transfiguration, we have seen a rapid development in distributed parallel computing, data communication software and machine learning. Industry giants such as Google and Yahoo have opened technologies and tools e.g. MapReduce and Hadoop to facilitate these advancements. Open source software communities like Apache Software foundation have further developed these tools to provide a complete ecosystem for handling Big Data and generate useful insights. The new specialized big data companies such as Cloudera and Hortonworks have emerged as catalyst for this data revolution. In this research, we try to formulate a model for end-to-end Big Data analytics platform based on these technologies that can ingest data from heterogeneous sources, process it in an efficient way, mine the data to generate the insights based on business logic and then present the information using interactive visualizations. This practical part of the research

includes the development as well as implementation of the mentioned Big Data platform to perform analysis on real life use cases and generate useful insights. The model is based on open source software components available free of charge. There are other closed source software alternatives that can fit into the presented model, but the discussions about these solutions are not included in this document.

The topic of research is inspired by European Union's Cities as drivers of social change (CIVIS) project under 7th framework. CIVIS project focuses on adoption of ICT tools and techniques for integrating social aspects of city life into production, distribution and consumption of energy. It aims to make city life as a functional unit for improving energy efficiency. The use of pervasive ubiquitous computing is driving the smart energy solutions. The smart energy devices as part of this ecosystem generate high volumes of data. This data needs to be instantaneously transferred, stored, analysed and visualized for knowledge discovery and improvements of services. The platform that was developed as part of this endeavour has the capability to automate the whole process.

The data from smart energy devices was analysed to detect the usage patterns and classify buildings on the basis of energy efficiency. Evaluation of some prediction models for energy consumption of household appliances was also included in the scope of research . These use cases provide the basis for designing, planning and implementing schemes for improving energy related services for achieving higher efficiency in both production and usage. The insights generated from these use cases can also help in educating the consumer about benefits of energy efficiency and spread the awareness about behavioural changes from which the society and the individuals can benefit.

This research is also supported by Technical Research Centre of Finland (VTT) as part of their Green Campus initiative. This project focuses on use of ICT based solutions for management and control systems to optimize the energy consumption without compromising the indoor environment of the buildings. VTT is also a supporter and partner of CIVIS project. VTT has installed specialized smart devices in selected test sites. VTT has contributed to our research by providing the data generated by these smart devices. VTT has also helped in scoping the use cases for energy efficiency with the experience and the knowledge they have gained from the related projects and research.

In a nutshell, this thesis focuses on providing a solution for collecting, storing, analysing and visualizing data generated by smart energy device for generating insights about energy consumption patterns and discovering the performance of different building units in terms of energy efficiency. The data analysis part of our research provides the models for knowledge discovery that

can be used to improve energy efficiency at both producers and consumers ends. The big data analytics platform developed as part of this project is not limited to be used only for energy efficiency. It has the capability of handling other big data uses cases. However, within scope of this document we shall only discuss its use for energy usage patterns detection and efficiency.

1.1 Problem statement

Energy efficiency can help to curtail production of energy to meet growth in demand. This in turn can help to reduce CO₂ emissions. To achieve this goal we need to understand and improve the energy efficiency on both producer and consumer ends. ICT enabled smart energy grids and devices are being installed globally to measure energy consumption and improve energy efficiency. These smart devices produce large volumes of data. The data generated by different devices is in different formats. For purpose of knowledge discovery, this data needs to be collected, stored and analysed. The extracted insights from the analysis needs to be visualized for easy and effective understanding . The challenge gets even tougher when data needs to be collected and analysed in real time. Then with the time, volume of data and scope of analysis is expected to increase. In order to respond to the above mentioned challenges, a highly scalable and flexible data analysis platform is required that can automate the whole process. This platform needs to be very cost effective for global adaptation.

In scope of this research we provide a model for big data analytics platform that can provide the solution for these requirements. We also implement the proposed model and test it with real life data from smart energy devices. The proposed solution is based on open source components that can be deployed on general purpose hardware that can be procured very easily and inexpensively. The proposed platform can be scaled according to data requirements and additional functional components can be integrated as per the scope of analysis. The data analysis within our research also provides advance analytics models to extract the information based on energy efficiency use cases from large volumes of data.

1.2 Helpful hints

For referencing, we use Vancouver system [35]. For discussing from authors point of view we use Author(s) name, year of publication along with reference numbers of bibliography. In case of quotation from author we use double

quotes e.g. “quotation from author”.

Throughout the document we discuss about energy. Due to our main focus, the term energy in our research and within this document refers to electricity or electric power. In case of all other types of energy we specifically mention the type name along with energy as a generic term.

In this document we discuss about the concept, development and use of a big data platform as our main environment for data analysis within our research. The terms like platform, data platform, and Big Data platform refers to the same concept. In case of a specific need of any other platform, we provide proper descriptions.

The mathematical text and the code snippets are differentiated from rest of the text using variation in font such as *for mathematical text* &

`code snippets font`.

1.3 Structure of the thesis document

This document has three parts i.e. header, body and tail. The header contains a title page, a cover page with an abstract of the content in the body part, an acknowledgement page followed by table of contents.

The main body of this document is divided into seven chapters. First chapter provides the introduction about the topic of research and the problem that we are trying to solve. Second chapter explains the main theoretical concepts and motivation for this research. We thoroughly discuss the other similar research endeavours in this chapter and their respective linkages to our research. The third and fourth chapters describe our methodology and practical implementation steps respectively. Fifth chapter provides the details of the data analysis and results that we produced. Chapter six presents a critical analysis of our approach and results. It also provides some possible directions for further research on this topic. The last chapter provides a summary of what we have achieved from our efforts and how can it be used in real.

The tail part contains bibliography with the list of sequenced references and appendices. Appendices contain the additional supplementary information to support content in the body of the document.

Chapter 2

Background

This chapter describes the main motivation and theoretical background behind our research. In a systematic stepwise approach we list and describe the main topics. We start with the motivation, inspiration and the partners of this thesis and then we explain the theoretical concepts with the reference to previous work done on the respective topics. For each topic we also describe how it has contributed for our research.

2.1 Smart grids

Energy industry across the globe is facing numerous challenges. There is a huge pressure from regulatory authorities and environmental organizations to reduce their carbon footprint, expand their renewable energy portfolios, and take energy conservation measures. The demand response (DR)¹ and its impacts on consumer behaviour requires rapid adaptations in energy service providers business models. According to United States Federal Energy Regulatory Commission (FERC)- “Demand response can provide competitive pressure to reduce wholesale power prices; increases awareness of energy usage; provides for more efficient operation of markets; mitigates market power; enhances reliability; and in combination with certain new technologies, can support the use of renewable energy resources, distributed generation, and advanced metering. Thus, enabling demand-side resources, as well as supply-side resources, improves the economic operation of electric power markets by aligning prices more closely with the value customers place on electric

¹Demand Response(DR); Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized.

power” [14]. Traditionally, power system participants have been strictly producers or consumers of electricity. The demand response and reliability issues with conventional electric power distribution models on consumer side are causing a major trend in motivating consumers to produce electricity at domestic level mostly using the renewable energy production methods. “Prosumer” is an emerging term used for an economically motivated entity i.e. [20]:

- Consumes, produces, and stores power,
- Operates or owns a power grid small or large, and hence transports electricity, and
- Optimizes the economic decisions regarding it.

The current energy grids support unidirectional distribution models and are centralized in nature. They are very limited to handle the prosumer needs. Line losses and hierarchical topology makes them less reliable. They usually become bottleneck when rapid adaptations are required for demand response. In [17], Farhangi defines smart grids as “The next-generation electricity grid, expected to address the major shortcomings of the existing grid. In essence, the smart grid needs to provide the utility companies with full visibility and pervasive control over their assets and services. The smart grid is required to be self-healing and resilient to system anomalies. And last but not least, a smart grid needs to empower its stakeholders to define and realize new ways of engaging with each other and performing energy transactions across the system”.

2.2 CIVIS project

CIVIS refers to European Union’s project for “Cities as drivers of social change” under 7th framework. It is the part of the programme for optimising energy systems in smart cities. CIVIS project is a collaborative effort of 10 European universities ². It aims to embed the social aspect into the advancements of energy technology. To unleash the full potential of this vision, smart grids need to be coupled with broader social and cultural considerations and understood as complex socio-techno-economic systems with

²1. Associazione Trento RISE, Italy 2. Aalto university, Finland 3. Imperial College London, UK 4. ENEL Foundation, Italy 5. Instituto Superior TÁ@cnico, Portugal 6. Karlsruhe Institute of Technology, Germany 7. Kungliga Tekniska Hogskolan, Sweden 8. SANTER REPLY SpA Italy 9. Nederlandse Organisatie voor toegepast Natuurwetenschappelijkonderzoek, Netherlands 10. Delft University of Technology, Netherlands

multiple decision making layers that are in effect at the physical, cyber, social, and policy making levels [16].

ICT acts as one of the main enabler for the smart grids. ICT also provides a lot of new mediums for the social aggregation e.g. internet based social media. CIVIS projects tends to connect these two different dimensions with innovative ICT solutions. An integrated approach to energy efficiency is the basic manifesto of CIVIS project. [16]

Understanding energy usage patterns and benchmarking energy efficiency performance of small units within cities are some preliminary items in the list of CIVIS objectives. Within scope of our research we analyse energy data to understand the consumption patterns and evaluate various factors that can effect directly or indirectly on the usage patterns. We also try to classify the buildings on basis of the energy efficiency and try to test the sensitivity of energy efficiency with respect to the ecological factors that can cause shift in usage patterns. For the CIVIS project aim of social aspect integration, we also present an ICT application framework that can be used to collect and analyse social media data. However the analysis of that data is not within the scope of this document.

2.3 Green campus initiative

Green campus initiative is a project by “Technical Research Centre of Finland” (VTT). It is part of the EcoCampus 2030 program. EcoCampus is an attempt to increase energy efficiency in districts and buildings by innovative management and control systems capable to optimize the local consumption without compromising the indoor environment, occupant comfort and building performance, and by introducing new ICT enabled business models [25]. The vision of the program is to realize a net zero energy model for a world class research, development and educational facility. Program focuses on co-designing this model with user by educating them and then collecting feedbacks for improvement. The main aim is to improve the energy efficiency of the building units and enable them to self sustain for the future. As a consequence, this performance based ecosystem can help both consumer and producers to adapt with the demand response.

Green campus initiative is a pilot project for EcoCampus 2030 program. VTT has installed smart devices inside Aalto University campus buildings in the cities of Espoo and Helsinki. These specialized devices are equipped with smart meters for energy consumption and indoor environment monitoring sensors. The data used for analysis in our research was collected from a subset of buildings as test sites of this project. The data includes hourly

consumption of electricity and electricity used for heating. For one of the test sites VTT has provided us the data with device level energy consumption details i.e. electricity used by different home appliances. This was achieved using smart NIALM-³[22] meters that can distinguish between different electric devices used on basis of their signal thumb print.

Apart from providing the data, The researchers from VTT green campus initiative have also helped us in formulating the use cases for this thesis research.

2.4 Big Data analytics

Big Data analytics is the application of advanced data analytics techniques on large volumes of data. Advanced analytics is a generalized term used for data analysis techniques: statistical analysis, data mining, machine learning, natural language processing, text mining and data visualization etc. [37]. Although the data volume is a widely used factor for qualification of the Big Data but when it comes to Big Data analytics there are few other important attributes i.e. variety, velocity, valuation and veracity. The concept of 3Vs (volume, variety and velocity) of data was first given by an analyst, Doug Laney from Gartner in a 2001 MetaGroup research publication, “3D data management: Controlling data volume, variety and velocity” [28]. Gartner used this concept to formulate a data magnitude index that can support decision making for selection of the solutions for tackling Big Data challenges. This concept is shown in Figure 2.1.

Number 0 to 3 represents the scale of the data that can be perceive on each dimension. Adding them together for a Big Data case can provide the data magnitude index. This method provides some basis for quantifying the data as Big Data, However it does not provide a definitive model as it allows presumptions to scale the data. Valuation and veracity are two other factors that are being used widely along with Gartner’s 3V. Valuation supports the decision making by considering the value of outcomes against the efforts required to collect, manage, process and analyse large amounts of data. While veracity refers to ambiguity in the data that can cause complexity. There is no standard definition of Big Data but most of the attempts to define Big Data can be associated with these five factors that we have discussed.

As a matter of fact, we are not attempting to provide a definition of Big Data as part of this study or stating any criteria for qualification of a data

³ NIALM stands for non-intrusive appliance load monitoring, is a process for analysing changes in the voltage and current going into a house and deducing what appliances are used in the house as well as their individual energy consumption

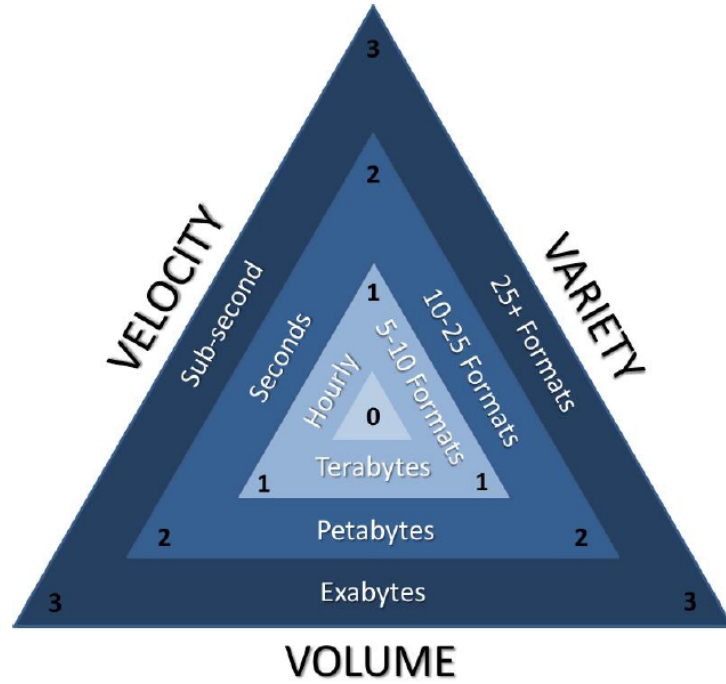


Figure 2.1: Gartner 3Vs of data and data magnitude index [28].

set as Big Data. Instead we are proposing an advance analytics model that should be capable enough to handle Big Data as well other smaller data sets. The modular architecture of the model platform can be tweaked to handle volume, variety, velocity, and veracity based on the requirements while trying to maximize the valuation for the use case. In following subsections we discuss some of the relevant technological advancements that enable handling of the mentioned challenges of Big Data analytics. These concepts, tools and techniques are also used in developing the data analytics platform and performing the analysis for our thesis research.

2.4.1 Parallel batch processing with MapReduce and Hadoop

It is hard to predict the size of data and computing power required to process the data when dealing with Big Data. Scaling up ⁴is an option that is always bounded by some maximum capacity limits. Also specialized hardware to scale up for higher capacity usually cost much more than general purpose

⁴When the need for computing power increases, a single powerful computer is added with more CPU cores, more memory, and more hard disks and used in parallel.

hardware. So the viable option is to scale out ⁵ using required number of smaller machines with relatively low computing resources in parallel. From programming point of view managing parallel running processes on different machines while ensuring low failure rate is a tough job. So the desired system should provide programmers an abstraction from lower level system details to enable rapid and fault tolerant development for Big Data applications. MapReduce is a parallel batch processing framework developed at Google for the purpose of web indexing. The concept of MapReduce was published by Jeffrey Dean and Sanjay Ghemawat in 2008 within their research paper “MapReduce: simplified data processing on large clusters” [15]. This paper describes MapReduce as “a programming model that provides a map function that processes a key/value pair to generate a set of intermediate key/value pairs, and a reduce function that merges all intermediate values associated with the same intermediate key. Programs written in this functional programming style are automatically parallelized and executed on a large cluster of commodity machines. The run-time system takes care of the details of partitioning the input data, scheduling the program’s execution across a set of machines, handling machine failures, and managing the required inter-machine communication”.

Hadoop is the open source implementation of MapReduce developed by Doug Cutting and Mike Cafarella. It was initially created in 2005 to support an open source search engine but then adapted to the published MapReduced framework [15]. It was released by Apache foundation. Apache foundation has also built various supporting tool around Hadoop framework to support end-to-end Big Data analytics ecosystem e.g. Apache flume for data collection, Hadoop File system (HDFS) for storing, Apache Pig and Hive for processing, Apache Mahout for machine learning.

MapReduce and Hadoop are batch processing frameworks that empower processing of large volumes of data using commercial grade low cost computing infrastructure. So they supports volume and valuation directly. Variety can also be supported with by different file formats in HDFS. Veracity is subjected to supported tools like data collection or data mining tools. Support for such tools is available in Apache Hadoop e.g. Flume, Mahout etc. Velocity however is the only feature that a batch processing framework like MapReduce and Hadoop cannot handle. The next subsection answers the question of velocity.

⁵When the need for computing power increases, the tasks are divided between a large number of less powerful machines with (relatively) slow CPUs, moderate memory amounts, moderate hard disk counts.

2.4.2 Real time Big Data processing

Real time data processing is generally associated with live streams of the data. The real time data can be processed and analysed on arrival or it can be buffered for small intervals to provide near to real time analysis. However in many modern data applications instantaneous data needs to be analysed in the context of large volumes of historical data. To apply advanced analytics models such as machine learning active feedback loops are also necessary. Even for stored (non live data) Big Data, applications require data processing system to answer queries very fast. To fulfil these industry-driven requirements technology is in rapid advance mode. In last twelve to eighteen months we have seen software like YARN (Hadoop 2.0), storm, spark, shark, cloudera impala etc. with near to real time processing capabilities. On top of it, tools like Mlbase and cloudera oryx have started to enable real time advance analytics. Most of these system, frameworks and tools are being developed as the evolution path for MapReduce and Hadoop. All of them have their own purpose, strengths, and limitations. They are mostly used in combinations depending on the use cases. We are not discussing or comparing these systems and tool. Instead, in this article, We briefly discuss the two prevailing architectural constructs that can enable real or near to real time Big Data processing.

2.4.2.1 Lambda architecture

Lambda architecture presents a hybrid model by using fast stream processing together with relatively slow parallel batch processing. It was developed by Nathan Marz on the basis of knowledge and experience he gained from his work with large data sets at Twitter Inc. His approach decomposes data processing system into three layers i.e. a batch layer, a serving layer and a speed layer. The stream of data is dispatched to both the batch and speed layers. Batch layer manages the historic data set and pre-compute the batch views. Serving layer indexes the batch views so the queries can be served with low latency as compared to traversing through complete data set. Speed layer deals with the recent data thus compensates for the change of data sets during updates of serving layer. An answer to the query is the merged view batch view and the real time view [33][9].

Figure 2.2 below shows the Lambda architecture. Lambda architecture can be implemented using combination of systems and tools e.g. Apache Hadoop along with Apache Storm.

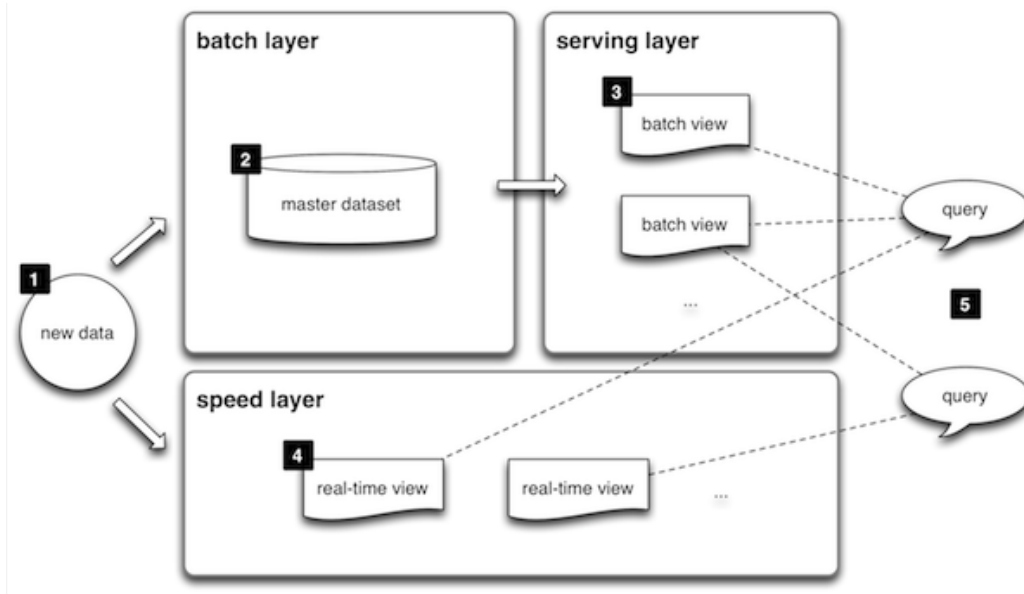


Figure 2.2: Lambda Architecture [9].

2.4.2.2 Massively parallel processing - MPP databases and query engines

MPP based architectures use multiple independent computing resources like servers, processors and storages to execute processing jobs in parallel. Most of the MPP based database approaches implements shared nothing (SN) architecture i.e. a distributed computing architecture in which each node is independent and self sufficient and there is no point of contention across the system. The SN concept for databases was first presented by Michael Stonebraker at University of California Berkeley in 1986 [38]. The SN databases have been very popular in commercial application primarily because of the high scalability offered by this architecture. Teradata warehousing solutions has been using SN database architectures extensively. Greenplum is an example for open source SN database.

Despite high scalability and other positive aspects, SN databases needs a lot of manual work in terms of partitioning the data, tuning the data and load balancing etc. Maintaining such database systems can be expensive. MapReduce and Apache Hadoop ecosystem provides high level of automation along with scalability, flexibility and fault tolerance. However parallel batch processing is not as fast SN based MPP databases. Merging of both models can solve all these issues. Cloudera Imapala is one of the example of a MPP based on-line query engine that runs natively on top of Hadoop [5]. It can

provide MPP like query response time performance with processing power and flexibility of Hadoop. For our research we have used Cloudera Impala for handling near to real-time velocity for Big Data processing.

2.5 Energy efficiency and eco-efficiency

In introductory chapter and sections 2.1, 2.2, 2.3 sections, we have highlighted the importance of energy efficiency. We discussed the advancements in pervasive smart energy devices, grids and their role in improving energy efficiency. We have also discussed the need for collecting and processing large volumes of data from smart energy devices and the available solutions. In this section we explain the main motivation and the theoretical concept behind data analysis.

Unprecedented challenges arising from increasing dependency on conventional energy are part of the global phenomena. Like other economies, countries in the European Union are also putting a lot of focus on energy efficiency to ensure energy supply security by reducing primary energy consumption and decreasing energy imports. It helps to reduce greenhouse gas emissions in a cost-effective way and thereby to mitigate climate change [6]. Member states agreed to reduce 20% of the EU's primary energy consumption by 2020 in the council of European Union in March, 2007. EU's Energy Efficiency Directive 2012 [6] defines energy efficiency as the ratio between output of performance, service, goods or energy, and the input of energy. This definition was first discussed in 2006 in European commission action plan for energy efficiency. This generic definition covers all major aspects of the energy efficiency i.e. production, distribution, consumption and the value created in comparison to the resources consumed during the whole process. However, to develop a methodology for measuring the energy efficiency and to evaluate the savings, project "Measuring and potentials of energy efficiency (EPO)" was started in 2008 [12]. As part of this project VTT published a report "Measuring energy efficiency Indicators and potentials in buildings, communities and energy systems" [19]. This report presents the model for calculating energy efficiency and its correlation with environmental factors. VTT's research presented in this report considers energy efficiency as a subset of larger eco-efficiency. The ecological factors that can affect energy efficiency are e.g. Temperature, CO₂, NO_x, SO₂ etc. The ecological efficiency itself is a way of measuring sustainable development. VTT summarizes the whole ecosystem in Figure 2.3 below

The concept of eco-efficiency provides the basis for data analysis in our research. We have applied basic and advanced analytics techniques on data

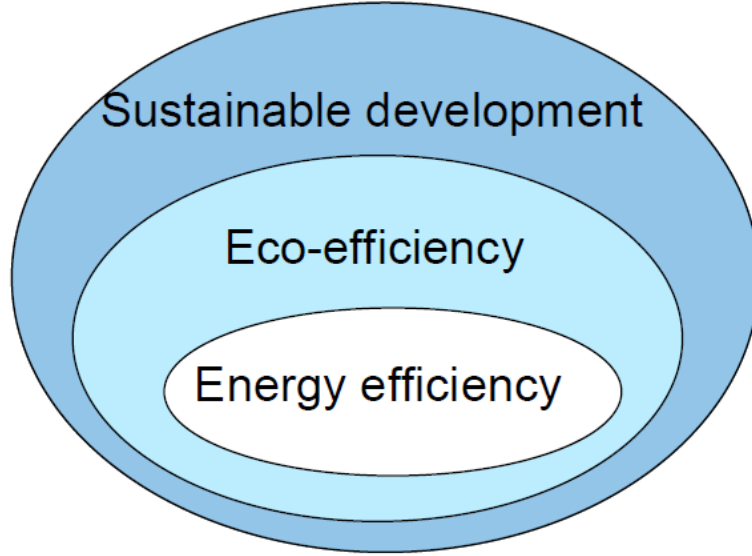


Figure 2.3: Energy efficiency, eco-efficiency and sustainability[19].

sets collected from building units that are part of VTT's green campus initiative pilot project with consideration of eco-efficiency model presented in VTT's report. We calculated energy efficiency of the buildings on basis of formula deduced in Chapter 5 (equation 5.1 and 5.2) of the VTT's report [19].

$$\text{Energy efficiency of a building} = \frac{\text{Energy consumed}}{\text{Built area}} \quad (2.1)$$

In case of a specific energy consumption (SEC) [19] equation 2.1 can be written as

$$SEC = \frac{Q}{A} \quad (2.2)$$

Where Q denotes the consumption for a single energy type for example electricity and A is the built area in meter square. In subsequent sections we shall be referring to these equations when we try to identify the usage patterns on building level, discuss the relevance of energy efficiency and then discuss a model for classifying buildings on energy efficiency .

2.6 Daily consumption patterns, base load and user load

Daily consumption pattern of a building unit corresponds to the respective usage of the building. Understanding daily usage patterns can help in identifying the optimization points for improving the energy efficiency of that building unit. Base load of a building is one important metric that can be detected through observing the daily consumption. Base load is the consumption that takes place regardless of the actual use of the building and of the user's energy consumption [19]. It is the permanent minimum load that a power supply system is required to deliver. The base load is usually caused by the continuous consumption for building maintenance like air conditioning, ventilation, or night time lighting. Sometimes base load also include some energy consumption by functional components inside building like computer servers, lab equipments, and refrigerators etc. However VTT differentiate base load from user energy load that is characterized by the direct involvement of the users of a building. For example an office building has peak load during day time because as user are using various additional appliances like personal computers, coffee makers, lights etc. compared to base load that is generated during night time when office building is not in use. Figure 2.4 illustrates the concept of base load and user load.

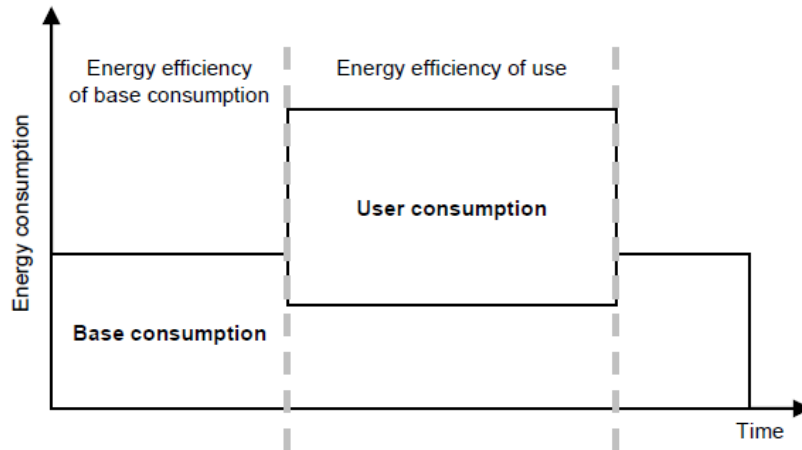


Figure 2.4: Base load , user load and energy efficiency [19].

In the Figure 2.4 base load is written as base consumption. Energy efficiency of base consumption and energy efficiency of user load can be calculated using equation 2.1 or 2.2. This provides a weighted metric that can

be benchmarked and compared. It can help to narrow down scope of research by referring to problematic buildings and their issues.

2.7 Energy consumption seasonal patterns

Energy consumption has high dependency on seasonal factors like weather. The energy consumption trends vary with outside temperature. Among other things, energy required for the air conditioning in the buildings is a major variable factor dictating the trends. Due to regional weather differences the seasonal energy consumption patterns are also different for different regions e.g. in cold regions of the world energy consumption surges in winters while in warmer regions energy consumption increase is expected in summers. Energy service providers usually conduct demand planning with consideration of seasonal trends. Consideration of seasonal trends is also very important while optimising for gaining energy efficiency.

In scope of our research we have also analysed the seasonal trends. It was not hard for us to perceive the trends while knowing the weather trend for localities of our test building. However, the interesting use case in our research was to check the sensitivity of other consumption patterns and analysis results against the seasonal trend. This will be more explained in the later part of document where we shall discuss the results of our analysis.

Previously, there have been many studies for both daily and seasonal trends in energy consumption. Due to regional differences in trends, many of these studies focused on consumption patterns within a country. Geoffrey K.F. Tso et. al [40] and Yigzaw G. Yohanis et. al [42] study the energy consumption pattern in Hong Kong and United Kingdom respectively. Buildings units e.g. residential houses apartments and commercial offices etc were considered as basic unit of analysis. Yigzaw G. Yohanis's methodology resembles most to our approach as he considered ecological factor along with energy efficiency in similar way. As discussed before, the main purpose of VTT's green campus initiative under EcoCampus 2030 plan is to develop a highly efficient model ecosystem for energy production, distribution and consumption that can be expanded further to any scale. Alligned to this goal, we have attempted to provide a data analysis model that is not specific to certain geographic locations. However detailed study is required for adapting such generic models to region specific requirements. In our research we have also attempted to classify the buildings on basis of energy efficiency that is explained in next section.

2.8 Classification of buildings based on energy efficiency

Earlier we mentioned that quantifiable energy efficiency through equation 2.1 and 2.2 can be used as a metric for benchmarking and comparison. For energy service providers, governmental energy regulatory agencies or research institute like VTT, it is very important to identify the problematic consumption units in larger number of highly optimized or average performing consumption units. Classification of these units into similarly performing groups can help them to narrow down the focus on problematic units. Sometimes it can also help in understanding the good practices applied by certain consumptions unit that has improved their energy efficiency performance.

Classification for fault detection analysis of a building energy consumption has been used previously. Xiaoli Li et. al [29] used classification along with outlier detection mechanism to identify the energy inefficient building. They provide a step wise approach to extract the features (types of energy, trends etc) from the data collected as a time series. Then detect identify the daily usage patterns using auto regression technique and pass the results to benchmark against any outlying data point that can refer to faulty behaviour. Imran Khan [26] proposes different clustering techniques to group building with similar level of energy efficiency together. In our research we used a hybrid method using feature extraction and trend detection techniques such as [29] and then applied a clustering technique proposed by Imran khan [26]. The clustering technique that we use is called K-means clustering. It is explained in the next subsection of this article.

2.8.1 K-means clustering

K-means is an algorithm for cluster analysis. In context to machine learning cluster analysis or clustering is an unsupervised task of grouping a set of objects in a way that objects in same group are similar to each other more than the objects in other group. K-means algorithm clusters the set of objects i.e. energy efficiency values in our case into predefined number of classes. We shall term these values as data points. K represents the number of cluster and groups that we can set in start of the process. K-means means algorithm was first proposed by Stuart Lloyd in 1957[30] but the k-means term was first used by James Mcqueen in 1967[31]. There have been many adaptations and optimizations in Lloyd's basic algorithm. K-means algorithm today has many variants like Fuzzy C-means clustering, k-medoids and spherical means etc. Even for original Lloyd's algorithm there has been some modification

in methodology. Two very commonly used methods are Forgy method [18] and Hartigan-Wong method[23]. In our approach we are using Hartigan-Wong method. We shall also use some references from Forgy method when explaining the K-means algorithm.

K-means groups the data points in cluster with a logical centre point. The aim of the K-means algorithm is to divide data points in certain dimensions into K clusters so that the within-cluster sum of squares is minimized [23]. Lets assume if we want to have K cluster for data points $D = \{x_1, x_2, \dots, x_n\}$ in d dimensions then

$$x_i \in R^d$$

K-means algorithm uses following steps to cluster data into groups [36].

1. Initialize the centroids randomly for each K i.e. for each group.
2. Data points are assigned to closest centroid.
3. Move the centroids to the mean of the data points assigned to that centroid in step 2.
4. Repeat 2 and 3 till convergence. Convergence means that the values have stopped changing for further iterations.

Mathematically randomly initialized centroid are

$$\mu_1, \mu_2, \dots, \mu_k \in R^n$$

If c^i is the distance of centroid to assigned data point then Step 2 and 3 with recursive distance minimization and mean adjustment can be explained as

For every i, set

$$c^i := \arg \min_j \|x^i - \mu_j\|^2 \quad (2.3)$$

The equation above used Euclidean distance formula for calculating distance between centroid and data point.

For every j, set

$$\mu_j := \frac{\sum_{i=1}^n 1\{c^i = j\}x^i}{\sum_{i=1}^n 1\{c^i = j\}} \quad (2.4)$$

The input to k-means is a set of feature vectors along with the number of clusters required. Before inserting data to k-means it is required to set the

similar scale for features as well set the standard variance to avoid errors in the results. We required to classify pilot site buildings into four groups with High efficiency, moderate efficiency, low efficiency and poor efficiency classes. So we have set K value as 4.

2.9 Forecasting the energy consumption

Estimating equipment-specific energy consumption has been a key focus area for energy service providers. It can help in demand planning, load forecasting, and understanding end user behaviour. Energy service providers can design better service offerings for their consumers. Unit energy consumption (UEC) is a term generally used for estimating equipment specific energy consumption. It is the average annual amount of energy consumed by a user device. As part of the green campus project VTT has used state of the art non-intrusive load monitoring (NIALM) [22] devices that can distinguish between the usage of different electric devices on basis of changes in voltage and electricity.

We are using the data collected by a NIALM device installed in one of a residential apartment included in VTT's pilot test sites. We use auto regression along with concept of the moving averages in form of a model known as Auto-regression Integrated Moving Averages (ARIMA) to estimate the future consumption of a device depending on its previous usage. This is an example of quantitative forecasting. Before we go to discuss about ARIMA models it is important that we briefly discuss the basic conditions for quantitative forecasting and the time series analysis as foundation for prediction model based on ARIMA.

2.9.1 Main conditions and Steps for Quantitative Forecasting

Rob Hyndman et al [24] discuss two main conditions for application of quantitative forecasting in their book "Forecasting: Principles and Practice":

1. numerical information about the past is available.
2. it is reasonable to assume that some aspects of the past patterns will continue into the future.

In case the conditions can't be met then qualitative forecasting is the only option. However, the qualitative forecasting is not in scope of our research for this thesis. In the same book authors mention following five step approach for solving forecasting problems.

1. Problem definition
2. Information gathering that includes statistical data collection.
3. Exploratory analysis of the data to evaluate the structure of the data and observing relationship between different variables.
4. Choosing and fitting the forecasting model. The model depends upon the relationships between variables. Every model has its own construct. So data needs to be fitted to that construct before applying that model. We discuss it more in data analysis part of this document.
5. Using and evaluating forecasting model. It generally includes comparison of results after applying different models.

2.9.2 Time Series Analysis

Time series is the sequence of a random variable collected over time. Among other examples of time series data, energy consumption data from metering devices can also be collected periodically hence constituting a time series. Comparison of a single time series at different point in times is termed as time series analysis [13]. A time series usually consists of a deterministic component and a random component[34]. So if X_t is a time series data then we can have

$$X_t = d_t + \epsilon_t \quad (2.5)$$

Where d_t is the deterministic component and ϵ_t is the random component. The deterministic component itself can be in form of trends, periods, and jumps etc. Figure 2.5 illustrates the examples of different time series. In each illustration there is atleast one stochastic random component with and without deterministic components.

In figure 2.5 illustrations 2,3 and 4 contain a deterministic component with a random component. Forecasting for such cases it is possible to predict even the random component by using the deterministic component. However for stochastic random time series data without any deterministic component it is very hard to predict anything accurately. The time series with no predictable pattern is generally termed as stationary time series.

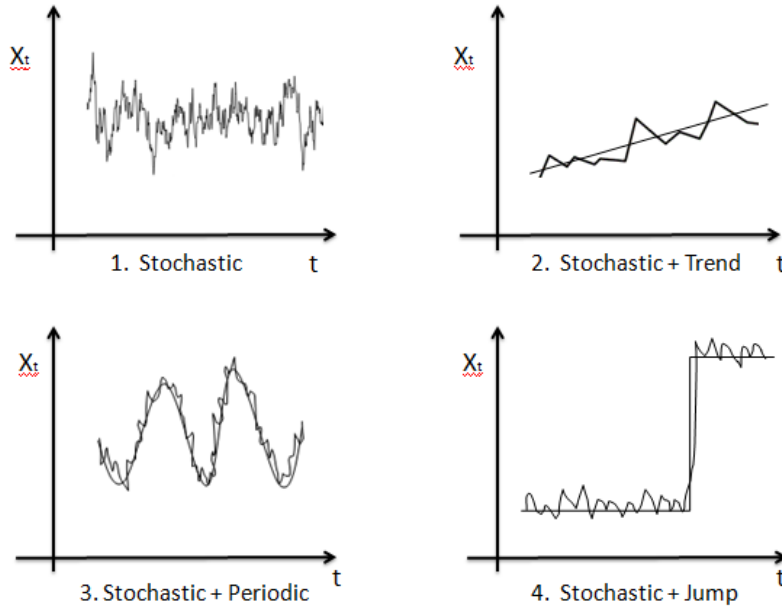


Figure 2.5: Time Series types[34].

2.9.3 Autoregression, Moving Averages and ARIMA Models

Rob Hyndman's book "Forecasting: Principles and Practice" [24] is the main reference for this section.

2.9.3.1 Regression

The concept behind basic regression techniques for forecasting is that we try to forecast a variable 'y' on the basis of another variable 'x'. For example a liner regression model forecast y assuming it has a linear relationship with variable x e.g. as in equation below.

$$y = \beta_0 + \beta_1 x + \epsilon$$

Parameter β_0 and β_1 represents the intercept and slope respectively for the line representing the linear relationship. β_0 represents the predicted value when x is 0. Linear regression for time series analysis can be written as

$$Y_t = \beta_0 + \beta_1 x_{t-1} + \epsilon$$

Here Y_t is the estimate with past value of x_t i.e. $\{x_1, x_2, \dots, x_{t-1}\}$. using differencing ⁶ error e_t in estimation can be calculated as

$$e_t = X_t - Y_t = x_t - \beta_0 - \beta_1 x_{t-1} - \epsilon \quad (2.6)$$

2.9.3.2 Auto-regression

Auto-regressive model is based on the concept of a variable regressing on itself. For auto-regression we can drive equation as

$$x_t = \beta_0 + \beta_1 x_{t-1} + e_t + \epsilon \quad (2.7)$$

The aim for good estimation is to select value of β_0 and β_1 that can minimize the sum of square of errors. Above equation can be used to estimate the value based on previous value. But in case we want to estimate based on multiple previous values e.g. 'p' values then we can write it as

$$x_t = c + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \dots + \beta_p x_{t-p} + e_t + \epsilon \quad (2.8)$$

We just replaced β_0 with a constant c as it is a constant value. Adding the summation to the historic values we can write

$$x_t = c + e_t + \sum_{i=1}^p \beta_i x_{t-i}$$

we have also taken out the random component ϵ that does not meet the basic conditions for forecasting as described in subsection 2.9.1. The model presented in equation 2.8 is referred to as AR(p) model.

2.9.3.3 Moving Averages

Moving averages model use past forecast errors in regression like manner to forecast future time series values instead of using past time series values as in auto-regression. Mathematically model can be explained as

$$y_t = c + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \dots + \theta_q e_{t-q} \quad (2.9)$$

OR

$$y_t = c + e_t + \sum_{i=1}^q \theta_i e_{t-i}$$

The model presented in equation 2.9 is termed as MA(q) model. In this model each value of y_t can be thought of as a weighted moving average of the past few forecast errors.

⁶The differences between consecutive observations

2.9.3.4 ARIMA Model

ARIMA stands for Auto-Regressive Integrated Moving Average. As the name suggests it is the combination of auto-regression and moving average models. ARIMA is one of the most commonly used forecasting technique e.g. ARIMA is being used widely in stock market prediction software solutions. ARIMA model can handle time series data with and without seasonality. We shall be discussing non-seasonal ARIMA because of the nature of the data we shall be processing in our analysis. The nature of the data will be discussed in data analysis part of this document. So combining the auto-regression and moving averages using equation 2.8 and 2.9 we can have

$$y'_t = c + e_t + \phi_1 y'_{t-1} + \dots + \phi_p y'_{t-p} + \theta_1 e_{t-1} + \dots + \theta_q e_{t-q} \quad (2.10)$$

In this equation y'_t is the difference series. This constitutes ARIMA(p, d, q) model where

- p is the order of the auto-regression.
- d is the number of the non seasonal differences.
- q is the order of the moving averages.

Now to simplify the complex time series equation back-shift notations are usually used e.g. $y_t - 1$ can be denoted by By_t i.e.

$$By_t = y_{t-1}$$

&

$$B(By_t) = B^2 y_t = y_{t-2}$$

&

$$y_t - y_{t-1} = (1 - B)y_t$$

In general a d th order difference is written as

$$(1 - B)^d y_t$$

Rearranging equation 2.10 and using back-shift notations, we can have following equation with labelled p, d and q for ARIMA model.

$$\underbrace{1 - \phi_1 B - \dots - \phi_p B^p}_{\text{AR}(p)} \underbrace{(1 - B)^d y_t}_{d \text{ differences}} = c + \underbrace{(1 + \theta_1 B + \dots + \theta_q B^q) e_t}_{\text{MA}(q)}$$

Explanation and the equations used in section 2.9.3 were cherry picked from Rob Hyndman's book "Forecasting: Principles and Practice" [24] as

reference to theory related to our research. For further details please refer to chapter 5 and chapter 8 of this book.

Fitting the ARIMA model and estimating the future time series values need intensive computation. We shall be using software e.g. R to solve these equations for our use cases.

Chapter 3

Methodology

In previous chapters we introduced our research problem, listed and explained the solution options with the theoretical background. In this chapter we shall try to explain our practical approach for carrying out the research along with the software development required to support the experimentation and data analysis for our research. On a practical level following were some major tasks that were required to fulfil scope of our research.

- Understanding energy efficiency, smart grids and available data.
- Requirement engineering and use case preparation.
- Understanding Data Analytics ecosystem, evaluating the big data tools and solutions.
- Exploratory data analysis and selection of algorithms and data analysis tools with respect to use cases.
- Developing an end-to-end big data analytics platform.
- Data collection, storage and preprocessing.
- Use case specific data analysis and evaluation of results.
- Visualization of results
- Documentation of the research, process, software development and results.

Some of these tasks were required to be performed in a sequential way e.g. requirement engineering and evaluation of big data tools were required before developing the big data analytics platform or selecting the algorithms. Similarly we need to have results before visualizations could be created. On the

other hand some of the tasks could have been executed in parallel. For example the documentation was an ongoing process along with all other tasks. Similarly literature review for understanding each component of our research was also an ongoing process through the time line for this thesis. The regardless of sequential and parallel tasks we need to iterate for continuous improvement.

To tackle these challenges we needed a methodology that can support sequential and parallel task execution with support for iterations to improve. Like most of scientific researches, fail fast and small to succeed was the key for us. In the list of tasks mentioned above. Most of them requires conceptualization and tested quickly using rapid prototyping. Taking it as a software development task initially, we had some candidate models such as water fall model, agile development model, spiral model and incremental model etc. Here we shall briefly discuss the advantages and disadvantages in context to our research project.

- **Waterfall model** offered the simplest approach of requirement engineering, design, implement, test and operate our research. However it is inherently sequential and had weak support for iterations.
- **Agile development model** Agile methodology[32] is rapid, iterative and supports quick prototyping but it requires additional communication and management overhead like scrum meetings. Managing it along with stakeholders like VTT and CIVIS projects was very hard.
- **Spiral Model** is a risk driven process model. It supports prototyping, provides good way of avoiding major failure risks, it is iterative. However it needs a lot of resources during planning phase specially when the spiral keeps growing in size. It is usually very successful for large projects but it has overheads for small projects like our thesis research. We shall be discussing more about using parts of the spiral model later in this chapter.
- **Incremental model** relies on small incremental steps with each step consist of independent design, implement and test phase. In the beginning, Incremental model was the best fit among other candidate models for our thesis research. We were able to prototype small functional units of the big data analytics platform very quickly while independently working on the use cases. However during platform development and data analysis part. It has started creating integration overheads. For example integrating two different data processing tools together for a single use case becomes difficult when they were configured in two different incremental steps.

Learning from the problems that we face from incremental model we altered our approach to adapted version of another very flexible software research and development methodology known as “Kumiega-Van Vliet Trading System Development Methodology” [27].

3.1 Kumiega-Van Vliet Model

Kumiega-Van Vliet Trading System Development Methodology ($K|V$) was developed in 2008 for software development required specifically for trading systems. It is the combination of three general purpose software and new product development models i.e. waterfall model, spiral model and stage gate model. We have already explained the waterfall and spiral models. Stage gate model consists of stages e.g. scoping, development, implementation, testing etc. Each stage or combination of stages can be controlled with an approval gate. Process can not move from a stage to other stage if the gate in between them is not approved. This model provides a good control over the development model to ensure quality. However it may cause delays because of the organizational hierarchies dictating the gates.

($K|V$) model tries to overcome the short comings of these three models by combining them to a single paradigm for trading system development [27]. In spiral model in start smaller time is allocated to four basic steps i.e. research planning implementation and test. These four steps can be performed again and again in cycles. To avoid spiral to grow too much after each cycle a stage gate controls if process can be passed to next stage or it needs to be sent back to perform another cycle in same stage. Just like waterfall there can be number of stages. But for continuous improvements process there is an iteration channel available unlike traditional waterfall model.

3.2 Adaptation of Kumiega- Van Vliet Model

($K|V$) model is designed for software research and development in domain of financial services. With the built in stage gate controls it requires some scale of hierarchical organizational structure to support the model. For our highly academic research case we have made certain adjustments. The most notable adaptation was to use deliverables and team reviews of respective deliverables as the main control for moving from one stage to other instead of stage gate approvals in ($K|V$) model. The waterfall model like stages helped in keeping our focus on the solution for our problem statement. The spiral model cycles enabled us to iterate within a stage and improve the

deliverables quality. Typically the decision of additional cycles was based on the feedback during the team review sessions. The inter stage iteration channels helped us in improving our overall quality. The lessons learnt or the new directions identified during one iteration was include in the scope of research for next iteration. It also allowed us to include supplementary topics in our scope without losing focus on mandatory issues.

In our approach, we have divided complete scope of research in four basic stages. Within each stage we had four steps. These intra stage steps were different for each stage. These steps were corresponding to the main tasks that we discussed in start of this chapter. A typical intra stage cycle ended with a set of deliverables. The deliverables were reviewed in a team review session. If required the other stockholders like VTT were also involved in some of the review meetings. We shall be discussing it in details when we describe our stage wise proceedings. At end of each review session a decision was made to either move to next stage or try to improve via additional cycle. Using all four intra stage steps for additional cycles was not a must. This was another minor adaptation to the $(K|V)$ model. Similarly iterations were mostly initiated after stage three. There were three major iterations. During the iterations change of deliverables were not mandatory. However in practice it was observed that iteration had caused some major or minor changes in stage deliverables as well. Small informal team structure reduced management and communication efforts. This also helped in rapid processing during iterations. Figure 3.1 illustrates our approach with the adapted version of $(K|V)$ model. Stage by stage description of our research methodology is explained in next section.

3.3 Stages, steps and cycles

We have already mentioned that there were four stages with each having four respective steps. Each stage was controlled via deliverables review sessions in a stage gate manner. While inside a stage, steps were executed in spiral cycles. First cycle of the spiral had to pass through the four steps. The additional cycles are initiated if the further improvements are decided for deliverables in review session. All Four steps were not mandatory for additional cycles. In this section we shall be listing and describing the stages along with respective steps. We shall be highlighting some major cycles and deliverables. However the iterations will be discussed in next section. Figure 3.1 will be our main reference through out this section. In this section we shall mention some functional components of our project e.g. logical architecture, data processing tools and algorithms etc. Details for these functional

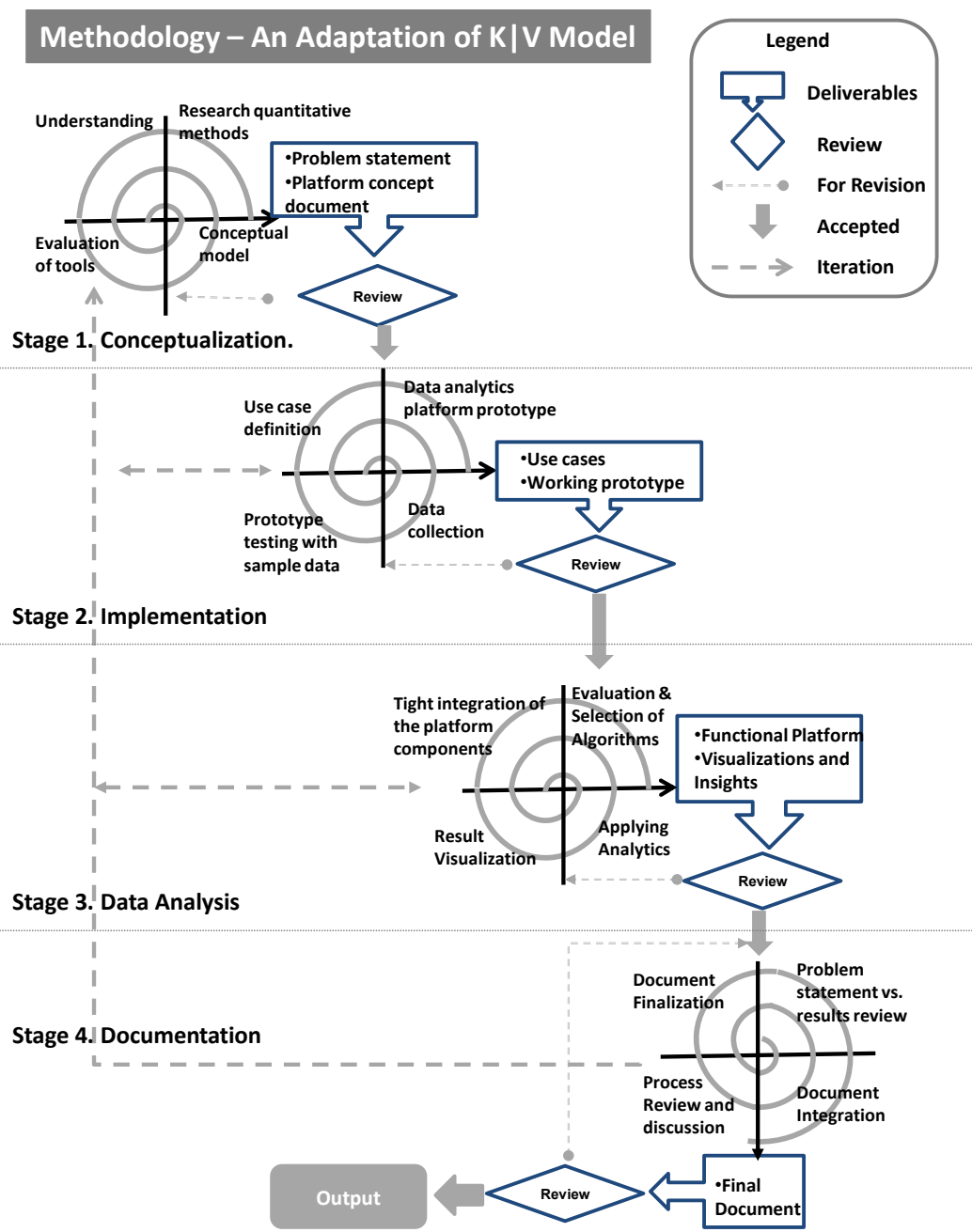


Figure 3.1: Methodology, An Adaptation of $K|V$ Model

components will be given in later part of this document.

3.3.1 Stage 1. Conceptualization

In start our research problem was mainly concerned about processing large volumes of data coming from smart metering devices and understand the consumption patterns. So the primary focus of the conceptualization stage was to describe our problem in detail, understand important factors related to it, find and evaluate methods and tools to solve the problem. The stage had following four steps.

3.3.1.1 Step 1. Understanding

From the start, our research had two focus areas i.e. energy consumption and big data . The main purpose of this step was to understand important concepts related to these topics. Follwoing are some main activities performed during this step.

- Intensive literature review.
- Participation in CIVIS project Helsinki- Use case workshop 26-27 January 2014. It gave good insights about ecological and social factors effecting energy production, distribution and consumption.
- Participation in VTT Green Campus Initiative Introduction session.
- Discussions and informal interviews with VTT's project lead for Green Campus Initiative.
- Aalto University courses.
 1. Scalable Cloud Computing, as a good introduction to parallel batch processing and its uses for big data processing.
 2. Information Visualization, as an introduction to effective communication through data visualization.

Literature review had been a constant step through out this stage, cycles, and iterations.

3.3.1.2 Step 2. Research quantitative methods

This step involved finding and evaluating the various quantitative methods used for measuring energy consumption and benchmarking energy efficiency. Data aggregation methods like daily, monthly consumption, and average consumption etc were evaluated. Identification and theoretical evaluation of advance analytical methods was also performed during this step.

3.3.1.3 Step 3. Conceptual Model

This step was dedicated for finding available open source solutions to make a conceptual model for an end-to-end big data analytics. This step was mandatory for the big data platform concept paper deliverable. This step was also repeated during various iterations, whenever change was required in data platform.

3.3.1.4 Step 4. Evaluation of Tools

This step was in pair with 3.3.1.3. All the tools listed in conceptual model were tested during this step. A checklist of evaluated and selected tools was maintained. This list is available as annex???

3.3.1.5 Deliverables of stage 1

There were two deliverables of this stage

1. Problem Statement. first two steps of this stage were the main contributors for this deliverable.
2. Platform concept document. A document as result of step 3 and 4 of this stage.

3.3.1.6 Stage 1 cycles

In this stage we observed two cycles i.e. cycle for producing the required deliverables and one additional cycle for modification of platform concept document. The main modification in additional cycle was the replacement of application frame work with an architecture diagram to clarify.

3.3.2 Stage 2. Implementation

This stage mainly includes requirement engineering and intensive software development to prototype and test the big data platform described in concept paper as a deliverable from stage 1. This stage had following four steps.

3.3.2.1 Use case definition

In this step, Based on the knowledge gained from stage 1. we decomposed our problem statement into lower level requirements that can be practically implemented using big data platform concept. Use cases went through several iterations. Details of iterations will be discussed later in this chapter. However here we shall list the final list of use cases.

1. Understanding the seasonal energy usage patterns and its sensitivity with outside temperature.
2. Understanding characteristics of building using daily energy consumption pattern.
3. Calculate the base load of the building to identify non user consumption of buildings
4. Classify building on basis of energy efficiency and analyse seasonal shifts in this classification.
5. Predict daily energy consumption of various house hold devices on basis of previous consumption pattern.

3.3.2.2 Data Analytics Platform Prototype

This step involved the practical implementation of platform concept. It covered installation, configuration, customization and integration of selected components as a proof of concept for an end-to-end big data platform that can collect, store, process, analyse and visualize data. Details of the components and implementation will be discussed in next chapter.

3.3.2.3 Data Collection

As mentioned before, real life energy consumption data was provided by VTT. This data was collected by VTT from the smart metering devices installed on test sites. We had prepared our prototype platform to collect this from VTT data repositories continuously in real time. However due to some policy constraints we were not allowed to integrate our platform with VTT's data repositories. The data was provided to us initially via file transfer from a FTP¹ server. In later a web service was opened for us to collect the

¹The File Transfer Protocol (FTP) is a standard network protocol used to transfer computer files from one host to another host over a TCP-based network, such as the Internet.

data. the details of the data will be provided later in the document however two types of data were collected during different iterations.

1. Hourly consumption of electricity, electricity used for heating, water, and reactive power in set of buildings as part of VTT's green campus initiative.
2. Device level electricity consumption data of home appliances used in two apartments of Aalto University campus residential housing blocks as test cases for VTT's green campus initiative. Real time data was also collected using the same platform to support some CIVIS projects objectives. However the real time data was not included in scope of analysis presented in this document.

3.3.2.4 Prototype testing with sample data

This step was only used during first cycle of this stage and first iteration of whole process. The purpose of this stage was to test the full flow from data collection to data visualization using the developed prototype. The sample data was the randomly selected records from hourly consumption data set. Although in this step we started with smaller sample and then kept on increasing it. The complete data set was also tested. In testing following functionalities were tested.

1. Data collection.
2. Raw data storage
3. Data cleaning to produce tidy data set.
4. Data pre-processing. Reducing the large data volume without losing insights.
5. Storing pre-processed data into databases.
6. Testing of advance analytics tools integrated within our prototype.
7. Data visualization.

3.3.2.5 Stage 2 deliverables

Following were two deliverables of implementation stage.

1. Use case definition
2. Working Prototype of big data platform concept.

3.3.2.6 Stage 2 cycles

Stage went through two additional cycles on top of the first mandatory cycle. Within two additional cycles all the steps were performed except data collection that was collected once during the this stage for first cycle. However data collection was repeated within iteration that will be discussed in later in this chapter. The major revisions inside cycles includes alteration in use cases e.g. effect of external temperature on seasonal energy pattern was identified during one of the review sessions. Within prototype and prototype testing the alterations were required to adapt for changes in use cases

3.3.3 Stage 3 Data Analysis

In this stage we used the data platform to analyse the collected data and produce the insights based on use cases. We applied the basic and advanced analytics techniques introduced in 2.6,2.7,2.8,2.9 sections. This stage has following four steps.

3.3.3.1 Tight integration of the platform components

In section 3.3.2.4 we tested all the units of the platform by manually enforcing the process i.e. taking out the output of one module manually as input to the other module on requirement basis. In this step we tried to automate the process by coupling the modules together in form of a single process per use case.

3.3.3.2 Evaluation and selection of algorithms

In this step we tried to find and compare various options of advance analytics algorithms available for supporting our use cases. It involved quantitative methods considered in section 3.3.1.2. However the focus was more on the advance analytics. The techniques explained in 2.6,2.7,2.8,2.9 sections were selected during this step. The selection criteria for each algorithm will be discussed in chapter 5. For evaluating the algorithms we were using samples from collected data as our training data.

3.3.3.3 Applying Analytics

In this step we applied the selected algorithm on the complete data sets. The insights generated from this steps are main results for our study. During the cycles of this stage, results from this step also affected the evaluation of

algorithms in previous step, section 3.3.3.2. Details related to this step will also explained in chapter 5.

3.3.3.4 Result Visualization

For the sake of ease to understand, the extracted insights in the previous step were visualized in form of data graphs. Different tools for visualizations were used in this steps. Visualization tools will be discussed in chapter 5. For data visualization we tried to implement the graphical practices discussed by Edward Tufte in his book “The visual display of quantitative information” [41]

3.3.3.5 Stage 3 deliverables

There were two deliverables of this stage.

1. Functional Platform. At the end of this stage, we had a fully functional platform capable of implementing the end-to-end data analytics.
2. Results and visualization of the results. Providing required insight for the use cases.

3.3.3.6 Stage 3 Cycles

There were several cycles in this stage. However as deviation from our adaptation of $(K|V)$ model, we just had one review session for this stage per iteration. Combination of different algorithms, their evaluation and then generating visualizations had to be repeated and tested many times. So reviewing in the intermediate cycles was very inefficient. This stage took longer time because of many cycles and the wider spiral required to produce good quality results.

3.3.4 Stage 4 Documentation

Documentation was an on going process throughout the stages and iterations. All of the stages had at least one deliverable in form of some document e.g. stage 1 has big data platform concept paper, stage 2 had use cases document, in stage 3 we had data analysis and insights report. The purpose of the last stage was to consolidate all the information in different documents together in shape of one single thesis report. Following were four steps for this stage.

3.3.4.1 Problem statement vs. results review

This step was the check for consistency of our results with the research problem that we had in the beginning. We earlier mentioned that documentation stage was not always part of the iterations. However this stage was used during all the iterations to keep track of the main focal points, the complementary and supplementary parts of our research.

3.3.4.2 Document Integration

This step was concerned with the main task of this stage i.e. to consolidate the information together in form of one consistent story. During this stage we tried to link the inter stage documentation together along with theoretical background and explanation of the process and functional components of the project.

3.3.4.3 Process Review and discussion

The purpose of this step was to provide a retrospective view of the whole process. Highlight the main findings and discuss what could have been done better or more to improve the process and produce further results. This step also indicate some future directions for the relevant research areas. The considerations of this stage will be discussed further in chapter 6.

3.3.4.4 Document Finalization

This step controlled the final thesis report publishing aspects like formatting, sequencing of topics, proof reading and version control etc.

3.3.4.5 Stage 4 deliverables

The final thesis report document was the mandatory deliverable as the main output of the process and our research project. There were some supplementary deliverables like source codes, code books and procedures etc. that we intended to open source as part of our research.

3.3.4.6 Stage 4 Cycles

to be written in end

3.4 Iterations

Iterative processes and work models do not require full specification right from beginning. Instead the implementation can start with small part of specification. Then in a step wise approach the next scope is defined with consideration of lesson learnt and new directions found from previous iterations. This inherent characteristic of iterative processes had a vital role in our research. We started with smaller scope i.e. two simple uses case. In earlier iteration we were able to focus on big data technologies and energy efficiency concepts more than the complex advance analytics topics. Findings and practical implementation in early phase enabled us to expand our scope later. We added more use cases with more focus on data analysis and application of big data for energy efficiency. Iterations also helped us in improving the quality of research.

In our approach, we went through 3 main iteration cycles. As mentioned in section 3.3 each iteration did not involve the complete four stages and their respective steps. First three stages were the main contributors in the iteration with step 3.3.4.1 of stage 4 as main source for reviewing our proceedings against our targets. Table 3.1 list the main activities in each iteration against respective stages and steps.

Stages	Steps	Iteration 1	Iteration 2	Iteration 3
Conceptualization	Understanding	Main Topics: Energy Efficiency, Eco-Efficiency, Demand Response, daily consumption, monthly consumption, smart grids, smart metering, NIALM, Big Data 3Vs, Parallel Batch Processing, MapReduce etc	Main Topics: Classification, clustering, K-means, Big Data Veracity and Valuation, Big Data Streaming, Lambda Architecture, Massively Parallel Processing etc.	Main Topics: Forecasting, Regression, Auto-regression, Moving Averages, ARIMA etc.
	Research quantitative methods	Sampling, Aggregation, Averages, Summation, standard deviation, distributions etc	Clustering, Centroid-based clustering; K-means, C-means, Distribution-based clustering; Cumulative distribution function, Density-based clustering; DBSCAN.	Time Series Analysis, Covariance, correlation, Regression, Auto-regression, Moving Averages, ARIMA, Random Forest etc.
	Conceptual Model	Model for parallel batch processing	Massively Parallel processing added for faster processing	Additional Machine learning modules (Forecasting)
	Evaluation of Tools	Apache; Hadoop, HDFS, Flume, Sqoop, oozie, Hive, Pig in Cloudera distribution. R, mahout, Tableau, D3.JS	Cloudera Impala, Spark, Hbase, MongoDB.	Weka, Cloudera Oryx, R (Forecast package)
Implementation	Use case definition	List of use cases: (1) Understanding the seasonal energy usage patterns and its sensitivity with outside temperature. (2) Understanding characteristics of building using daily energy consumption pattern.	List of use cases: (3) Calculate the base load of the building to identify non user consumption of buildings (4) Classify building on basis of energy efficiency and analyse seasonal shifts in this classification.	(5) Predict daily energy consumption of various household devices on basis of previous consumption pattern.
	Data analytics platform prototype	Parallel batch processing with capability to collect data from data from data servers and public social media streaming API s. Machine learning modules integration . Visualization using Tableau Public.	Integration of on-line query engine with Cloudera Impala. This enabled near to real life big data processing.	Use of additional data mining and machine learning tools like Weka.
	Data collection	Hourly electricity and electricity for heating consumption data from VTT's smart metering devices on pilot sites for Green Campus Initiative.	Device level electricity consumption data from VTT's NIALM devices installed in two selected residential apartments.	One month twitter data collection for Green Hackathon using collection of energy related keywords.
	Prototype testing with sample data	Testing with samples from hourly consumption data. Testing with complete hourly consumption data.	Testing with NIALM device data.	Testing the prediction model using NIALM device data an additional data mining and machine learning tools. Performance comparison between non parallel executing, parallel batch processing and Masively parallel processing tools.
Data Analysis	Tight integration of the platform components	End to End workflow implementation i.e. from data collection, storage, preprocessing and analysis to visualization of results. Limited to batch processing only	Integration of Impala.	
	Evaluation & Selection of Algorithms	Selected quantative methods: Basic aggregations e.g. averages , summations and groupings.	Selected quantative method: K-means clustering	Selected quantative methods: ARIMA, linear regression and Random Forest forecasting techniques.
	Applying Analytics	Applying basic aggregations according to use case 1 and 2.	1) Basic Aggregation for use case 3 2) K-means clustering for use case 4	ARIMA and Random Forest algorithms for use case 5.
	Result Visualization	Using Tableau Public	Using Tableau Public	Using R plots and Weka
Documentation	Problem statement vs. results review	Results for use case 1 and 2 reviewed.	Results for use case 3 and 4 reviewed.	Results for use case 5 reviewed.
	Document Integration	Step not used	Step not used	Integration of platform concept paper, data analysis report and use documentation.
	Process Review and discussion	Step not used	Step not used	Theoretical background explanations and linkages to research. Future directions for related work.
	Document Finalization	Step not used	Step not used	Document formatting.

Table 3.1: Details of the iterations

Chapter 4

Concept and Implementation of Big Data Analytics Platform

We have referred to big data platform concept and implementation on many occasions in previous chapters. In chapter 2 we have discussed the basic concepts of big data with various technological advancements and solutions available for handling big data. In chapter ?? we mentioned the functional components and their implementation during different stages, cycles and iterations. In this chapter we shall first explain the concept and a sample application framework for a big data platform based on available open source components. Then we shall present the part of this concept that we have implemented for handling the energy and social media data for our energy efficiency use cases listed in section ?? of previous chapter.

Before we move to our conceptual model of the big data platform it is important that we mention basic challenges that drive the design of a big data solution and briefly explain a typical big data analytics process.

4.1 Big data challenges

As discussed in section ?? of chapter 2 there are five main challenges that influence the solution design criteria for big data analytic systems. These challenges are generally termed as 5V s of big data.

1. **Volume** refers to the size of the data. Volume is the most commonly associated feature with the big data. The big data analytics platform in our scope of work is based on Hadoop File System (HDFS) which is a highly scalable system. It has been tested with upto 4000 scaled out serving nodes capable of handling upto 10 Petabytes (PB) of data.

2. **Velocity** refers to the data processing speed. Velocity is crucial for the business use cases that need to process huge volumes of data in real time to produce insights for decision making. Our model is designed for batch processing, however we have integrated additional components that can process the data with near to real time capability.
3. **Variety** refers to structure of the data. Traditionally the relational data base system can store data with fixed schema. The fixed schemas mean that the stored data must have a definitive structure. Such databases are designed on basis of these data structures. In context to big data sometimes it is hard to perceive the structure of data so the storage systems needs to be designed for data in any structural format i.e. structured, unstructured or semi-structured formats. In our conceptual model we have added various components that can handle all formats of the data. However, In our implementation we shall be processing the data that had known fixed schema.
4. **Veracity** refers to the complexity due to noises and inconsistencies of the data. In real life scenarios for big data it is very rare to find data in absolute consistent. Most of the time some values will be missing or the data will be in wrong format or there will pollutions in data. For good analysis we need to take care of such inconsistency and errors in data. Our conceptual model is capable of handling inconsistencies and in our implementation we had catered for some inconsistencies that we shall discuss in next chapter 5.
5. **Valuation** refers to the benefits of processing big data against the efforts required. It is an emerging feature for big data analysis design. Just like the other IT systems, organizations tends to decide about big data investments by looking at the business cases. In our concept we shall be discussing a model based on open source components. So there should be no cost of acquiring software. There is no specialized hardware requirements for implementing our model and any commercially available hardware with moderate specifications can be used to deploy this software. Hardware maintenance is required for running the service based on our model. However their are cloud alternatives that can be use within our model with some costs. However we shall not be discussing such alternatives in scope of this document or our research.

4.2 Data Analysis work-flow

The data analysis process involves collection of data from multiple heterogeneous sources including both social media data, consumer data, sensors data, and already data from data servers or databases etc. The collected data in its original form can be ingested directly into Hadoop file system (HDFS). If required some filters can also be applied while collecting the data for efficient use of storage space. Collected data can be structured, semi structured or unstructured and some pre processing can be done to format it i.e. form a schema or structure that can be stored and accessed for data mining in database(s). A data mining engine with flexibility to plug and use various quantitative and qualitative research tools can then be used to analyse the data as per use case requirements. Data mining engine requires a feedback loop to pre-processing unit to adapt to the requirements of the use cases. Another feedback channel for processed data storage can be provided for direct data manipulations. Results of the data mining can be stored in the database. A RESTful API or data driver can be used to extract data from database for visualization frontends. Figure 4.1 shows the high level process flow.

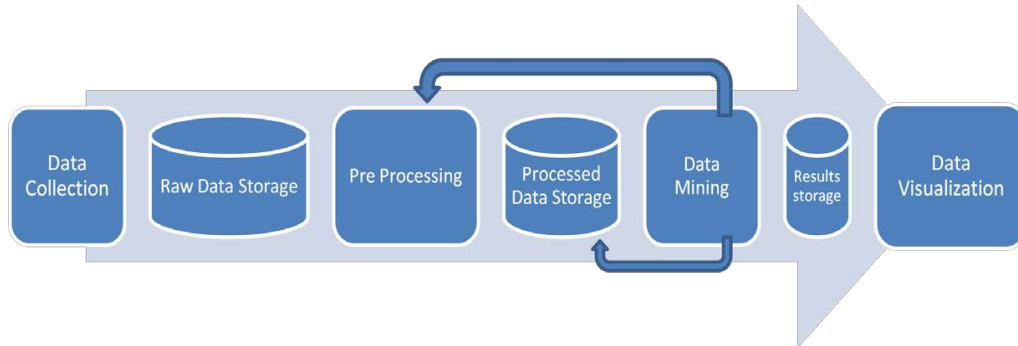


Figure 4.1: High level data processing flow.

4.3 Platform concept

This section presents an end-to-end big data analytics platform aligned with the data processing flow described in previous section. The proposed platform is based on software components that are available open source free of

cost. However use of each software components is subjected to its respective license under a specific open source licensing scheme. There are closed source and paid cloud services components available that can be used as efficient alternatives for parts of this model. However this paper does not contain information about these alternatives. Figure 4.2 illustrate the proposed concept

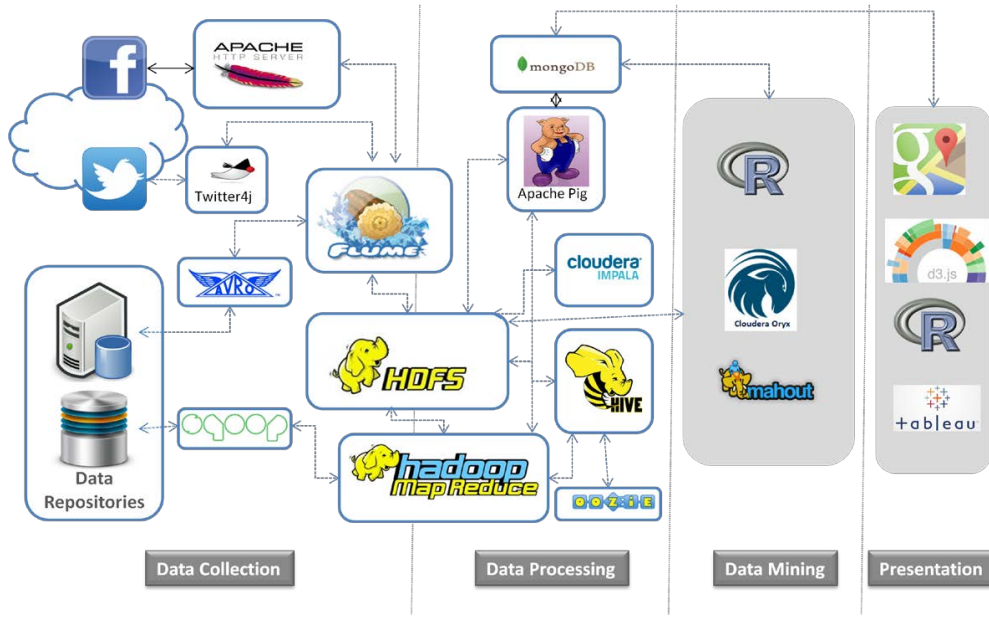


Figure 4.2: Conceptual model of big data analytics .

4.3.1 Data Core

Before we go into details of each and every process step and respective components, it is beneficial to discuss the data core of the platform that is based on Apache Hadoop MapReduce and the Hadoop file system (HDFS). These two components are also shared between data collection and data processing steps. Apache Hadoop is a framework that allows the distributed processing of large data sets across clusters of computers and HDFS is a distributed file system that provides high throughput access to application data[11] thus providing a highly efficient and scalable solution for handling big data. We have described Hadoop and MapReduce in section 2.4.1.

4.3.2 Data Collection

The proposed platform is capable of collecting and aggregating data from multiple data streams i.e social media data, consumer data, or server log files etc. The data can be live streaming data or data residing in server file systems or databases. Data can be collected as it is so there are no dependencies on format or structure of the data. Some filtering can also be applied while collecting data e.g. collecting only the geo tagged tweets or collecting logs with error notifications only. Following two components are recommended for data collection

4.3.2.1 Apache Flume

Apache Flume is a distributed service for efficiently collecting, aggregating and moving large amount of data [1]. Multiple flume agents can be configured to collect data from heterogeneous sources, channel the data to configurable destinations and store on desired locations. In the proposed model Apache flume is using Twitter4j library to stream data from Twitter, Apache HTTP REST API for collecting Facebook data and Apache Avro[10] data serialization system to collect log data from file systems of remote servers. Flume is then ingesting data directly into hadoop file system (HDFS). Flume can also read from databases and it is particularly useful while reading from document stores (NoSQL databases). However for reading from relational databases Apache foundation has another useful tool called Sqoop.

4.3.2.2 Apache Sqoop

Apache Sqoop [4] is designed for efficiently transferring bulk data between relational databases and Hadoop. So in most of the consumer data cases Sqoop can be used to collect data and feed it into HDFS through running multiple parallel Hadoop MapReduce jobs.

4.3.3 Data Pre-processing

Once the data is available in HDFS then it can be normalized to definitive structured forms e.g. schema. Furthermore, certain filtering can be applied for example in case of tweets, tweet text can be separated from other information for qualitative analysis and then natural language processing techniques can be applied to get it ready for further text mining. Usually pre-processing also helps in filtering out the unwanted information and make data lighter for mining process. In the proposed model Apache Pig and Hive are used to pre-process the data. Apache pig and hive both use Hadoop Mapreduce as

parallel batch processing. For sake of fast pre-processing Cloudera Impala is also added to the model.

4.3.3.1 Apache Hive

Apache Hive [2] is data ware house software that provides a way of providing schema to the stored data with SQL based query language to extract, transform and load data (ETL). Apache hive is further supported by another Apache Hadoop ecosystem tool called Oozie. Oozie is acting as a workflow scheduler for Hadoop i.e. while loading the data into Hive it can create partition for tables arrange the data for optimized querying.

4.3.3.2 Apache Pig

Apache Pig [3] provides a high level scripting language to analyze the data stored in HDFS using MapReduce.

4.3.3.3 Cloudera Impala

In section 2.4.2.2 we have already introduced Cloudera Impala as a massively parallel processing database engine. We also explained the concept of massively parallel processing databases. In this section we shall emphasize on how Cloudera Impala fits into Hadoop ecosystem.

Cloudera Impala uses HDFS as its main data source. It can read data directly from a HDFS directories. The HDFS directory path can be configured before each run. Data can be read from a single or multiple files stored within the configured directory. A schema needs to be created inside Cloudera Impala. Based on schema it can project the data in HDFS directory files as a table. The data can then be queried using a subset of SQL (structured query language). Cloudera Impala provides much faster processing than Hive and Pig that uses parallel batch processing. However Cloudera Impala currently supports limited data structures. For handling some complex data formats e.g. Avro serialized JSON format data. For such cases it can be configured to work together with Hive and Hbase etc.[8]

4.3.3.4 Databases

For storing the pre-processed data various choices of available open source databases can be applied in this platform. While document stores like MongoDB seems a natural choice because of the flexibilities to handle any structure data and easy maintainability but the relational databases can still be

integrated and used within this platform. The availability of tools like Cloudera Impala can fit very well with SQL based databases like mysql to build online query engines. Apache Hive in this model is also acting as a projection on top of mysql.

4.3.4 Data Mining

The real value of any analytics platform lies in its ability to make sense of the data. Data collection and data pre-processing modules of the platform can bring and normalize data from multiple streams to be further analyzed by the data mining modules in the platform. There are various open source data mining and statistical analysis tools available online with power of most advanced machine learning, text mining and statistical modelling algorithms built in them. The proposed platform can provide a plug n play environment for most of these tools to be applied on use case requirements. Some example of these tools as presented in figure 2 i.e. Apache Mahout, R Project, and Cloudera Oryx.

R does not provide scalability or parallelism without special configurations. It process data in memory so it requires large RAM (Random Access Memory) for large data sets. The real power of R is in availability of large number of statistical and advance analytics algorithms. With proper data pre-processing using big data tools like Apache hive, pig and Cloudera Impala the amount of data processing can be reduced for R without losing key insights.

Apache Mahout and Cloudera Oryx can fit well with Hadoop ecosystem tools to provide scalability and parallelism for applying data mining and machine learning on big data. Cloudera Oryx is designed particularly for velocity. However it is still in development phase and has support for less number of data mining and machine learning algorithms. It is expected that it will take over Mahout completely if it can match the Mahout's algorithm library.

4.3.5 Presentation

For visualizations of the results, this model presents some tools to build interactive dashboards. These dashboards should be able to zoom in and out of data. They should provide flexible way of managing visualizations based on use cases. Also they can be integrated into user interfaces of web based or mobile applications. The suggested components are Tabelau Public, d3.js, google maps and R project.

Tableau public provides the easiest solution to visualize data through static and interactive graphs. Tableau public is a free service. The paid version of Tableau can give additional tools like connecting directly to data bases and Hadoop ecosystem tools like Apache Hive. Tableau software are based on VizQL (Visual Query Language) paradigm [21]. Once connected to the data source VizQL provides a very flexible way of interacting with graphs. The idea is to focus on the insights that are required rather than spending more efforts on programming the queries to generate those insights. Tableau automatically generates the queries and visualize the results.

D3.JS provides a comprehensive library in Java Script for making customized information graphics. It is very flexible and powerful. However it need programming skills in Java scripts and a reasonable effort is required to prepare or change the graph formats.

Google maps is a powerful tool for geo-spatial info graphics. In many big data use cases geo spatial mapping provides a smart way of presenting information.

R - project also have additional packages and libraries like “ggplot” to visualize the results after applying statistical analysis and data analytics. Like D3.JS R infographics also need programming to visualize the results.

4.4 Implementation

In this section we shall be discussing our implementation for analysing the energy consumption data for our energy efficiency use cases and collecting social media data for supporting CIVIS project. The implement model is the subset of the conceptual model presented in previous section with at least one additional component that we shall discuss later in this section. Figure 4.3 shows the implemented model. The details of configurations are available in Appendix B.

4.4.1 Implementation Environment

Cloudera distribution including Apache Hadoop (CDH) version 4.7 was used for implementation of our big data analytics platform. Following is the list of the components used with their respective version numbers.

Apache Flume	flume-ng-1.4.0+97
Apache Hadoop (MapReduce+HDFS)	hadoop-2.0.0+1603
Apache Hive	hive-0.10.0+258
Apache Oozie	oozie-3.3.2+102

Apache Pig	pig-0.11.0+43
Cloudera Impala	Impala 1.3.1

Cloudera CDH 4.7 was used in form of a pre-configured quick start virtual machine (VM) capable of running on top of any known operating system e.g. Microsoft Windows xp/7/8 , Linux RHEL/Centos, and Ubuntu etc. Cloudera CDH 4.7 quick start VM itself was running on Centos 6.2 operating system. Following Hardware resources were allocated to run the VM for our analysis.

- 3 x 1.8GHz intel i7 4500 CPU
- 4GB RAM
- 64 GB VMDK storage

During testing phase we have also test multi node cloudera CDH 4.7 configuration on cloud. However there was cost associated to running the set up on cloud and the requirement of our use cases were also fulfilled by single node quick virtual machine. So we preferred not to run analysis using multi node cloud deployment.

In addition to pre-configured components in Cloudera CDH 4.7 we also added some additional components as part of our platform. Following is the list of those components with their respective versions.

Apache Avro	v 1.7.6
R	v 3.0.3
Tableau	public , v 8.0
Weka	v 3.7
Twitter4J	v 3.0.3

For ease of use we had been using R, Weka and Tableau outside quick start VM environment. Typically we were using Windows 7 with similar dedicated hardware resources as for quick start VM. Tableau public is a web service running in public cloud.

4.4.2 Implemented data processing work flows

As mentioned before, we utilized the implemented platform for two purposes.

- Analysing energy data for energy efficiency use cases.
- Collection of social media data to support CIVIS project activities.

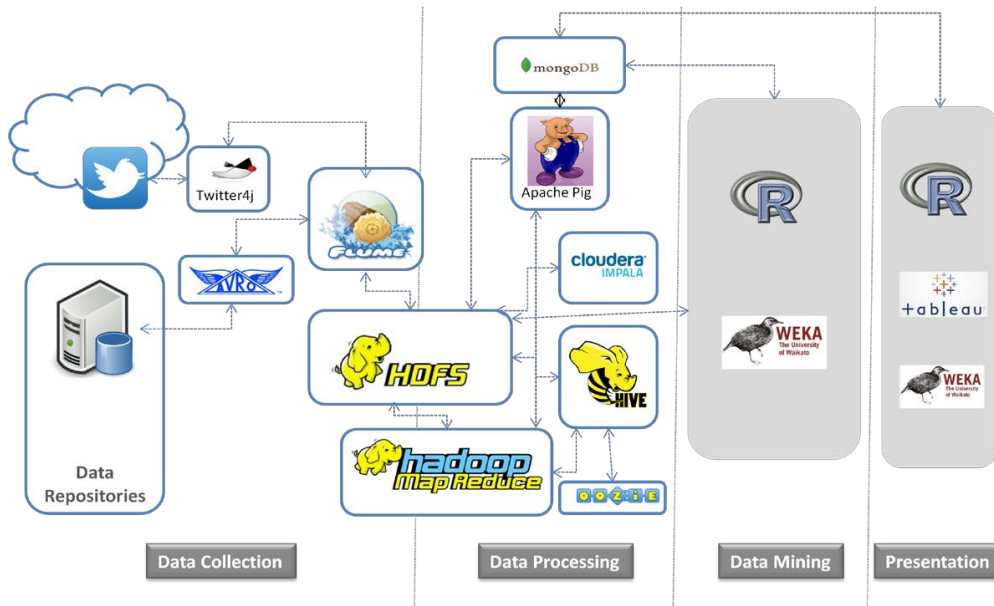


Figure 4.3: Implemented big data analytics platform .

In this section we shall explain the data processing work flows for both scenarios. These work flows are aligned with the process we explained in section 4.2.

4.4.2.1 Data processing for energy efficiency use cases

For analysing the energy consumption data, we designed and implemented the platform to automatically collect data from VTT's data servers and ingest it into Hadoop Files System. For data collection we configured Apache flume to collect and aggregate the data. Apache Avro was configured within Apache Flume to serialize the data. Unfortunately due to some policy issues at VTT, we were not allowed to integrate our platform to there data servers. Instead data was provided to us through an FTP server. In later stages we were also given access to a web service from which we can download data in off-line mode. Here off-line mode means that data was not collected automatically and human intervention was required to collect the data.

The collected data was then ingested to HDFS manually. Once the data is available on HDFS then data pre-processing tools can access it. Selection of the preprocessing tool is based on use case requirements, format and volume of data. As discussed before, VTT provided us two types of data i.e. hourly

electricity consumption data from smart metering devices and second set of NIALM device level data. For first data set of hourly electricity consumption data we used Apache Hive to pre-process the data. The decision was based on the fact that data had fixed schema and Hive has good support for such data types. Alternatively, Apache Pig and Cloudera Impala could have also been used but a choice was made on basis of preference. For performance test purposes we had used Cloudera Impala and Apache pig. We shall discuss details of that in next chapter. For data analysis purpose following schema was created in hive and data was loaded as per following schema.

```
CREATE EXTERNAL TABLE hourly_data
(
    devid string ,
    building string ,
    meternumb int ,
    type string ,
    day string ,
    hour int ,
    consumption int
)
ROW FORMAT DELIMITED FIELDS TERMINATED BY ','
```

After loading the data was processed to prepare inputs for data mining and advance analytics modules as per use case requirement e.g. for classification on basis of energy efficiency the input matrix for K-means algorithm was produced. For producing this input matrix 1.2 Million records (*rows*) were reduced to 343 rows. Making it very simple for R to apply K-means algorithm. Then from R we saved the results of classifications to comma separated file. This file was then read by Tableau Public. We then generated the visualizations for our analysis. Tableau can connect to data files in live mode so the updates in files can directly be imported and projected on created visualizations. However this was not required for our case.

For the second data set of NIALM device data, volume of the data was too small. So we analysed it in R without pre-processing. We used both R and Weka to apply and evaluate different analytics techniques. Weka was used only in evaluation step as describe in section 3.3.3.2 as it provides a quick mechanism for analytics prototyping. It can not be used in tight integration within platform so our conceptual model does not include Weka as an option. For visualizations we used R plots and Weka graphs.

4.4.2.2 Social media data collection for supporting CIVIS project

To support CIVIS project activities we configured our platform to collect and store Twitter data using Twitter streaming API. The implementation procedure for achieving this case was based on a Cloudera Tutorial “How-to Analyze Twitter Data with Apache Hadoop” [7]. We configured Apache Flume with Twitter4j Java library to capture the twitter stream data. A twitter application was registered with our Twitter account to get the access to streaming API. The keyword filtering was applied using twitter4j to target the concerned tweets only. Tweets were then stored to HDFS by Apache Flume HDFS sink mechanism. Hive table was created with the a subset of twitter provided schema. This helped us in shedding the unwanted header data to reduce the storage size. Apache Ozie workflow was implemented to archive hive data in manageable format i.e. creation of twitter data partitions on basis of hourly data. This is a very helpful feature in reducing the query processing time. Within our scope we did not analyse the twitter data.

Chapter 5

Data Analysis and Results

In section 3.3.2.1 we listed the energy efficiency use cases. In chapter 2 we explained the relevance of these use case with energy efficiency and also introduced and explained the basic concepts of suitable statistical and advance analytics techniques to extract insights from data for these use cases. In 4 we explained the implementation of a model big data platform for providing an environment to perform these analysis. In this chapter we shall try to explain how we performed our data analysis using the knowledge and capabilities we developed through our work explained in previous chapters. We shall also present our results along with the critical analysis for their respective use to improve energy efficiency. Before we go into details of the use cases, analysis and results it is important that we explain the data sets.

5.1 Data sets

In our analysis we shall be using two distinct data sets provided by VTT. Both the data sets are collected by specialized devices installed on test sites as part of the Green Campus initiative. The description of data sets are as follows.

5.1.1 Data set 1: Hourly energy consumption data

This data set contains hourly readings of the energy consumption taken by specialized meters installed by VTT (Technical Research Centre of Finland) on 40 different test sites in cities of Espoo and Helsinki. Each site has at least one or more meters installed. Each installed meter on a particular site can record a particular type of energy feature consumption on hourly basis. In some cases a site have more than one meter even for same energy fea-

ture. There are four energy features considered for test sites i.e. Electricity, Heating, Water and Reactive power. We shall consider only electricity and heating in the scope of this paper. Heating feature is explained in terms of electricity consumed to produce heating. In rest of the chapter energy features will be termed as “feature” and each record representing hourly consumption of a feature type will be called “observation”. There are approximately 1.2 Million observations taken from 144 installed meters on 40 different sites for 11 months period starting from 1st January 2013 till 30th November 2013. Each row in data represents an observation with following information in exact sequence separated by commas.

”Device ID”, ”Destination Address”, ”Building Name”, ”Meter”, ”type”, ”date”, ”hour”, ”Consumption”

Device is a unique id for each installed device. To avoid the confusion the site will be termed as building in rest of the document, For sake of anonymity both “Destination Address” and “Building Name” fields are masked as BuildingXX (where XX ranges from 01 to 40). “Meter Number” shows the number of meter on same building for one or multiple meters. Type shows the feature, date is the day date in format of YYYYMMDD, hour is the hour number of the day (0 to 23) and consumption is the consumption of the feature in respective units based on features. Since only electricity and electricity consumed for heating is considered in this paper so units are Wh (Watt hour). To fix the scale of consumption to Kilo Watt Hour, each consumption value should be divided by 100.

The data set is not consistent and has unequal number of observations for some building per energy type per day . Figure 5.1 illustrates the summary of data set and shows the inconsistencies. From figure we can see that number of records for each building are not equal. In an ideal consistent data they should be same. The inconsistency can be because of the multiple number of devices collecting data, However exploratory analysis reveal that for some buildings values were totally missing. In some cases the all the days in 11 months were not accounted for or in some cases all the hours of the day were not recorded.

Apart from the inconsistencies shown by number of records, some building names and addresses were also missing. To handle inconsistent data, we had to adapt our analysis using aggregation techniques like averaging. We shall also explain other data cleaning and pre-processing techniques in section preprocessing of data. The implementation level details of data are available in Appendix C

To support this data set for analysis we also collected Real Estate data that include floor area of each building included in data set one. The Real Estate data was collected using following Espoo city information website.

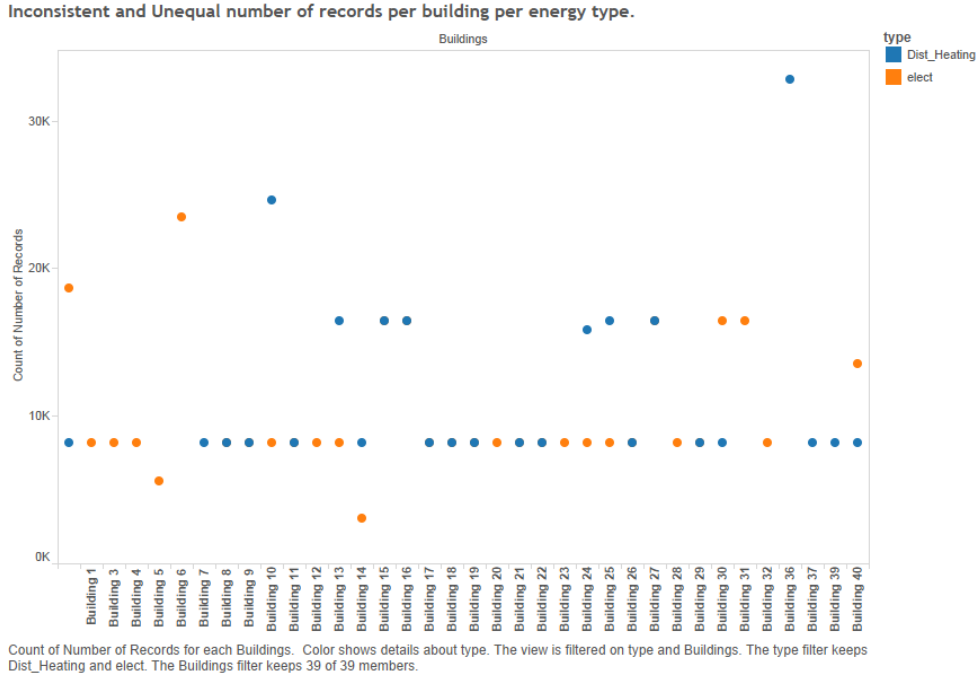


Figure 5.1: Data Inconsistencies in hourly energy consumption data.

<http://https://arska.espoo.fi/>

5.1.2 Data set 2: Device level data

This data set contains device level consumption of electricity collected from a residential apartment included as a test site for VTT’s Green Campus initiative. The device level means that electricity consumption was collected for various home appliances used in that apartment. These appliances were differentiated on basis of their respective electric signal thumbprint using NIALM metering devices described in section 2.3. The data was collected from 1st May 2013 to 30 th April 2014 in form of a text file from a VTT web service. The different fields in the data were separated by “;”. The data set have following fields.

”Device”,”Timestamp”,”Consumption(Wh)”

Device field was a label for the respective home appliance e.g. Refrigerator, Freezer, TV, and Stove etc. Time stamp contains the date, hour, minutes and seconds of the recorded in YYYY-MM-DD HH:MM:SS format.

The Consumption(*Wh*) field contains the value of electricity consumed and recorded at the instance of time. The devices that are used on demand for example TV, stove, coffee maker etc records the consumption values right after at the end of the use. For continuously used devices like refrigerator and freezer etc. NIALM devices has their inbuilt mechanism to keep recording the data. For our research we take the data record as it appears in the data set.

5.2 Use Case Categories

As listed previously in section 3.3.2.1 of this document, Following are the main use cases for our research.

Use Case 1: Understanding the seasonal energy usage patterns and its sensitivity with outside temperature.

Use Case 2: Understanding characteristics of building using daily energy consumption pattern.

Use Case 3: Calculate the base load of the building to identify non user consumption of buildings

Use Case 4: Classify building on basis of energy efficiency and analyse seasonal shifts in this classification.

Use Case 5: Predict daily energy consumption of various house hold devices on basis of previous consumption pattern.

Data set 1 was used for use cases 1,2,3 and 4 while data set 2 was used only for use case 5. In the similar way we grouped the use cases into two categories for analysis. Use case 1 to 4 were referred to as “Energy Consumption patterns and classification of buildings on basis of energy efficiency”. While use case 4 was labelled as “Prediction model for forecasting energy consumption of household devices ”

5.3 Energy Consumption patterns and classification of buildings on basis of energy efficiency

In section 2.5 we discussed the concept of energy efficiency in context of the ecological factors. In section 2.7 we discussed the impact of outside temperature on energy usage. Similarly we established the relationship between daily load, based load and energy efficiency in section 2.6. Now using all these concepts together we shall try to analyse our data set 1 and try to detect the

daily and seasonal trends of electricity usage in green campus imitative test buildings. We shall also try to find out the base loads for the building to see which building is consuming more energy during the off peak hours when users are not present in the building. Finally we shall try to classify the building on basis of energy efficiency a per section 2.8. Following subsections will describe the each step along with explanation of the analysis and results.

5.3.1 Data cleaning and pre-processing

For preparing a tidy data set for analysis following steps were performed

1. Analysis was intended to be performed only for electricity and heating features so the relevant observations were extracted from the data. In rest of the document we shall consider these extracted observations only.
2. To check the consistency and quality of data in terms of number of observation per building per month per day, a quick statistical analysis was performed. Result of the analysis is illustrated in figure 5.1.
3. The consumption scale was set to KWh (Kilo Watt Hour) by dividing consumption value of each observation by 100.
4. For each feature the distinct building were listed to see how many building has which type of feature available. The result shown that 32 out 40 building has observations available for electricity while 24 has observation for heating. In both the cases there were observation with null “Destination Address” and “Building Name” fields. Such observations were updated with “Unknown” for the respective fields. This step was particularly useful for clustering and classification part of analysis.
5. There were some other pre processing steps that are explained with their respective use cases.

5.3.2 Seasonal variation in energy consumption

Seasonal variation in use of electricity is a very obvious phenomenon. However the important aspect for our analysis was to first see the sensitivity of energy usage with change in outside temperature as per use case 1 and then see the impact of seasonality on classification of building on basis of energy efficiency i.e. to check if a building of particular class shift to another class

with change in temperature. This provides basis for use case 4. Since all of the test building are in cities of Helsinki and Espoo which are geological located close to each other so it can be safely assumed that both city has similar temperatures throughout the year. The upper graphs in figure 5.2 shows the aggregated consumption values in a time series for all the buildings represented by two lines representing electricity and electricity used for heating respectively. While the lower graph shows the average temperature of Helsinki and Espoo during the same time of the year. The temperature data was collected using Finnish Meteorological Institutes's data API.

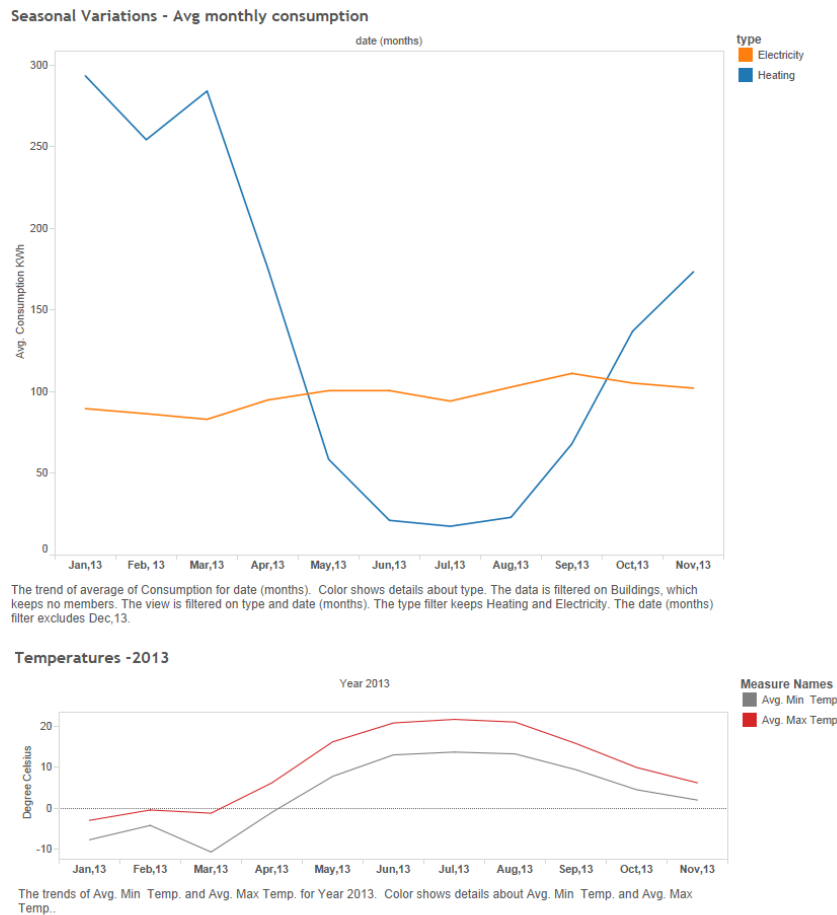


Figure 5.2: Seasonal patterns in usage of electricity and electricity used for heating .

Figure 5.2 shows that electricity used for heating is more sensitive to temperatures than electricity used for other purposes that shows a relatively

stable trend through out the eleven months period. For service providers improving heating distribution systems can contribute more to energy efficiency.

5.3.3 Daily trends

Detecting and projecting daily trends from data set 1 can provide us two very important insights that corresponds to the use case 2 and 3. It can provide us information to suggest characteristics of a building without having any before hand information of the building. For example if the use of energy is higher during the work hours of the working days and lesser during night times and on weekends then we can suggest that the building is an office building. The second insight about the off time load or base load can refer us to the building where there can be possible electricity leakage. Rectifying such issues can improve the overall energy efficiency of the buildings.

In our analysis we detected the daily trends of the buildings by averaging the consumption of each building separately for each hour of the day. Normalizing the data for missing values was very important so instead of averaging on the total number of days for each building we took averages with the number of days for which data is available.

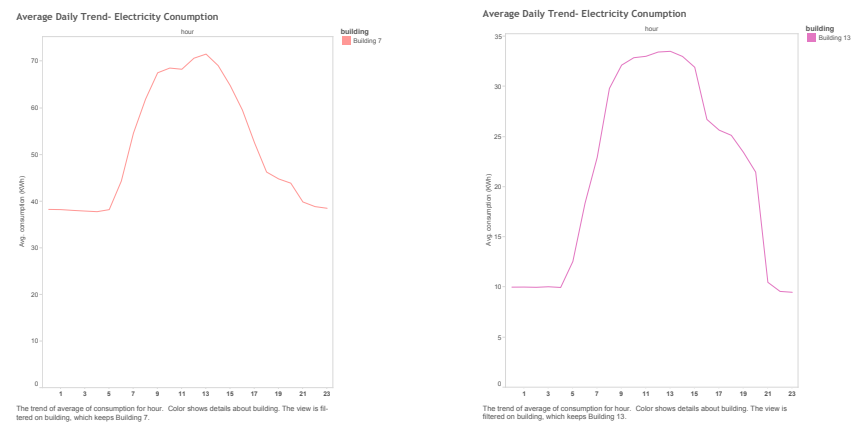
Figures 5.3a and 5.3b shows the average daily electricity consumption of two buildings from our data i.e. Building 6 and 13 respectively. While 5.3c and 5.3d shows the electricity consumption for heating for same buildings. Both type of consumptions are higher during office hours suggesting the purpose of building. While each building has different base loads. Base load hours are very visible in the the daily trends graphs. An interactive dashboard is available to observe the trends for all the buildings is available on following website.

<http://https://arska.espoo.fi/>

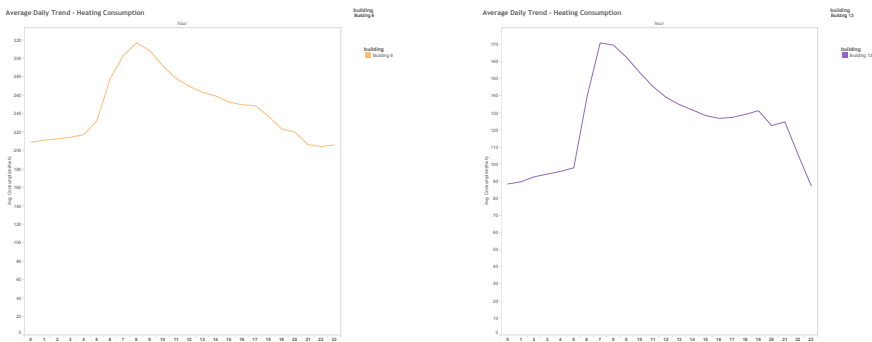
A quick exploratory analysis of the trends suggests that all buildings are office buildings . Secondly the base load hours are hour 0,1,2 and 23. The base loads can then be calculated by averaging the consumption for these hours. Appendix D contains the list of calculated base loads for each building in each month of the year within available data.

5.3.4 Classification of buildings on basis of energy efficiency

Classification on basis of energy efficiency can be used as a tool to benchmark and segregate inefficient energy consumption units from efficiently performing buildings. Such classification can narrow down the scope of research



(a) Building 6: Daily electricity consumption trend (b) Building 13: Daily electricity consumption trend



(c) Building 6: Daily electricity for heating consumption trend (d) Building 6: Daily electricity for heating consumption trend

Figure 5.3: Daily energy consumption patterns

for finding the possible energy leakages and faults. We discussed the main concepts and the k-means clustering technique we used for our analysis in section 2.8. The existence of some similarity is a pre condition for any cluster analysis technique. To test this on our data set we calculated average hourly energy efficiency using equation 2.2 for each building. Figure 5.4 confirms the availability of similarly behaving buildings in terms of energy efficiency.

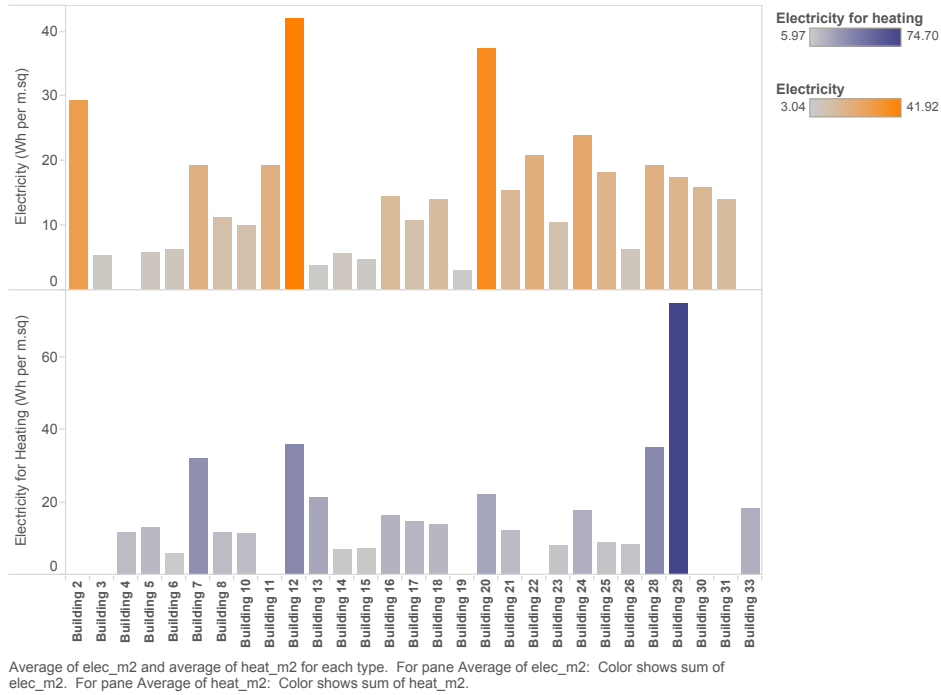


Figure 5.4: Energy efficiency of buildings with hourly average consumption.

5.3.5 Data processing for cluster analysis

K-means algorithms needs input data in form of a matrix, where the values of each feature are defined in their respective columns while each row represents a data point that will be grouped together in forms of clusters. In our case we had two energy features i.e. electricity and electricity used for heating. While average monthly energy efficiency value for each month and each building was represented by a row in input matrix. The reason for

considering average monthly values for buildings was to analyse the energy efficiency of the building through out the eleven months period. So in this way our input matrix consisted of

Number of rows, $i = 2$

Number of columns, $j = \text{Number of buildings} \times 11$

Following are the main data processing steps that we performed on data for producing a tidy input matrix for our cluster analysis. These steps are performed on the data set that we had as output of the preliminary data pre-processing described in section 5.3.1.

1. We segregated the electricity and electricity used for heating records from each other.
2. We calculated the average daily consumption for each building and each energy type first and then calculated the average monthly consumption in similar way. It was important to normalize the data by taking the averages on basis of number of records available for hours within a day and then days within a month.
3. We then arranged calculated average monthly consumption values for each energy type in form of a matrix labelled with building and month names as separate columns. We called this matrix as “energy consumption matrix”.
4. At this stage our energy consumption matrix had few buildings for which consumption values were missing for either type of energy. We removed these building to avoid inconsistency in data for cluster analysis.
5. We then introduced the real estate data i.e. ground floor area of the respective buildings into our energy consumption matrix. Using equation 2.2, we calculated the energy efficiency values for each energy type. We termed the resulting matrix as “energy efficiency matrix”.
6. Till this moment we had energy efficiency in units of Kilo Watt hour per meter square. We converted the values into Watt hour per square meter. This was an optional step and it was performed just to avoid handling small decimal values.
7. To prepare the final input matrix we removed the labels and leaving two columns of energy efficiency values for two target types of energies.

8. To finalize the K-means input matrix. We used R programming **scale()** function to set the unit variance for all matrix elements. This function could have also normalized the scale of measurement, However in our case it was already a similar unit for both energy types i.e. (Wh/m^2).

Our use case requirement was to classify the buildings into four categories of high efficiency, moderate efficiency, low efficiency and poor efficiency buildings. So we had the pre-defined K value of 4. We applied k-means clustering on our input matrix using R programming **kmeans()** function.

As a post processing step we combined the resulting cluster values to the energy efficiency matrix in front of their respective labels (*BuildingName + MonthName*) and energy efficiency values (*electricityandelectricityusedforheating*). We termed this matrix as “clustered matrix’. The clustered matrix was then fed into Tableau public as a CSV file to create interactive dashboard and visualizations. Figure 5.5 visualizes the result of clustering.

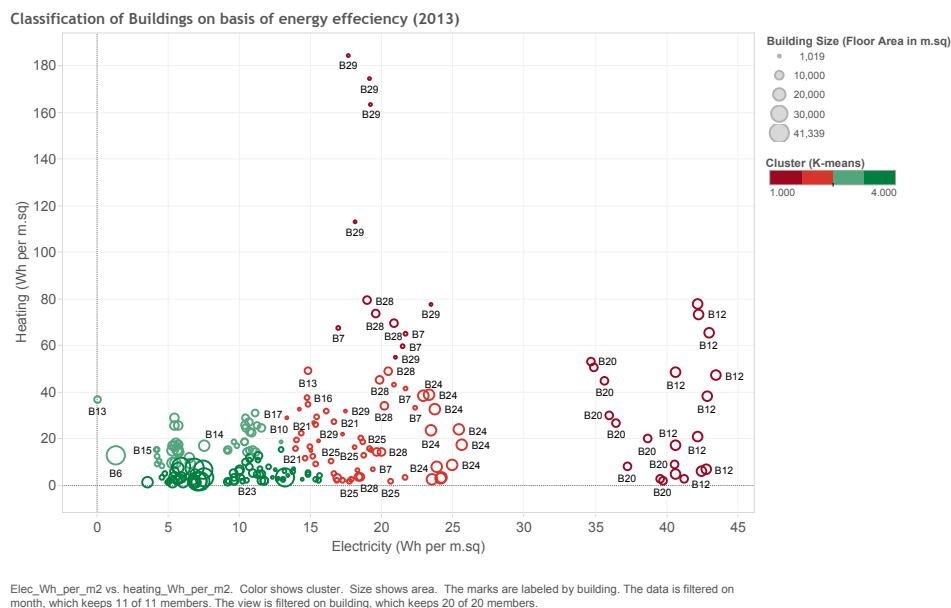


Figure 5.5: K-means clustering, Average monthly energy efficiency per each building.

Each bubble on the graph represents a months average energy efficiency

value for a particular building. The colour of the bubble represent the respective cluster or class. While size of the bubble represents the size of the building. Cluster numbers are from 1 to 4, where 4 represents the highly efficient cluster and 1 is for the most energy inefficient cluster of the buildings. Figure 5.6 shows the one month subset of the clustered values. Each bubble represent average energy efficiency in month of January.

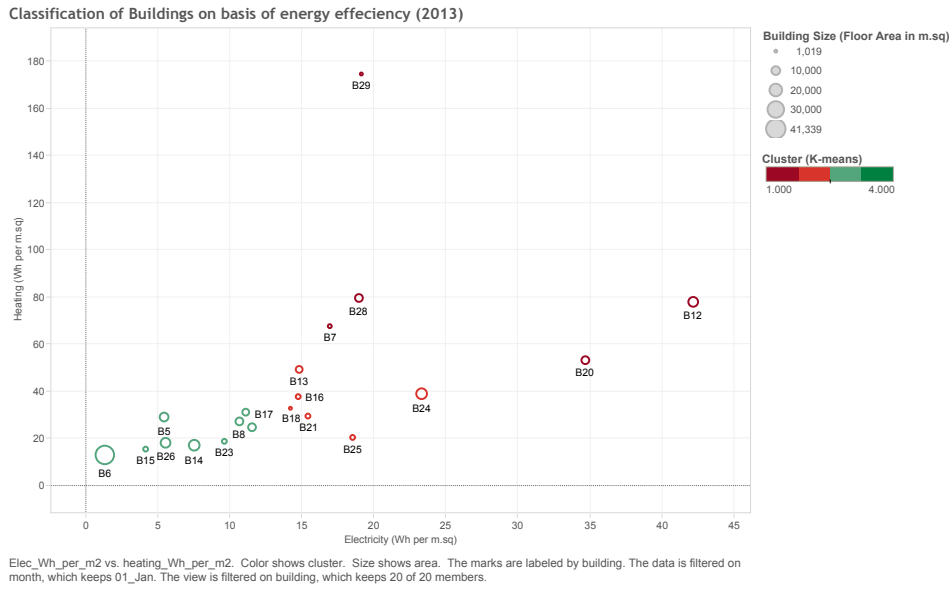


Figure 5.6: K-means clustering, One month view.

Insight: Figures 5.5 and 5.6 reflect a very important insight that some of the bigger size buildings are in high or moderate efficiency clusters while some of the smaller buildings are in inefficient clusters. Such extreme case can be good targets for case studies. The low efficiency buildings may have some energy leakages, faults or inefficient usage practices while the high efficiency buildings may suggest good practices for using energy.

As part of the use case, we also studied the behaviour of buildings using same cluster analysis. Figure 5.7 illustrates the behaviour of different buildings during the 11 months period. Figures 5.7a and 5.7b presents the behaviour of building 29 and building 7 respectively. Both the buildings shift among three different clusters. While figures 5.7c and 5.7d represents the buildings 16 and 24 that shows shift between two clusters and no cluster shift respectively.

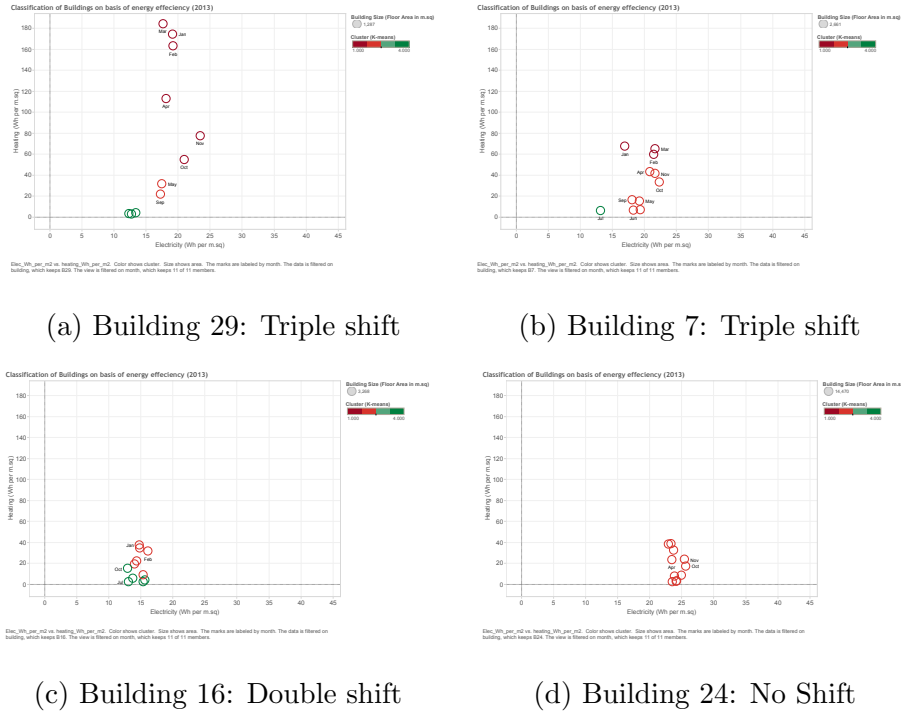


Figure 5.7: Energy efficiency cluster shift during 11 months

Insight Figure 5.7 shows the fact that buildings are not equally energy efficient or inefficient through out the year.

An interactive dashboard is available for viewing the behaviour of all the buildings in 11 months of data via following web address under a classification tab.

<http://catalyc.net/>

5.4 Prediction models for forecasting energy consumption of household devices

We discussed the data set collected by NIALM devices in section 5.1.2. Using this data set we tried to evaluate different prediction models using limited amount of our data set. There were nine different appliances included in our data set i.e. Refrigerator, Freezer, Dishwasher, Laundry machine, Coffee maker, Stove, TV or PC, and Microwave oven. Some of the devices are generally in continuous use e.g. freezer and refrigerator. While others are use on need basis e.g. stove, coffee maker, laundry machine etc. Even in

such devices, frequency of usage can be different e.g. stove, coffee maker etc are usually used on daily basis while laundry machine can be used once in a week. The limited use of data set means that we are not dealing with all this diversity. Instead we forecast only for those devices which are in continuous usage e.g. freezer and refrigerator. The predicted values are on the daily consumption basis for a particular device.

5.4.1 Important considerations for forecasting

Following were some important considerations while evaluating the prediction model.

1. We collected NIALM data in two phases. First data contains consumption values from 1st May 2013 to 3rd February 2014. This data was used as training data for prediction models. While the second data was collected with consumption values from 4th February 2014 till 30th April 2014. This set was used as the test data to measure the accuracy of prediction model.
2. Prediction models were evaluated using consumption data of Freezer usage.
3. A time window of previous 30 days was used to predict values for next 30 days with 80% confidence interval.
4. The accuracy of the prediction models were compared on basis of mean absolute error (MAE).

5.4.2 Data processing steps

Following are the main steps that were performed to evaluate prediction models.

1. Data was reshaped to form continuous time series. The missing daily values were filled with zero value.
2. Data was aggregated to calculate the daily consumption for each device.
3. The Freezer data was extracted from the processed data set to apply prediction models.
4. Three forecasting models were applied on the training data i.e. Linear Regression, ARIMA, and Artificial Neural Networks (ANN). We used

R for ARIMA modeling and Weka for Linear Regression and AAN. We shall discuss about the usage of these tools in next chapter 6.

5. We calculated the accuracy using test data and mean absolute error formula.

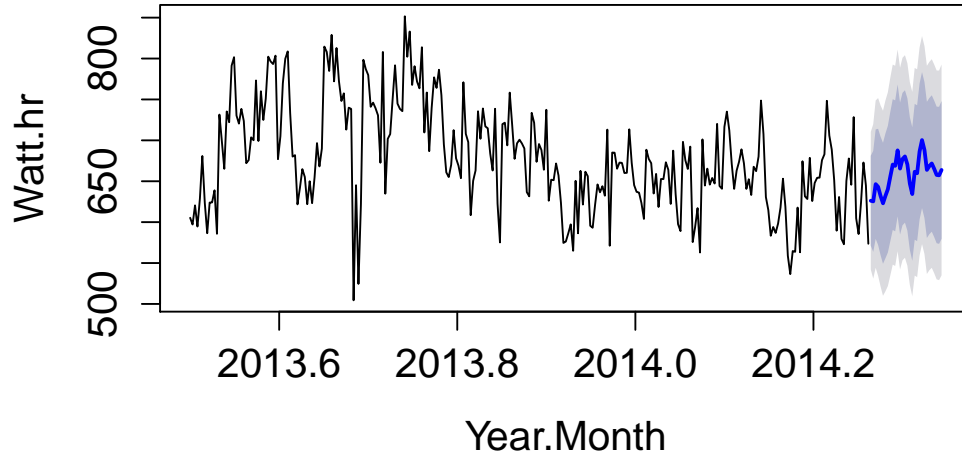
5.4.3 Forecasting results

Figure 5.8 shows the resulting forecasts from the three prediction models. In figure 5.8a, predicted values using ARIMA model with 80% confidence interval are represented by the bold blue line, while shaded geom represent the higher and lower 80%,95% confidence intervals respectively. Figure 5.8b and 5.8c illustrates the predictions using linear regression and artificial neural networks (ANN) models respectively using 80% confidence interval. Circular dots in the graph shows the predicted daily values while The dotted line geom present the higher and lower 80% confidence interval prediction ranges. Due to use of different analysis tools the ARIMA graph is different from the linear regression and ANN graphs. Both X axis and Y axis in all the graphs represents days and electricity consumption(Watt.hour) respectively. However label of the days in axis is in figure 5.8a is showing respective months with year while label in figures 5.8b and 5.8c represents the number of the day starting from first day in the data.

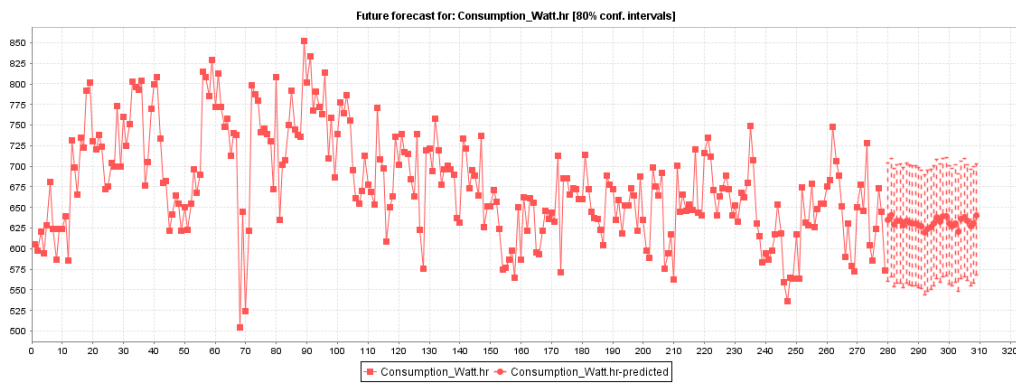
Table 5.1 lists the mean absolute error (MAE) values for each prediction model. Forecasting with ARIMA model shows the lowest MAE values. For this reason, we included ARIMA forecasting as part of our implemented platform. We use R to perform calculation described in section 2.9.3 using packages like “Forecast” for fitting ARIMA model and forecasting and “zoo” for handling time series data structure. p,d,q values for predicting monthly values based previous 30 days were 30,0,30 respectively.

	ARIMA	ANN	Linear Regression
Mean Absolute Error (MAE)	32.6	47.5	42.4

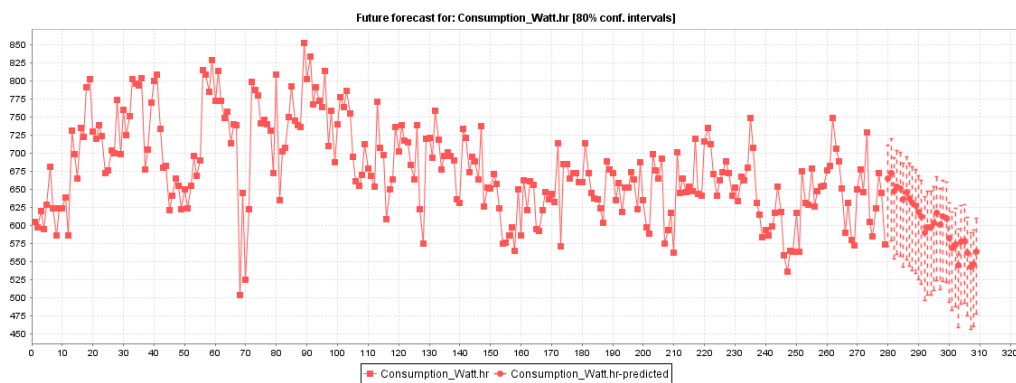
Table 5.1: Mean absolute error values for prediction models.



(a) ARIMA with 30 days AR and MA



(b) Linear Regression Model



(c) Artificial Neural Network Model

Figure 5.8: Forecasting monthly energy consumption for home appliances based on previous observed monthly consumptions

Chapter 6

Discussion

In this chapter we attempt to summarize our work with a critical analysis of our approach and results while highlighting some possible future directions related directly or indirectly to our research. Our research have three main constituents i.e. (i) Big Data tools and techniques (ii) Big Data analytics (iii) Using BIG Data analytics to facilitate in improving energy efficiency. We pivot on these topics for our discussion in this chapter.

6.1 Big Data tools and techniques

In our approach, we tried to cover data volume, velocity, variety, veracity and valuation as the five major aspects of Big Data. The concept and implemented platform are horizontally scalable to meet the large data set requirement. We performed most of our analysis on small size hardware described in section 4.4.1. For the proof of concept we also tested the implemented platform in a multi server environment by scaling out to 4 serving nodes of similar hardware specifications as explained in section 4.4.1. We used both public cloud and dedicated on-premises hard to test multi server implementation. But for the purpose of data processing during our analysis we used single hardware server node in pseudo distributed mode i.e. using resources within a single server in distributed parallel mode. This single node configuration in pseudo distributed mode provided us enough computing power to handle the data we collected from VTT.

The largest data set collected for our research was approximately 250MB file with around 1.2 Million records in it. This is a small volume compared to the volumes that are generally associated with Big Data. It is important to mention the fact that this data was collected from only 40 buildings for period of 11 months as a pilot project. The real life commercial scale use

of such projects can include thousands of building and data processing may require to include data recorded during several years. To test our systems readiness for large data sets we replicated the collected data several times in form of larger file sizes in multiple numbers.

In terms of velocity, we analysed our data using distributed parallel batch processing. For sake of fast and near to real life data processing speed we also tested Cloudera Impala. The performance of Cloudera Impala in terms of speed was many times faster than the batch processing tools like Apache Pig and Apache Hive. However Cloudera Impala has a very limited support for handling complex and composite data structures. There are some new emerging tools like Apache Spark and Apache Shark that can enable much faster data processing and offers support for complex data structures. Adaptation of our data platform with these new emerging tools can further enhance its data processing capabilities.

Data variety and veracity was managed on the basis of our use case requirements and collected data sets. We built our data platform on top of Cloudera CDH that provides basic Apache Hadoop ecosystem data processing tools like Hive and Pig. On top of it we also integrated database system like MongoDB that can ingest schema less data too give flexibility for handling unstructured data. Statistical programming capabilities using R were also available to clean and process data. The whole platform was based on open source software and the model has the inbuilt flexibility for use in any kind of deployment models e.g. public or private cloud, own premises general purpose hardware, or combination of them.

In an ideal data platform, The processes and work flows should be fully automated. This means that after configurations, The platform should be able to collect, process, mine and visualize data automatically. Our data platform covered the end-to-end process for data analytics. All the components were integrated to implement the required work-flows. However some manual interventions were required to execute the work-flows e.g. extracted insights were fed to visualization tools in form of off-line CSV files. This can be improved to provide full automation using some paid services like database connectors to visualization. Another automation can be added for operations and maintenance of platform using tools like Opscode Chef and PuppetLabs AutomateIT tools. It is worth mentioning here that Cloudera CDH provides a management control panel to manage resources. But this control panel is limited to tools within CDH.

6.2 Big Data Analytics

The real value of processing data lies in revelation of the hidden unknown valuable knowledge. Big Data analytics is about processing large volumes and diverse varieties of data on need basis basis to discover the hidden patterns, underlying correlations and useful information. Statistical analysis tools like R, SPSS and Matlab have diverse range of powerful advance analytics libraries and packages that can be used to extract the information from data. But these tools allow scalability only in terms of scaling up. Such scalability is always limited and requires specialized expensive hardware. Combining the data processing power of Apache Hadoop and MapReduce with these statistical tools can enable us to process huge amounts of data and the mine the required information through tools like R.

We used this concept for data processing and analysis in our reserach. We leveraged on power of Hadoop to pre-process our bulky data and transformed it into smaller size while keeping the useful information intact. We then applied the advance analytics using R to generate the required insights. This is a very useful approach. But in order to build a continuous data processing and mining pipeline it has its limitations e.g. manual or off-line mode for transfer of processed data between data processing an data mining phases.

There is a new emerging paradigm of Big Data analytic tools that can execute variety of advance analytics techniques directly on top of Hadoop file system. Apache Mahout is one example that can integrate withing Apache Hadoop ecosystem and provides powerful advance analytics capabilities. Mahout uses parallel batch processing so inherently it is limited for use in online streaming analytics. Cloudera Oryx and Mlbase are two new emerging tools in this ecosystem that can integrate with Apache Spark and Hadoop 2.0 to provide on-line analytics on streaming Big Data. Integration and use of these tools can improve the capabilities of platform discussed in scope of our thesis research.

6.3 Using BIG Data analytics for energy efficiency

We used R in combination with Apache Hadoop in our data analysis for energy efficiency use cases. We described data sets in details in section 5.1. In the same section we mentioned about the respective use cases of each data set. For the hourly energy consumption data set we analysed the daily and seasonal usage patterns using simple aggregation methods like summation

and averaging. These patterns provided the basic information about the impacts of ecological factors on consumption of some specific types of energies. We also observed the sensitivity of consumption patterns to the variations in these ecological factors. Identified seasonal trends in the data also laid for our next important use case i.e. classification of buildings on basis of energy efficiency.

We tried to quantify the energy efficiency of the buildings in our data set using VTT's previous research on the topic. Then we attempted to group the similarly performing (in terms of energy efficiency) buildings together and classify them into four categories ranging from highly energy efficient to highly inefficient buildings. Within our classification we also tried to observe the seasonal trends on the classification. We used cluster analysis technique with K-means algorithm to classify the buildings. K-means algorithm requires predefined number of cluster. In our case we had our basic requirement to categorise building into four categories. In other possible use case where there are no predefined categories, other advance analytics techniques e.g. Hierarchical agglomerative clustering can be used. The use of such classification is to identify the possible opportunities to improve the energy efficiency and learn from good practices. As an obvious next step to our research, the respective buildings with lower energy efficiency should be explored to identify the possible energy leakage, faults and bad usage practices. Similarly the good practices can be learnt from the energy efficient buildings. Our energy efficiency classification is limited to the general purpose usage of the buildings. This classification model may raise false red flags for buildings with specialized usage like data centres building, laboratories and factories etc.

For NIALM data set with device level energy consumption information, tried to compare different prediction models that can help energy service providers to plan for the demand response, production and distribution. Our comparison was limited to the prediction model for continuously used devices like refrigerators and freezers. We predicted the future one month usage on basis of previous monthly usage. This comparison can actually be the first step for building prediction model for energy service providers while a recommendation engine for users that can learn from user behaviour and the energy tariff data and provides recommendation to user to improve energy efficiency as well as reduce spending on energy. This model can be improved further by adding more historic consumption data that further can affirm the seasonal and usage specific trends.

Chapter 7

Conclusion

Global energy needs are continuously growing. The conventional methods for producing more energy to meet the demand pose a great threat to environment. Among other solutions, Energy efficiency has become a major tool for minimizing the need of producing more energy to cater for the growing demand. Inherently, the cause of improving energy efficiency relies on understanding the usage patterns, identifying the problematic areas, establishing the good energy consumption practices and rectify the faults to reduce energy leakages. The advancement in sensors, ubiquitous computing and communication technologies has provided basis for effectively collecting the usage data to understand energy usage. The collected data needs to be processed to generate generates leads for improving energy efficiency. The quality of insights generated from data improves if we consider the current data in context to historic data. This means that data volume for processing will keep on increasing. There can be multiple sources of data so the data formats can also vary. Then on the use case basis, data processing requires flexibility for customization and variation in speed of data processing. These all data features refers to application of Big Data technologies for energy efficiency.

Distributed parallel computing programming models like MapReduce provide the basic environment for handling Big Data. We leveraged on power of MapReduce using Apache Hadoop ecosystem tools to present an end-to-end Big Data analytics tool. Hadoop supports scalability to meet large volumes of data sets while the there are other tools that can integrate with Hadoop to process complexity in data. We used the model platform to process real life energy data and generated insights that can be used to improve the energy efficiency. The proposed model provides a plug and play environment for many other analytic tools to integrate on need basis. It is based entirely on open source software components and can be deployed using general purpose hardware or any cloud based model.

We observed the strong sensitivity in consumption of specific energy types to the ecological factors like external temperature. The visualization of the average daily consumption of each building suggested the respective use of the buildings. It also provided the information about base loads of the building. Optimizing the base load of the building improves the energy efficiency. We also calculated the energy efficiency of the buildings in our sample data set and classified them on the basis of calculated energy efficiency. The classification provided us a reference point to identify the buildings where we can focus to locate the possible faults, energy leakages and bad consumption practices. This classification can be an important tool for organization working on improving the energy efficiency as it can help to isolate the problematic buildings. Our results also show a dynamic behaviour of buildings energy efficiency performance during different months in the year. This particular insight can be use as another reference to isolate the causes for energy inefficiency for a target building.

We also compared different prediction models to forecast the future energy usage of different home appliances on basis of their previous usage. The prediction model it self can be useful for energy service providers to understand and plan for user specific demand. However, this can also be used as the first step towards building a decision support system for user to effectively use home appliances. The decision support system can predict the usage pattern and then recommend the best options on basis of configurable parameters e.g. best tariffs or best time to use green energy etc.

In a nutshell, our research provides a proof of concept of how emerging Big Data technologies can be applied in energy industry to improve energy efficiency and data driven decision making. We presented and demonstrated the concept of a Big Data analytics platform an applied it to solve real life use cases from energy industry. The output of our research is a working Big Data analytics platform and the results generated from advance analytics techniques applied specifically for solving energy efficiency problems.

Chapter 8

Conclusions

Time to wrap it up! Write down the most important findings from your work. Like the introduction, this chapter is not very long. Two to four pages might be a good limit.

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Appendix A

List of Evaluated Platform Components

Appendix B

Platform Configurations

Appendix C

Data Descriptions

Appendix D

Detailed Results