AN INVESTIGATION INTO VISUALISATION AND FORECASTING OF REAL-TIME ELECTRICAL CONSUMPTION BASED ON SMART GRID DATA

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Declaration

I declare that this dissertation is my own, unaided work, other than where specifically acknowledged. It is being submitted for the degree of Master of Science in Engineering in the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in any other university.

Signed this______ day of ______________________2014

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Rodwell Mangisi

Abstract

The smart grid, and in particular smart meters, is a growing world-wide phenomenon which has allowed for the availability of detailed real time usage data to the user in ways that were not possible in the past. South Africa has been slow-moving in adapting smart meters, but in the past two years this has changed and smart meters are becoming the new standard. This has given rise to the need for software applications to help both the South African consumer and local power utilities get the most out of the smart meter data. The purpose of this research is to investigate the possibilities offered by smart grid data obtained from advanced metering infrastructures, with particular emphasis on real time energy usage visualisation and peak load forecasting. Previously, detailed energy usage data has not been available to consumers hence there has not been much research focusing on utilising this data for direct consumer benefit. The focus of most research has mainly been on the power utilities supply side where attention has been on visualising their consumers' usage and forecasting consumer demand in order to supply them with electricity continuously and efficiently. In this dissertation a benchmarking model for developing smart grid data visualisation dashboards is proposed and this model is used to present and prototype a consumer side dashboard. The prototype implements real time data visualisation techniques, as well as a Multiple Linear Regression model based forecasting algorithm for half hourly peak load forecasting using data collected from the University of the Witwatersrand's advanced metering infrastructure. In this study the Multiple Linear Regression model is built through a comprehensive analysis of 2 years' worth of energy usage data from the University of the Witwatersrand and 3 years' worth of hourly temperature data from the South African Weather Services. The prototype's performance is evaluated with reference to the proposed benchmark and a user technology acceptance evaluation done by the University's Property and Infrastructure Management division as well as 10 other independent users. The dashboard is found to be a useful and acceptable tool in energy monitoring at the University. The forecasting model performs well with a mean absolute percentage error of 3.69%. The inclusion of a forecasting functionality within the energy management dashboard is shown to have the ability to help the university reduce its electricity bill by being able to shave their peak loads. The analysis highlights the importance of better data archiving and smart meter monitoring thereby ensuring that the meters are always online and no data goes missing which is vital for accurate forecasting results.

Dedicated to my parents, Miriyemu Mangisi and the late Golden Ray Mangisi for their selfless sacrifices in giving me the best possible education and upbringing

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List of Abbreviations

AAM: Advanced Asset Management

ADO: Advanced Distribution Operations

AI: Artificial Intelligence

AMI: Advanced Metering Infrastructure

ANN: Artificial Neural Networks

API: Application programming interface

ATO: Advanced Transmission Operations

DMS: Distribution Management System

DSD: Demand side Dashboard

EMS: Energy management systems

FNN: Fuzzy neural networks

GA: Genetic Algorithm

GDR: Generalised Delta rule

GIS: Geographic information system

GPS: Global positioning system

GUI: Graphical User Interface

HEMS: Home Energy Management System

LTLF: Long Term Load Forecasting

MLR: Multiple Linear Regression

MAE: Mean Absolute Error

MAPE: Mean Absolute Percentage Error

MTLF: Medium Term Load Forecasting

NERSA: National Energy Regulator of South Africa

PEOU: Perceived ease-of-use

PIMD: Property and Infrastructure Management Division

PLC: Programmable Logic Controller

PU: Perceived usefulness

ROF: Radio over fibre

RSS: Rich Site Summary

SANEDI: South African National energy Development Institute

SASGI: South African Smart Grid Initiative

SAWS: South African weather service

SCADA: Supervisory Control and Data acquisition

STLF: Short Term Load Forecasting

TOU: Time of use

UML: Unified Modelling Language

Chapter 1: Background

1. Introduction

The electrical grid is an interconnected network of devices responsible for the generation, transmission and distribution of power to billions of people across the world. While the traditional electrical grid has evolved and served its purpose well for decades, many factors such as rising costs, environmental effects of electricity generation and rapid improvements in technology mean that these grids are not sustainable for the future and must not stay and operate in their current form. This has led to the introduction of a new kind of electrical grid termed the "Smart Grid".

A Smart Grid is defined as an electricity network that can intelligently integrate the actions of all users (generators, consumers and those that do both) connected to it in order to efficiently deliver sustainable, economic and secure electricity supplies [1]. Smart grids offer a two way communication system between devices which provides for easy control and automation of the grid.

Many countries including South Africa have already started upgrading their traditional grids by introducing smart technology. The introduction of smart meters and smart devices to make the Smart Grid a reality inevitably means a lot of data will be passed to and from the different interconnected smart devices that make up the smart Grid. Studies in Belgium have shown that an estimated 1.28 Terabytes of data per year can be produced by 3 million smart electricity meters [2]. Scaling this by the billions of households in the world this can easily translate to billions of terabytes of data which need to be stored, analysed and visualised easily such that control measures can be carried out from the resultant analytics. Such amounts of data are not easy to collect, intelligibly visualise and analyse and this poses a very big challenge to smart grid data management and analysis tools.

1.1 A Brief History on Smart Grids

Although the term "Smart grid" is relatively new, the idea of a smart grid is not new. From as long back as 1882 in the days of Thomas Edison research into how to actively and remotely control and monitor the electrical grid had already started but was limited by technological capabilities [3]. This research was mostly driven by utilities who wanted to handle peak loads, monitor usage trends; limit unaccounted for power usage and maximises profits.

As technology has advanced in the past century as well as people becoming more aware of the environmental impacts of power generation, a need for more consumer control and the need to produce affordable, reliable and a sustainable electricity supply, governments across the globe have started funding research and the implementation of smart transmission grids. Fangxing Li et al [4] describes in a well detailed diagram shown below the driving forces behind the evolution of the traditional grid into a smart grid as well as the framework for the modern day transmission grid.

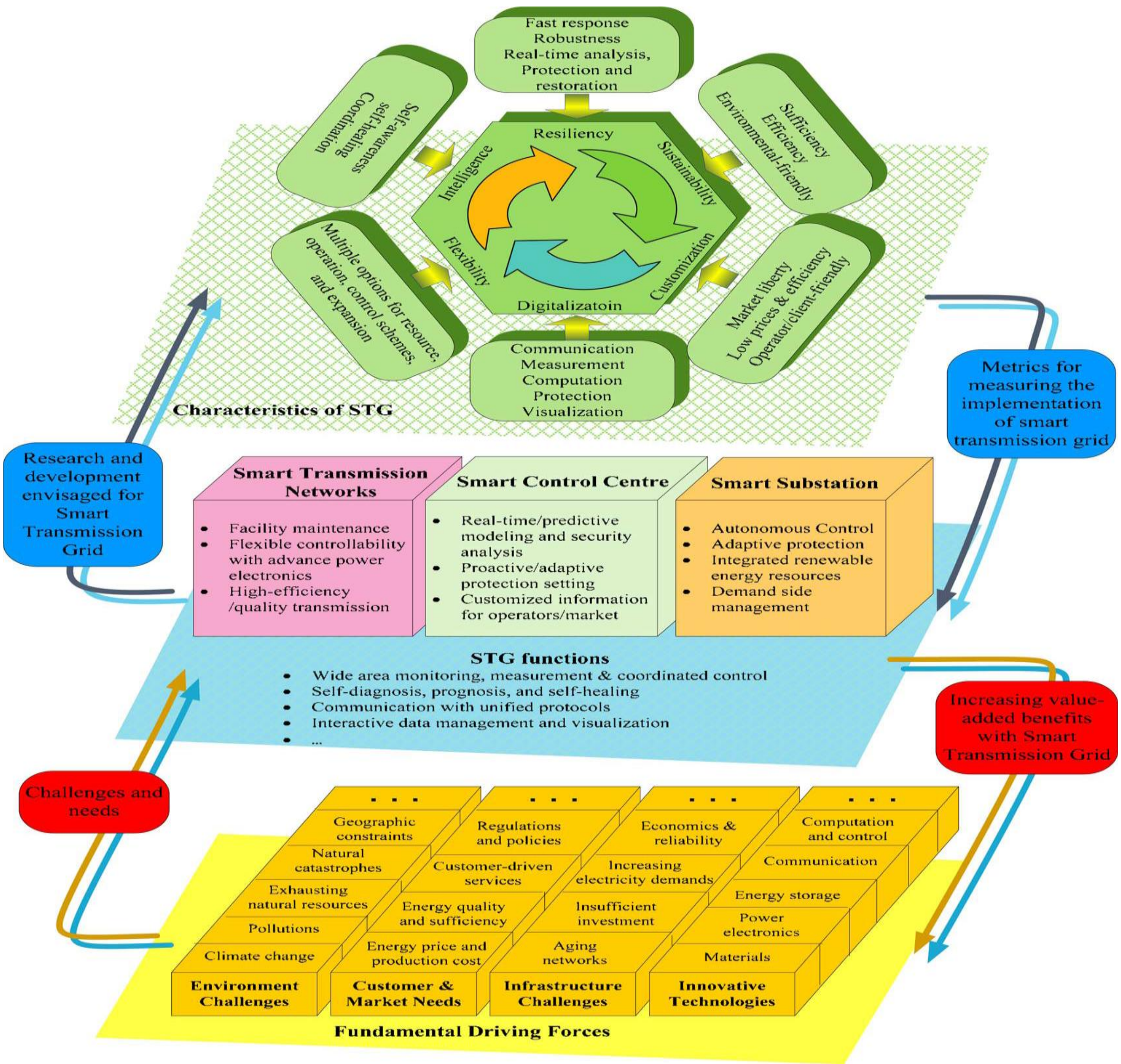

Figure 1: Vision of the Smart Grid [4]

It must be noted that the driving forces and the stages in the development of the smart grid might differ from country to country.

1.2 Why the Smart Grid?

The move to the smart grid has been due to the seemingly infinite world of possibilities and benefits that it brings. Some of the benefits are listed but not limited to the ones below [4]–[10] :

- Improve reliability of power quality and transmission;
- Increased power distribution efficiency and conservation ;
- Reduced costs for electric utilities;
- Reduced expenditures on electricity by households and businesses;
- Lower Greenhouse Gas(GHG) and other gas emissions;
- Enable active participation by consumers;
- Accommodate all generation and storage options;
- Enable new products, services, and markets;
- Provide power quality for the range of needs in a digital economy;
- Optimise asset utilisation and operating efficiency;
- Anticipate and respond to system disturbances in a self-healing manner;
- Operate resiliently against physical and cyber-attack and natural disasters;
- More efficient transmission of electricity;
- Quicker restoration of electricity after power disturbances;
- Reduced operations and management costs for utilities, and ultimately lower power costs for consumers;
- Reduced peak demand, which will also help lower electricity rates;
- Increased integration of large-scale renewable energy systems; and
- Better integration of customer-owner power generation systems, including renewable energy systems.

1.3 A Look at the Smart Grid Architecture

The smart grid architecture includes most of the components of the traditional grid with the addition of smart meters, smart devices and an intelligent bidirectional communication network. It can be broken down into 4 major technology categories proposed by the United States department of energy [11] as follows:

- Advanced Metering Infrastructure (AMI) ;
- Advanced Distribution Operations (ADO);
- Advanced Transmission Operations (ATO); and
- Advanced Asset Management (AAM)

Figure 2 below shows a conceptual overview of the smart grid [6][12][13]. All of the components shown are vital to the smart grid delivering its objectives of providing improved user control and home efficiency as well as sustainable, reliable and efficient power generation, transmission and distribution. The sections following the diagram briefly describe what each of these layers represent.

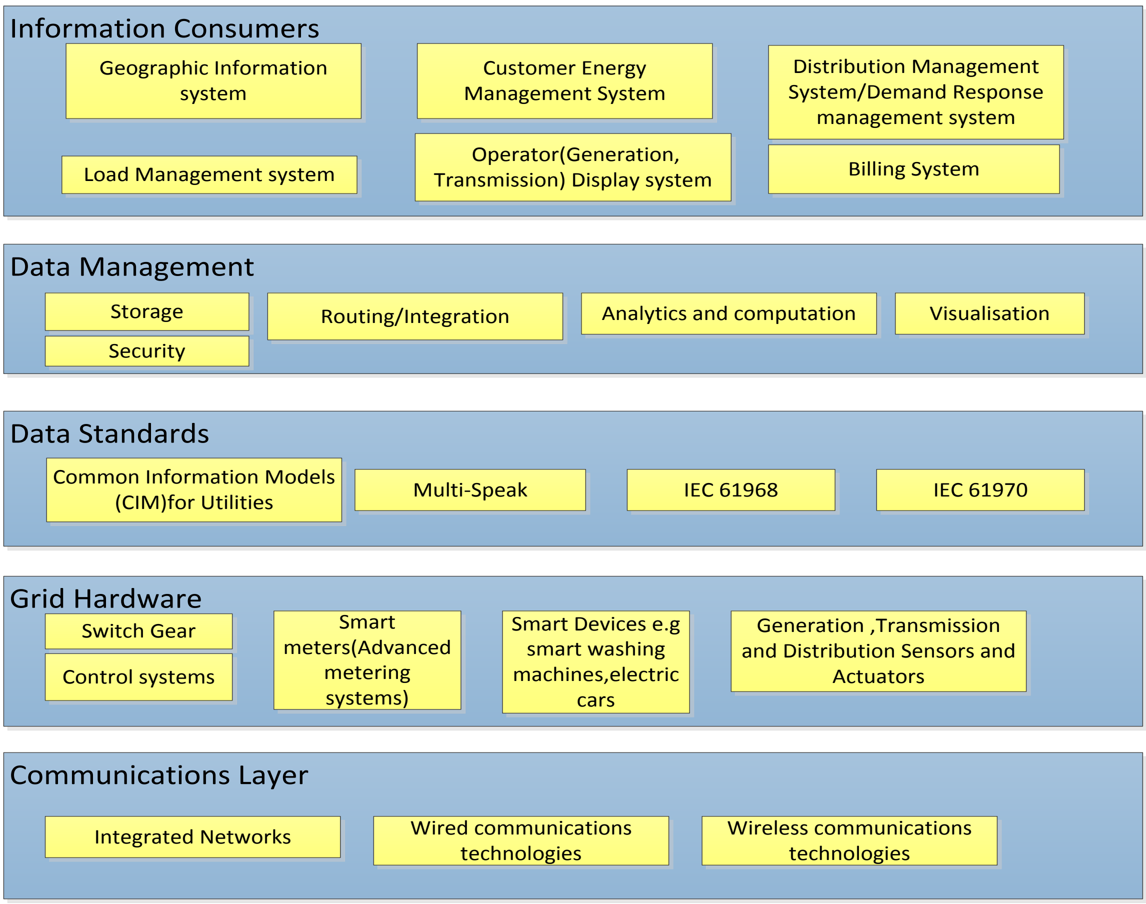

Figure 2: Smart Grid Architecture

1.3.1 Information Consumers

The information consumers' layer of the architecture represents the consumers of the data produced by the smart grid. These are namely the end users and the different management systems of all the entities making up the grid. An example of these entities is a household consumer and they are be able to get real time billing information, real time power cost as well as information regarding their power usage from the smart grid. Other entities like distribution and generation control centres are able to get demand and forecast information as well as the grids general health information. This information helps them to manage national grid systems.

1.3.2 Data Management

As more and more utilities around the world transform their grids into smart grids the amount of data produced by these smart devices will continue to grow exponentially [13][14]. The Data management layer is responsible for handling all the operations pertaining to the management of this large amount of data. Operations such as securing, analysing, visualizing and storage of data are represented by this layer.

1.3.3 Data Standards

The smart grid will see the interconnectivity of millions of devices offering two-way flow of data. There has to be a standard for these devices to communicate and exchange data securely and effectively [15]. The Data standards layer represents some of the common standards used in the grid such as Multi-speak and CIM. Other standards like IEC 61968 which enables inter-application information exchanges among distributed software application systems supporting the management of utility electrical distribution networks within a utility's enterprise systems environment are still being developed [15].

1.3.4 Grid Hardware

The IEEE describes the smart grid as a complex system of systems [15]. These interrelated systems are made up of the hardware represented by this layer. The system consists of but is not limited to sensors, smart devices, electric vehicles, advanced metering infrastructure, monitors, switch gear, control gear and data storage devices. Typical smart grid components are as summarised below [16]:

- **Intelligent appliances**: Appliances that use pre-set customer preferences to decide when to consume power. This can allow the consumer to shave their peak loads which has a major impact on electricity generation costs – alleviating the need for new power plants and cutting down on damaging greenhouse emissions. The consumer also benefits from a lower energy bill.

- **Smart power meters:** meters that offer two-way communications between consumers and power providers. This gives the ability to automate billing data collection, detect outages and dispatch repair crews to the correct location faster.

- **Smart substations:** substations that can monitor and control critical and non-critical operational data such as power factor performance, breaker, transformer and battery status, security, etc.

- **Smart distribution:** distribution that is self-healing, self-balancing and self-optimizing, including superconducting cables for long distance transmission, and automated monitoring and analysis tools capable of detecting or even predicting cable failure and failures based on real-time data about weather, outage history, etc.

- **Smart generation:** generation that is capable of 'learning' the unique behaviour of power generation resources to optimise energy production, and to automatically maintain voltage, frequency and power factor standards based on feedback from multiple points in the grid.

1.3.5 Communications Layer

In any infrastructure or network, the communications system is the glue that binds everything together. This is particularly true in the smart grid network. Since this is a highly intelligent network of integrated smart devices and control systems, there needs to be an equally adaptable, secure, reliable, high quality and intelligent communication system. This is what this layer represents. The smart grid consists of sophisticated wired and wireless communication networks .Some of the new communications technologies used in the smart grid network are the broadband over power line, radio over fibre (ROF), 4th generation mobile networks [17][18] etc.

1.4 University of the Witwatersrand Advanced Metering Infrastructure

An Advanced Metering Infrastructure (AMI) is a network of automated two way communication between a smart meter with an IP address and a utility company or home energy management system. The goal of such an infrastructure is to provide utility companies or private customers with real time and profile data about energy consumption and allow customers to make informed decisions on energy usage [19].

The Wits School of Electrical and Information Engineering Energy Group in collaboration with the Wits Property and Infrastructure Management Division (PIMD) set up an AMI network across all the universities campuses. There are over 150 smart meters across all the campuses and more meters continue to be added. Figure 3 below shows some of the Strike Enermax smart meters that have been placed on the campuses [20].

Figure 3: Medical School Networked Smart Meters

As can be seen from the pictures these meters are connected to a computer network via the Ethernet cables shown. This infrastructure has enabled the university to operate a smart grid data management system. After analysing the capabilities of these meters from the user manuals [20][21], it can be deduced that the infrastructure has the potential to:

- Automate meter reading;
- Implement time of use (TOU) metering;
- Provide user/PIMD with usage information via a user interface;
- Allow for management of non-essential appliances in peak periods and hence manage the university's power peaks via the building management system;
- Monitor and manage meter level malfunctions, tampers and outages;
- Accurately estimate the university's energy bill and compare it to the one provided by the power utility(City Power Johannesburg);
- Remotely connect and disconnect specific buildings; and
- Detect and reduce energy theft.

Although the infrastructure has a lot of potential, unfortunately at the present moment the potential has not been fully realised. This system just has a backend which collects the data but it does not have a user interface nor does it have any intelligent visual analytics to make use of this data. This is where this research becomes useful. The author has made a proposal to the energy group to design and implement a dashboard to help the PIMD use this infrastructure to its full potential and to also realise savings on their electricity bill using this data. The proposal shown in its entirety in Appendix A and has been made part of the energy group Google® document library [22]. This dashboard forms the test prototype for the research presented in this dissertation.

1.5 The Research Report

The purpose of the research question presented in this dissertation is to critically evaluate the suitability and role of visualisation techniques, graphical user interfaces and short term load forecasting in the decision support tools that grid operators, managers and consumers use. It is the goal of this research to investigate advanced data visualisation and forecasting techniques that will give dynamic, interactive, real time and predictive graphics. This is done through a literature survey as well as an investigation into advanced data visualisation. An implementation, testing and evaluation of an energy monitoring prototype tool based on these techniques is carried out. This research falls under the data management layer of the smart grid architecture in Figure 2 above. The contents of this dissertation are presented as follows.

Chapter 2: Literature survey of visualisation techniques, the state of these techniques, load forecasting and motivation why research must be done in this area;

Chapter 3: Research questions being addressed, expected outcomes and the methodology followed;

Chapter 4: Modelling of a conceptual Consumer/Demand Side Dashboard benchmark model;

Chapter 5: Multiple linear regression (MLR) load forecasting model;

Chapter 6: Requirements, specifications and design of the prototype developed;

Chapter 7: Evaluation and results of forecasting model and dashboard usability; and

Chapter 8: Conclusion and recommendations.

Appendix A: Dashboard Proposal

Appendix B: South African Weather Services none disclosure forms

Appendix C: Model A Statistical analysis using R®

Appendix D: Model B Statistical analysis using R®

Appendix E: ICONIX Process

Appendix F: Dashboard Source Code

Appendix G: User interface Screenshots

Appendix H: Usability Questionnaires and test case feedback forms

Appendix I: Wits Energy Team correspondence during design and development

Appendix J: Conference Paper (*Pan African International Conference on Information Science, Computing and Telecommunications (2014))*

Chapter 2: Survey of Literature

2. Introduction

The literature review carried out in this research can be broken down into two parts which are the data visualisation aspect of the research as well as the load forecasting algorithms component. This chapter discusses the importance, goals and business case of data visualisation in power management systems. It looks at the state of visualisation techniques and approaches used in the current power grid management systems. It also looks at the available load forecasting algorithms as well as current research in the field of visualisation and load forecasting techniques within the smart grid data visualisation context.

2.1 Importance of Smart Grid Data Visualisation

The old adage "A picture is worth a thousand words" holds true to this day. Pictures are still the most effective way to describe, analyse and summarise a large dataset. This is because human beings are extremely well built for visual analysis and tend to make quicker and better decisions if data is presented to them in pictures, graphs or charts compared to text or any other form of data presentation [23]. This has meant that almost all data analysis tools are highly graphical and use advanced visualisation techniques.

Francis Anscombe, a world renowned statistician in his 1973 paper [24] demonstrated and argued the case of the power of graphs to accurately analyse and visualise data. He successfully demonstrated how four seemingly statistically identical (same mean, variance, correlation and regression) data sets actually portray vastly different information when they are viewed as graphs. His conclusion was that a computer should make both calculations and graphs. Graphs help to perceive and appreciate some broad features of data and a lot of thought and ingenuity must be devoted to devising good visualisation tools.

The American National Energy Technology laboratory in their presentation to the U.S Department of Energy [17] on the key components of improved interfaces and decision support for grid operators, noted that data visualisation was one of the key components. They argued that with the advent of the smart grid, large amounts of data will be available to operators but the amount of time available to them to make crucial control decisions has now shortened from hours to minutes and sometimes even down to seconds. The same publication also points to the unavailability of data visualisation tools in power systems management making it more and more difficult for operators and other users to gain an intuitive understanding of the actual real time operations and control of the grid. This means visualisation techniques that present this enormous information in a quickly-grasped visual format to support operator actions and decisions are crucial to the success of the smart grid. The goal of such techniques is to remedy the problem of a lack of operator situational awareness by giving operators a real time view of the power system and its parameters quickly, efficiently, accurately and in a way that enhances their ability to assess the situation and respond appropriately and rapidly to challenges [25]. According to the US-Canada power system outage task force set up after the August 2003 blackout that left more than 50 million people without power, the situation could have been avoided or effects reduced if the following recommendations had been in place [10]:

- Communications systems and displays that give operators immediate information on changes in the status of major components in their own and neighbouring systems had been present;
- In the control centre, use a dynamic line loading and outage display board to provide operating personnel with rapid and comprehensive information about the facilities available and the operating condition of each facility in service; and
- Give control centres the capability to display to system operators computer-generated alternative actions specific to the immediate situation, together with expected results of each action.

It can be seen that the key component in each of these recommendations is effective information display. As the power grid has evolved and smart devices become ubiquitous there is a growing need for visualisation techniques to keep up with the growing volume of data collected. Data visualisation techniques are important in that they will help prevent information overload which could prevent operators to identify problems quickly. If enormous amounts of data are presented in traditional tabular reports, charts and spreadsheets it becomes extremely difficult to quickly find patterns, trends and irregularities. Such traditional methods applied to large datasets can even lead to operators coming to the wrong deduction. This exposes the importance of improved and advanced data visualisation techniques.

2.2 The Goal of Data Visualisation

After the September 11 attacks in the United States the Department of Homeland Security established the National Visualisation and Analytics Centre (NVAC) with the mission to inspire next generation technologies and talents to reduce the risk of terrorism by advancing the state of the visualisation and analytics science to enable analysts to detect the expected and discover the unexpected from massive and dynamic information streams. The panel defined visual analytics as the "*science of analytical reasoning supported by interactive visual interfaces*" and along with the visualisation research community defined some of the minimum deliverables for visual analytics tools [26]–[29] which are applicable to any data intensive field. In summary they recommended that visual analytics tools must:

- Facilitate understanding of massive and continually growing collections of data of multiple types;
- Enhance recognition of patterns;
- Provide frameworks for analysing spatial and temporal data;
- Reduce search time;
- Support the understanding of uncertain, incomplete, and often misleading information;
- Provide user and task adaptable guided representations that enable full situation awareness while supporting development of detailed actions;
- Support multiple levels of data and information abstraction, including integration of different types of information into a single representation;
- Facilitate understanding historical and current situations, as well as the trends and events leading to current conditions;
- Facilitate identification of possible alternative future scenarios and the signs that one or another of these scenarios is coming to pass;
- Monitoring current events to identify both expected and unexpected events;
- Support the decision maker in times of crisis;
- Provide a manipulatable medium; and
- Present and communicate the results of an analysis efficiently and effectively.

2.3 Hallmarks of a Good Visualisation Tool

Edward Tufte a pioneer in the field of data visualisation provides an excellent checklist for excellent graphics and data presentation. He argues the following minimum criteria for data visualisation in his book [30]. He says graphical displays that communicate complex ideas with clarity, precision and efficiency should:

- Show data;
- Induce the viewer to think about the substance rather than about the methodology, graphic design, the technology of graphic production;
- Avoid distorting what the data has to say;
- Make large data sets coherent;
- Encourage the eye to compare different pieces of data;
- Reveal the data at several levels of detail from a broad overview to the fine structure;
- Serve a reasonably clear purpose, description, tabulation or decoration; and
- Be closely integrated with the statistical and verbal descriptions of a data set [30].

The conceptual model developed and proposed in this research applies this checklist in the energy data presentation and visualisation.

2.4 The Evolution of Data Visualisation

As technology has evolved at a rapid rate and the Internet has become pervasive, enormous amounts of data have inevitably been produced. This data in its raw form is useless to many users and visualisation techniques to keep up with this data production must be developed. Although data visualisation techniques are not a new field of study and have been there for decades it is important that the techniques evolve with the evolving data and technology. Fortunately the study of data visualisation has not stood still and has itself undergone major developments in a number of fields. These developments include investigating ways of applying visualisation techniques and systems for more efficient manipulation, interpretation and presentation of data [31]. Although not specific to power management systems these developments can be applied to this field. The following sections detail the new developments in data visualisation techniques. These are an improvement to the traditional spread-sheets, static graphs and charts which cannot effectively cater for the enormous and dynamic data generated by the smart grid. An overview of many of these new developments is presented in [32] and the following section summarises the notable ones. Although many of these techniques are already being used in organisations for business intelligence they have not yet made their way into power management tools which still use traditional visualisation techniques. It has been noted in previous research that power operators do not prefer moving to new techniques due to their familiarity with traditional methods [33] e.g. the use of 2D one line diagrams which do not have a representation of time instead of new 3D techniques that have a time representation allowing for time variation display in contingency severity visualisation [34]. It was one of the goals of the research described in this dissertation to change the attitude of power operators by including them in the design and development of these new tools.

2.4.1 Visual Querying

Visual querying is the ability to return data that matches set criteria by manipulating visual portions of graphs or charts [32]. By clicking on certain controls of the graphical interface users can drill down to specific filtered details that one would normally get by writing a complex database script. This technique works by translating the user interactions into database queries which then retrieve the data from the backend without the user being aware of it. This means users can at the click of a button ask for a very complex data filter query without needing to know how to actually formulate one. With the improved connectivity speeds and computer processing power the extraction of data from local or remote databases is now almost instantaneous and the user experience when using tools which implement visual querying is seamless. This technique allows the systems users to be able to easily analyse complex datasets.

2.4.2 Dynamic Data Management

Dynamic data management takes advantage of the fact that live data is always being updated and changing. In visualisation the graphical controls will be linked to this live data and as data is updated the controls also update to reflect these changes. This allows operators to always be aware of the current state of the environment they are monitoring.

2.4.3 Animated Visualisation

Animated visualisation is the technique of helping a user work through the logic behind an idea by showing the intermediate steps and transitions, or show how data collected over time changes [35]. It is a more vivid display of data. Animation is basically data storytelling and can sometimes effectively and efficiently reveal data relationships that other techniques cannot reveal. Although very powerful, the use of animation can be confusing if misused. Animation should always be used within context and with a clear and concise purpose.

2.4.4 3D Data Modelling

This technique involves modelling and presenting data in a multidimensional format specifically 3D instead of the traditional 2D modelling. In particular, 3D data representation often provides a more enhanced and intuitive approach than a two dimensional approach [36]. 3D visualisation also has the potential to include information of more dimensions within a display without creating excessive display clutter and confusion [37].

Figure 4 below shows a comparison of data, 2D and 3D representation, showing exactly the same data. 3D data presentation allows the user to manipulate the data and see it from a variety of angles. According to studies by Hubona et al [38] this improves the users understanding of the data.

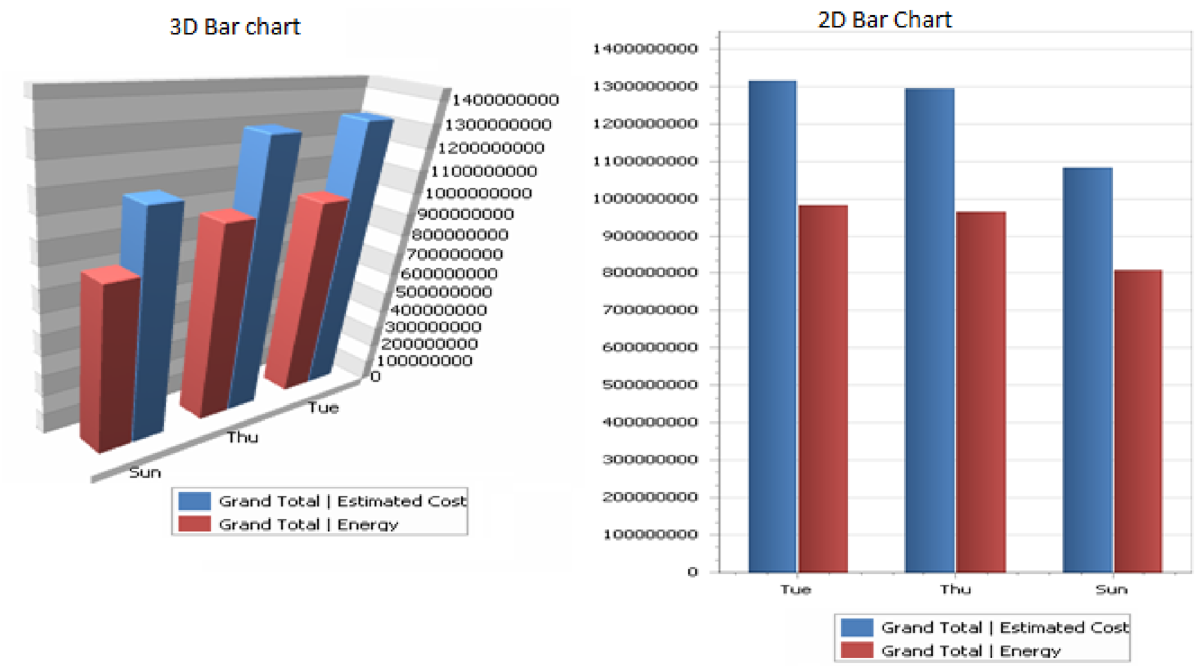

Figure 4: 2D vs. 3D data presentation

In the entertainment, meteorology and business world this technique has really taken off and is used by leading visualisation tools [39]–[42]. As recommended by Overbye et al [34], it is about time that the electricity generation, transmission, distribution and power consumer world adopted this technique.

2.4.5 Direct Manipulation of Interfaces (Haptic Interfaces)

Golbeck [43] defines direct manipulation as the ability for system users to physically interact with the operating system instead of typing commands and allowing the operating system to act as an intermediary. It allows the user to interact directly with file icons and widgets [43]. Although this technology has been there for a number of years [44] it has now taken a different direction with the introduction and improvements in touch screen technology. Direct manipulation has now evolved in such a way that it allows a user to use gestures, manipulations and interactions with the actual user interface elements. Users can do this via touch interactions drag, pinch, stretch, zoom, pan, rotate and scroll [45]. This ability can prove valuable in power control rooms if operators could have this kind of interactions as they work with multiple dashboards on multiple terminals.

Shneiderman [44] elegantly describes direct manipulation systems as "*offering the satisfying experience of operation on visible objects and making the computer transparent such that users can concentrate on their tasks"*. This description was written in 1983 but applies more so now due to the way we interact with computers today.

2.4.6 Intelligent User Interfaces (Personalisation Techniques)

As the amount of data available to a user increases it is important to be able to filter and classify information based on the person using it. The techniques used by intelligent user interfaces to personalise information are called personalisation techniques and they help users who would normally be overloaded with information to efficiently locate specific information. GUI personalisation can be broken down into categories such as content, context and role based personalisation [46].

The goal of personalisation according to [47] is for a system to adapt its services to each individual user's preference. It is to filter, classify and then present information to a user based on their preferences. If you think about it for a moment, it is like your very own desktop where you know exactly where everything is as well as everything being exactly where you personally want it to be. This means you can easily get the information you want quickly and effortlessly. Everyone has their own preference in terms of arrangement so it does not make sense anymore in this day and age to have a "one size fits all" attitude in interface design. Jiming et al [48] says the design and complexity of a software system's user interface largely determines the ease with which users can efficiently operate the system. Making user interfaces more intelligent and personalised is a step in the right direction in terms of visual tools becoming more user friendly. Interaction with a poorly organised GUI decreases the ease of navigating the system as well as reduces the usefulness of the system at the same time frustrating users [49].

2.4.7 Geographic Information Tools

Great strides have been taken in the field of geographic information system (GIS) technology. Technology and data that used to be reserved only for the military is now available in the public domain [50] and accessible across all fields for free or at a minimum cost. This means that smart grid management tools can take advantage of this technology together with the ubiquitous global positioning system technology (GPS) to improve on the geographic visualisation of the grid. For example if a specific meter or substation has a problem ,using that device's geo-coordinates one can now get unique visual effects on maps or satellite images to see exactly where that meter is located as well as the surrounding areas. This means if there is a problem, operators can easily and quickly at a glance see affected areas and the best strategies to apply in order to contain or solve the problem. This technology has been in the energy industry for a while now but not at the level of sophistication available now. This means that the utilities can now receive much more detailed and accurate geographic information about the power grid than previously available [51].

2.5 Information dashboards

Information dashboards are user interfaces that show a visual representation of the current as well as historical state of a system. Bose [52] described dashboards more eloquently as "*a software application that provides a single screen display of relevant and critical business metrics and analytics to enable faster and more effective decision making".*

Dashboards are used by their operators to make quick, but well-informed decisions. Using information from a variety of sources [53]–[56] as well as the authors own observations information dashboards help their operators to:

- Get information quickly and clearly;
- Get current status(snapshot);
- Get historical trends of key performance indicators;
- Generate detailed reports; and
- Query system for specific information.

Energy control centres rely heavily on dashboards and without them the grid system operators cannot function optimally and effectively. With the introduction of new visualisation techniques as discussed in section 2.4 above, it is a partial goal of this research to propose and implement a framework for a modern enhanced dashboard for both the energy consumer and supplier. Using the author's own observations, it can be summarised that information dashboards are used as the graphical user interface for energy management systems (EMSs) and helps operators to:

- Maintain sufficient primary frequency response resources;
- Assess current system state at a glance;
- View real time power consumption and production;
- Determine dispatch and commitment schedules;
- View consumer usage(this is useful to both supplier and consumer);
- Act as an interface used by control room operators for remote monitoring and controlling of the grid;
- Maintain grid security and integrity by quickly detecting and mitigating threats against it [57]; and
- Maintain sufficient online and offline generation reserves [58].

From a customer point of view a dashboard or home energy management system would help the customer to:

- View current and historical energy usage [59];
- Access to real time billing information [60];
- View devices using the most energy in the home;

- View utility billing information especially for areas with dynamic pricing [60]; and
- Compare and query their own readings with those provided by the local utility.

Information dashboards are not easy to design properly and a lot of times software designers get it wrong. The need to compress and squeeze a large amount of information into a small finite amount of space resulting in a display of information that is easily and immediately understandable is no menial task. Stephen [53] put it excellently when he argued that although dashboards are potentially powerful, this potential is rarely realised and preoccupation with superficial and functionally distracting visual characteristics of dashboards has led to a rash of visual design problems that undermine their usefulness. He presented the following thirteen common mistakes in dashboard design [53]:

- Exceeding the boundaries of a single screen;
- Supplying inadequate context for the data;
- Displaying excessive detail or precision;
- Choosing a deficient measure;
- Choosing inappropriate display media;
- Introducing meaningless variety;
- Using poorly designed display media;
- Encoding quantitative data inaccurately;
- Arranging the data poorly;
- Highlighting important data ineffectively or not at all;
- Cluttering the display with useless decoration;
- Misusing or overusing color; and
- Designing an unattractive visual display.

The arguments brought forward by Stephen [53] on the above points are excellent and have a solid scientific basis. The proposed framework in this research adheres to this advice in a bid to propose and implement a world-class dashboard. It also adheres to Jakob Nielsen's 10 heuristics points for user interface design [61] which he explained as follows:

- **Visibility of system status:** The system should always keep users informed about what is going on, through appropriate feedback within reasonable time;
- **Match between system and the real world:** The system should speak the users' language, with words, phrases and concepts familiar to the user, rather than system-oriented terms. Follow real-world conventions, making information appear in a natural and logical order;
- **User control and freedom:** Users often choose system functions by mistake and will need a clearly marked "emergency exit" to leave the unwanted state without having to go through an extended dialogue. Support undo and redo;
- **Consistency and standards:** Users should not have to wonder whether different words, situations, or actions mean the same thing. Follow platform conventions;
- **Error prevention:** Even better than good error messages is a careful design which prevents a problem from occurring in the first place. Either eliminate error-prone conditions or check for them and present users with a confirmation option before they commit to the action;
- **Recognition rather than recall:** Minimise the user's memory load by making objects, actions, and options visible. The user should not have to remember information from one part of the dialogue to another. Instructions for use of the system should be visible or easily retrievable whenever appropriate;
- **Flexibility and efficiency of use** Accelerators, unseen by the novice user, may often speed up the interaction for the expert user such that the system can cater to both inexperienced and experienced users. Allow users to tailor frequent actions;
- **Aesthetic and minimalist design**: Dialogues should not contain information which is irrelevant or rarely needed. Every extra unit of information in a dialogue competes with the relevant units of information and diminishes their relative visibility;
- **Help users recognise, diagnose, and recover from errors:** Error messages should be expressed in plain language (no codes), precisely indicate the problem, and constructively suggest a solution; and
- **Help and documentation**: Even though it is better if the system can be used without documentation, it may be necessary to provide help and documentation. Any such information should be easy to search, focused on the user's task, list concrete steps to be carried out, and not be too large.

In following the above standards proposed by Stephen [53] and Nielsen [61], it is possible to come up with a well-founded dashboard design benchmarking model.

2.6 Types of Dashboards

Many types of dashboards exist and there are many schools of thought on the exact definition of a dashboard. It is thus important for one to know exactly the type of dashboard that one wants to implement. The team at Juice Analytics [55] gave the following overview of the different types of dashboards as summarised in Table 1 below.

Table 1: Dashboard Properties

Dashboard Properties	Option	Description
Scope	Broad	Displaying information about the entire organization
Scope	Specific	Focusing on a specific function, process, product, etc.
Business role	Strategic	Provides a high-level, broad, and long-term view of performance
Business role	Operational	Provides a focused, near-term, and tactical view of performance
Time Horizon	Historical	Looking backwards to track trends
Time Horizon	Real time	Monitoring activity as it happens
Time Horizon	Snapshot	Showing performance at a single point in time
Time Horizon	Predictive	Using past performance to predict future performance
Customisation	Customisable	Functionality to let users create a view that reflects their needs
Customisation	One Size fits all	Presented as a single view for all users
Point of view	Prescriptive	The dashboard explicitly tells the user what the data means and what to do about it
Point of view	Exploratory	User has latitude to interpret the results as they see fit
Level of detail	High	Presenting only the most critical top-level numbers
Level of detail	Drillable	Providing the ability to drill down to detailed numbers to gain more context

Using this checklist it can be seen that a control room dashboard would fall under all the options of the time horizon section as well as all of the options in Level of detail and Point of view sections of the above diagram. The other options are higher level and geared towards management and not control room operators.

2.7 Load Forecasting Algorithms

For commercial and large scale consumers of energy such as the University of Witwatersrand it is important to be able to control their peak loads (Peak shaving). This is because utilities will charge penalties for certain peaks and as is the case with City Power Johannesburg, when charging the University of the Witwatersrand; they average the bill on the highest cycle peak reached in that day. In these scenarios it becomes paramount that these kinds of consumers be able to control their usage especially their peaks to avoid large bills or being charged penalties [62]. In order for these large energy consumers to shave or control their peak loads one of the things they can do is to implement short term load forecasting (STLF). Load forecasting is the estimation of future load demand. Load forecasting is not an easy task as the nature of a load profile is complex and depends directly or indirectly on a variety of mostly uncontrollable and uncertain factors such as the season (weather elements like temperature, humidity, wind speed etc.), day of the week, hour of the day, weekend or no weekend, holiday or no holiday and historical load profiles. To carry out this complex task forecasters use a number of algorithms implemented using various techniques notably classical statistics and Artificial Intelligence (AI) based techniques [63]–[65]. In this section we take a brief review at these two load forecasting techniques.

2.7.1 Statistical Methods

Traditional statistical methods have been used in load forecasting for a very long time dating back to the early sixties [66]. The common methods are based on regression and time series approaches. These approaches are based on relating load profiles to the other variables (temperature, time of day, previous load) through a mathematical model. The sections below detail the common statistical methods.

2.7.2 Time Series Approach

A time series is a collection of data recorded over a period of time using a determined interval e.g. hourly, daily, monthly etc. This keeps a record of historical data and based on the notion and assumption that history normally repeats itself (in some seasonal pattern) this data is used for forecasting. The time series approach is based on the idea that reliable predictions can be achieved by modelling patterns in a time series plot and then extrapolating these patterns to the future [67].

Hagan and Behr [66] showed in their study that the time series approach in particular using Box and Jenkins models is suited for load forecasting. In their study, data from the Southwestern power utility Oklahoma was used. Hourly system load profiles and temperature readings for 2 years were used to develop the models for each season of the year. They showed that because the Box and Jenkins transfer function model is a linear model it does not accurately reflect the load/temperature relationship which is a big disadvantage of this approach and introduces errors. In order to counteract this they applied a nonlinear transformation to the temperature data before using it in the transfer function model and this greatly improved the results. The average error for the summer forecasts using their non-linearizing of temperature was 3.55% compared to 4.17% when using only the Box and Jenkins models.

2.7.2.1 Multiple Linear Regression

Multiple linear regression (MLR) is one of the oldest and widely used statistical technique in electrical load forecasting [68]. MLR is a statistical method used to model the linear relationship between a dependent variable and one or more independent variables. The goal of MLR is to identify a function or mathematical model that best approximates the relationships of these variables so that the value of the dependent variables can be predicted using a range of these independent at variables. Amral et al [69] designed, implemented and analysed an hourly STLF system on the Sulewesi Island – Indonesia Power System, using MLR with good results. In modelling the system they divided the year into 2 seasons, rainy season and dry season. They also divided a 24 hour day based on known user behaviour into 3 intervals (01:00 to 06:00, 07:00 to 17:00 and 18:00 to 00:00). These 3 intervals were then modelled separately. In all the mathematical models the relationship between load, temperature and time of observation was not modelled linearly but in a polynomial form since it is not a linear relationship. The general form of the equations is:

$$Load(t)_i = \alpha_0 + \alpha_1 \left(Temp_i(t) - \left(Temp_i(t-1)\right)\right)$$

$$+\alpha_2 \left(Temp_i(t-1) - \left(Temp_i(t-2)\right)\right) + \alpha_3 t + \alpha_4 t^2 \qquad (1)$$

Where:

$Load(t)_i$= Predicted load at hour t in the interval i of the day

α = Regression parameters

$Temp_i(t)$=Temperature (^{0}C) at time t in the interval i

t= Time of observation

Their study yielded a mean average percentage error (MAPE) of 3.52% in the dry season and 4.34% in the rainy season. The error values were attributed to things like load shedding and inaccuracies in the forecast temperature data used. They also concluded that for this particular area where the dominant portion of the load is residential lighting, daylight (brightness) of the day should be considered hence they split the day into intervals.

2.7.3 Artificial Intelligence (AI)

Artificial intelligence in load forecasting is a broad category that includes systems using AI approaches such as expert systems [64], fuzzy logic [70], neural networks [71], support vector machines [72], genetic algorithms (GAs) [73] and wavelet networks [74]. This subsection deals with the 2 most popular approaches which are neural networks and fuzzy logic based systems.

2.7.3.1 Artificial Neural Networks

Artificial neural networks (ANN) are inspired by animal biological nervous systems. Animals can adapt to changes and various stimuli in their external and internal environments, they can learn from their environment and use very low energy in the process [75] hence the basic idea behind ANNs is to try and simulate the animals' nervous system and achieve similar responses in artificial systems. At the heart of the biological nervous system is a basic unit called the neuron and the nervous system is made up of a complex network of billions of these units. Similarly artificial neural networks can involve multiple interconnected elements to make up a massive computing network. Dr Robert Hecht-Nielsen the inventor of one of the first neuro-computer defined a neural network as *"...a computing system made up of a number of simple, highly interconnected processing elements, which process information by* *their dynamic state response to external inputs*” [76]. Jain et al in their 1996 tutorial on ANNs published in the IEE computer society magazine give a very informative comparison summary of the traditional computer compared to the biological neural system inspired ANN system. This summary is as shown in Table 2 below.

Table 2: Von Neumann Computer versus biological neural system [75]

	Von Neumann Computer	**Biological Neural System**
Processor	Complex high speed(single or multiple)	Simple Low speed(large number)
Memory	Separate from the processor, Localised, Non content addressable	Integrated into Processor. Distributed content addressable
Computing	Centralised sequential stored programs	Distributed parallel ,Self-learning
Reliability	Very vulnerable	Robust
Expertise	Numerical and symbolic manipulations	Perceptual problems
Operating Environment	Well defined, well constrained	Poorly defined ,unconstrained

Unlike the conventional serial computing neural networks respond in parallel to the pattern of inputs presented to it and can capture and model various kinds of relationships which may be difficult or impossible to model in any other way. In ANN techniques the neural network is trained to learn the relationship between various input variables and historical data patterns. In the case of ANN techniques in load forecasting the inputs could be weather patterns and historical load data. Unlike statistical methods the artificial intelligence neural network based techniques do not require a mathematical model for them to be implemented. A number of variables however do need to be considered when using ANNs and these are: the neural network structure, input variables(e.g. previous load, temperature, wind speed), forecast load(hourly, daily etc.), size of training data, activation functions and size of test data [67].

There have been numerous studies done in this area from as early as 1990 where Park et al [77] presented an ANN approach to electric load forecasting using the generalised delta rule (GDR) [78] to train a layered perceptron type ANN. This was applied to data for the

Seattle/Tacoma area in the interval between 1st of November 1989 and 30th January 1989. The ANN was trained to recognise Peak daily, hourly as well as total daily load and this was used to give hourly and 24 hour forecasts. The result was an average absolute error of 1.40% and 2.06% for the hourly and 24 hour forecasts respectively. Since then further studies and improvements using ANN techniques have been done around the world in countries like South Africa [79] using data from ESKOM, China [80] using data from the Hang Zhou Electric Power company, Canada [81] using the Hydro-Quebec power utility load data, Egypt [82] using data from the Egyptian electrical utility ,Iran using data from the Electricity market of Iran [83] and Indonesia [71] using South Sulawesi regional data from the Indonesian state electricity company.

2.7.4 Artificial Intelligence Techniques: Fuzzy Neural Networks

Fuzzy neural networks are a hybrid of ANNs and Fuzzy logic. Fuzzy logic is a problem solving approach which attempts to move away from the two valued, Boolean way of problem reasoning where there is only true or false, fixed and exact. It introduces a new concept of fuzzy sets and variables that exist in ranges and not exacts [84]. In the same way that ANNs try to simulate the animal neural system, fuzzy logic attempts to mimic how a person would make a decision based upon vague, ambiguous, imprecise, noisy or missing input information. The only difference is fuzzy systems reach their decision much faster [85]. This means fuzzy systems can yield an approximate solution to a problem using vaguely given inputs. This is an advantage over the ANNs discussed above which need a lot of training and learning from historic data. A disadvantage of fuzzy systems however is that tuning the fuzzy system is done heuristically since there is no formal approach to it. This tends to be time consuming and prone to error [86]. The solution to get the best out of fuzzy systems is to combine the best of both worlds by combing fuzzy systems with ANNs to form fuzzy neural networks (FNNs).

Dr Rudolf Kruse in [86] defines a fuzzy neural network as "*.. a learning machine that finds the parameters of a fuzzy system (i.e. fuzzy sets, fuzzy rules) by approximation techniques from neural networks*". By combining fuzzy logic and ANNs all apparent weaknesses of these two concepts are removed and a robust hybrid concept is formed. This has led to FNNs becoming a very attractive option in load forecasting systems and numerous studies have been carried out on FNNs [70], [87]–[92]. Bakirtizis et al [93] designed and implemented a

FNN based STLF system which was tested on actual data from the Greek interconnected power system supplied by the Public Power Cooperation (PPC). 168 FNNs were used one for each day type and hour of the day. This meant they could forecast load profiles for any day of the week and the results showed that forecasting could be achieved at a great accuracy. The average error ranged from between 2.43%-3.22%. The study compared the results against those achieved on the same data but using an ANNs. Although the average percentage error was comparable it was shown that the FNN training was much faster than that of ANNs.

2.8 The State of Smart Grid Data Visualisations Technologies

Although the development of advanced data visualisation tools for the smart grid is still in its infancy and control rooms across the world still use traditional visualisation methods such as text based displays, trend plots, graphs, charts and one line diagrams, numerous research has been done and a host of ideas proposed although few have been implemented [94][95][96][34]. At the moment very few companies have managed to develop smart grid data visualisation tools. The leading companies in this field are Powerworld® [97] and Areva® [98] who both have got smart grid visualisation software on the market. Since this technology is still new it unfortunately comes at an inhibiting price .For instance the Powerworld single site license starts at approximately R 2,200,500 [99]. These are large figures especially in an African context where the cost of just upgrading the existing infrastructure is already a stumbling block with organisations and governments struggling to maintain and upgrade the existing equipment. It is thus necessary for more tools to be developed that can be accessed at a much lower cost. This in itself is good enough motivation for more research in this field.

2.9 The Business Case for Smart Grid Data Visualisation

The evolution of the smart grid and data management software means that there are a number of possibilities in the field of energy management and analytics. This will be of major financial benefit to all parties involved i.e. generation, transmission and distribution utilities, consumers as well as the companies developing the hardware and software tools for the grid. For most countries the introduction and implementation of the smart grid will encourage economic growth and generate increased revenue due to improved, optimised and advanced generation, transmission and distribution of power.

From an operational point of view if the utilities utilise sophisticated analytics and alarm systems that will be offered by smart grid visualisation software it will allow them to deliver more reliable service, rapid remote (dis)connection, and better outage detection and recovery to its entire customer base at a lower overall cost [100]. This would be particularly helpful in the African context where the transmission and distribution networks are weak and overstressed and urgent investment is needed in upgrades and maintenance [101]. As an example, the South African government estimates that just keeping up with growing demand from industries and the population will require doubling its generating capacity by 2025 at a cost of USD 171 billion. Of that amount, USD 45 billion was needed in 2013 [102]. If the South African utilities can upgrade to a smart grid and use the analytics tools being developed this would go a long way in lowering their costs. Zambia is another African example where over USD 2 billion is needed to expand generation to meet the current demand because at the moment load shedding is a common occurrence due to supply not meeting demand.

By using new sophisticated smart grid data visualisation tools, utilities will be able to quickly identify stressed equipment so that relief can be provided or equipment replaced before a breakdown can cause a costly outage [57]. They will also be able to efficiently identify the location of system assets, human resources, portable equipment and physical landmarks such as roads, bridges, city streets thus enabling them to significantly improve worker and public safety and to create a safer environment for completing restoration work [57].

An important goodwill benefit for the utilities is that the availability of accurate usage data will improve customer relations and satisfaction. This is something that has been a real source of frustration for the majority of utility customers.

Other benefits to utilities will include a detailed report on usage, outages and faults based on real time data. This gives a great degree of operational improvement especially in terms of accurate billing and early warning systems. Availability of data using GIS visualisation components means utilities will also be able to make more informed decisions when planning where to locate new grid resources.

The environment is also a major beneficiary in this grid evolution as utilities will be able to improve their understanding of the environmental impact of grid resources and thus balance that impact with economics in the dispatch of centralised generation, potentially lowering carbon emissions.

Faruqui et al [100] described four dominant customer segments when it comes to energy consumption as:

- **Basic:** For consumers who do not wish to engage at all;
- **Comfort:** For those with large load homes with air conditioning, pool pumps, smart appliances, minimal interest in energy engagement, and limited concern about their bills;
- **Saver:** For those primarily motivated by the opportunity to save money on their bills or mitigate potential bill increases; and
- **Green:** For those motivated by environmental concerns and willing to be more engaged.

Regardless of the type of customer, grid analytics tools and meters allow for in-home display of real time usage and pricing statistics. This means at any time users are aware of the amount of energy they are consuming as well as the time period (peak or off-peak) that they are operating in. For countries like South Africa this would be a welcome development as utilities will be able to move from a flat (fixed designation between peak and off peak period) pricing strategy to a more dynamic utility rate pricing where the price of power is made high during high demand periods e.g. on a very hot summer day when air conditioner and swimming pool usage raises energy demand the price could be pegged at a higher rate than on a cooler day. Dynamic rating schemes would incentivise consumers to respond to utility energy warnings and price signals. Customers could also use new capabilities offered by smart grids such as setting up an alert to be warned if their bill has reached or is approaching a certain threshold. This kind of awareness leads to a change in consumer behaviour and the consumers will start to consciously manage their consumption. It is estimated by the Mckinsey consulting group that in the United States alone successful deployment of smart grid technologies could yield savings to society of USD 130 billion annually by the end of this decade [103].

Customers will also be able to know exactly which devices in their buildings are not efficient and need upgrading to energy efficient equipment. This energy usage awareness of consumers does not only benefit the consumers in terms of lowering their bills but at the end of the day the utilities greatly benefit as well since daily peaks would be greatly reduced meaning reduced generation costs for the supplier. An estimated USD 16 billion will be saved by American utilities due to improved customer behaviour [103].

Development of Smart grid data visualisation and analytics will mean that a large amount of data is collected and available to consumers. This means consumers become more engaged in determining alternate lower cost solutions for power production [104] and not be passive about it. This will have an effect of spurring new technology and process development. Software firms, telecommunications companies, semiconductor producers, IT and grid hardware providers also get to benefit from the smart grid evolution with an estimated USD 30billion worth of annual opportunities in customer applications development comprising of things like pricing, in-home displays, smart appliances and information portals all aimed at encouraging customers to smooth (avoid peaks) and reduce consumption [105]. There is also the possibility of more business opportunities for these companies as they will develop monitoring, controlling and automation tools for the different generation, transmission and distribution utilities [105].

Other collective benefits of using advanced grid data visualisation and analytics tools are as follows:

- Put pressure on manufacturers to design and manufacture energy smart and efficient products;
- Reduction in electricity theft (A major problem for Eskom at the moment). This cost is carried by both customers and suppliers;
- No more estimated bills as all bills can now be itemised and time stamped;
- Removal of inactive and “Ghost” meters; and
- Reduction in the number of unexpected outages.

2.9.1 The Other Side of the Business Case for the Smart Grid

Although the business case for smart grids argued above looks rosy, a sober mind must still be maintained and both sides of the coin looked at. The smart grid uses an entirely new technology and the costs involved in migrating to this new technology and equipment will prove and are proving to be a major limiting issue for a lot of governments. Large upfront costs relative to the initial benefits have to be pumped into the evolution of the grid and since this technology is naissance there has been no precedence and a lot of investors will be wary of investing the required sums of money with no guarantees of returns. Not only are there not guarantees but regulations make it difficult for utilities to raise rates and recover costs [106] which might dissuade some utilities and investors from upgrading their traditional grids and pumping in money respectively. A good example is the case with Eskom which has been battling to get a five year annual increase approved. After 2 years of battling with the National Energy Regulator of South Africa (NERSA) they were finally awarded an 8% average increase per annum over the next five years starting from 2013. The initial request for Eskom was a 16% annual increase and they still did not get it approved. They are also still battling to get a 20% annual increase for intensive energy users [107]. This example shows how difficult it is for utilities to raise rates and recover costs whether their reasons are justifiable or not.

A lack of standards (communication and interface standards for the new technology) [108] is another argument given against investing in smart grids. People in this school of thought argue that the lack of collaboration amongst manufacturers is a major barrier to the advancement of smart grids. Companies like IBM® however have taken a major step in the right direction by forming GridWise alliance [109] and the Global intelligent utility network coalition which has a number of utility companies who as a collective group service over 115 million customers globally [110]. Their goal is to work towards implementing the smart grid as well as driving standards and emerging technologies [110].

Another major concern for utilities and investors of the smart grid is that there is a big belief which is completely justifiable that more research still needs to be done in terms of security issues to guard against cyber-crimes. Putting the entire grid online creates a major vulnerability to cyber-crimes.

2.10 Key Smart Grid Visualisation Areas

The challenges facing utilities in smart grid data visualisation can be broken down into the following key areas:

- Wide area visualisation;
- Integrating new measurements provided by the new equipment e.g. phasor measurement;
- Visualisation of time varying information;
- Enhanced alarming and fault management;
- Visualizing and managing non-permanent loads i.e. Hybrid/electric vehicle;
- Visualizing Transparent consumption & pricing for the consumer e.g. time stamped itemised billing;
- System logging and auditing for troubleshooting and security purposes;
- Asset management;
- Online customer account management;
- Dynamic pricing;
- Monitor/surveillance of networks to manage failure, topology, performance etc.; and
- Provide customers with visualisation of aggregated consumer-specific usage data, i.e. instantaneous usage, interval usage, volts, amps, VAR, power factor etc.

The research looks at some of these key areas and a benchmarking model and prototype developed.

2.11 The State of the Smart Grid in South Africa

This research is primarily concerned with the state of smart grid data visualisation in the South African context. It is thus necessary to know where South Africa stands in terms of the available tools and infrastructure to support a smart grid.

ESKOM is South Africa's only major electricity utility. ESKOM with the help of local municipalities is in charge of generation, transmission and distribution of electricity in South Africa. The ESKOM power grid is a traditional grid and has an Energy Management System (EMS) and a Distribution Management System (DMS) which provide control and supervisory functions to the network via legacy Supervisory Control and Data Acquisition (SCADA) systems at an operation level. The electrical network is just a one way end to end connection from generation to the consumer without any intelligent data management system. The network only has one interface with the customer i.e. metering, whose sole purpose is to collect consumption data for billing [111]. The majority of the ESKOM grid is over 50 years old and is outdated, ageing, stressed, prone to breakdowns and is in need of a major upgrade. As if this is not enough from about 2007 the country's reserve margin fell to 5.6% [112] due to economic growth and a greater demand for power. This has seen to warnings of an impending rolling load shedding being given by ESKOM on national TV and radio. ESKOM needs a reserve margin of about 15% to be able to cope with unexpected problems. This has led to construction and proposals of new power generation plants like the Medupi [113] power station which is currently under construction in Limpopo province which will supply a much needed 4788MW to the national grid.

This brief state of the South African grid serves to show that in a South African context the energy utilities have much bigger problems than trying to transition an existing grid to a smart grid. It is going to be costly for South Africa to address the grid infrastructure problems at the same time modernising it for the smart grid. This has led to very slow progress in the smart grid technology arena in South Africa. The encouraging news is that ESKOM and the South African government has not entirely forsaken the smart grid movement. In March 2012 [114] Eskom started to deploy a hybrid smart grid model that supports its old system whilst gradually introducing smart grid ready systems. They also started an AMI programme by rolling out over 10 000 smart meters in the Sandton area in Johannesburg [115] targeting high concentration areas and customers consuming 500kWh and above per month. In May 2012 the South African Smart Grid Initiative (SASGI) [116] was launched as an extension of the South African National energy Development Institute (SANEDI). SASGIs' mandate is to provide direction and support to the South African industry in respect of smart grids and they have already made great strides in this respect. SASGI has a number of work groups whose roles and functions are to [116]:

- Pro-actively identify opportunities/areas to facilitate/enhance the implementation and roll out of smart grids in South Africa;
- Identify appropriate smart grid best practices and solutions for the South African market;
- Address specific challenges pertaining to the roll out of smart grids as identified by the industry through SASGI;
- Facilitate smart grids standardisation within the industry;
- Optimise smart grid investments in South Africa; and
- Pro-actively contribute to the policy and regulatory framework from a smart grid perspective.

SASGI was only launched in May 2012; this only shows how young the smart grid movement in South Africa is. This means there are not yet a lot of tools to be used with this technology. This serves to motivate why this research into a smart grid data visualisation framework and prototype tool was carried out and its importance to South Africa. Consumers and utilities need advanced visualisation tools for their advanced metering infrastructure. Without these tools the data might be available but not useful to the parties involved.

2.12 Technology Acceptance

Constantine [117] described what software users want from the tools developed. He said users want systems that are easy to learn and easy to use and that help them to do their work. They want software that does not slow them down and that does not trick or confuse them, does not make it easier to make mistakes or harder to finish the job. When designing or proposing a new software application or framework such as the one presented in this research it is important to keep the users of the system involved at all stages of the design and development. This means the software designer will be able to get a first-hand experience of end user to system interaction and will know exactly what the user wants as described by Constantine [117]. The designer will also be able to visualise user experience as well as get the user empathy. This line of thought falls under agile software development and is discussed in more detail by Wang et al [118].

The downside of not involving system end users in the design process is that they might develop a negative attitude towards the new system. This stems from users not getting a full picture of what the new system has to offer and hence perceive the system as not useful. Fred Davis [119] defined perceived usefulness (PU) as the degree to which a person believes that using a particular system would enhance his or her job performance. He also defined Perceived ease-of-use (PEOU) as the degree to which a person believes that using a particular system would be free from effort.

In order for end users to deem the new system as useful as well as giving them the confidence that the system is easy to use, keeping them in the loop throughout the development cycle would go a long way to achieving this.

A lot of factors affect how users react to new systems or applications. It could be the person's level of experience (or lack thereof), level of education, age or gender. A good example is how very experienced people who hypothetically have over 20 years' of experience using a particular system. These types of people are very difficult to convince to move to something new since the old system is their comfort zone and sometimes they might be intimidated by the new technology or they can see it as a way of the company trying to replace them with younger people. Venkatesh et al [120] created a model based on this theory and they present it as shown below.

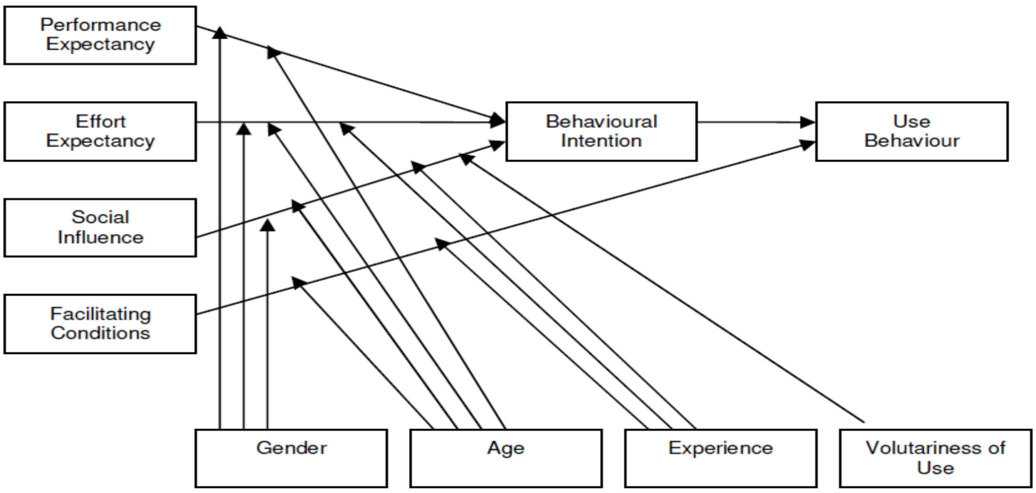

Figure 5: User Acceptance Unified View [74]

If the proposed prototype fails user acceptance tests then this research would be deemed a failure. With this in mind care was taken in this research to involve the team at the PIMD during the design and implementation of this framework and prototype since they are potential end users and they also helped set up the smart meter network at Wits University. Continuous interaction was maintained throughout the design and implementation and Davis [119] model of using questionnaires was also used to get more feedback from the users.

2.13 Similar Research

Smart grid infrastructure roll outs have been going on in the developed parts of the world since about the year 2009 [121] [122]. Although the hardware has been quick to be rolled out the software tools needed to get the most out of the grid are lagging behind. In terms of visual analytics tools, research has been carried out in a number of countries including Malaysia [95], Sweden [123] and the USA [94]. This research has come to the same conclusion as the research presented in this dissertation; that there is a lack of grid data visualisation tools that use novel and advanced visualisation techniques such as animation of power system flow values, interactive 3D visualisation and leveraging of smart grid visualisation tools on the ubiquitous GIS technology. Another study funded by the Victorian (Australian) government also concluded that the user interface technology is the least mature of the smart grid system and that there is no market leading interface that naturally presents itself to fulfill this functionality [124]. It is thus the goal of this research to implement these techniques and propose a benchmarking model that will improve the development of current and future smart grid data visualisation tools.

CHAPTER 3: Research Question and Methodology

3. Introduction

The literature review exposed that advanced user interfaces are lacking in the evolution of the smart grid. The smart grid data visualisation tools have failed to keep pace with the roll out of smart grid hardware. A key problem has been found to be a lack of investment and research in the area of smart grid data visualisation. Extensive studies and development in this area needs to be carried out. Tools will also need to be designed and implemented.

Although some research has been done in a few first world countries, nothing has been done in Africa and it is important for African power and software engineers to put themselves on the global map by designing, developing and implementing smart grid data visualisation tools for the Africa market and possibly the world.

Graphical interfaces are required by control room operators as well as any other power consumer in order for them to benefit from the information that can be provided by analysing smart grid data. The research presented in this dissertation will focus in providing such interfaces from the point of view of the end user (Demand side energy management system).

With all the above in mind core questions arise that this dissertation aims to address. These are:

1. What are the requirements for developing and deploying a customer side smart grid energy usage monitoring and reporting dashboard at the University of the Witwatersrand?
2. Is a smart grid energy dashboard a usable and acceptable tool for real time monitoring of energy usage at the University of the Witwatersrand?
3. Can smart grid data be used to give accurate half hourly load forecasts?
4. Is a dashboard an effective way of visualizing smart grid data based on smart grid data collected from the University of the Witwatersrand smart grid network?
5. What are the user benefits of having a smart grid data monitoring dashboard at the University of Witwatersrand?

3.1 Expected Outcomes

The main objective of this research is to provide a Consumer/Demand side smart grid data visualisation model and to evaluate and implement modern advanced data visualisation techniques to be used in smart grid data visualisation analytics. The simplicity, complication, strengths and weaknesses of these techniques are evaluated based on the developed model which is based on industry accepted standards. Table 3 below gives a summary of the expected outcomes.

Table 3: Research Expected Outcomes

Outcome	**Detail**
Develop and propose a model for a demand side energy management interface.	The model should cover all the requirements for a customer side graphical interface. It should adhere to data visualisation industry standards and provide a model of how this can be used to standardise demand side Graphical user interfaces (GUIs).
Develop and propose a peak load forecasting model	A prototype which implements some form of load forecasting using smart grid data must be developed and tested.
Provide Dashboard prototype	An implementation of the proposed model using the evaluated visualisation techniques in the form of a functional Energy management Dashboard to be used by the Wits university PIMD.
Technology Acceptance	Carry out technology acceptance based on section 2.9. Give a feedback report on user reaction.

3.2 Methodology

The research methodology adopted in this dissertation in order to answer the research questions involves the steps described below:

- Literature Review of :
    - The current state of the smart grid especially in a South African context;
    - Modern and advanced data visualisation techniques and their adaptation in the power industry; and
    - Demand and supply side visualisation interface requirements.
- Propose a model for a demand side energy management user interface based on identified hallmarks of an excellent data visualisation interface as well as demand side interface requirements;
- Design, build and test a consumer side energy management Dashboard/tool based on the proposed model;
- Carry out technology acceptance based on users of the developed tool; and
- Evaluate the developed dashboard based on the testing and user acceptance and give recommendations and conclusions on the overall research.

The first stage of the methodology is the literature review found in chapter 2 of this dissertation and it looks at the background of the smart grid evolution. Questions on what motivated the transition from the traditional grid to this advanced smart network are discussed and answered. The benefits and challenges facing this technology are discussed and evaluated. The current state of the technology is also evaluated and the gaps that need to be filled are noted and the solution to some of these gaps forms part of this research. Advanced Data visualisation techniques that are being used in other scientific fields are evaluated with the intention of adapting these into the smart grid industry so as to take advantage of the power they bring to visualisation in an industry that has been left behind by these new developments.

The second stage of the research methodology is the proposal of a benchmarking model for a demand side energy management user interface. The goal here is to develop a model by which any demand side visualisation tool that is developed can be measured against. This is basically a standard for demand side management interfaces. This model is based on the vision for the smart grid more specifically on the demand side data management vision of the smart grid discussed in Chapter 2 as well as tried and tested data visualisation industry standards and heuristics from the power industry and other scientific fields. The model development makes up Chapter 4 of this dissertation. Ability to forecast peak loads is an important part of the proposed prototype hence chapter 5 is dedicated to the design of a MLR forecasting model.

The third stage of the research methodology is to design, build and test a consumer side energy management dashboard based on the model proposed in the second stage. The motivation behind choosing a consumer side energy management dashboard instead of a supply side one is that the smart grid infrastructure from which the data is being collected at the University of the Witwatersrand (Wits) is a good example of a demand side (Advanced metering infrastructure) AMI set up which does not have the necessary visualisation tool to meaningfully use this data hence such a tool is prototyped in this research. The prototype is tested and evaluated based on the benchmarking model developed in chapter 4 as well as user acceptance tests. Chapter 6 of this research presents the specification, design, development and testing of the dashboard prototype.

The fourth stage of the methodology involves a technology acceptance approach to the design and development of the prototype as described in Section 2.12 of this dissertation. A variety of users were approached to test the application. Staff at the Wits PIMD and Energy Management Group was also involved at all stages of the dashboard development.

The fifth and final stage of the research methodology is the prototype evaluation. This is done by carrying out user acceptance testing using questionnaires and observations. A thorough analysis of the forecasting model is also carried out and results given. The prototype is also evaluated against the proposed model and recommendations and conclusions given. This evaluation is presented in Chapter 7 of this dissertation.

CHAPTER 4: Theoretical Demand Side Dashboard Benchmarking Model

4. Introduction

When new technology is introduced it is important that frameworks and standards are set as different parties will always come up with different approaches to standard or common features. Smart grid data visualisation is a new field and at the time of this research a standard or benchmarking model by which the demand side energy data visualisation tools can be measured or compared against did not exist [124]. Every vendor provides their own unique systems, configuration and control strategies and this has an effect of confusing the customers in their choices, acceptance and level of involvement [125]. Energy dashboard designers and developers need to make informed design, implementation and functional decisions from both the perspective of the utility providing energy as well as the customer consuming the energy. In order to do this there needs to be an agreed framework, standard or model from which to base these critical application development decisions and help the designers to conform to requirements and specifications. Standards help design engineers to not only have usable software but to also have consistency across products from different companies. They also save time by not reinventing the wheel.

It is the goal of this chapter to present a first step towards a novel benchmarking model for future design and implementation of demand side smart data visualisation and management dashboards. This is in a bid to simplify the design and development of smart grid data visualisation dashboards and make the developed tools user friendly, meet certain minimum user requirements and adhere to the vision of the smart grid. Software developers can more easily create the basis of their dashboard specifications and requirements by instantiating this model. Customers of energy utilities will also benefit from this model as it is aimed at not confusing customers when it comes to common features hence improving customer satisfaction. This model proposal also hopes to initiate more interest and research into demand side dashboard design and implementation.

The proposed model is based on characteristics of a good dashboard design, hallmarks of good visual presentation, the smart grid vision from a demand side perspective and what energy consumers want.

4.1 Definition of Demand side dashboard

This research proposes a definition for a demand side energy visualisation dashboard as a customisable multi-function user interface showing a visual representation of real-time user energy consumption data as well as a reporting interface to see current and historical billing and pricing information. It is also a portal via which the energy utility can send and receive messages to and from the user. Depending on available technology it can also be a portal via which the user can remotely manage their devices.

4.1.1 Demand Side Dashboard Objectives

The main objective of the Demand Side Dashboard (DSD) is to allow consumers to view their whole energy usage thereby targeting energy savings and maximizing energy efficiency in the home, office or anywhere energy is consumed. This is done by providing an interface through which the consumer can monitor energy usage at their premises and drill down to energy usage per device. It also serves to act as an alarm system to warn the consumer of any malfunctions within their power system as well as current tariff and pricing schemes from the utility. These objectives allow the consumer to change usage behaviour as well as to shave energy peaks [125] (utilities charge on peak usage) thereby reducing energy consumption. Studies have shown that such feedback is vital and that the greatest power savings are achieved when residents are provided with energy usage data for each of their appliances [126].

4.2 The Demand Side Dashboard Model

This section looks at the benchmarking aspects of the DSD, the proposed minimum functional characteristics, user interface aspects and usability standards. Table 4 below shows a list of the functional requirements for a DSD. The functionality shown here are both the optional and the required minimum functionality. Justification on why some functionality is optional and yet the other functionality is a minimum requirement is detailed in the subsections below.

Table 4: DSD Functional Requirements

Functionality	Is this a minimum Requirement? (Yes/No)
Basic Remote control Commands	Y
Advanced Remote control Commands	N
Show device by device consumption data	N
Security and Privacy	Y
Show time stamped energy data	Y
Show itemised energy data	N
Support Real time pricing and Billing	Y
Consider Customer preset settings	N
Show weather warning	N
Show Energy consumption forecast	N
Access via both PC and mobile devices	Y
Customisable User interface	Y
Show historical consumption data	Y
Show latest meter reading	Y
Monitor Network Devices	N

In the following sections a description of each functionality as well as motivation why it is optional or required is given.

4.2.1 Basic Remote Control Commands

Remote controlling of devices refers to the ability for device users to control devices remotely via a set of commands. Basic remote controls commands are simple commands such as to put a device in standby, get current status, switch off, and switch on. Although remote controlling of devices is an optional requirement, the functionality for offering basic remote control commands such as turn device on or off is not optional. What this simply means is that if remote controlling functionality is available on a DSD, then basic remote controlling functionality must be available whilst advanced remote controlling capabilities like user defined control rules are optional.

4.2.2 Advanced Remote Control Commands

Advanced remote control commands refer to commands that average users will need training to use. These are commands such as defining how a device must apply energy saving rules. Such capabilities depend on the device technology and the physical home energy management architecture available on the premises and thus cannot be a standard. Hence if remote controlling functionality is available the offering of advanced remote control commands is not mandatory.

4.2.3 Device By Device Consumption Data

Device by device consumption data collection deals with the collection of energy usage data at the device level and not just on the meter level. This functionality depends on the sophistication of the technology available on the devices in the home as well as on the Home Energy Management System (HEMS) architecture available [127]. This means it is difficult to make this a standard.

4.2.4 Privacy and Security

Privacy is a critical issue in designing information systems [128] as people do not want their information compromised. Users of the DSD must own their usage data and be able to determine what information from their usage data is sent out from their devices and to whom [126], thereby honouring their right to privacy. It is also important for customers to be able to opt out of any demand response programs that they might have opted into.

The DSD must also offer security such that usage data is kept private and protected from malicious and unwanted parties. This can be done by adding features such as access control and data encryption. Privacy and security are not optional in the DSD.

4.2.5 Show Time Stamped Energy Data

Time stamped energy data is also known as interval energy data. This is usage data collected by an interval meter. At the end of every interval period it records how much energy was used in the previous interval [129]. In South Africa most customer energy usage is measured and billed in 30 minute cycles. The peak value in the 48 thirty minute cycles in a day is used to bill the entire day. This is the case for the University of the Witwatersrand. This means it is vital for users to maintain a very low thirty minute peak. Showing time stamped data helps this cause. Users can be able to view when peaks are occurring and investigate the course as well as see if any energy is being stolen e.g. If a business that is closed for business on a Saturday realises it is using the same or even more energy on this closed day as they would use during a normal operating day, an alarm can be raised. Time stamped energy data collection and displaying does not depend on the HEMS network infrastructure but only on advanced smart meters hence this is not optional.

4.2.6 Show Itemised Energy Data

Itemised Data is a very detailed way of presenting usage data to customers. It shows customer usage at the level of each circuit or load in the distribution board or down to the appliance level. Such billing helps consumers identify inefficient appliances as well as actively manage their devices in order to reduce wasted energy. Itemised Energy is ideal for large buildings/campuses that require much more detail [130]. Itemised data collection depends mainly on the HEMS network infrastructure hence this is optional.

4.2.7 Real Time Pricing And Billing

Real time pricing and billing refers to a continuous update of the consumers' bill as they use energy. The DSD must be able to support this functionality. This means given the current pricing rates by the utility the dashboard must give an estimate of the user expected bill on a continuous basis. As an example ESKOM recently launched a new Time of Use (TOU) tariff called home flex [131] using data from advanced smart meters installed in homes. With such a tariff system and smart meters the dashboard can use the ESKOM energy prices to give an estimate bill to the user even before the utility sends them the bill.

4.2.8 Customer Preset Settings

Depending on the underlying energy management network available, the DSD must allow customers to configure certain settings. These could be settings such as switching off lights and appliances at particular times or days. Since this is dependent on the available appliance technology and physical HEMS infrastructure such as programmer logic controllers or similar technology this is optional.

4.2.9 Weather Warning

Weather warning systems serve the purpose of alerting, warning or informing the user of future danger. These can be freezing conditions, hail storms, cyclones or any acts of nature. Weather affects energy demand, supply and distribution which means it is beneficial to both supplier and user to know in advance the weather conditions. For example if there is going to be a cyclone or heavy rains there is a very high likelihood of power supply interruptions. Informing consumers of this possibility helps them make contingency plans. Dashboards designers can easily plug their dashboards into weather centre RSS (Really Simple Syndication) feeds to give their users weather information. This feature is however optional since connectivity to weather centres as well as internet connectivity might not be available to everyone.

4.2.10 Energy Consumption Forecast

Energy consumption forecasting involves the accurate prediction of the amount of energy consumers such as a household, enterprise, suburb or even entire cities will use in the immediate or foreseeable future. The energy usage forecast is based on expected load at the forecast time. Typically load forecasting is classified in terms of the planning horizons duration, as short term (STLF), medium-term (MTLF) and long-term load forecasting (LTLF) [132]. If consumers can predict their energy consumption then it is possible for them to shift usage peaks by any counter measures necessary. In the case of the University of Witwatersrand advanced metering infrastructure program discussed in section 1.4, predicting consumption means they can easily avoid peak usage by switching on the standby generators or even switching off non-essential devices via the building management system. As discussed in the literature review in section 2.7 load forecasting is done by using complicated algorithms such as regression based methods [133] and computational intelligence techniques (fuzzy systems and artificial neural networks) [64]. This feature is very important in demand side energy management and must form a prerequisite of the standard.

4.2.11 Access via both PC and Mobile Devices

With the advent and ubiquitousness of the smart phone it is not enough for applications to only be available as desktop applications on personal computers. The energy management dashboard must be available to the customer via both the personal computer and on mobile devices. In this day and age this is the direction of all applications and hence this is not optional for energy management dashboards. It is important to keep up with trends in other industries.

4.2.12 Customisable User Interface

Section 2.4.6 described intelligent user interfaces as interfaces where the GUI is based on context, content, user role and preferences. It is important that any energy management dashboard designer keep this in mind and design and develop interfaces where users can customise the GUI to their liking. Users also do not want to see what does not apply to them so the GUI must adjust according to the role and preferences of the users. This feature is not optional as it has become a standard in most software applications and users of energy dashboards will expect this to be a standard as well.

4.2.13 Historical Consumption Data

In any data analytics applications historical data collection is critical for anomaly detection, forecasting, predictions as well as performing historical queries. It is important for the energy management dashboard to offer such functionality in the form of at least access to 12 months historical data. The author suggests a 12 month minimum limit because with 12 months of previous data it is possible to generate trends and forecasts but with anything less this becomes extremely difficult. For this functionality to be realised, some sort of back-end either on the device or on the cloud would be needed for data storage. It is not of importance what back-end designers decide to employ. This feature is not optional as this functionality is critical to other features of the dashboards such as forecasting.

4.2.14 Show Latest Meter Reading

Meter readings show the total amount of electricity used by a consumer (household, enterprise etc.). This allows the consumer to see the actual amount of energy in kilowatt hours, as shown in the meter in Figure 6 below, instead of using utility estimates. In developed countries such as the USA it helps to know the actual energy a premise is consuming and what the utility is charging as there is an option to even change the service provider and get a better rate.

Figure 6: Digital Meter Reading (D J du Plessis Building Wits University)

In countries like South Africa where there is a problem of power utility companies using estimates of consumption instead of actual meter readings, having a dashboard that always displays the current consumption as displayed on the meter helps the user to easily and quickly see any anomalies on their utility bill. Customers always pay either too much or too little due to lack of usage awareness. This is a basic but necessary functionality and in the proposed model this feature is not optional.

4.2.15 Monitor Electric Network Devices

Monitoring of the electrical network in the building involves checking the health of the devices connected to the system. This functionality depends on the available technology on the devices connected to the energy management system. If the devices are smart devices they are able to send important information such as fault codes to the management system.

This information can then be used to present a warning or alarm to the user to indicate a malfunction in the device. Smart meters should also be monitored as they also tend to malfunction. A case experienced during this research is a good example. One of the meters at the Wits Medical School was disconnected from the network during construction and the energy management dashboard was able to pick up that there was a problem by zero readings coming through on the real time graphs.

4.3 Interface Standards

The proposed model would not be complete if the graphical user interface standards are not discussed and set. This section describes the graphical user interface section of the proposed model. These are the recommended minimum characteristics of the user interface.

4.3.1 Interface Consistency

The majority of people who will use the proposed energy management dashboard will have previously used other software applications in their day to day lives.

It is thus important that the GUI on these dashboards be consistent with industry standards. Things such as reserved words and icons should not have a different meaning in the dashboard to what it would mean in for example Microsoft® Word. Successful user interfaces are those that share common characteristics. Table 5 and Table 6 below summarise a few examples of the commonly reserved icons and words that must be adhered to. It must be noted that the prototype is based on Windows® Operation system software application standards but can be easily ported to any other operating systems like Linux® and OSX®

Table 5: Reserved Icons

Icon Picture	Meaning	Identify an Application	Identify a Function	Text label
	Warning Message	No	Yes(identifies a warning message box)	None
	Question Message	No	Yes(Identifies a question message box)	None
	Error Message	No	Yes(Identifies an error message box)	None
	Information Message	No	Yes(identifies an information message box)	None

Table 6: Reserved Words[134]

Word	Meaning and Expected Behaviour	Appears on a Button	Appears on menu	Shortcut Keystrokes
OK	Accept the data entered or acknowledge the information presented and remove the window	Yes	No	Return or Enter
Cancel	Do not accept the data entered and remove the window	Yes	No	Esc
Close	Close the current task and continue working with the application; close the view of the data	Yes	Yes	None
Exit	Quit the application	No	Yes	Alt+F4
Help	Invoke the application's help facility	Yes	Yes	F1
Save	Save the data entered and stay in the current window	Yes	Yes	Shift+F12
Save As	Save the data with a new name	No	Yes	F12
Undo	Undo the latest action	No	Yes	Ctrl+Z
Cut	Cut the highlighted information	No	Yes	Ctrl+X
Copy	Copy highlighted information	No	Yes	Ctrl+C
Paste	Paste the copied or cut information at the insertion point	No	Yes	Ctrl+V

The author proposes that at a minimum all energy management dashboards adhere to the above standard keywords and icons. The DSD developer must always keep in mind the industry standard of doing any task they might be implementing.

4.3.2 User Friendly Interfaces

When designing user interfaces it is important to always keep the user in mind and avoid frustrating situations for the user. Table 7 lists a guideline of recommended interface behaviour that will make dashboard systems less frustrating to use for the user.

Table 7: Recommended Interface Characteristics

Recommendation	**Description**
Progress bar	Show user how much longer before a process finishes.
Quick Access buttons	Place only frequently used commands at the top level.
Primary Window (main application display)	Software applications are strongly recommended to always have and initially display a primary window. Displaying a primary window assists in setting the application context for the user.
Order Screens Sequentially	Screens should appear to user in the order that they are more likely to use them.
Use of Colour	Use colour to differentiate information groups, button states, backgrounds, boundaries ,show important elements, etc.
Group elements logically	According to Gestalt principles [135] users tend to expect like elements to exist in the same area not extreme ends of the interface. It is thus recommended that GUI elements are always grouped based on some common or similar property.
Default settings option	An option to revert back to the default interface settings should always be available to the user. This is important for novice users want to revert back to the default settings after they have mistakenly or knowingly changed the settings.
Tabulate Data	Tabulating data allows for efficient labeling of related data and makes it easier and quicker for users to search and filter data.
Give users control	The interface should be user driven rather than the application dictating which events occur.
Adhere to standard Window elements	Show window title, minimise, maximise, restore and close boxes.

When software developers use GUI controls they sometimes go overboard. Hobart [134] proposed excellent and practical limitations for different controls as shown in Table 8 below. This is the standard that is adopted and proposed for the controls in the energy management dashboard model.

Table 8: Guidelines for Using Controls

Control	Number of Choices in the Domain Shown	Type of Control
Menu bar	Maximum of 10 items	Static action
Pull-down menu	Maximum of 12 items	Static action
Cascading menu	Maximum of 5 items, 1 cascade deep	Static action
Pop-up menu	Maximum of 10 items	Static action
Push button	1 for each button, maximum of 6 per dialog box	Static action
Check box	1 for each box, maximum of 10 to 12 per group	Static set/select value
Radio button	1 for each button, maximum of 6 per group box	Static set/select value
List box	Maximum of 50 in the list, display 8 to 10 rows	Dynamic set/select value
Drop-down list box	Display 1 selection in the control at a time, up to 20 in a drop-down box	Dynamic set/select single value
Combination list box	Display 1 selection in the control at a time in standard format, up to 20 in a drop-down box	Dynamic set/select single value; add a value to the list
Spin button	Maximum of 10 values	Static set/select value
Slider	Dependent on the data displayed	Static set/select value in range

4.4 Interface Behaviour

The following table describes the user interface behaviour that is recommended for all energy management dashboards.

Table 9: Recommended Interface Behaviour

Behaviour	Description
Configurable panels	Users should be able to add, remove and dock panels on the dashboard as they see fit. This allows them to set up the interface to suit their needs.
User specified themes	This functionality allows the system to remember user specific preferences e.g. color schemes, panel positions etc.
Drag and drop functionality	This functionality allows users to drag and drop elements from one place to another on the screen.

4.5 Recommended Visualisation Techniques

Section 2.4 of the literature survey detailed the evolution of visualisation techniques and how the power industry has been left behind by the developments in the data visualisation industry. This section recommends some new visualisation techniques that must be utilised in the energy management dashboards. The traditional methods of data visualisation are assumed and not mentioned here. The minimum recommended techniques that would make the dashboard visually rich are:

- 3D data modelling;
- Real time line graphs;
- Heat maps;
- Data animation; and
- GIS.

For detailed description of these techniques see section 2.4.

4.6 Benchmarking Model Overview

This chapter has introduced a benchmarking model for customer side energy management dashboards. Figure 7 below shows an overview of the developed model. This is the model that the developed prototype will follow.

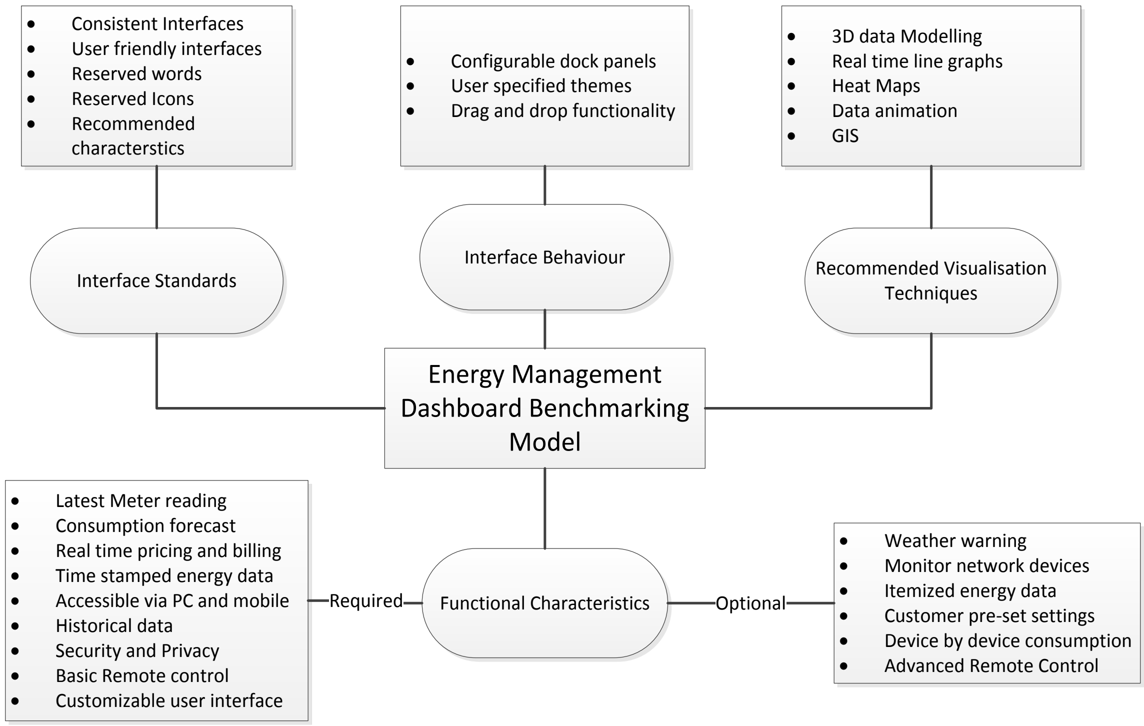

Figure 7: Energy Management Dashboard Benchmarking Model

4.7 Conclusion

This chapter introduced a customer oriented dashboard benchmarking model. It is the belief of the author that by following this proposed model energy data visualisation dashboards designers have an easy reference point for future developments. Chapter 5 which follows describes a design and implementation of a forecasting algorithm. Chapter 6 then details the design and implementation of a prototype dashboard using this proposed model. This will help see if there are any gaps in the model or if it is helpful at all to dashboard developers.

CHAPTER 5: Forecasting Model Design

5. Introduction

Forecasting capability is a prerequisite according to the model proposed in the previous chapter. In order to offer this functionality a Multiple Linear Regression (MLR) model is designed and implemented. This section details the design of the MLR models used as well as the data collection and analysis done to come up with these models. All the statistical analysis is carried out using R statistical package, a free software environment for statistical computing and graphics [136].

5.1 Background

As briefly discussed in chapter 1, the University of the Witwatersrand energy group has set up an advanced metering infrastructure across the campus. They want to use this system to forecast half hourly peak loads in order to shave their peaks since they are billed by Johannesburg City Power on the highest peak achieved. In order to do this the proposed dashboard must implement a forecasting algorithm that can forecast peak load for the next half hour cycle such that the Wits Property and Infrastructure Management Division (PIMD) control room can be notified and take action (starting up generators, load shedding etc.) to avoid reaching set peaks.

5.2 Used Data

Half hourly load data for 2 years (2012-2013) from the University of the Witwatersrand west campus is used in this study. The data is collected from the advanced metering system set up across the campus. Hourly historical temperature (^{o}C) data for Johannesburg for the same time period (2012-2013) is used with special permission from the South African Weather Service (SAWS). In order to acquire and use the historical temperature data in a non-commercial application a disclosure agreement from SAWS had to be signed, a copy is attached in Appendix B.

5.3 Data Analysis

The energy and temperature data is analysed in order to see any trends and relationships. This is important for the selection of appropriate and meaningful variables to use in the MLR model. It also helps to identify which variables are qualitative and which ones are quantitative.

5.4 Data Cleanup

In order to get accurate models the data is first analysed for any errors and missing data. This is done by means of a graphical analysis. This section details the data cleanup operations carried out.

5.4.1 Load and Temperature Data Clean Up

The plot in Figure 8 below shows all the available instantaneous power readings for the two years of data. The plot shows that there are a lot of sections with missing readings notably between August 2012 and September 2012. The missing data is due to load shedding, construction work and meters going offline due the glitches in the University's network. There are also cases shown by the plot where the meters give zero values. The time instances of these zero values together with the missing readings are not considered in the dataset used to create the model.

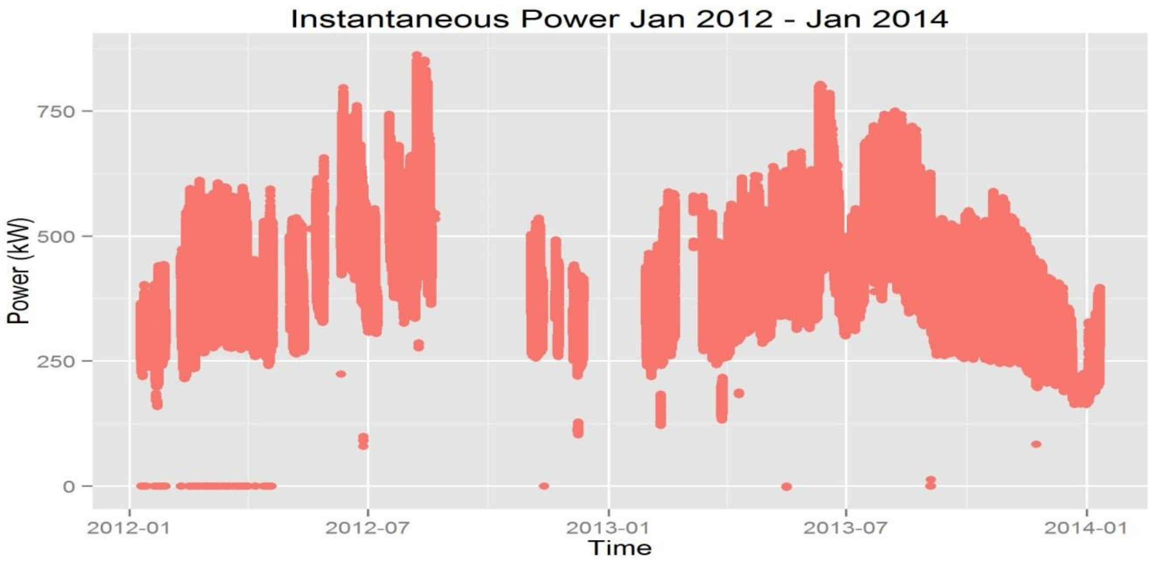

Figure 8: Instantaneous power January 2012 -January 2014

The temperature data is also plotted as shown in Figure 9 below. This data is found to be complete with no missing or zero values. A year by year analysis of the temperature data is carried out and the data is plotted as shown in Figure 10, Figure 11 and Figure 12. The plots show repeatability in the weather patterns year by year. This repeatability is important as the proposed forecasting model uses forecast temperature values to forecast the load.

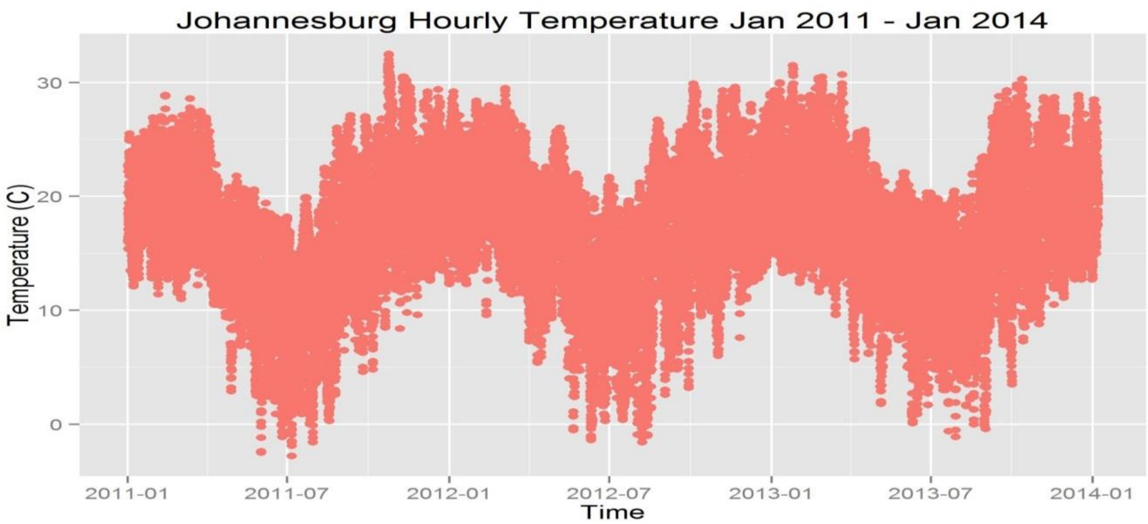

Figure 9: Johannesburg Hourly Temperature January 2011-January 2014

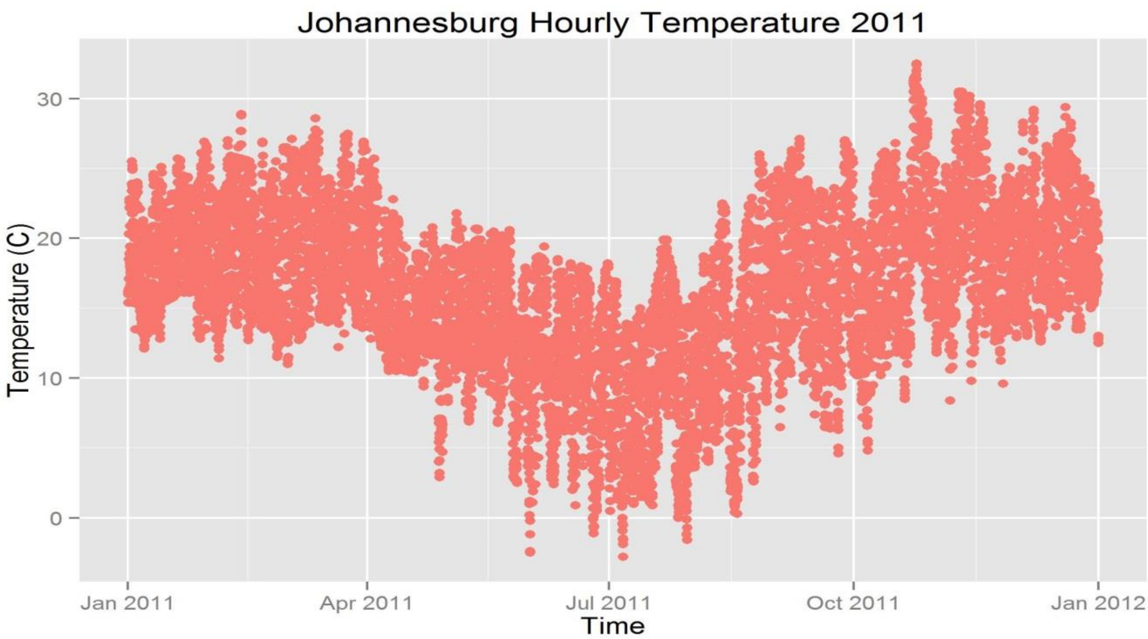

Figure 10: Johannesburg hourly temperature 2011

As expected of the Johannesburg climate the winter (May to August) has the lowest temperatures and summer has the highest temperature.

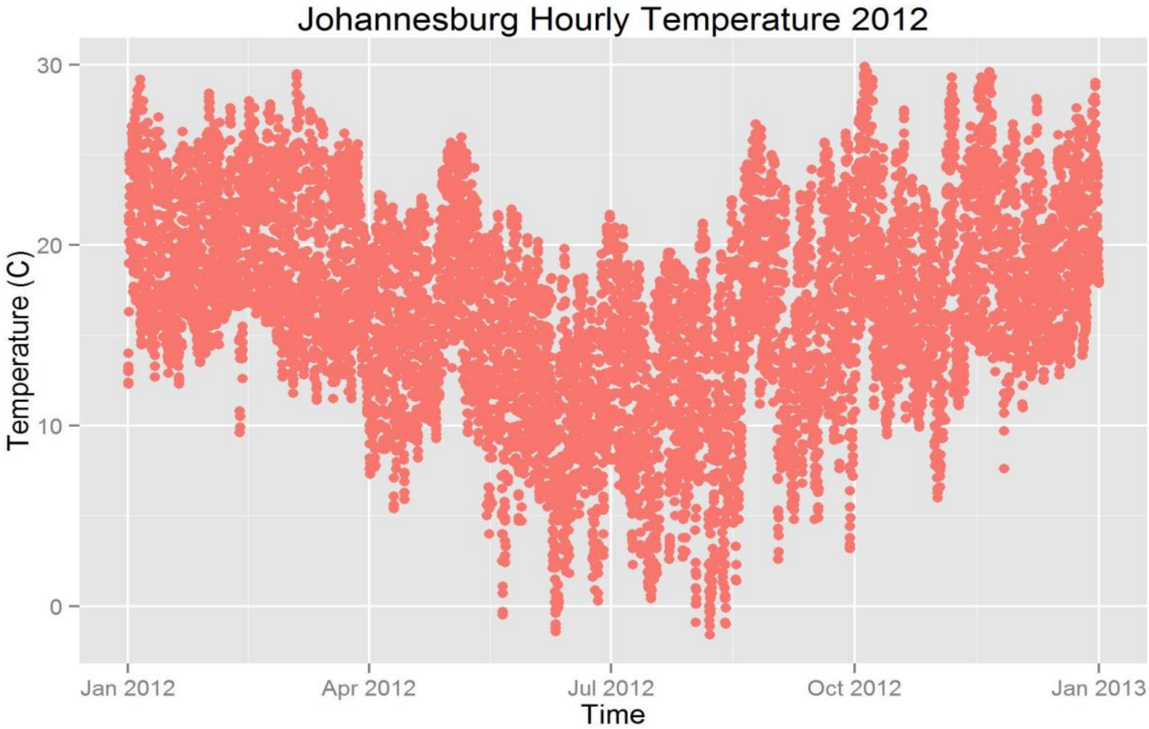

Figure 11: Johannesburg Hourly Temperature 2012

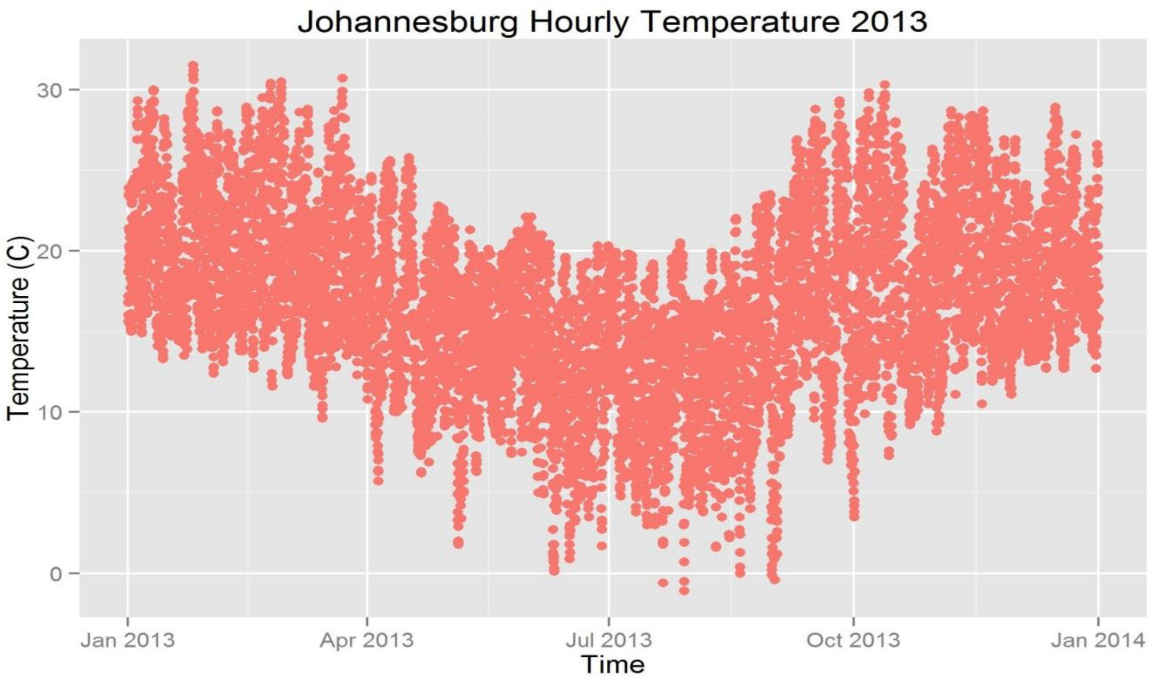

Figure 12: Johannesburg Hourly Temperature 2013

5.5 Trends Investigation

Energy demand and usage behaviour is based on a number of external influences. Factors such as temperature, month of the year, day of the week and time of day play a big role in the demand behaviour. Since the load forecasting is for a University campus, factors such as whether the campus is on holiday or not, weekend or school day are also important influences. The following sections analyse how these factors affect the university's load if at all. The results are then used to put these variables into a suitable MLR model.

5.6 Load Predictability

The load analysis for the past 2 years shows that the demand trend in 2012 almost matches that of 2013. Looking at Figure 8 from previous section; Figure 13 and Figure 14 below, it can be seen that although there are cases of missing values, the load trends for 2012 and 2013 are comparable for the sections where data is present. In both years the average highest peak is approximately 800kW occurring in the winter months from May to August. The 2013 values are on average 5% higher due to the new buildings that have been added to the West campus in the past 2 years and are now operational. These buildings have resulted in an increased energy demand.

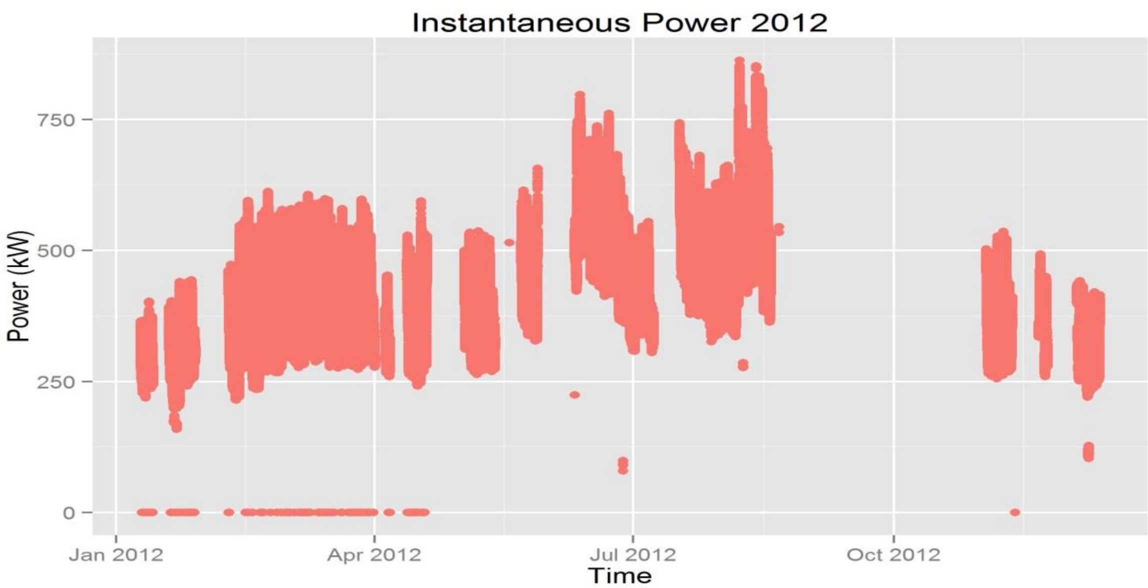

Figure 13: Raikes Road Incomer Instantaneous Power January 2012 -December 2012

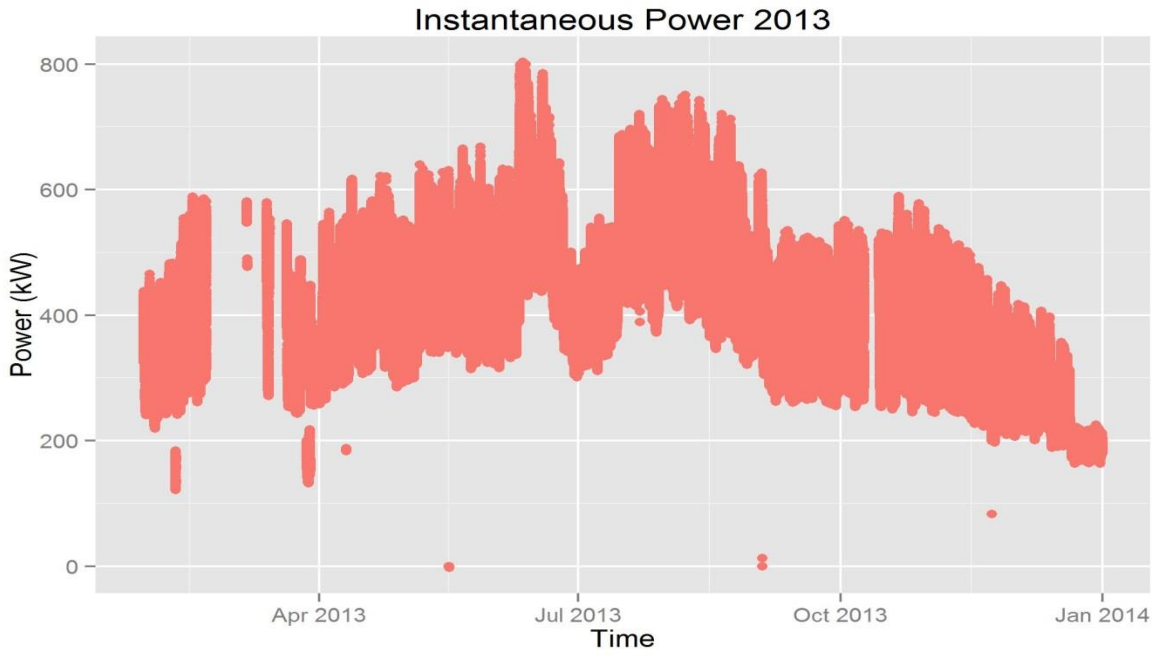

Figure 14: Raikes Road Incomer Instantaneous Power January 2013-December 2013

This repeatable energy usage behaviour supports the notion that with the right variable and model selection the load consumed can be accurately forecast.

5.6.1 Load Time of Day Trend

Figure 15 below shows the Raikes road incomer meter energy usage behaviour for 2012 to 2013 split according to the day of the week and shown for the hour of day. The Raikes road incomer meter feeds the west campus of the University.

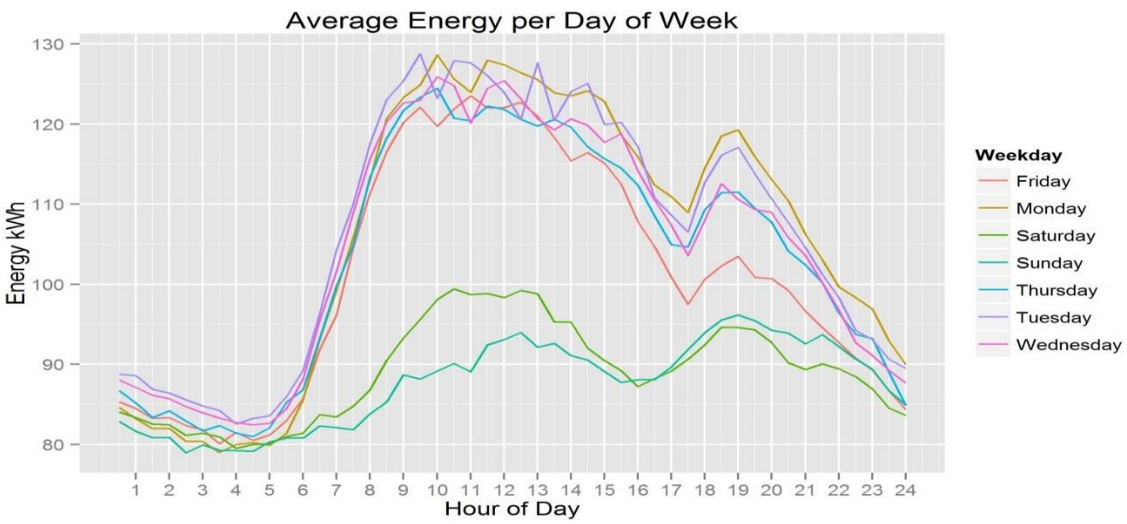

Figure 15: Average Energy per Day of Week

The plots show that energy usage depends on the day of the week. It also shows dependability on whether the day is a weekend or week day. The usage for Saturday and Sunday is shown to have the lowest values compared to the weekly days. The plot also shows some expected trends for the hour of the day as tabulated below:

Table 10: Hourly Demand Behaviour

Trend	**Possible Reason**
Energy demand between midnight and 5am is very low	People on campus residences are sleeping; non-resident students and staff have left the campus at this time, devices and equipment not in use.
Demand starts rising from around 6am till about 11am	People on campus residences start waking up, heaters, water boilers, air conditioning, cooking equipment starts being switched on. Non-residents start arriving on campus.
Demand starts decreasing from 11am till about 4:30pm	This period constitutes a time where water boilers are not being used to their maximum. Also from about 12pm some non-resident people start leaving campus and most equipment starts being shut down.
Demand start increasing from 5pm until about 8pm	Cooking equipment starts being switched on. Resident students start switching on their devices in their rooms, part time classes also start around 6pm.
Demand starts decreasing from 8pm to midnight	Most resident students start going to bed, devices shut down, no demand on water boilers, heaters or air conditioning.

The load dependence on time of day and day of week is further analysed for each month of the year and all the months have this same behaviour as shown in Figure 16 below. This behaviour is repeatable and consistent providing evidence that week day and hour of day are important variables to add to the model.

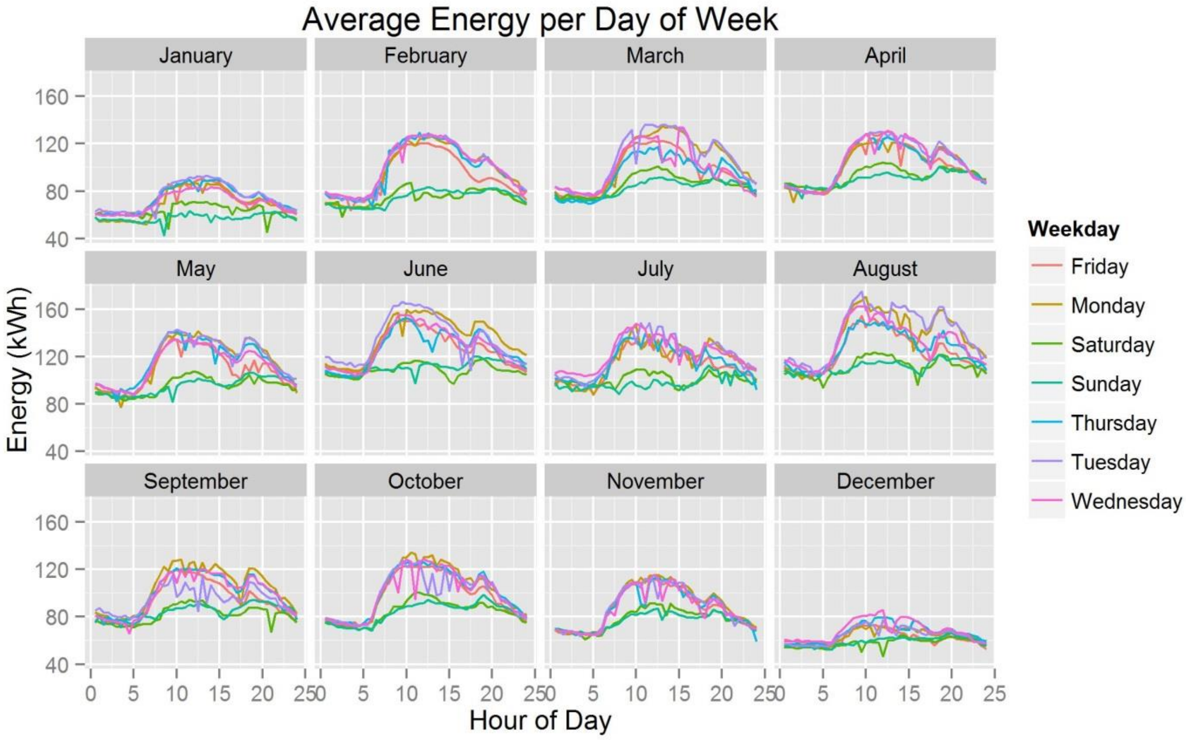

Figure 16: Average Energy per Day of Week for all months

5.6.2 Load Dependence on Campus State

The data used in this study is for a University campus. It is important that an analysis is done to see how the load depends on the state of the campus. In this research the campus state is introduced and defined as the operational state of the campus broken into the following

- Is campus closed (campus on holiday);
- Is campus open (campus fully operational); and
- Special state (campus in administrative state i.e. registration period, orientation week and exam times).

The plot in Figure 17 below shows that an introduction of the campus state variable is important. It is shown that during the closed state energy usage is at its lowest. In the open state as expected the energy usage is at its maximum and it reduces slightly for the special case. This supports the introduction of this variable as the different states cannot be treated the same since they have a major impact on usage behaviour.

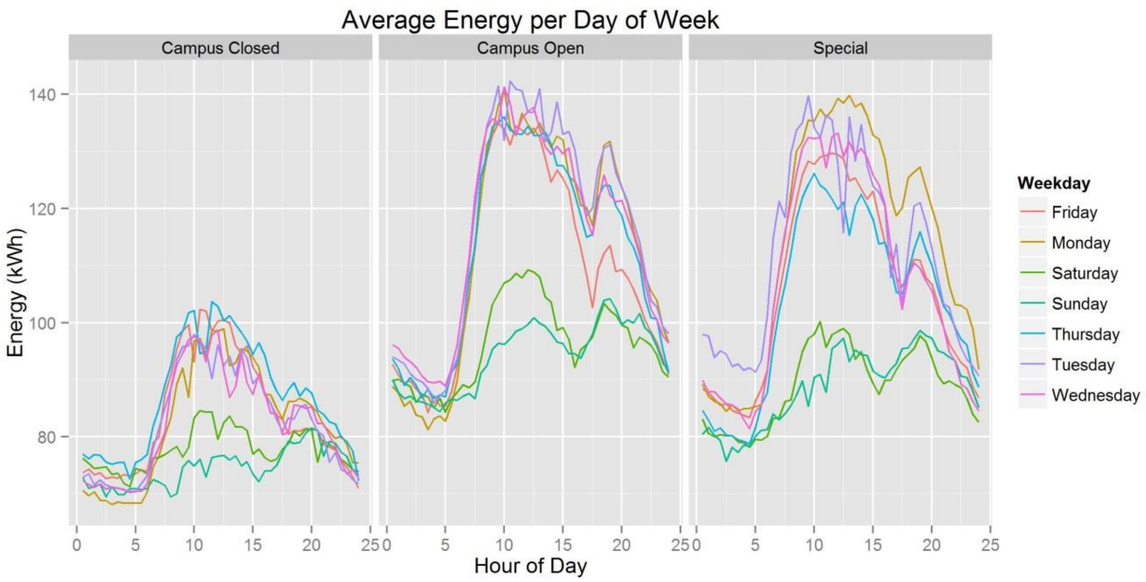

Figure 17: Load profile for different campus operational states

5.6.3 Load Dependence on Temperature

A relationship between the load and temperature is done and plotted in Figure 18 and Figure 19 below. The data is plotted separately for 2012 and 2013 load profiles. It can be seen that as temperature increases the load decreases up to a certain point before it starts going up.

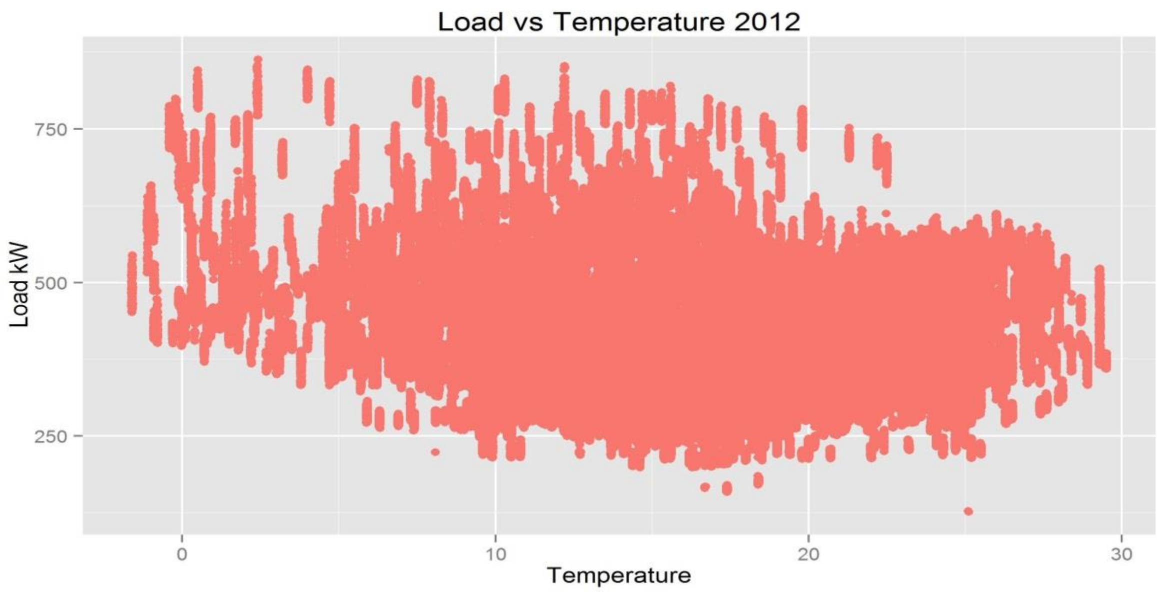

Figure 18: Load – Temperature plot 2012 profile

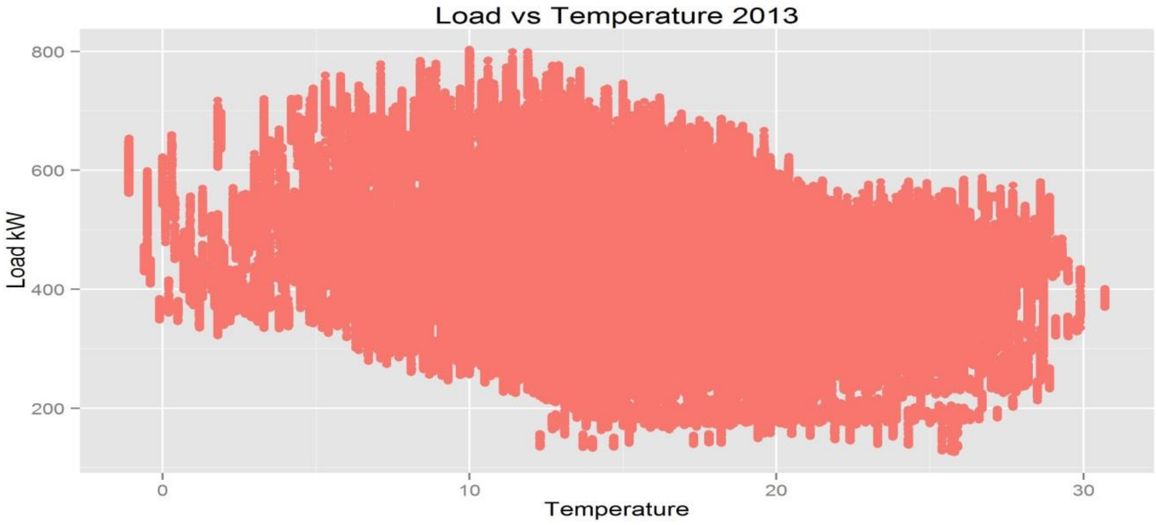

Figure 19: Load – Temperature plot 2013 profile

The relationship is explained as tabulated in Table 11 below:

Table 11: Load-temperature analysis

Trend	Possible reason
As temperature reduces load increases	In low temperatures geysers use more energy to maintain hot water; People tend to switch on heaters and also stay indoors and hence have a lot of devices operational for longer.
Load decreases with increasing temperature up to a point and starts increasing again but to a lower peak than at lower temperature.	As temperature goes up people tend to switch off the heaters. But as temperature increases past comfortable levels people will start switching on air conditioners to maintain comfortable levels.

The load and temperature relationship detailed in the plots (Figure 18, Figure 19) and Table 11 above show that temperature should be considered as a variable in the forecasting model. The plots and trend analysis above also show that the load and temperature relationship is not linear. Studies have shown that this relationship can be taken to be a third order polynomial relationship with good results [66]. The model also uses this third order polynomial relationship.

5.7 Variable Selection

The previous sections analysed the relationships between the load and a number of variables. Using the conclusions of the analysis the following variables are selected as important for the MLR model.

- Temperature;
- Campus State (Open, Closed or Special);
- Day of the week;
- Time of day; and
- Previous half hourly load.

Table 12 below explains these variables and indicates if it is a qualitative or quantitative variable. For the qualitative variables a breakdown of the categories are listed.

Table 12: Variable selection

Variable	**Type of variable**	**Categories**
Temperature	Quantitative	n/a
Campus State	Qualitative	Open, Closed and Special
Day of the week	Qualitative	Sunday to Saturday
Time of day	Qualitative	1 to 48 (24 hour day divided into 48 half hour cycles)
Previous peak load	Quantitative	n/a

5.8 Training and Test Data

The available energy data is only for 2 years and the year 2012 has been shown to have a lot of missing data. In order to make the most of the available data for the training and testing of the model the data is split into two parts so that one part can be used for training and the other part as test data. The data is split into an 80% training data portion and a 20% portion for testing the model. Instead of splitting the data by a date interval the data points are randomly picked into the 2 portions. Before they are randomly picked the data points are first assigned a continuous time index, cycle of day and a timestamp so as to maintain the order and then 80% of the data is randomly picked to form training data and the remaining 20% forms the test data.

5.9 Proposed MLR Models

Two models that capture the interactions of the selected variables are proposed below. As discussed above, a third order relationship of load and temperature is taken into account as well as the previous half hour peak load.

5.9.1 Model A

The first model (named Model A) considers each of the variables in Table 12 along with the multiple categories of the qualitative variables. This model is shown in equation 2 below.

$$\boldsymbol{Load} = \boldsymbol{\alpha_0 T(t)} + \boldsymbol{\alpha_1 (C)} + \boldsymbol{\alpha_2 D} + \boldsymbol{\alpha_3 M} + \boldsymbol{\alpha_4 L(t-0.5)} + \boldsymbol{\alpha_5 T(t)^2} + \boldsymbol{\alpha_6 T(t)^3} + \boldsymbol{\alpha_8 h} \qquad (2)$$

Where:

$Load$= Forecast Peak load

$T(t)$= Temperature at time t

$L(t-0.5)$= Peak load of previous half hour cycle

$\alpha_{(0-8)}$ = Regression parameters

M= Month of the year (classified as 1 to 12)

D= Day of the week (classified as 1 to 7)

h= Half Hour cycles of the day (classified as 1 to 48)

C= Campus state (Open, Closed and Special)

Fitting this model to the training data using the 'lm' function in R [136] the equation parameters are solved for and are shown in Appendix C. The 'lm' function is used to fit regression models in R. The R code for running this model is shown in this appendix as well as the significance of each variable used in the model. Due to the half hour cycle, month of the year and day of the week having 67 categories amongst them the results sheet in Appendix C is long as it solves and shows the parameters applicable for each of these categories. The model has an R-squared value of 0.9411 and the residuals are shown in Table 13 below.

Table 13: Model A Residuals

Min	1Q	Median	3Q	Max
-95.896	-2.555	-0.026	2.534	62.811

Although the min and max show that the model is sometimes out by these large numbers (-95.896kWh and 62.811kWh) the interquartile range is small (5.089) indicating that most forecasts are very close to the mean (-0.026) hence accurate. The R-squared value is also very close to 1 indicating a strong fit of the data to the model. These indicators are all supported by the residuals scatter plot below showing all the data bunched around with very few outliers.

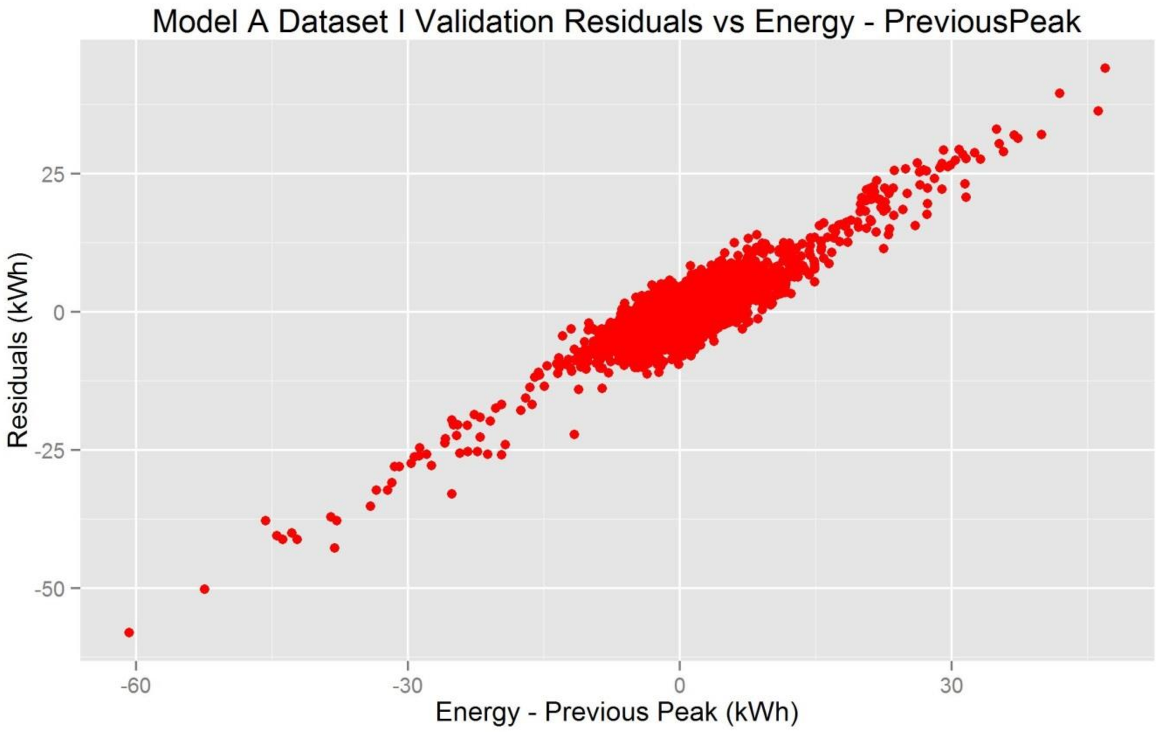

Figure 20: Model A residuals scatter plot

5.9.2 Model B

The second model (named Model B) is different from model A in that it applies a transformation to the data before an equation is formulated. The applied transformation introduces a single variable (named Baseline) to replace the half hour cycle, day of the week, month and campus state. This reduces the number of parameters required in solving the model. The transformation process is applied to the training data by first segmenting the data by half hour cycle, day of the week, month and campus status. For each segment, the mean of all peak energy values is calculated and this becomes the baseline value. Essentially the baseline variable is the expected peak energy before day of forecast and then on the day of forecast the temperature and previous peak are added to the model to give the forecast peak.

The baseline variable captures the effects of half hour cycle, day of the week, month and campus status. Model B is represented by the following equation:

$$\boldsymbol{Load} = \boldsymbol{\alpha_0 T(t)} + \boldsymbol{\alpha_1 L(t-0.5)} + \boldsymbol{\alpha_2 T(t)^3} + \boldsymbol{\alpha_3 B} + \boldsymbol{\alpha_5 (T(t) * B)} \qquad (3)$$

Where:

$Load$= Forecast Peak load

$T(t)$= Temperature at time t

$L(t-0.5)$= Peak load of previous half hour cycle

$\alpha_{(0-5)}$ = Regression parameters

B= Baseline variable

Fitting this model to the training data using the 'lm' function in R [136] the equation coefficients are solved for and are shown in Appendix D together with the R source code. The results show that all the parameters chosen in this model are significant unlike in Model A where some of the variables did not have an effect on the model. The measure of significance values are shown and indicated in Appendix D. The residuals of Model B are tabulated below. They show a small Inter quartile range of 5.057. The R-squared value is 0.9492 which indicates a strong fit of the data to the proposed model.

Table 14: Model B residuals

Min	1Q	Median	3Q	Max
-73.518	-2.387	0.110	2.670	47.186

The residuals scatter plot shown below also shows and supports the above results showing a strong fit with all points bunched around the zero value. This shows small deviations of forecast values from actual values. More plots showing the performance are in part 2 of Appendix D, these plots show how the model is more accurate for moderate temperatures and is at its worst performance in extreme temperatures.

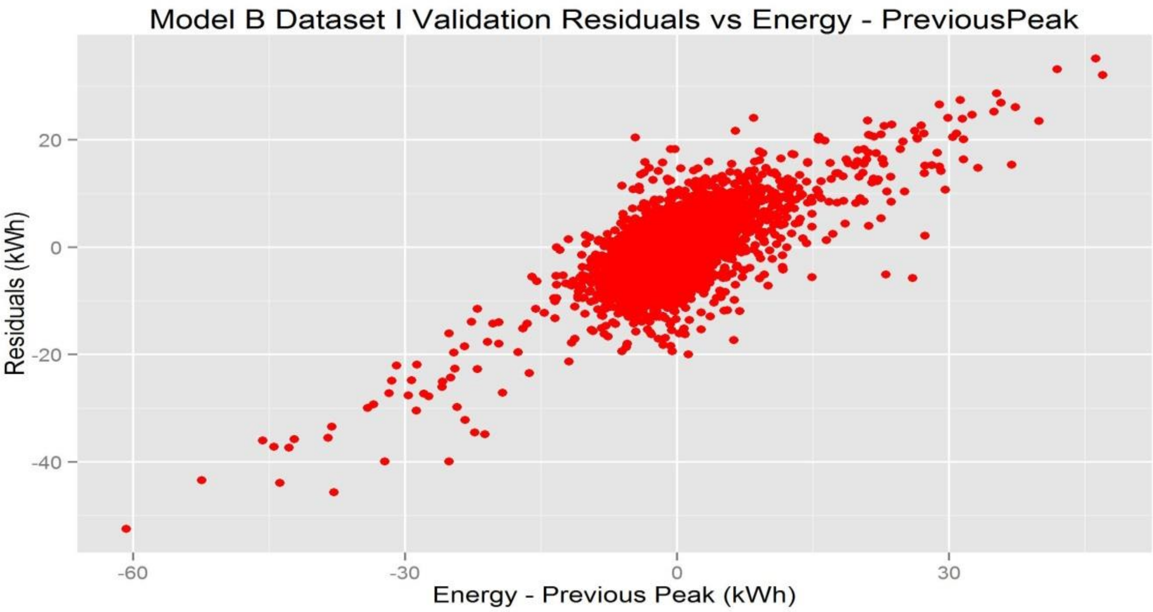

Figure 21: Model B residuals scatter plot

5.9.3 Model Selection

From the above discussions it can be seen that Model B has a higher R-Squared value, small interquartile range and provides a better fit for the data than Model A. It also uses a transformation variable hence there are less parameters in the model. With this in mind Model B is chosen and implemented as the forecasting model in the proposed prototype.

5.10 Conclusion

In this section the relationship of the load with a number of independent variables has been analysed and two mathematical forecasting models proposed. Model B is chosen to be implemented in the prototype. In chapter 7 the forecasting models results and performance is evaluated.

CHAPTER 6: Dashboard Specifications and Design

6. Introduction

Chapter 5 proposed a conceptual model for an energy management dashboard design. This chapter goes a step further and applies this model to the design and development of a prototype energy management dashboard to be used by the PIMD team at Wits University. Focus is also made on the design and implementation of the STLF algorithm that was implemented.

6.1 Problem Domain

With the advent of smart meters a world of possibilities has been opened in the power data management and analytics arena. Smart meters and the data they provide can allow energy consumers to analyse, control, manage and forecast power usage. Energy consumers have realised that if they take advantage of these capabilities they can save themselves a lot of money by intelligently managing their energy consumption [100]. The problem spaces being evaluated through the development of this dashboard are as follows:

- Half hourly energy demand forecasting;
- Smart grid data mining;
- Real time instantaneous power (kW) visualisation;
- Real time energy (kWh) usage visualisation; and
- Real time energy billing estimations.

6.2 Requirements

The set of requirements for the dashboard are according to the benchmark model discussed in chapter 4. According to the proposed model an acceptable dashboard must at least have the following functionality:

- Latest Meter reading;
- Consumption forecast;
- Real time pricing and billing;
- Time stamped energy data;
- Accessible via PC and mobile;
- Historical data;
- Security and Privacy;
- Basic Remote control; and
- Customisable user interface.

The requirements marked as optional in the benchmarking model are not implemented in this proof of concept.

6.3 System Design Methodology

Agile software development using the ICONIX process is adapted as the software development methodology for this prototype. The ICONIX process is a Unified Modelling Language(UML) driven analysis and design of a software application [137]. It provides a step by step analysis of system objects and use cases in a bid to turn them into working code. The motivation behind this approach is that this process produces software of high quality which is maintainable, reusable, reliable and efficient. The ICONIX process provides a tried and tested step by step method which ensures the design engineers do not fall into the analysis paralysis pitfall which wastes valuable time [137]. The overall system use case for this application is shown in Figure 22 below and a detailed analysis of the ICONIX process detailing all the stages is documented in Appendix E. This appendix is a standalone report for this process and it includes all the class diagrams for the prototype.

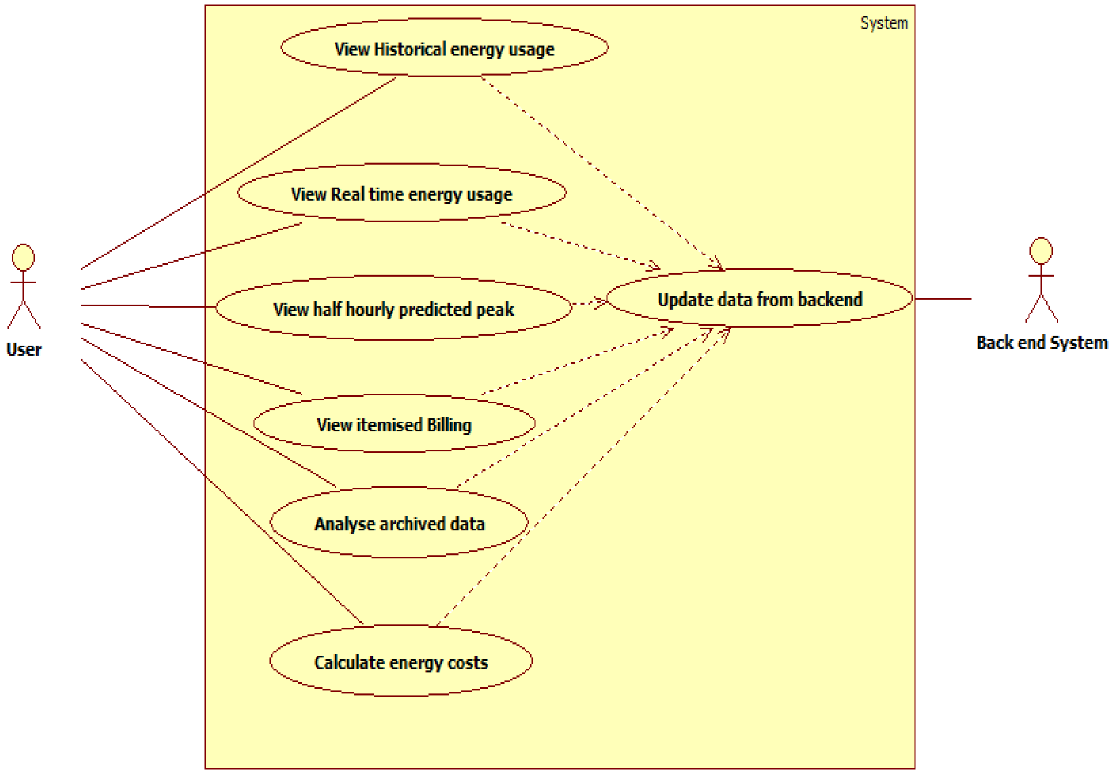

Figure 22: Overall System Use Case

6.4 Application Architecture Modelling

A multi-layer architecture model is used for the application architecture. The decision to use such a model is because the application lends itself well to this kind of architecture since it has user interaction via a user interface, logic to perform specific tasks, as well as the need to store data on to a database. The application is thus separated into four layers, namely the presentation layer (user interface), the application (business logic) layer, data access layer and database layer as shown in Figure 23. Appendix F details all the source code implemented in the development of this dashboard. The application is developed on the Microsoft® .Net framework using C#.

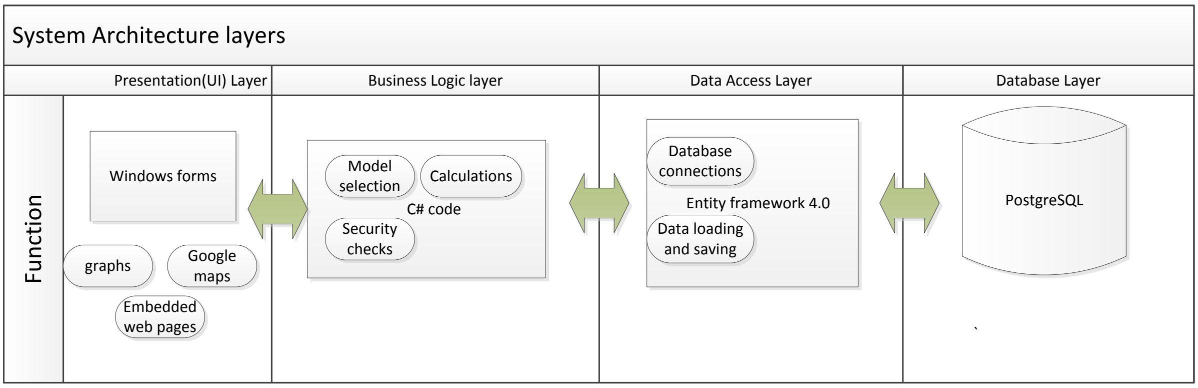

Figure 23: Applications Multi-Layer Architecture

6.4.1 Presentation Layer (User Interface)

The application proposed is a dashboard hence the presentation layer is one of the most important layers of this system. Microsoft® Windows forms are used to create a configurable user interface. Users have the ability to drag and reposition different dock panels to suit their preferences. The overall interface of the dashboard looks as shown in Figure 24 below. As can be seen the dashboard has a lot of panels that retreat into the sides of the screen and can be brought to the front on demand or if the user desires they can be docked to different positions on the screen as shown in Figure 25. The different available panels show the following:

- Real time Power and energy graphs per available meter;
- GIS panel showing meter position on a map;
- Energy readings archive that allows users to visualise past usage on graphs;
- Itemised energy values and actual Rand cost on an Excel like grid;
- Settings panel for inputting cost per hour;
- Settings panel for inputting thresholds that trigger alerts; and
- Embedded web page showing current and forecast weather.

Refer to Appendix G for more screenshots of these panels. These panels hold graphs that collect and summarise various data from the back end. Real time energy usage graphs are presented on an interface as shown in Figure 24. Users can also get a summary of the current total usage and cost of the energy as shown in Figure 25. Drop down buttons are available to navigate across the different meters and users can select which meter they want to interrogate.

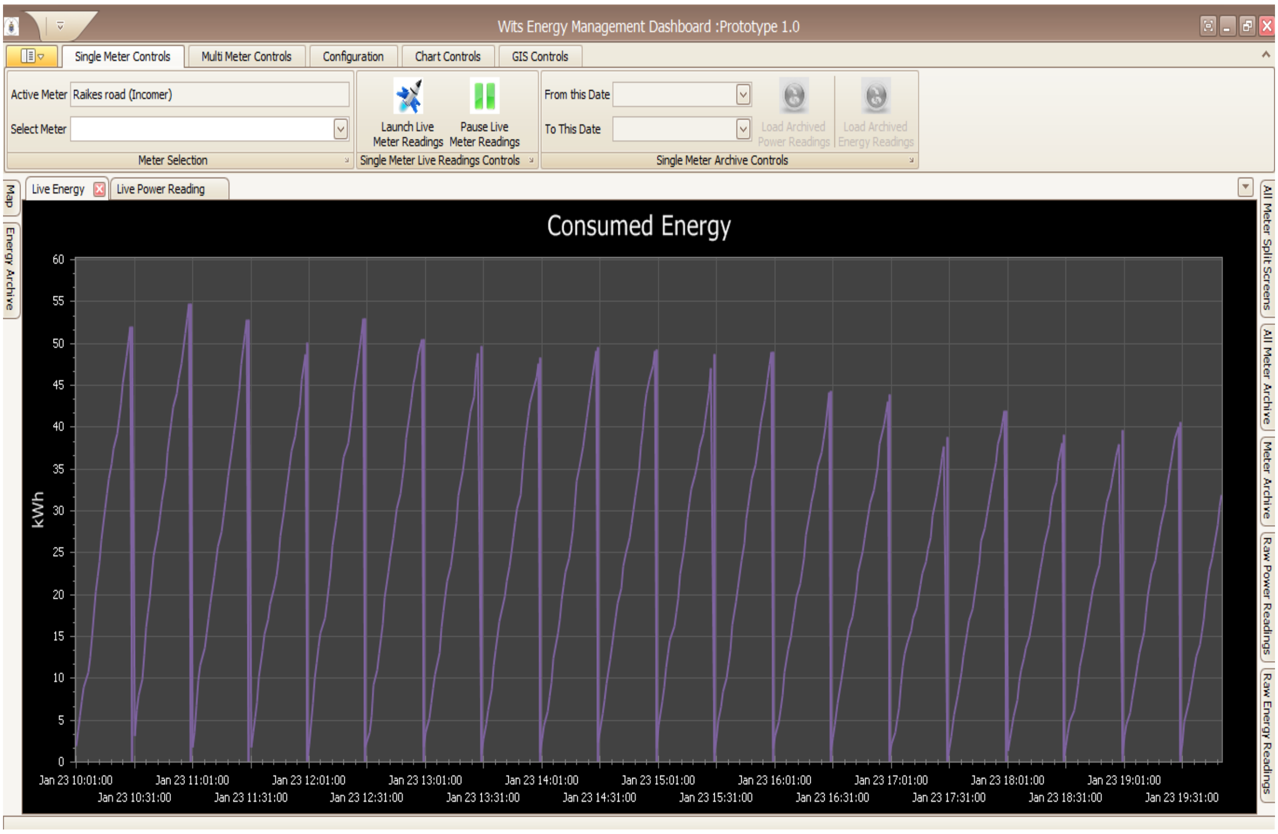

Figure 24: Dashboard Home Screen

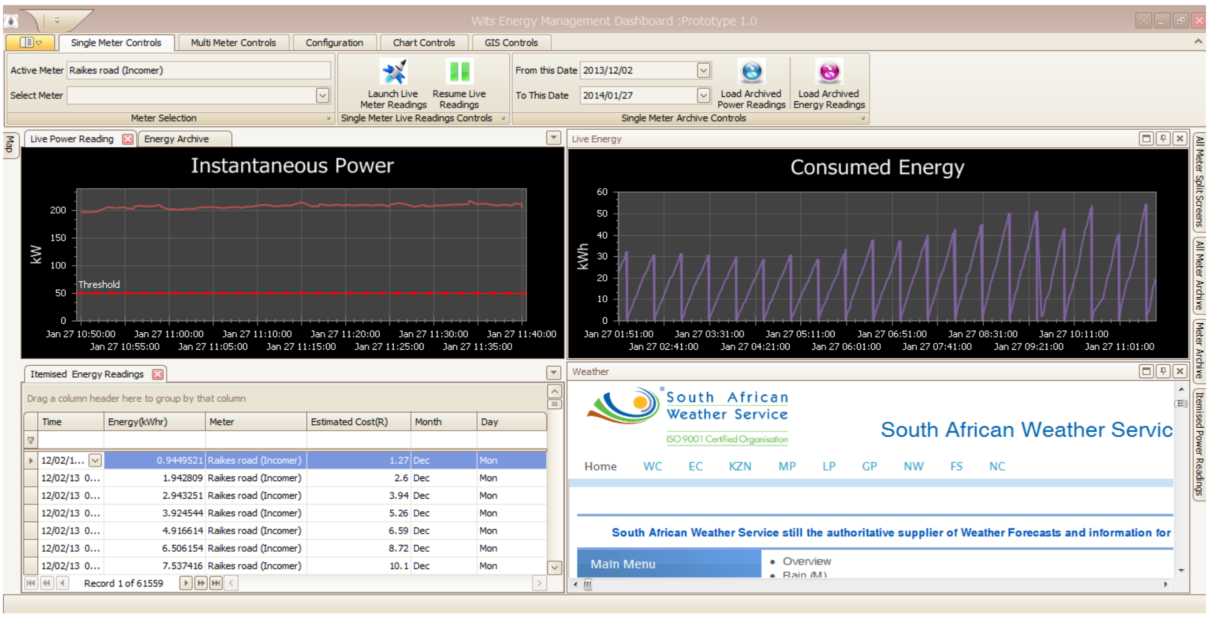

Figure 25: Dashboard with multiple screens docked

For the advanced user the dashboard also allows for data analytics by allowing users to select data and to view it in different chart formats as shown in Figure 26. The same advanced users (e.g. PIMD team) can also interact with the forecasting algorithm by entering values manually instead of depending on forecast details which are automatically fed to the model. This will give a more accurate forecast as values like temperature will be actual values not forecast values. The actual values can easily be acquired via the weather panel as shown in the right bottom panel of Figure 25 above.

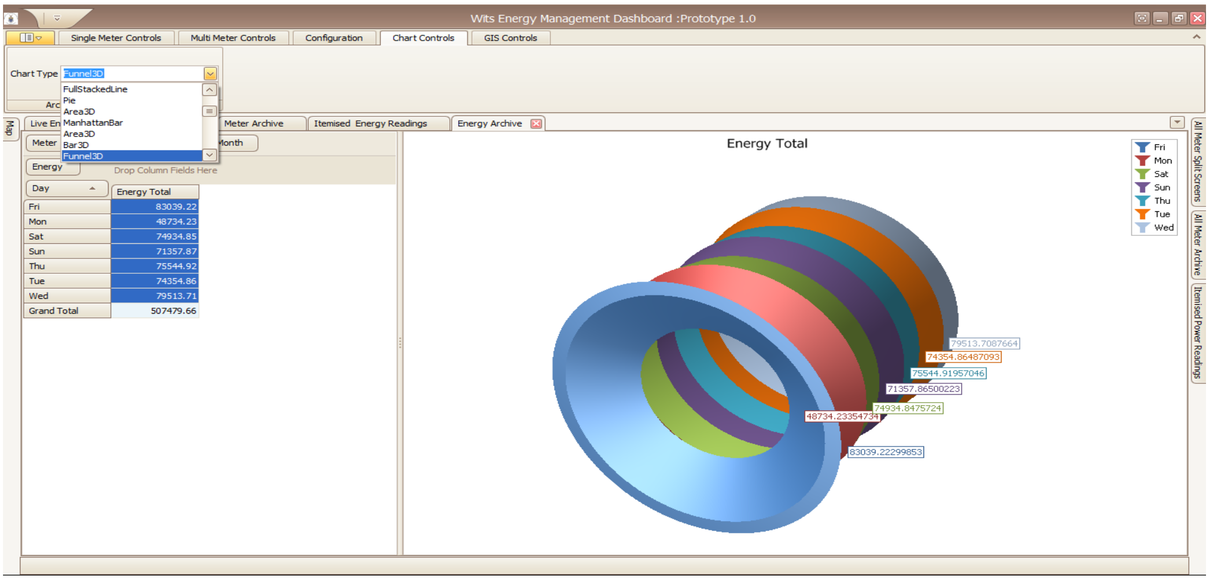

Figure 26: Data Analytics Screen

6.4.2 Business Logic Layer

The business logic layer contains all the rules and is the engine of the whole application in that all the control, logical processing and rule enforcement action is done in this layer. This layer is separated into logic classes such that anytime new rules are added to the application then one will easily change the logic in this class without interfering with the rest of the application. The following functionality is carried out in this layer before any results are passed to the user interface.

- Triggering alerts and warnings;
- Calculating energy costs;
- Selecting appropriate MLR peak energy forecasting model parameters;

- User authentication; and
- Updating GIS components.

6.4.3 Data Access Layer (DAL)

Good programming standards insist that when working with data driven applications developers must not be tempted to embed the data specific logic into the presentation layer even though it always seems to be the faster and easier option [138]. Embedding data specific logic into the presentation layer means that in the future if a decision is made to move away from a specific data provider e.g. from PostgreSQL® to MySQL®, porting will be easier and cleaner since all calls to the database are localised in this layer. In this dashboard application the DAL is where all the loading calls are made to the database. The following calls are implemented here:

- Loading users;
- Loading all meter information(status and location);
- Loading real time power readings; and
- Loading real time energy window readings.

For a detailed breakdown of these classes refer to the source code in Appendix F.

6.4.4 Database Layer

The data storage physically creates, retrieves, updates and deletes data in a persistent data store. Values such as energy window readings, instantaneous power readings and meter information are all stored in this database. PostgreSQL is chosen as the backend for the energy management architecture. The biggest draw card besides its ability to offer the required functionality is that PostgreSQL is an open source software and is also used by many big companies such as Fujitsu, Cisco, Skype and Sun Microsystems to name a few.

6.4.5 Algorithm Logic

As described in section 2 one of the functionalities of the prototype is to forecast the next half hourly peak load based on the developed MLR model. The logic that carries out this forecasting functionality is as summarised in the flow chart below.

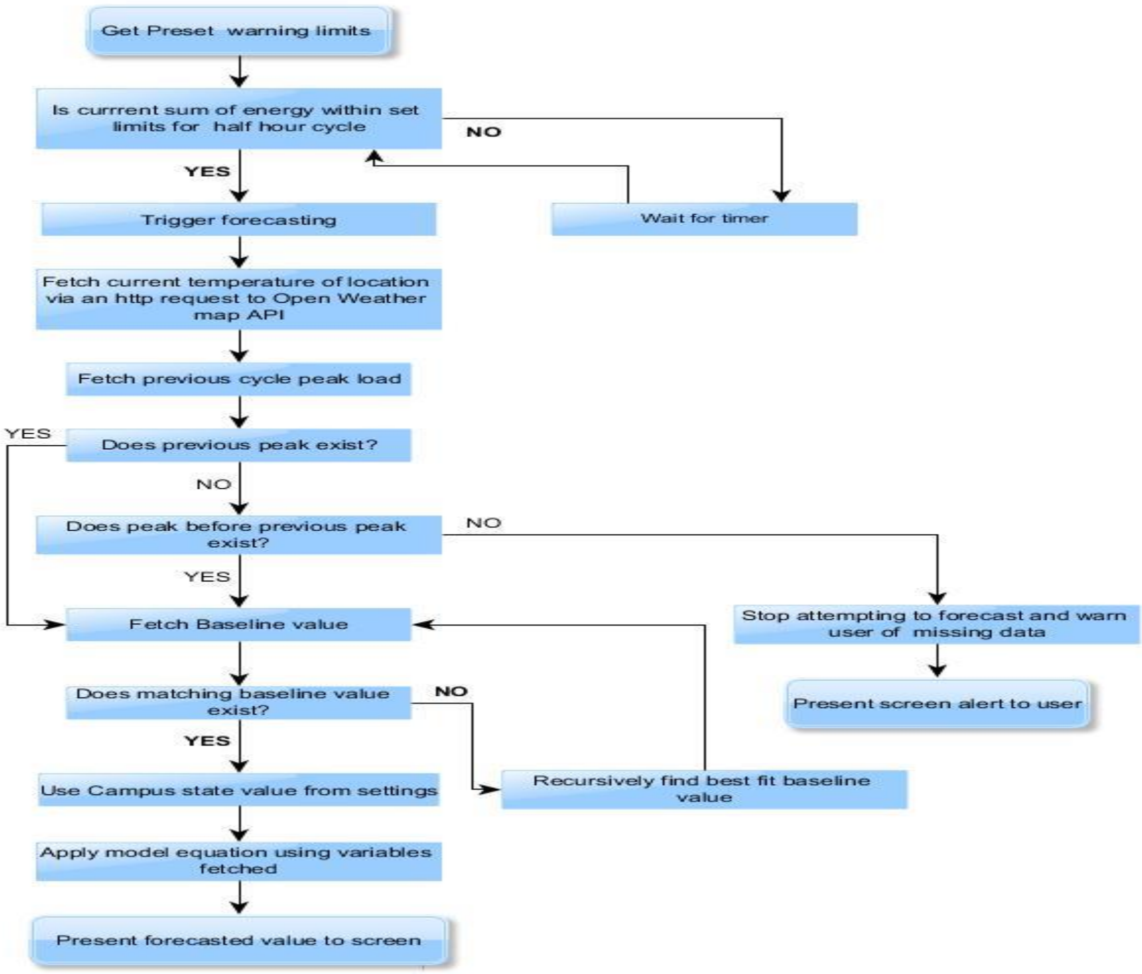

Figure 27: Peak load forecasting logic flow chart

This involves the looking up of baseline values, getting current Johannesburg temperature values from the open Weather application programming interface (API) [139], getting the campus state from the user input settings and applying these values to the MLR model.

6.5 Conclusion

The system design and architecture of the proposed prototype has been discussed. The prototype is shown to be a multi-tier system and each of the layers has been presented. A flow chart representing the logic flow of the MLR model application within the prototype is given. The prototype is successfully developed using the Microsoft® .Net framework in C#. Chapter 7 which follows gives a presentation and evaluation of this prototype.

CHAPTER 7: Evaluation and Results

7. Introduction

Chapters 5 and 6 dealt with the design of a load forecasting model and an energy management dashboard respectively. This chapter looks at the results of the forecasting algorithm and evaluates its performance. It also presents the dashboard prototype and evaluates the results of the usability testing.

7.1 Forecasting Algorithm Results

The MLR model B developed in chapter 5 is applied to the test data. The two scatter plots below show the forecasting variations of the forecasted data.

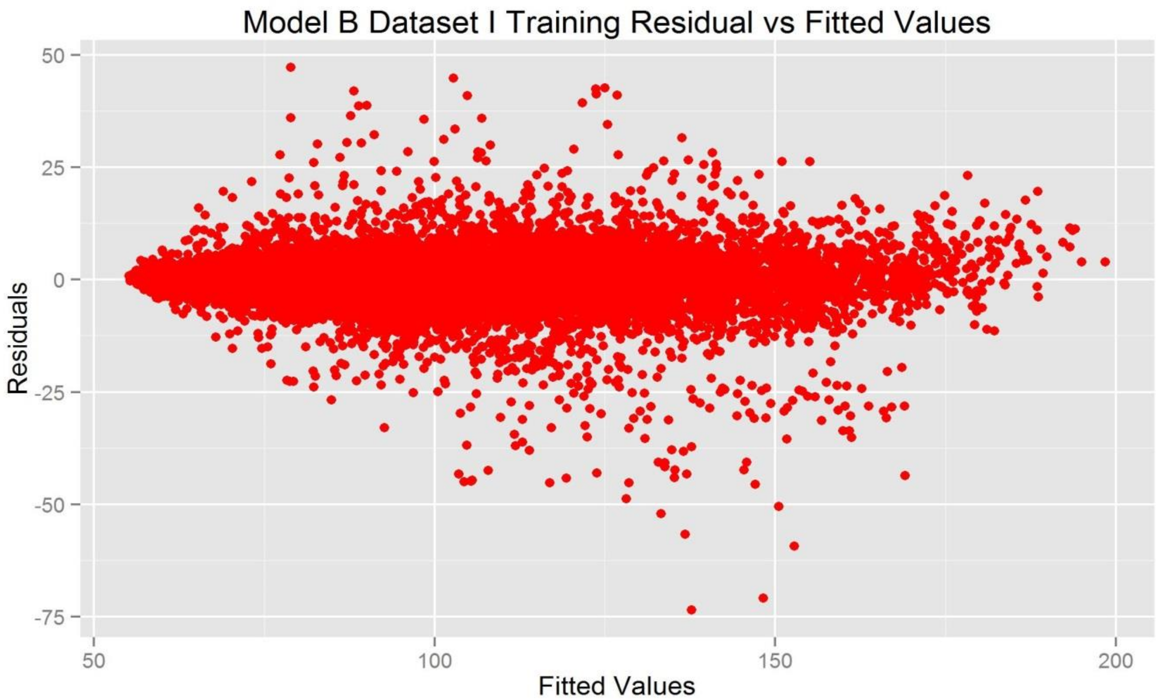

Figure 28: Model B residuals on forecast values

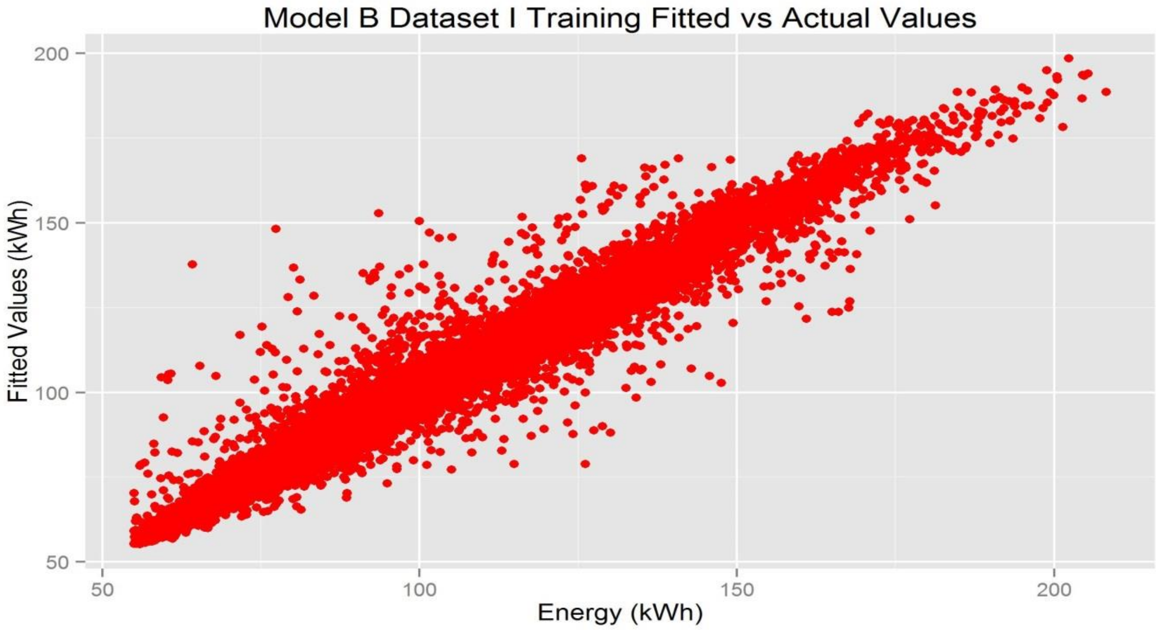

Figure 29: Model B Forecast vs. Actual Values

As can be seen in Figure 28, most of the values are within 10kWh to the actual predicted value which is a small and acceptable value compared to the highest peak values that are important in the load forecast. The plot in Figure 29 shows a very strong fit of the predicted values to the actual values. Using R statistical package [136] the model is shown to have a mean absolute percentage error (MAPE) of 3.69% calculated in R using the equation 4 below. The R code and detailed results are in Appendix D. The mean absolute error (MAE) is calculated to be 3.76 kWh.

$$MAE = \frac{\sum_i^n e_i}{n} * 100 \qquad (4)$$

Where:

$$MAE = Mean\ Absolute\ error$$

$$e_i = error\ values$$

$$n = number\ of\ time\ periods$$

In comparison with model A, model B is marginally better as model A is shown in Appendix C to have a MAE of 3.78kWh and a MAPE of 3.79%.

7.2 Weekly Forecasting Results

Model B is applied to two weeks actual data and the forecast results are as shown in the plots below. The test is run for a week in April 2013 (April 1st to the 7th) and another week in

September 2013 (September 1st to the 7th). The results of the forecast values are then plotted against actual measured values. The plots show a very close match of the two graphs showing the effectiveness and accuracy of the forecasting model.

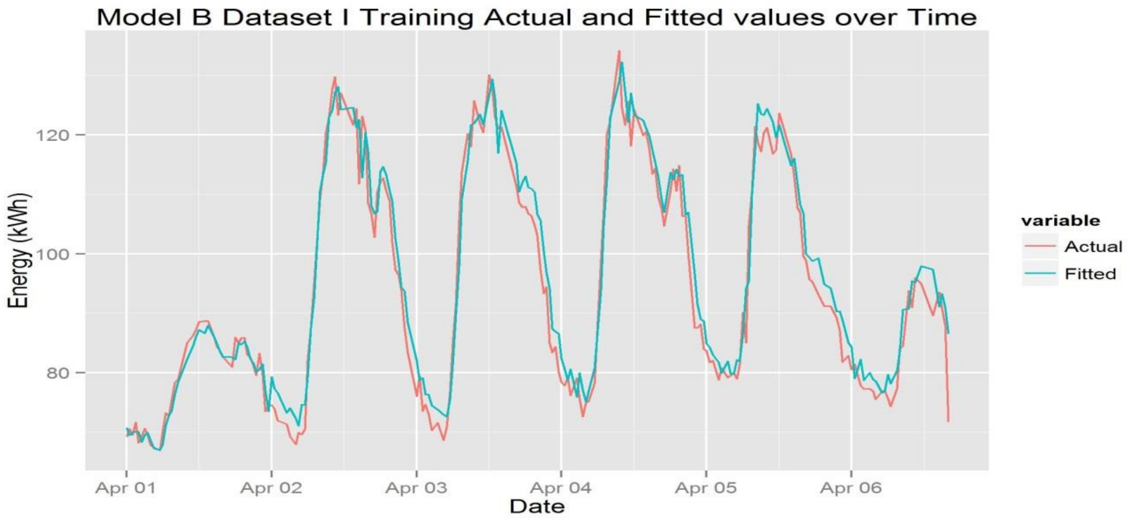

Figure 30: April week 1: Actual and forecasted half hour loads

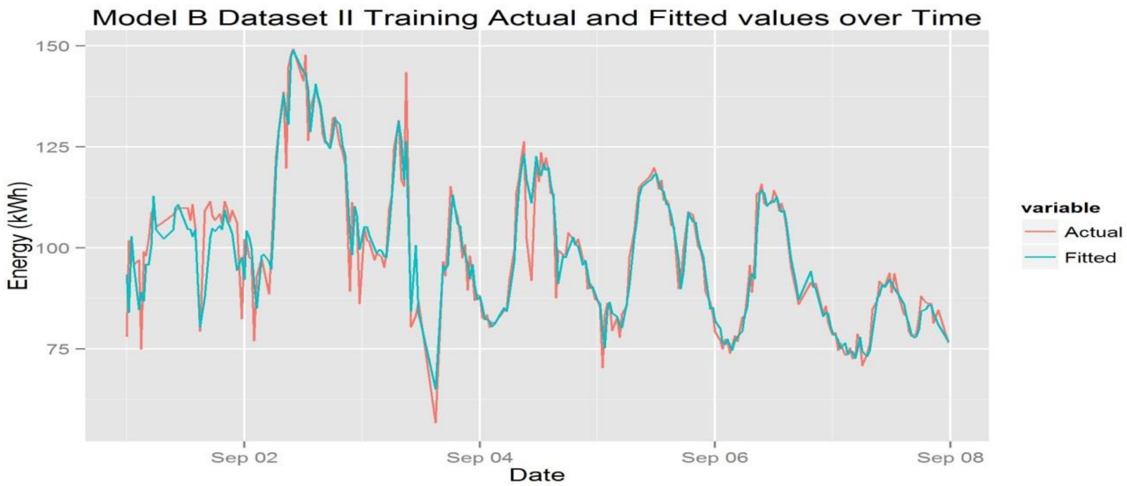

Figure 31: September week 1: Actual and forecasted half hour loads

7.2.1 Forecasting Results Conclusion

This section demonstrates that the designed forecast model is able to forecast half hourly loads within a reasonable accuracy (3.69 % MAPE). The model is applied on test data and results have been plotted and documented to support the use of this model. This answers question 3 of the research questions raised in chapter 3 which asked "*Can smart grid data be used to give accurate half hourly load forecasts?"*. This model is embedded into the dashboard for the forecasting functionality.

7.3 Dashboard Evaluation

A dashboard is designed and implemented using the benchmarking model of chapter 4 as a guideline. Table 15 below shows the functionality that is implemented on the prototype compared to the minimum requirements of the model.

Table 15: Achieved benchmarking model requirements

Feature	Implemented?
Latest Meter reading	Yes
Consumption forecast	Yes
Real time pricing and billing	Yes
Time stamped energy data	Yes
Accessible via PC and mobile	Yes
Historical data	Yes
Security and privacy	Yes
Basic remote control	No
Customisable user interface	Yes

The only functionality that is not implemented is the basic remote control. This functionality involves switching off and on appliances remotely via the dashboard. To offer this functionality a lot of hardware changes are necessary on the university's infrastructure since things such as Programmable Logic Controllers (PLC) are needed. Currently this hardware is not available and a recommendation is given for the purchase of such hardware.

7.4 User Interface Presentation

The user interface presentation is important in the success criteria for a dashboard. The developed prototype uses Microsoft® Windows Forms for the presentation layer which gives a user a lot of control and functionality. The series of pictures below show some of the UI functionality available to the dashboard user.

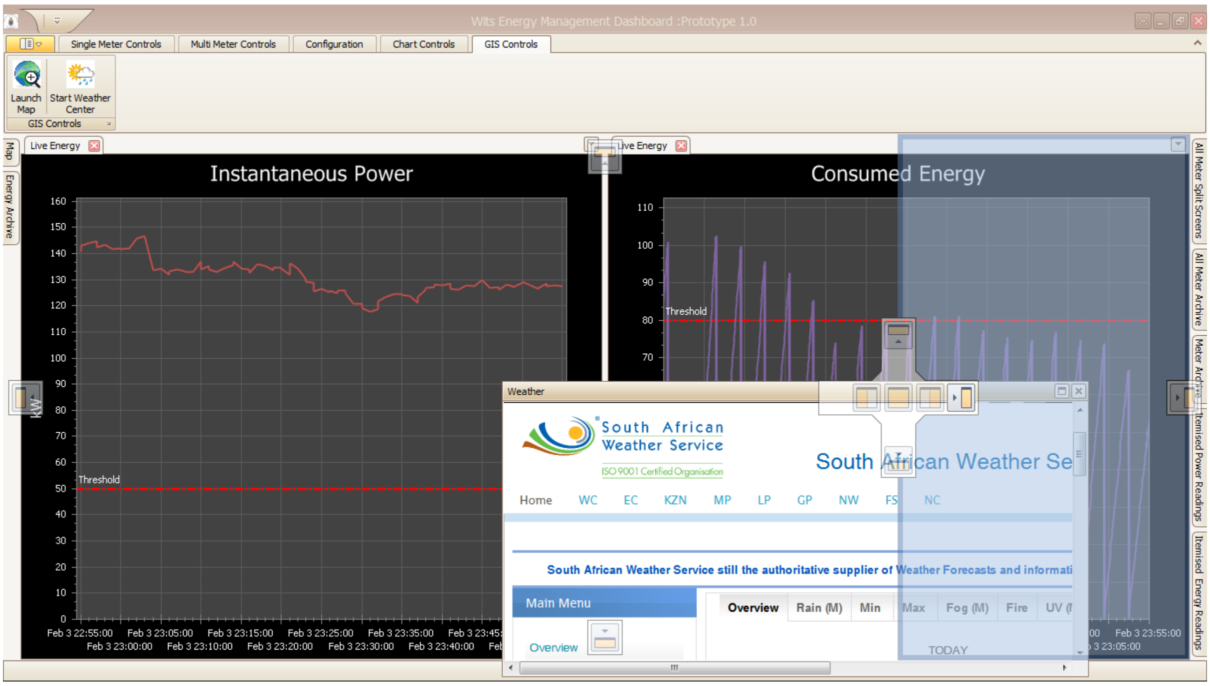

Figure 32: Drag and Drop functionality showing how a user can drag a window to any position

Figure 32 above shows how a user can move the screens to any location. Panels can be distributed across multiple screens as done in big control rooms. The panels can be taken out of the dashboard area onto any other space on the available screens. This functionality gives the user the ability to customise to their preferences as well as to be able to view everything in one glance.

The user is able to view the current power and energy readings at a glance. The time stamp and actual readings are shown as indicated in Figure 33 below.

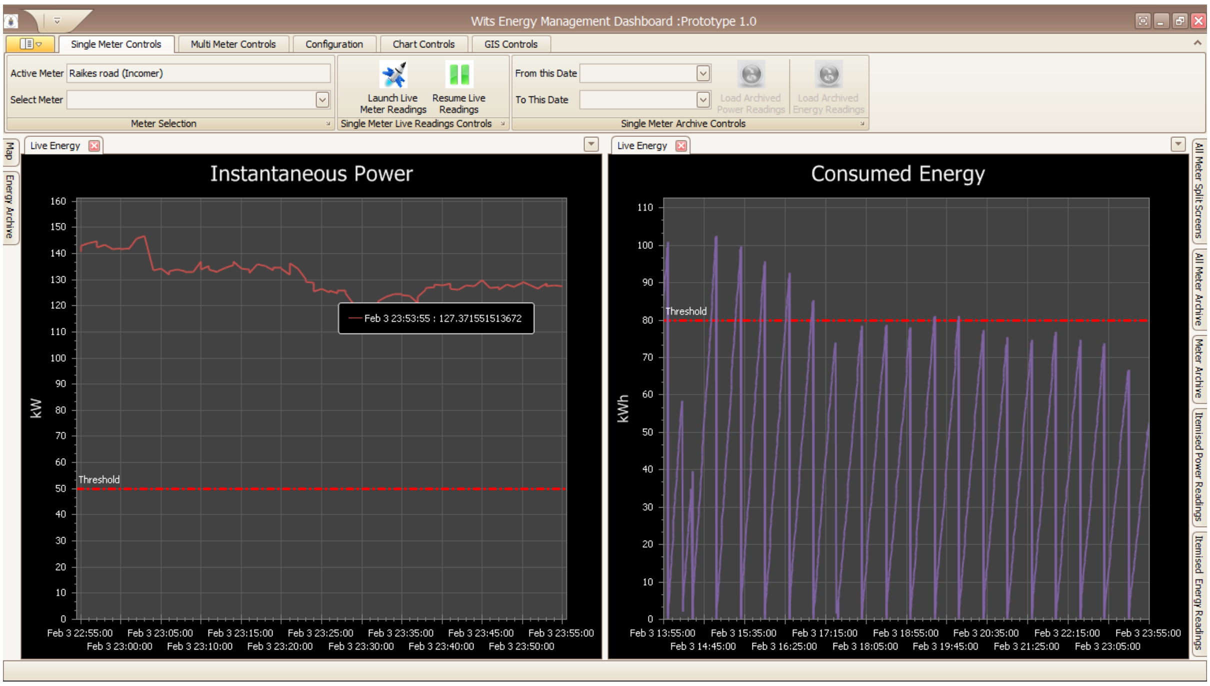

Figure 33: Current meter instantaneous power and energy readings with a timestamp

When a user selects a meter to view the geographical position of that meter is shown on a Google map component as shown in Figure 34 below. The same figure also shows on the left panel an embedded web page which shows the forecast weather for any location the user is using the dashboard from. This is important as users have an option to override the sourced weather forecast and use their own weather values which can be more accurate.

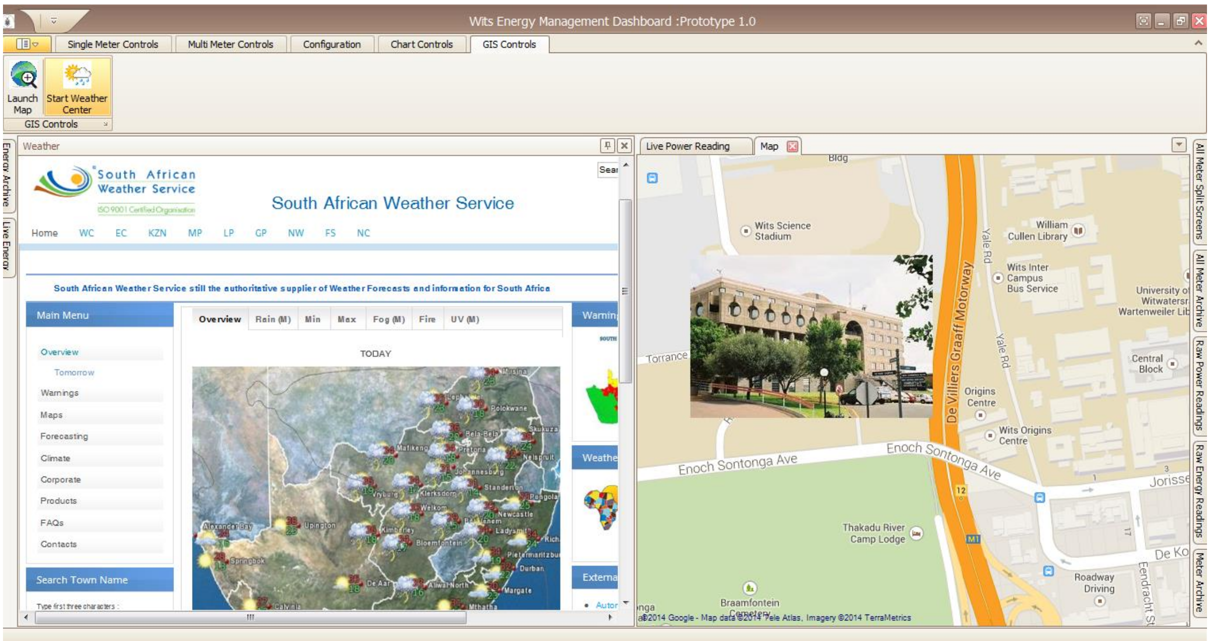

Figure 34: GIS component showing weather forecast and current meter location on a Google map

The dashboard user is also able to visualise the current energy values in an itemised format as shown in Figure 35 below.

Itemised Energy Readings

Drag a column header here to group by that column

Time	Energy(kWhr)	Meter	Month	Day	Estimated Cost(R)
02/04/14 00.00.22	0.7669907	Raikes road (Incomer)	Feb	Tue	1.03
02/04/14 00.00.53	1.854219	Raikes road (Incomer)	Feb	Tue	2.48
02/04/14 00.01.24	2.947065	Raikes road (Incomer)	Feb	Tue	3.95
02/04/14 00.02.20	4.901472	Raikes road (Incomer)	Feb	Tue	6.57
02/04/14 00.02.51	5.978343	Raikes road (Incomer)	Feb	Tue	8.01
02/04/14 00.03.22	7.059029	Raikes road (Incomer)	Feb	Tue	9.46
02/04/14 00.04.14	8.875017	Raikes road (Incomer)	Feb	Tue	11.89
02/04/14 00.04.45	9.966255	Raikes road (Incomer)	Feb	Tue	13.35
02/04/14 00.05.32	11.63663	Raikes road (Incomer)	Feb	Tue	15.59
02/04/14 00.06.03	12.73571	Raikes road (Incomer)	Feb	Tue	17.07
02/04/14 00.06.34	13.83824	Raikes road (Incomer)	Feb	Tue	18.54
02/04/14 00.07.05	14.95072	Raikes road (Incomer)	Feb	Tue	20.03
02/04/14 00.07.46	16.41097	Raikes road (Incomer)	Feb	Tue	21.99
02/04/14 00.08.17	17.50827	Raikes road (Incomer)	Feb	Tue	23.46
02/04/14 00.08.48	18.60132	Raikes road (Incomer)	Feb	Tue	24.93
02/04/14 00.09.40	20.41951	Raikes road (Incomer)	Feb	Tue	27.36
02/04/14 00.10.11	21.49482	Raikes road (Incomer)	Feb	Tue	28.8
02/04/14 00.10.42	22.56562	Raikes road (Incomer)	Feb	Tue	30.24
02/04/14 00.11.18	23.81504	Raikes road (Incomer)	Feb	Tue	31.91
02/04/14 00.11.49	24.89672	Raikes road (Incomer)	Feb	Tue	33.36
02/04/14 00.12.20	25.98256	Raikes road (Incomer)	Feb	Tue	34.82
02/04/14 00.13.42	28.85206	Raikes road (Incomer)	Feb	Tue	38.66

Record 1 of 16837

Figure 35: Itemised energy readings showing estimated cost

In order to use this feature the user must first input the cost of energy in their area as given by the utility. This is input into the settings ribbon bar as shown in Figure 36 below.

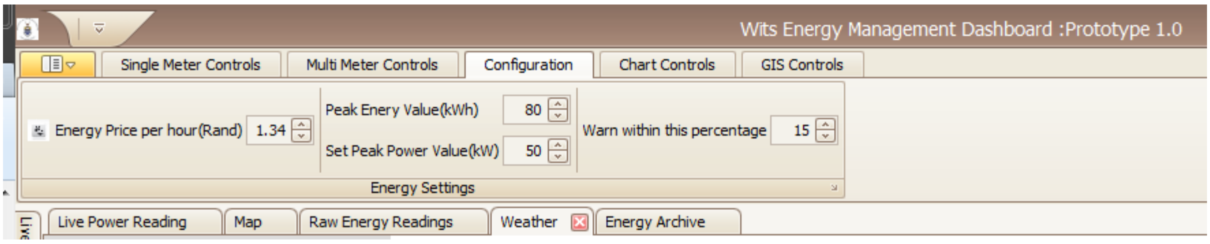

Figure 36: Settings screen

Users can then manipulate the itemised billing to show the total cost based on a number of properties like hour of day, day of the week or month as shown in Figure 37.

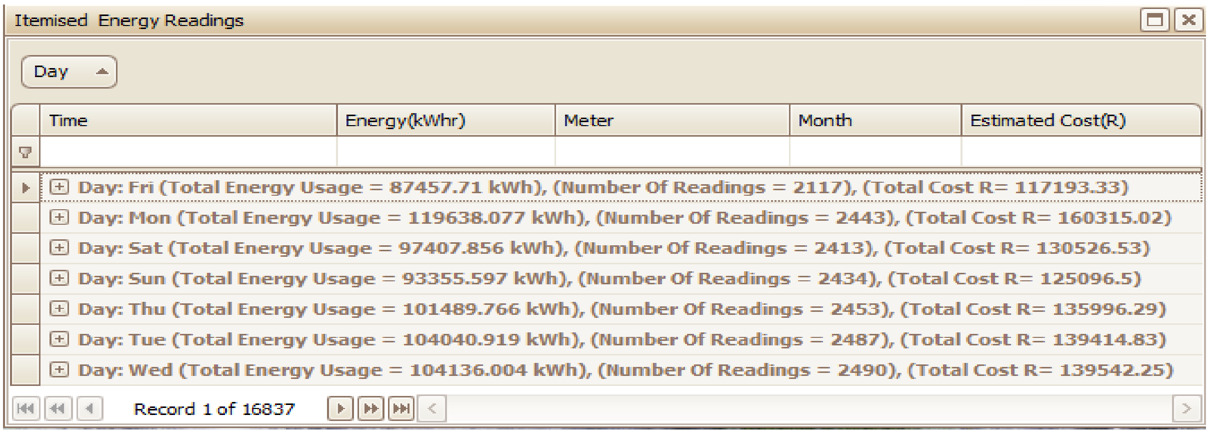

Figure 37: Estimated usage and cost grouped by day of week

Advanced users can also be interested in comparing their usage over time. The dashboard allows for this through the charting and analytics screen as shown in Figure 38 and Figure 39 below. The charting functionality allows the user to view and analyse archived or live energy data using over 10 different charts and multiple pivoting options. The figures below only show bar and pie charts, for more charts that can be generated in the dashboard refer to the screenshots in Appendix G. Figure 38 shows a comparison of usage for 2 months whilst Figure 39 shows a comparison of usage for each week day separated into different months. A lot of complex grouping combinations and pivot tables can be achieved using this functionality. The charts shown below are 3D but users have the option of normal 2D charts.

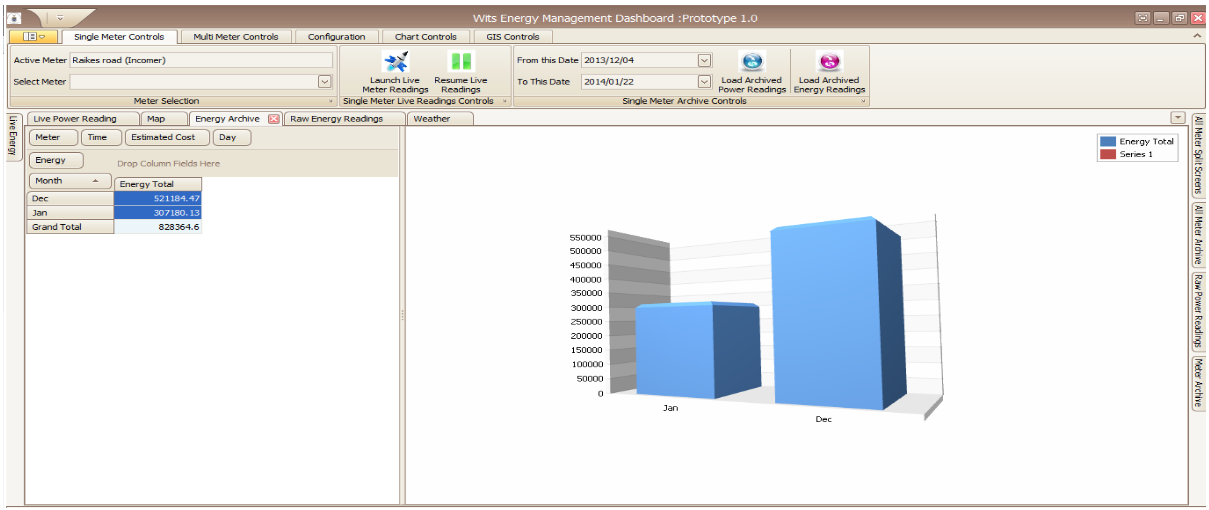

Figure 38: Graph and Charting Capability for analysing past usage

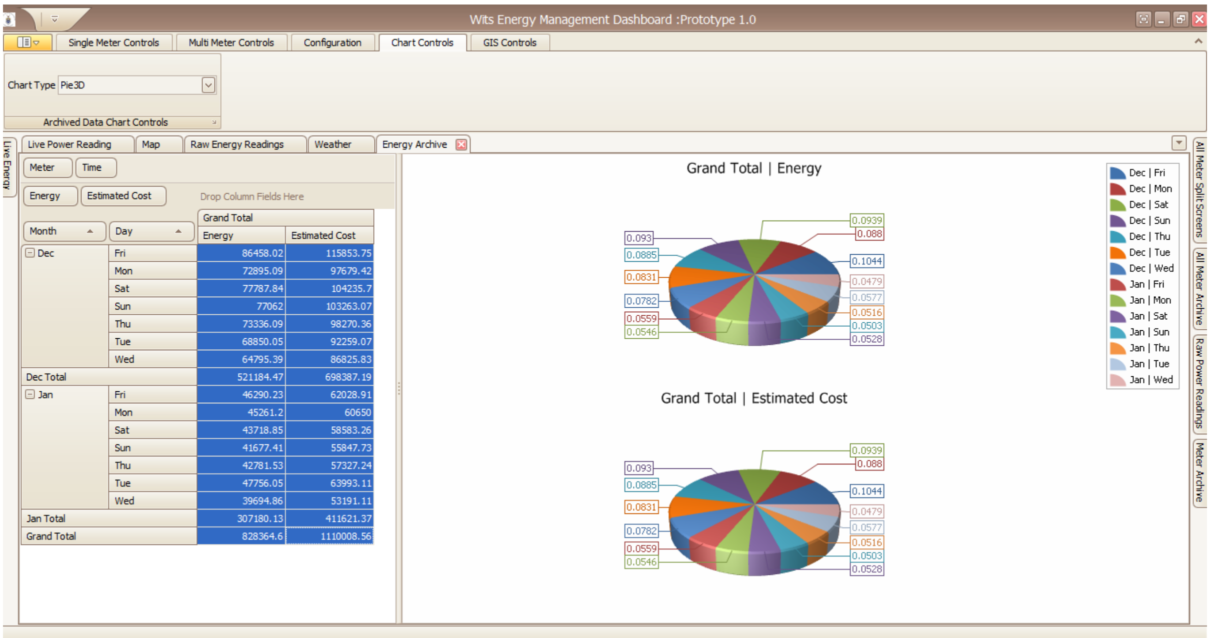

Figure 39: Comparative Graph and Charting Capability for analysing past usage

This analytics functionality is not limited to only single meter data. It can be used to compare historical usage for multiple meters. This is important for reporting and strategic planning.

7.4.1 Dashboard Presentation Conclusion

The presentation of the dashboard interface starts to answer question 4 of the research questions raised in chapter 3 which asked "*Is a dashboard an effective way of visualizing* *smart grid data based on smart grid data collected from the University of the Witwatersrand smart grid network*?". The dashboard is shown to be more than fit to be used to for visualising smart grid data. It has been shown to be able to visualise both live and archived load data. The effectiveness of the visualisation is answered by the usability tests carried out in the next sections. The analytics section of the dashboard also shows that the dashboard can be used to be a very effective reporting tool on energy usage.

7.5 Usability Evaluation

The dashboard is evaluated for usability and potential usefulness using a variety of techniques namely user observations and questionnaires. The results of this evaluation are important in order to get user feedback and to fine tune the prototype before it goes into production. This section details the evaluation methods used and feedback received from a wide range of potential users.

7.6 Usability Feedback

Ten people from different walks of life were approached to be testing participants. The approach taken in getting user feedback is to demonstrate the prototype then train the user on how to operate it. The user is then given time to interact unaided with the dashboard and thereafter asked to fill in a questionnaire. The questionnaire is based on the measurement scales discussed by Davies [119] that help in measuring perceived usefulness of a system. The questionnaires and responses are attached in appendix H.

The PIMD and energy management team were involved in the design and development of the dashboard from scratch and are already using the online dashboard version so they are excluded from the testing participants so as to get a fresh perspective of independent people. The energy teams' continuous feedback via emails and all the design meetings held are attached in Appendix I.

7.6.1 Test Procedure

The following steps were followed in carrying out the usability tests

Prepare usability questionnaires;

- Select and approach testing candidates;
- Demonstrate and train candidates;

- Allow candidates to operate dashboard;
- Observe and document candidates as they operate dashboard;
- Get candidates to fill in the questionnaires;
- Also get verbal feedback from candidates;
- Analyse questionnaire responses; and
- Write up results and recommendations.

7.6.2 Test cases

In order to get the best out of usability testing, test cases must be developed and stated. The test cases must cover the most important functionality and not be too broad that the user can lose concentration. The approach taken in this usability study is to list down the important tasks which the user must at least attempt and then they have the freedom to try any other functionality. Only three tasks have to be done in a specific order but the rest of the tasks the user is allowed to perform in any order. The important test cases are tabulated in Table 16 and the order indicated.

Table 16: Test cases

Test case	**Order**
Start and log into application	1st
Select meter	2nd
View live power readings graph	3rd
View live energy readings graph	Any
View forecasting details	Any
Set warning limits and alerts	Any
View itemised energy readings	Any
View itemised bill by day	Any
View itemised bill by month	Any
Analyse archived readings using at least one chart	Any
View weather forecast	Any
View meter position in Google maps	Any

The users are given a checkbox form to indicate which of the tasks they achieved as well as to make any comments. These forms are attached in Appendix H.

7.6.3 Test Environment, Data and Equipment

All the tests are carried out using the University of Witwatersrand advanced meter infrastructure and data. The participants are each given time with the researchers' laptop as their own computers do not have access to the university network. The testing is done at the participants' own premises (office, home and campus) since the University's smart meter network can be accessed remotely.

7.6.4 Analysis of Usability Test Results

In order to quantify the participants' responses from the questions in the questionnaires of Appendix H, the responses are taken as a fraction of the total available score. The scores are then summed up for all the participants and average percentage values plotted for analysis. Excel spreadsheets used for analysing the results are in Appendix H. The charts below show these plots question by question. Each question is given a percentage score ranging from a very negative response (0%) to a very positive response (100%). This is done for each section of the questionnaire. All ten participants responded to all the questionnaires and the responses were consistently positive. The charts below analyse each questionnaire subsection.

7.6.5 Task Completion Difficulty

Figure 40 below shows the average response values for the difficulty level in completing the tasks the users are given. On average all the users found the tasks achievable without too much difficulty. The most difficult task as seen from the chart as well as from the observations seemed to be using the statistical analysis functionality to analyse usage data using charts. The majority of the users did not have a statistics background and were not familiar with using statistical tools such as pivot tables.

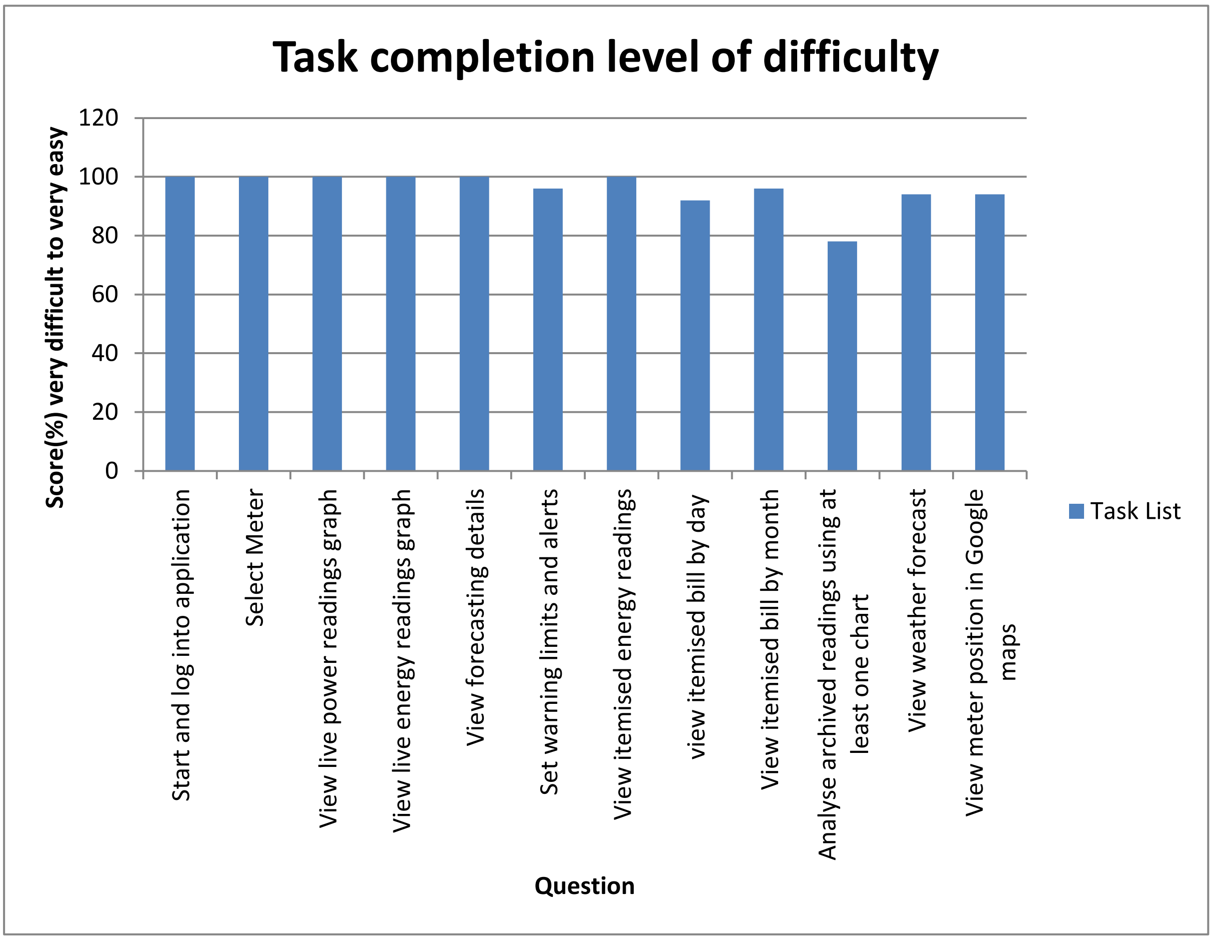

Figure 40: Task Completion Level of Difficulty

The users all asked for help in using this functionality but the encouraging observation is that once they were shown again how to use the functionality they all managed to then use successfully.

7.6.6 Screen Organisation

The responses for the screen organisation were all above 80% satisfaction. From observing the users they were all excited with the ability to customise the screens to suit their preferences.

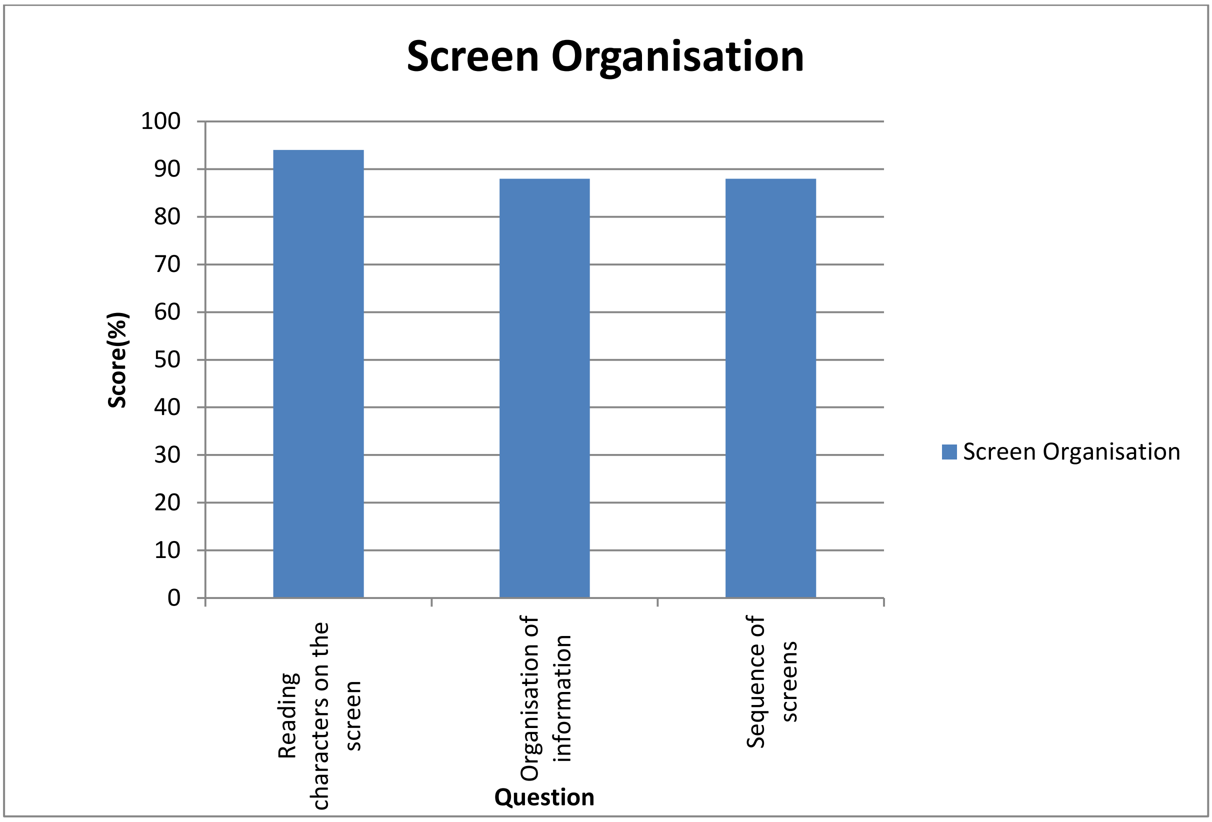

Figure 41: Screen Organisation feedback

7.6.7 Adherence to Technology and Information Standards

The test participants were on average happy with the way the dashboard stuck to the normal standards in terms of the terminology and icons used in the dashboard. One user commented that all the icons were either normal Microsoft® Windows standard icons or self-explanatory icons which made it easy for him to use the application. Figure 42 below shows a chart of the question and response values.

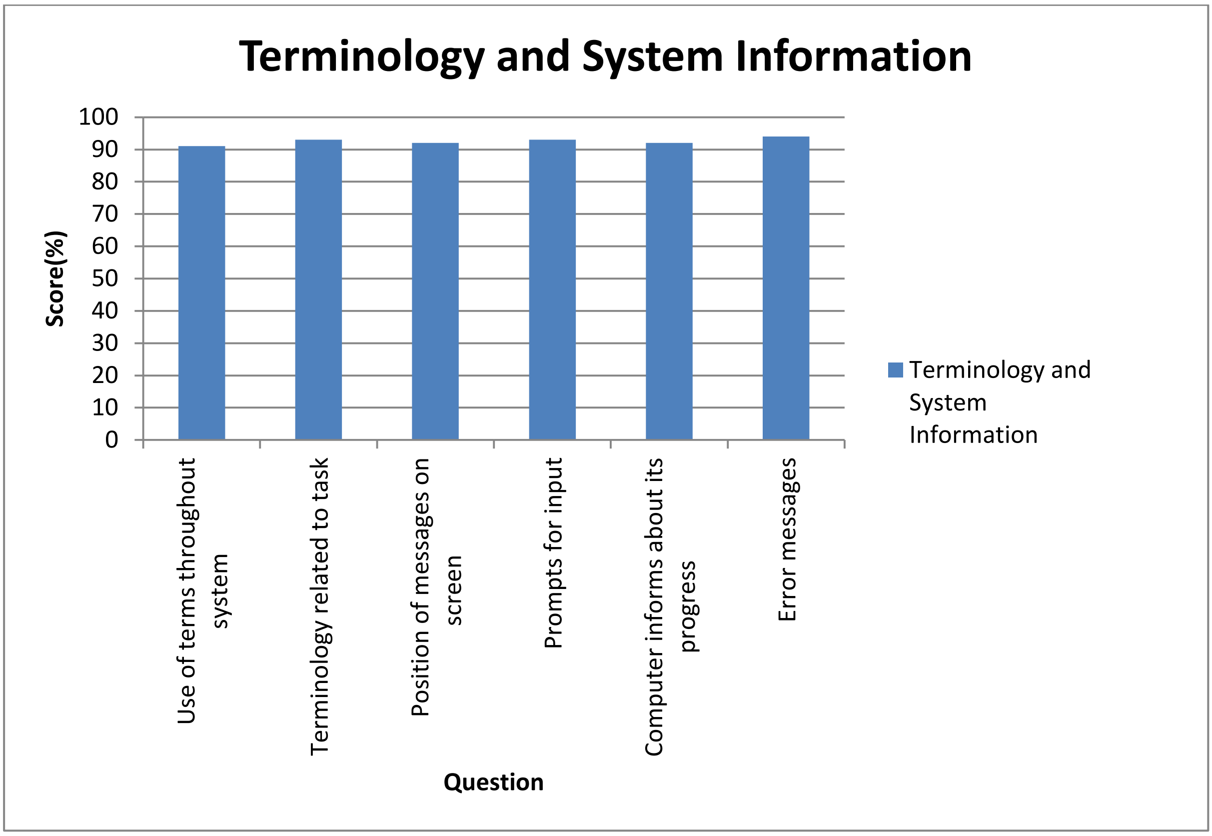

Figure 42: Adherence to technology and information standards

7.6.8 Learning Difficulty

The participants found the dashboard to be easy to use although they did feel a detailed user manual would help in making it even easier. Participants also asked for a more detailed progress bar when the dashboard is carrying out tasks that requires the user to wait. Currently only a wait cursor is shown.

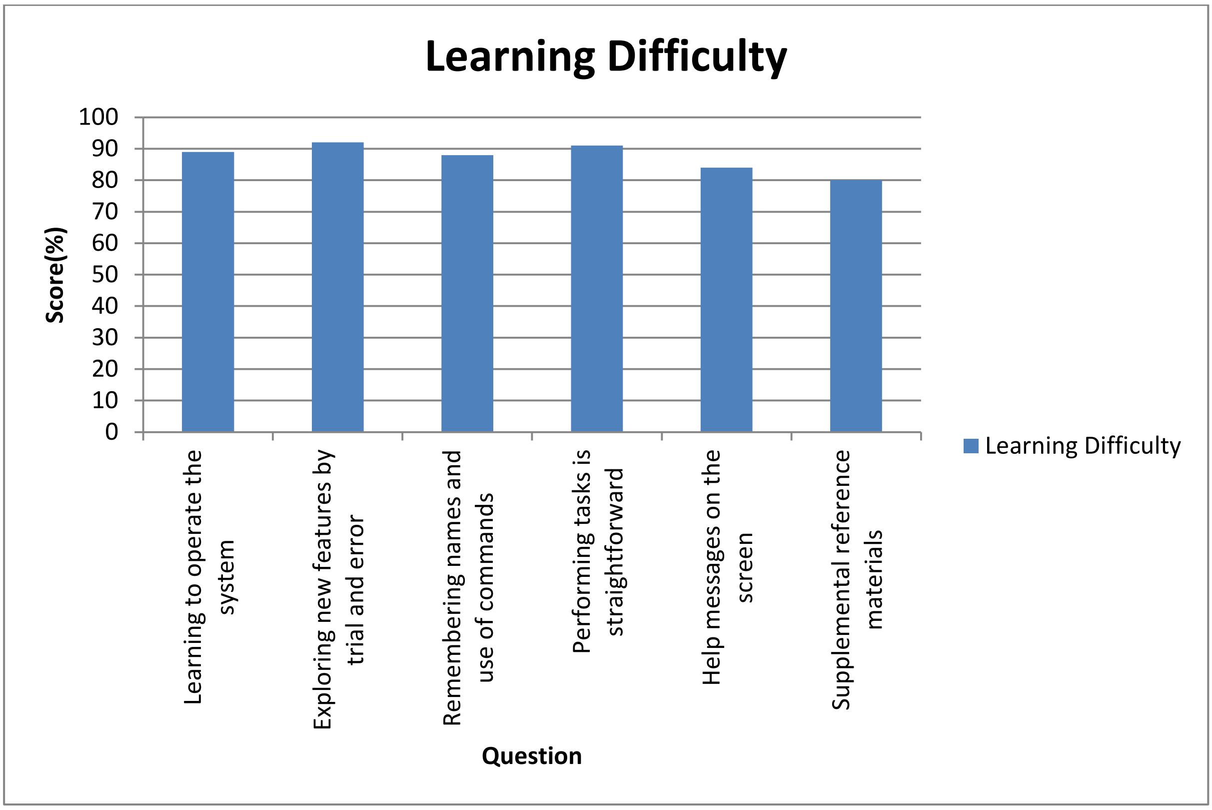

Figure 43: Learning difficulty

7.6.9 System Capabilities

The response scores for this section were on average lower than for all other sections reviewed so far. The participants were not happy with the speed and reliability of the system. Looking at their feedback and speaking to them it was not a matter of the system not working but the system responded slowly and would freeze when updating the live readings. This problem is however because the users were using the dashboard off site (connected remotely to the Wits network). This made the data updates very slow compared to someone using it locally on the University of the Witwatersrand network. The other issue was that due to technical issues at the university, most of the meters are down and the users could only interact with 2 meters. This made them rate the reliability low. It was explained to them that the dashboard simply read what was available online. Figure 44 shows the response scores for this section.

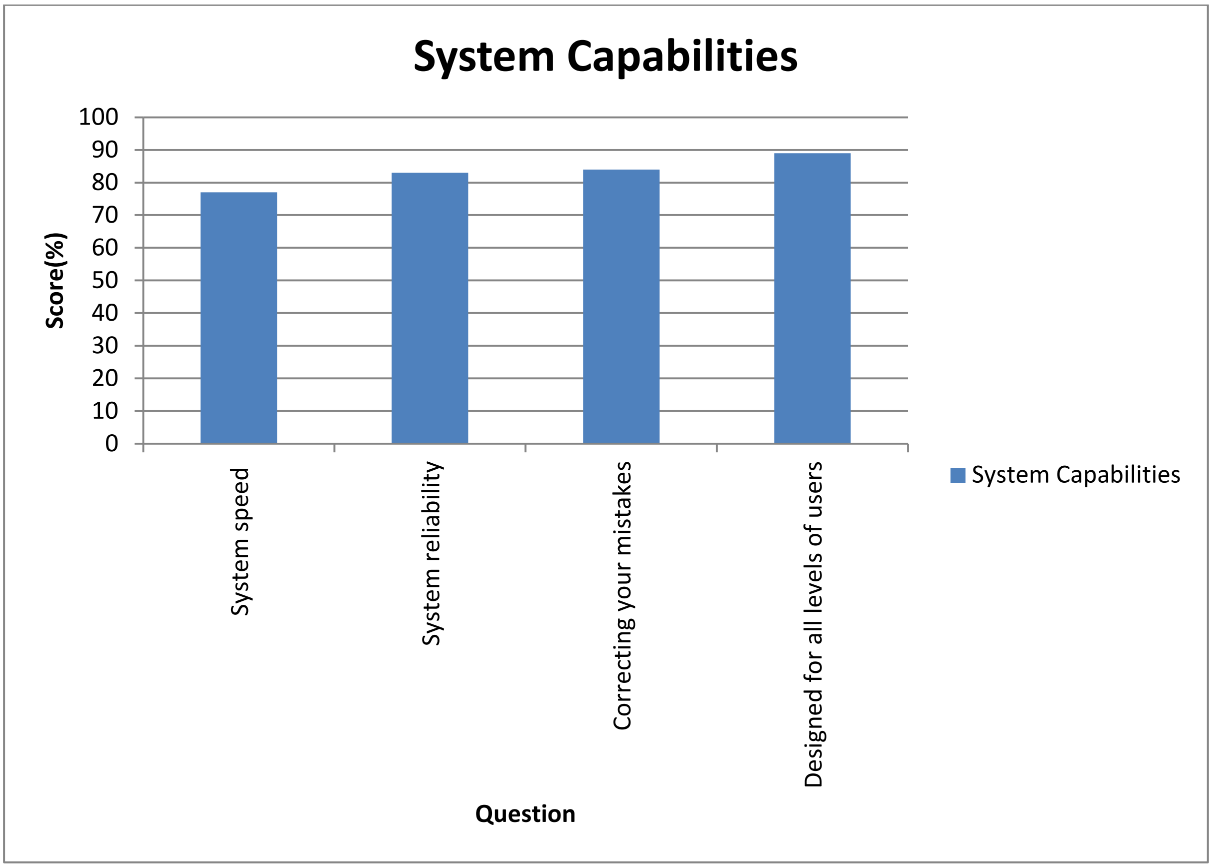

Figure 44: System Capabilities

7.6.10 Perceived Usefulness

The response with regards to how the participants perceived the usefulness of the dashboard was particularly pleasing. Irrespective of their backgrounds all the participants could see the value in having such a system in their homes and offices. Some of the participants could already picture how such a system if it was connected to smart devices in their homes could help them cut down on energy usage. The response scores are as shown in Figure 45 below.

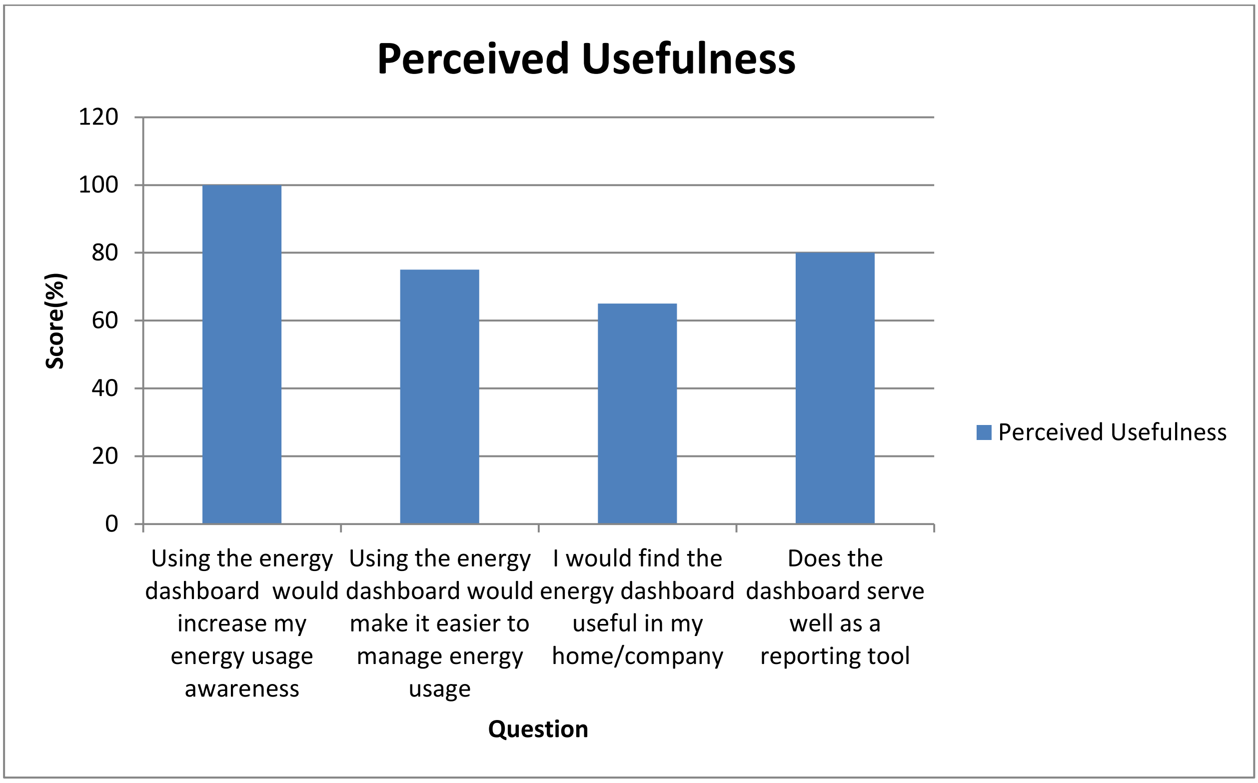

Figure 45: Perceived Usefulness

Although the Energy management team did not take part in this process it must be noted that they have been giving feedback continuously as they use the system and a great example of the usefulness of the dashboard can be found in Appendix I in an email dated 27 June 2012 in which Prof Cronje (Head of energy team) noticed an unusual dip in energy usage via the dashboard and raised the alarm. This was later explained by Barney Marques of the PIMD as a problem caused by a contractor whilst trying to gradually migrate campus load from City Power to a backup generator. More details are in the same email trail of 27 June 2012 in Appendix I.

7.6.11 Perceived Ease of Use

This section is also another one with low scores. All the participants said that given time they would find it easy to get the most out of the dashboard but initially it would take time to adjust. Analysing the scores closely and mapping them to the background of the participant it could be seen that most of the low scores came from participants with little or no technical background. The scores are shown in Figure 46 below. Appendix H details the test results and the forms also show the participants occupation.

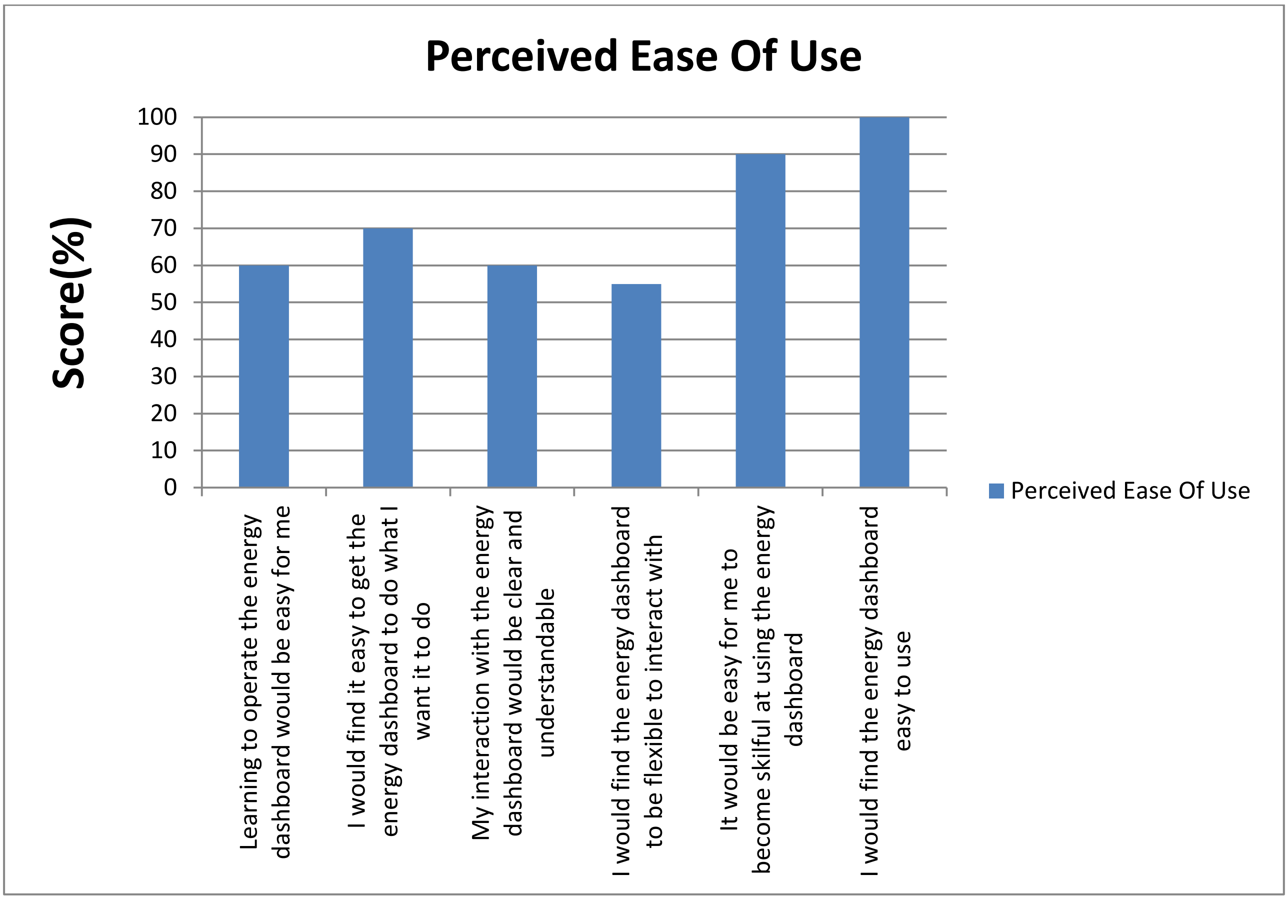

Figure 46: Perceived Ease of Use

7.6.12 Overall Reaction to the Software

All the participants were happy with the dashboard and its functionality. The general feedback was that this is something that is very practical and something they would all use if it was made available for their home use. Most of the user reaction is captured in the comments they made on the questionnaires of Appendix H.

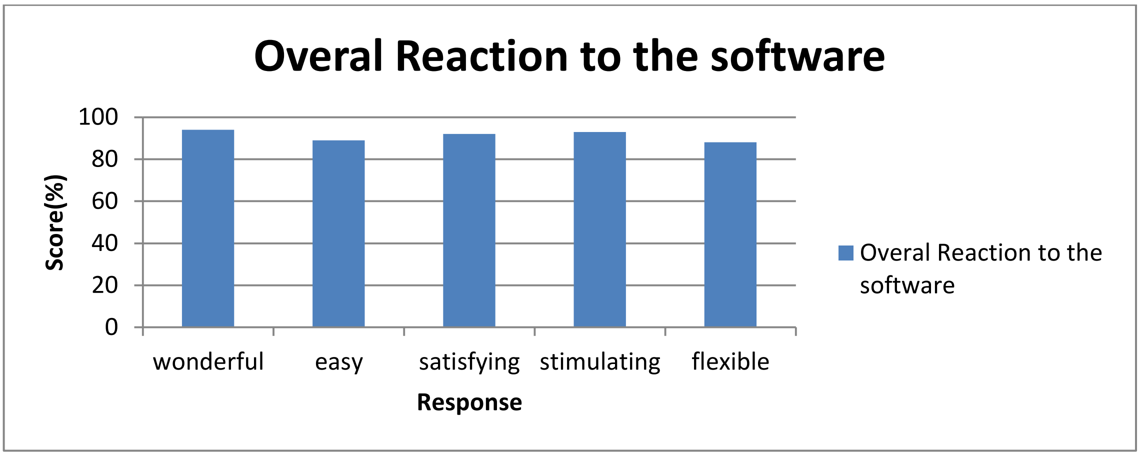

Figure 47: Overall Reaction to the Software

7.6.13 Usability Evaluation Conclusion

A user evaluation of the developed prototyped has been carried out. The general feedback is positive and users are very receptive to the proposed dashboard and its functionality. Users can already picture how visualising their usage in real time can change their behaviour hence leading to saving energy as well as cutting down their costs. The user acceptance valuation has served to answer questions 1 and 4 of the research questions which asked "*Is a smart grid energy dashboard a usable and acceptable tool for real time monitoring of energy usage at the University of the Witwatersrand?" and "What are the user benefits of having a smart grid data monitoring dashboard at the University of Witwatersrand?*". The dashboard uses a Microsoft® Windows feel and look (ribbon control themes) and the users found this to be familiar and easy to use since it feels like Microsoft® Excel and Microsoft® Word interface. The only negative feedback is the connectivity speed as well as reliability of the meters.

7.7 Technical Recommendations

After evaluating the performance of the forecasting algorithm as well as carrying out a usability study the following technical recommendations can be made:

- Archiving of historical usage data is very important for training an accurate forecasting model. It is thus advised that all the smart meter data be archived properly to avoid missing any data. With a complete profile of usage data a more accurate forecasting model can be achieved;
- The meters sometimes record zero values if the network through which they send data is busy. It is advised that for institutions like the University of the Witwatersrand with hundreds of meters they should have a dedicated intranet network infrastructure for smart meters;
- In order to offer remote control functionality for switching off or on devices remotely new hardware such as PLCs must be purchased; and
- The analytics functionality of the dashboard is difficult for most users thus on training potential users care must be taken to spend enough time on this functionality to get all users up to speed.

7.8 General Recommendations

Judging from the user reaction, the functionality offered by the energy management dashboard is something that ordinary users would appreciate in their homes and offices. Energy usage behaviour can be altered leading to direct benefits such as reduced bills for the user and less energy demand for utilities. It is recommended that utilities such as Eskom who have been on an energy saving drive should introduce dashboards like the one proposed in this research to their consumer. Although at the moment the dashboard is being used by the energy management group only at the University of Witwatersrand, the usability tests and user feedback indicate that if the dashboard was available online for all students to see their direct energy usage it would change their behaviour resulting in overall reduced energy usage. It is thus recommended that the energy management group offer this dashboard online for all students to see energy usage for their particular building. It is also recommended that they put up monitors on all buildings showing the current energy use in the building. These online dashboards would allow the students to see the real time energy as well as read only functionality such as querying for archived data. A conference paper accepted for publication at the Pan African International Conference on Information Science, Computing and Telecommunications 2014 in Tanzania is attached in Appendix J and gives a summary of the research carried out in this dissertation.

CHAPTER 8: Conclusion

The University of the Witwatersrand has installed hundreds of smart meters across all their campuses. They have also installed multiple 2.2 MW generators to act as the university's own independent power supply. It is important for the university to reap some tangible technological and financial benefits from this advanced metering infrastructure. The City Power utility bills the university based on the highest half hour load peak reached in a day which is then used as the average for the reminder of the day. This has led to the institution paying millions of Rands in electricity bills. Using the prototype dashboard proposed in this dissertation, the university's energy profile can be lowered. The amount that the load profile is lowered by depends on the percentage of the peak load the PIMD decide to shave based on the forecasted load.

The research gives an introduction and background of the smart grid technology and in particular the University of the Witwatersrand's Advanced Metering Infrastructure is detailed in chapter 1 of this dissertation. Chapter 2 demonstrates an extensive survey of literature which looks at the following important segments of this research:

- Data visualisation with an emphasis on smart grid data;
    - Importance of data visualisation
    - The goal of data visualisation
    - Hallmarks of a good data visualisation tool
    - The evolution of data visualisation
    - The state of smart grid data visualisation technologies
- Dashboards;
    - Information dashboards
    - Types of dashboards
- Load Forecasting Algorithms;
    - Statistical methods
    - Artificial Intelligence
- Technology acceptance;
- The state of the Smart Grid in South Africa; and
- Similar Research

Chapter 3 describes the research questions that this dissertation attempts to answer as well as the research methodology used to answer these questions. A build, test and recommend approach is taken to carry out the research. Chapter 4 describes the proposal and design of a demand side dashboard benchmarking model. Chapter 5 and 6 then detail the specifications for design and implementation of a load forecasting model and the dashboard respectively. The evaluation of the dashboard prototype and forecasting algorithm are then given in chapter 7.

The proposed prototype dashboard has a half hourly load forecasting mechanism. The forecasting functionality provides accurate half hourly load forecast results which if used by the PIMD team to shave load peaks can result in reduced bills for the institution. The prototype also uses advanced real time smart grid data visualisation techniques which have been shown in the usability tests to have the potential to change user behaviour for the best. If the university implements the recommendation to make the dashboard online for all of the university community this behavioral changing effect can have direct financial benefits to them as they will start being energy wise.

Two MLR forecasting models, Model A and Model B are proposed and implemented. The models achieved a low mean absolute percentage error of 3.79% and 3.69% respectively even though there is a lot of missing data. If the university can archive historical data better and also have an independent network for the meters to avoid downtime there would be a more complete dataset. A complete dataset could improve the algorithm training and further reduce the forecasting error.

The developed prototype is a desktop application but an online version is also available. The online version is a basic dashboard showing only the real time energy usage graphs without the full range of functionality available. In the future the online version can be improved to have all the functionality that the desktop dashboard poses. The developed dashboard does not possess any remote control functionality for turning on and off devices remotely. Research into this can also be done in the future and the functionality added to the dashboard.

In this research a conceptual energy management dashboard benchmarking model has been proposed and used to implement a working prototype. The benchmarking model details all the requirements for building a working dashboard. The dashboard has been shown through usability tests and usage by the energy management team to be an effective tool for forecasting and monitoring real time energy usage. Potential users are shown to be receptive to the technology and are excited about the cost saving potential of the tool.

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Appendix A: Dashboard Proposal to the energy group

Software Requirements Specification (SRS)

(Modified IEEE Standard 830-1998)

Wits University Energy Management Web portal

Author: Rodwell Mangisi

Date : 24 June 2012

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6 Logging

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8 Proposed timeline

1 Document Control

Change History

Revision	Date	Author	Description
0.00	26 June 2012	Rodwell Mangisi	First draft of the specification document

Reference Documents

Document Title	Document (Full File Name)	Date

Version Control

Document Sections	Release Date	Software Version

2 Business Context

This document fully details the specifications and required functionality of an energy management dashboard and website to be used by the Witwatersrand University Property and Infrastructure Management Division team (PIMD) for monitoring and controlling the real time power consumption across all the university's campuses. The website will also be open to ordinary users for viewing energy and power consumption across all campuses.

3 Application Overview

3.1 System diagram

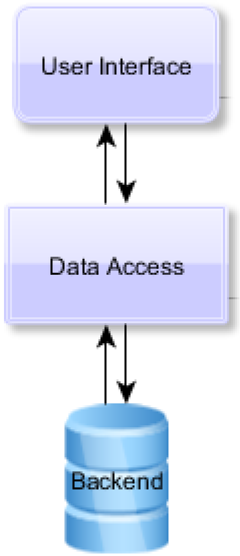

Figure 1: System Diagram

3.2 Application Overview

This application is a new concept and development for Witwatersrand University. It will serve the following purposes:

- Provide actionable information on the energy performance of the building systems and the facilities
- Proactively monitor and detect the energy and power readings/consumption.
- Integrate energy information for reporting and management utilization

3.3 Features

The application will have a minimum of the following functionality/features. These features are explained in detail in section 5:

- Real time power readings visualization per campus.
- Real time energy readings visualization per campus.
- Peak consumption approaching predictive warning and alert system.
- Overall campus consumption comparison.
- Give alert if backend meter polling is down.
- Allow the display of graphs (in computer science terms). Buildings on campus (nodes) are connected in a tree structure with campus feeds forming the roots. Displaying the tree will help us determine how the energy per incoming feed is consumed.
- Web pages on a variety of energy management topics.
- Estimated energy costs.

3.4 User Hierarchy & Functions

Two user classes have been identified for access and utilization of this application. The first user class is the PIMD team. The second class is the Wits staff and students who will have view only access to the application.

Table 1:User Roles

User	**Usage Description**	**Access Level**
PIMD e.g Barney	Monitor energy peaks and take corrective action. E.g. start up the backup generators	Administrator privileges
Wits Students and staff e.g Leonard	View energy usage on web portal or mounted monitors	Interaction with system.

3.5 Operating Environment

The application is web based hence the following minimum requirements apply:

- Any web browser with java script installed and active.

3.6 Constraints & Limitations

The following constraints and limitations apply to this application:

- Must be web based
- Must endeavor to use only open source tools and libraries e.g PHP, Postgresql

3.7 Documentation

Two kinds of documents will be made available. A technical manual will be made available for the developers and a user manual will be made available for the Users. The user manual will be packaged together with the application and downloadable from the web portal whilst the technical manual will be uploaded to the applications SVN repository.

3.8 Dependencies

The application will depend on some third party libraries for the graphing functionality. E.g High-stock charting library

4 Application Features

4.1 Features Introduction

4.1.1 Real time power readings visualization

4.1.2 Description & Importance

This allows the users to view the power consumption in real time. This feature is critical to the whole application as all other readings and graphs are derived from this. It also provides an easy visual of the state polling meters i.e. if they are any missing values or if they are down.

A. Actions & Results

This feature depends on the backend continuous polling of meters. The graphs are live and do not require any user input.

B. Functional Requirements

A power vs. time live graph will be plotted. When zero readings are polled from the meter these will be averaged and shown in a different colour on the live graphs. This will show the user that there was a problem either with the meter or the network in polling data at that particular timestamp. If there are 2 continuous zero readings then these will not be averaged and will show a dip/gap in the live readings. This will indicate to the user that there was a serious problem with the polling and they can then investigate the possible causes if they are administrative users.

4.1.3 Real time energy readings visualization per campus

A. Description & Importance

This allows the users to view the energy consumption in real time. This feature is critical to the application as the energy consumption is what the university is billed against. The billing 30 minute windows used by city power will be modelled on this graph. Users will be able to see the peak usage for every 30 minute cycle.

B. Actions & Results

This feature depends on the successful calculation of energy values from the live power readings. The graphs are live and do not require any user input although users will be able to scroll back in time.

C. Functional Requirements

Energy vs. time live graph will be plotted. This graph will be a cumulative graph of the energy readings in 30 minute intervals. The graph is reset after every 30 minutes.

4.1.4 Peak consumption approaching warning and alert system

A. Description & Importance

This allows the users to be aware that the cumulative energy in a 30 minute window is approaching the pre-set Peak energy value. A notification email will be sent to the energy control team as well as an onscreen pop shown when the peak is approaching.

B. Actions & Results

This feature will depend on the pre-set values supplied by the PIMD team. The preset value will be represented by a constant energy value line drawn across the live graphs.

C. Functional Requirements

Energy vs. time live graph will be plotted but it will be constant for all time values. The objective is that the cumulative 30 minute cycle window energy values must not pass this pre-set value and a warning must be sounded if the energy values are approaching this value. E.g. at 80% of peak value an email will be sent and at 90% some form of onscreen notification will be shown.

4.1.5 Overall campus consumption comparison

A. ***Description & Importance***

This feature will allow users to be able to view and compare energy consumption across all the campuses. It is not critical but would provide interesting information for users. Users will be able to compare consumption for all campuses or any specific campuses they choose.

B. ***Actions & Results***

This feature will depend on the calculated energy values and it will be done for a specific time cycle. e.g. every hour it is updated.

C. *Functional Requirements*

This will just be different types of comparison charts or graphs using energy values for all the campuses in a specific time period.

4.1.6 Web pages on a variety of energy management topics

A. *Description & Importance*

The vision is that we are going to have a fully functional website for the energy management group and the dashboard will be part of this site. The website will have a variety of pages e.g. introduction to energy course 101, energy saving and green tips, energy management team description etc.

B. *Actions & Results*

General users of the website e.g. students will have the opportunity to read and learn more on energy usage and saving by just browsing the website.

C. *Functional Requirements*

This will be a structured website that allows users to browse through a number of pages.

5 Interfaces

5.1 User Interfaces

A number of interfaces will form this website. Below mock ups of the main interfaces have been sketched. Please note these are just sketches and will evolve as we go through the development cycle and more detail added.

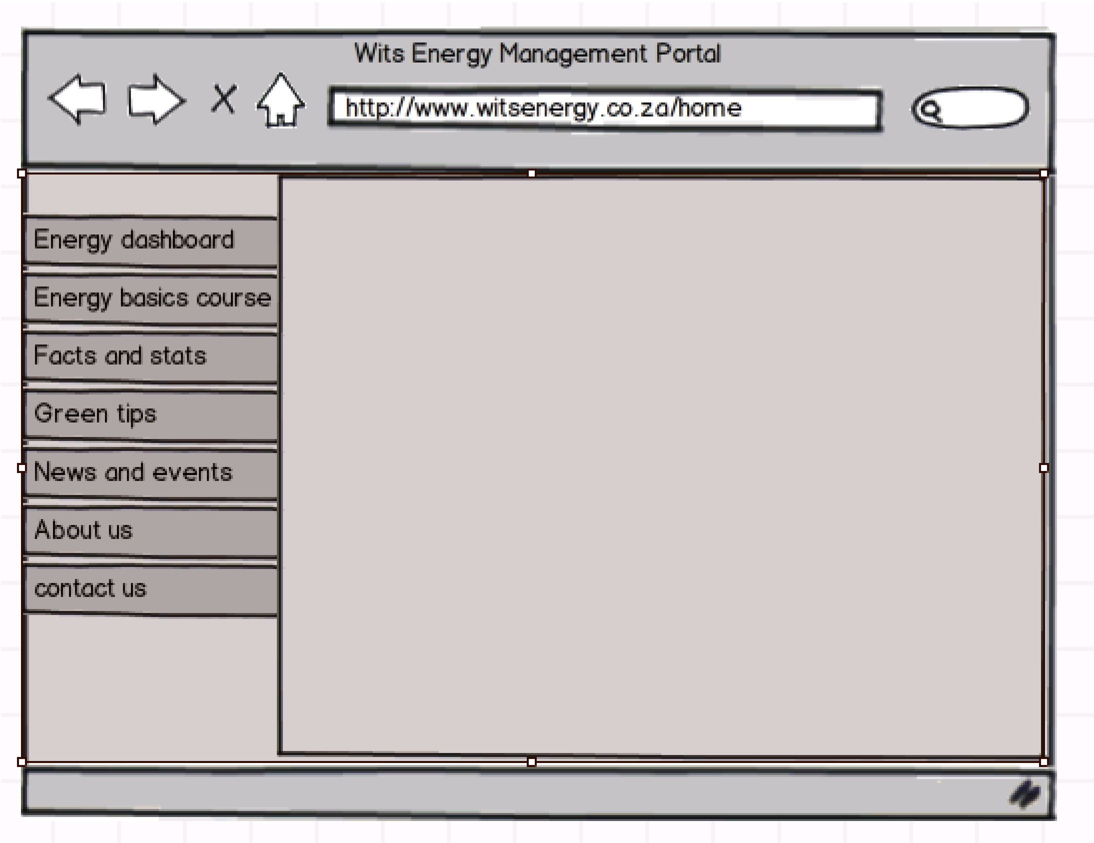

Figure 2: The home page

The site will not only have a dashboard but will provide other functionality as shown in Figure 2 above. More functionality will be added as the site evolves.

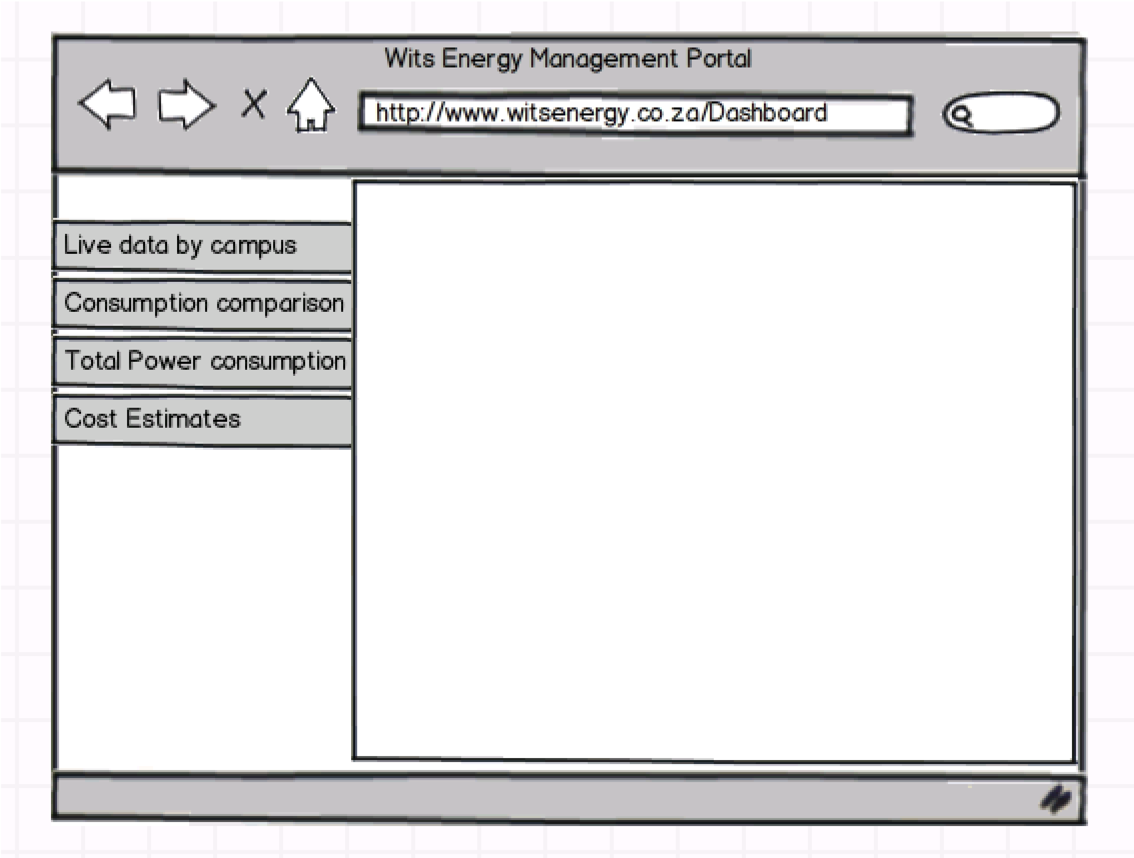

Figure 3: Dashboard home page

The dashboard will have a lot more functionality and things to offer besides the live data.

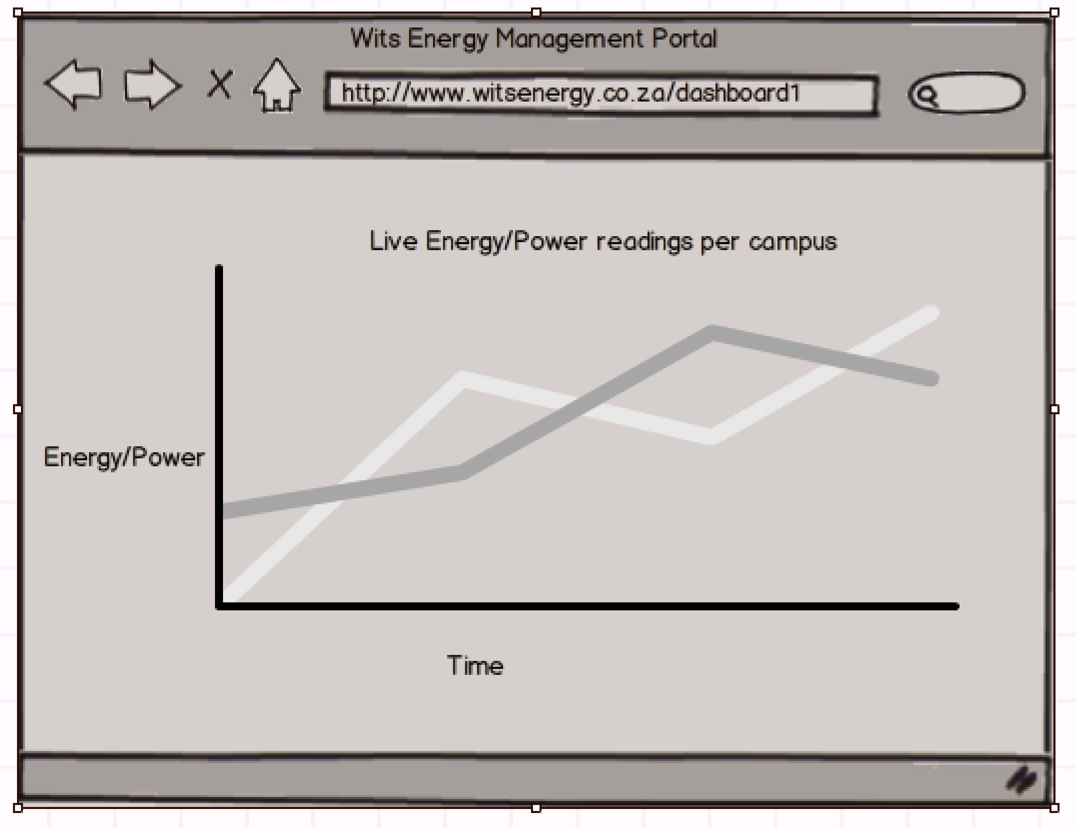

Figure 4: Live data graphs

The live graphs will be for energy as well as for power consumption. These will be on 2 different graphs. In future versions users will have the option of viewing different kinds of live graphs e.g. in a speedometer format.

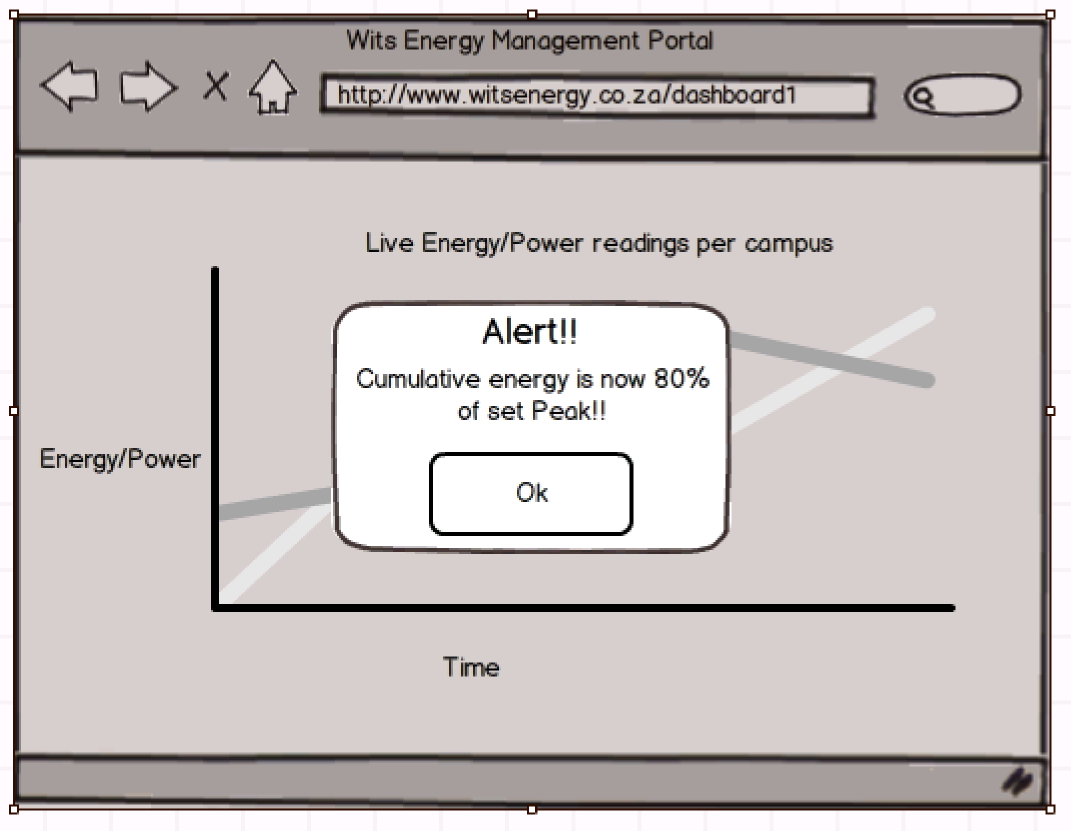

Figure 5: Peak approaching alert

The alert system will be built in such a way that when any of the campuses are approaching the pre-set peak value an alert is given.

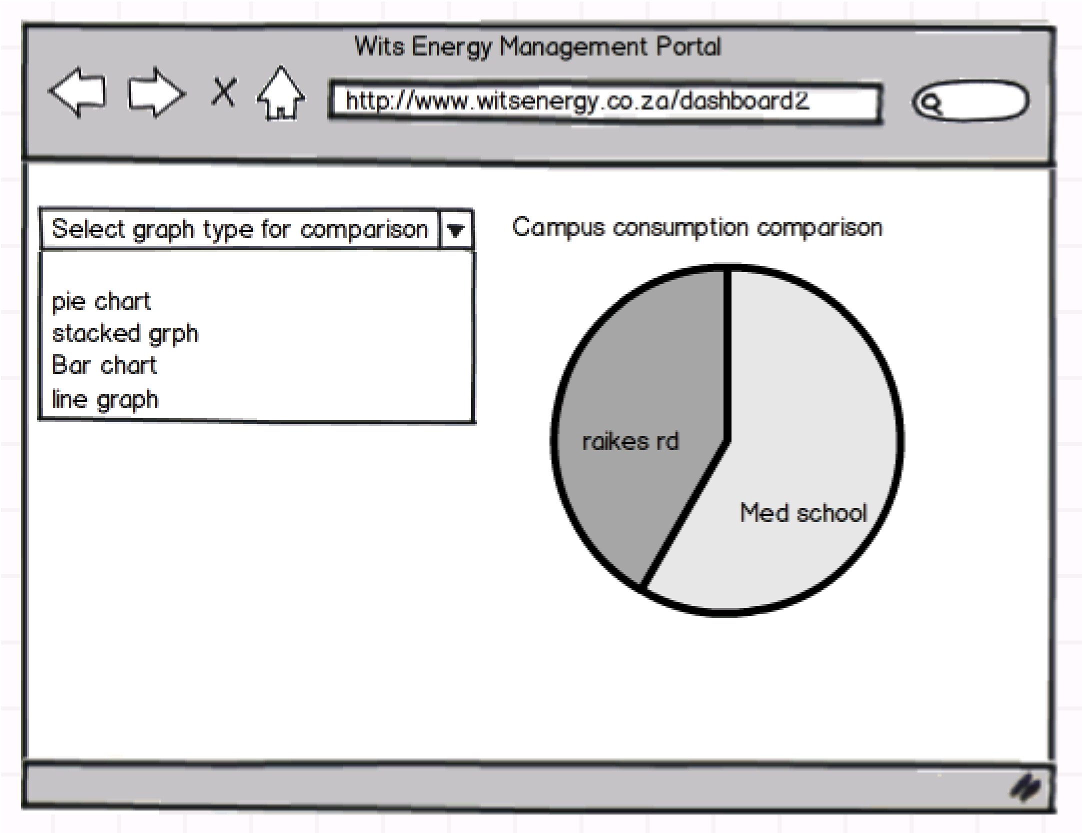

Figure 6: Dashboard sub-page consumption comparison

The users will be able to view overall campus consumption as well as comparison between specific campuses. This feature will be available using different charts and graphs.

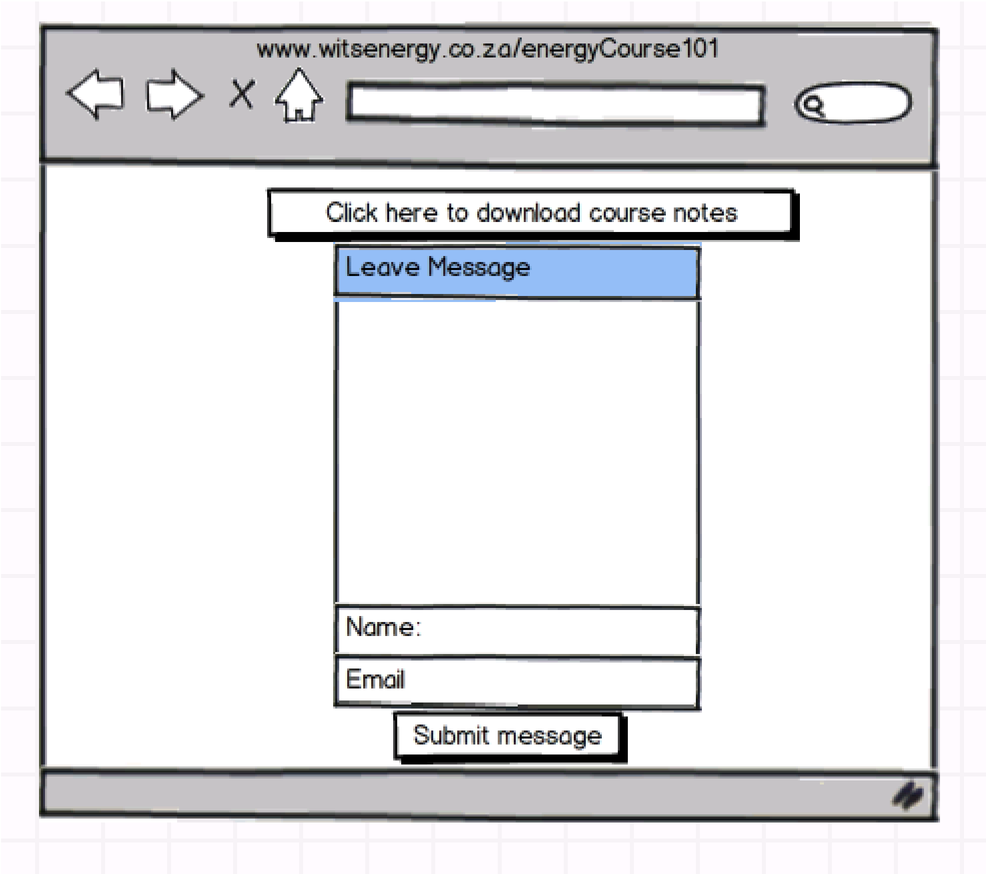

Figure 7:EnergyBasics101 course notes page

Visitors to the site will be able to navigate to the many pages that will be available on the site including the course notes for the energy basics 101 course amongst other pages.

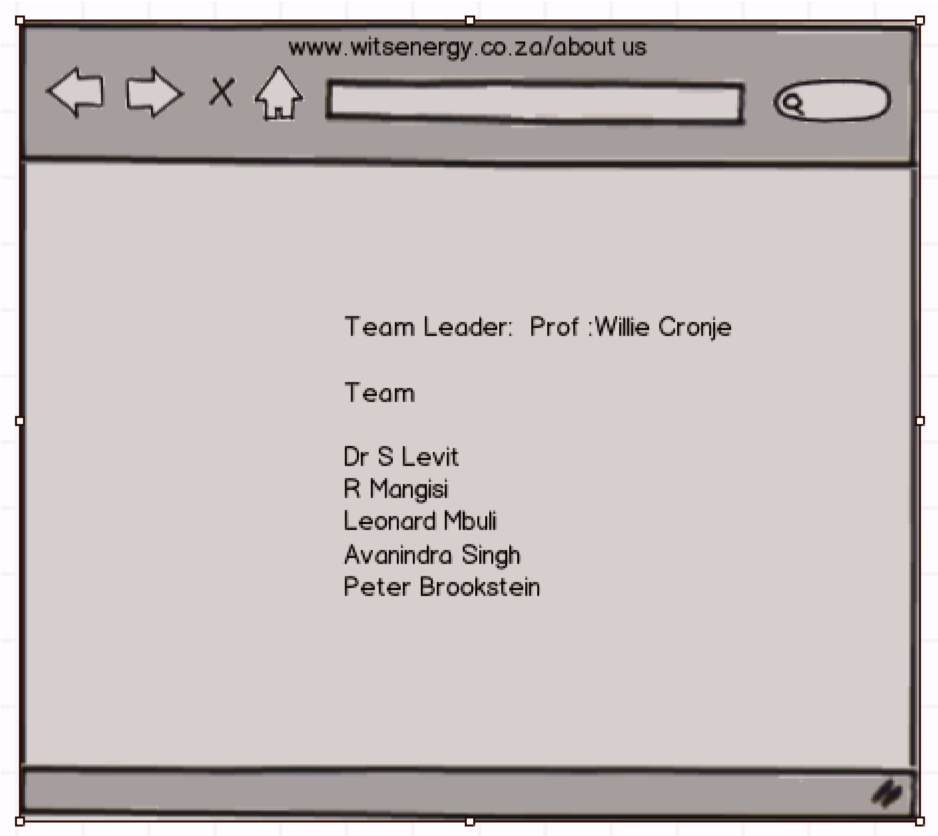

Figure 8: About us page.

A number of pages will be available on the site. These will include pages like research activities of the energy team, available research topics, description of team members, news etc.

5.2 Hardware Interfaces

This application depends on the smart meter network that the team has placed around wits. The interfacing of these devices is beyond the scope of this document. It is however available on our online repository on https://www.assembla.com/spaces/wits_energy_metering

5.3 Software Interfaces

The application will depend on the software running on the backend which is responsible for the necessary calculations and data persistence.

6 Logging

6.1 Logging process

6.1.1 Log data

Log data will be captured for this application. This will assist in debugging the system.

6.1.2 File Type/s

The log data will be saved in text files.

6.1.3 Location

The log file will be saved in the log folder on the main project trunk of this app.

7 Non-functional Requirements

7.1 Performance

The main use of this application will be the real live data readings. It is therefore necessary that the system not experience any downtime. It will be expected that the system will load data for graphs seamlessly and efficiently without hanging or crushing the browser. The site will be available 24 hours daily.

7.2 Security

As explained in section 3.4. This system is targeted to 2 kinds of users. Administrative users e.g. PIMD and the general user e.g. students. The system will therefore have user control access to differentiate between these users and give them the correct privileges.

7.3 Safety and Data Integrity

The system will not have any write privileges to the database and will use views for data reading. This will ensure that malicious users cannot corrupt the data.

7.4 Software Quality

In future the site will be open to the world hence it should be of the highest quality.

8 Proposed timeline

A summarised breakdown of the proposed project timeline, with deadlines, expected and project milestones are given below.

Table 2: Project milestones we will need to discuss this in detail.

Milestone	Date
Version 1(all functionality that is on old site i.e. live energy and power graphs)	27 July 2012
version 2(Consumption comparison page added, About us page added)	03 August
Version 3(2 more web pages added e.g. energy basics 101,team summary)	11 August

Appendix B: South African Weather Services Disclosure

DISCLOSURE STATEMENT

South African
Weather Service

The provision of the data is subject to the User providing the South African Weather Service (SAWS) with a detailed and complete disclosure, in writing and in line with the requirements of clauses 1.1 to 2.4 (below), of the purpose for which the specified data is to be used. The statement is to be attached to this document as Schedule 1.

1 Should the User intend using the specified data for commercial gain then the disclosure should include the following:

1.1 the commercial nature of the project/funded research project in connection with which the User intends to use the specified data;

1.2 the names and fields of expertise of any participants in the project/funded research project for which the specified data is intended; and

1.3 the projected commercial gains to the User as a result of the intended use of the specified data for the project/funded research project.

2 Should the User intend using the specified data for the purposes of conducting research, then the disclosure should include the following:

2.1 the title of the research paper or project for which the specified data is to be used;

2.2 the details of the institution and supervisory body or person(s) under the auspices of which the research is to be undertaken;

2.3 an undertaking to supply SAWS with a copy of the final results of the research in printed and/or electronic format; and

2.4 the assurance that no commercial gain will be received from the outcome from the research.

If the specified data is used in research with disclosure being provided in accordance with paragraph 2 and the User is given the opportunity to receive financial benefit from the research following the publication of the results, then additional disclosure in terms of paragraph 1 is required.

The condition of this disclosure statement is applicable to the purpose and data requirements of the transaction recorded in Schedule 1. This statement is effective from 24 May 2012.

SCHEDULE 1

Please note: The South African Weather Service will only act upon customer requirements noted on this disclosure statement and not from any other correspondence.

FULL PERSONAL DETAILS OF USER

Full Names: ________Rodwell Mangisi______________________________________

____

University/school/organisation: ______________University of the Witwatersrand______________

____

Student Number: (where applicable) 0403253V____

____

Email address: rodwell.mangisi@students.wits.ac.za____

Postal Address: box 316 Wits 2050____

Supervisor: _______Professor Barry Dwolatzky________________________________

____

Project/Thesis Title: AN INVESTIGATION INTO THE POSSIBILITIES OFFERED BY SMART GRID DATA WITH FOCUS ON REAL-TIME LOAD VISUALISATION AND HALF HOURLY PEAK LOAD FORECASTING IN A SOUTH AFRICAN CONTEX _______

Registered Course: (where applicable) _____________ELEN8000 Msc Electrical Engineering_________

The data will be used as one of the input variables to an energy forecasting algorithm

---

THE PURPOSE

(Please indicate a detailed description of the purpose for which the data will be used).

DATA REQUIRED

(Please include the <u>weather elements</u> (e.g. rain, temperature), <u>place/s</u> and <u>period</u>)

Hourly temperature data for Johannesburg for the past 4 years.

I hereby accept that:

- SAWS will be acknowledged in the resulting dissertation/project or when published, for the data it provided.
- SAWS will be provided with a copy of the final results in printed or electronic format.
- The data received shall not be provided to any third party.

Signature of the User: Date:

Rodwell Mangisi

(*Please sign the document and do not type your name in as this is a legal document and requires a signature*.)

Appendix C: Model A Statistical Analysis using R

1. Introduction

This appendix details the statistical analysis input and output of the R® statistical analysis using the inbuilt R Multiple linear regresion modelling tool.

2. R input

Energy ~ Temperature + CampusStatus + Weekday + Month + PreviousPeak + T^2 + T^3 + Cycle_f

3. R Output

```
Call:

lm(formula = Energy ~ ., data = D2STA)

Coefficients:

        (Intercept)           Temperature  CampusStatusCampus Open
         11.1780559            -0.0576930                3.0905827
  CampusStatusSpecial        WeekdayMonday         WeekdaySaturday
          2.2475178             0.8190740               -1.9734399
      WeekdaySunday         WeekdayThursday          WeekdayTuesday
         -2.2441068             0.5680232                1.0268073
    WeekdayWednesday          MonthFebruary              MonthMarch
          0.8893736             0.5212903                0.9334397
         MonthApril                MonthMay               MonthJune
          0.6754532             2.0221195                5.0072130
          MonthJuly             MonthAugust          MonthSeptember
          3.0904280             3.7718695                0.2596929
       MonthOctober           MonthNovember           MonthDecember
```

0.4451526	0.3658413	-0.1790913
PreviousPeak	T2	T3
0.8471421	-0.0194735	0.0005985
Cycle_f2	Cycle_f3	Cycle_f4
0.2809052	-0.2470252	0.5585940
Cycle_f5	Cycle_f6	Cycle_f7
-0.3542319	-0.1179969	-0.2838859
Cycle_f8	Cycle_f9	Cycle_f10
-0.2969707	-0.1562415	0.6388672
Cycle_f11	Cycle_f12	Cycle_f13
1.5759263	2.6174012	6.5788295
Cycle_f14	Cycle_f15	Cycle_f16
6.1635144	7.8504822	8.4797269
Cycle_f17	Cycle_f18	Cycle_f19
9.2873291	8.4020813	8.2842372
Cycle_f20	Cycle_f21	Cycle_f22
7.1119499	6.4217314	6.6481341
Cycle_f23	Cycle_f24	Cycle_f25
7.5200319	7.0700504	7.0273971
Cycle_f26	Cycle_f27	Cycle_f28
6.5795833	5.2513839	6.1794259
Cycle_f29	Cycle_f30	Cycle_f31
6.2699481	4.8518557	4.4267302
Cycle_f32	Cycle_f33	Cycle_f34
3.6976751	3.3088678	2.5510132
Cycle_f35	Cycle_f36	Cycle_f37
4.9862513	8.2586058	7.8190245
Cycle_f38	Cycle_f39	Cycle_f40

```
      6.0228027        3.2116758        3.0615896
      Cycle_f41        Cycle_f42        Cycle_f43
      2.4814352        1.8106806        1.9132834
      Cycle_f44        Cycle_f45        Cycle_f46
      0.7930801        0.4840959        1.3088556
      Cycle_f47        Cycle_f48
     -0.6775602       -0.0984046
```

```
Call:
lm(formula = Energy ~ ., data = D2STA)
Residuals:
    Min      1Q  Median      3Q     Max
-95.896  -2.555  -0.026   2.534  62.811

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)            11.1780559  0.7240288  15.439  < 2e-16 ***
Temperature            -0.0576930  0.0989133  -0.583 0.559720
CampusStatusCampus Open  3.0905827  0.1935869  15.965  < 2e-16 ***
CampusStatusSpecial     2.2475178  0.1821810  12.337  < 2e-16 ***
WeekdayMonday           0.8190740  0.1858346   4.408 1.05e-05 ***
WeekdaySaturday        -1.9734399  0.1884010 -10.475  < 2e-16 ***
WeekdaySunday          -2.2441068  0.1948761 -11.516  < 2e-16 ***
WeekdayThursday         0.5680232  0.1816179   3.128 0.001766 **
WeekdayTuesday          1.0268073  0.1852856   5.542 3.04e-08 ***
WeekdayWednesday        0.8893736  0.1840797   4.831 1.37e-06 ***
MonthFebruary           0.5212903  0.3397489   1.534 0.124965
MonthMarch              0.9334397  0.3465335   2.694 0.007075 **
```

MonthApril	0.6754532	0.3579057	1.887	0.059146	.
MonthMay	2.0221195	0.3574661	5.657	1.57e-08	***
MonthJune	5.0072130	0.3719813	13.461	< 2e-16	***
MonthJuly	3.0904280	0.3553097	8.698	< 2e-16	***
MonthAugust	3.7718695	0.3820406	9.873	< 2e-16	***
MonthSeptember	0.2596929	0.3582429	0.725	0.468519	
MonthOctober	0.4451526	0.3658290	1.217	0.223686	
MonthNovember	0.3658413	0.3272233	1.118	0.263576	
MonthDecember	-0.1790913	0.3461540	-0.517	0.604902	
PreviousPeak	0.8471421	0.0041099	206.124	< 2e-16	***
T2	-0.0194735	0.0072188	-2.698	0.006991	**
T3	0.0005985	0.0001583	3.781	0.000157	***
Cycle_f2	0.2809052	0.4817385	0.583	0.559829	
Cycle_f3	-0.2470252	0.4866635	-0.508	0.611748	
Cycle_f4	0.5585940	0.4793392	1.165	0.243898	
Cycle_f5	-0.3542319	0.4891039	-0.724	0.468925	
Cycle_f6	-0.1179969	0.4838142	-0.244	0.807320	
Cycle_f7	-0.2838859	0.4848267	-0.586	0.558192	
Cycle_f8	-0.2969707	0.4872449	-0.609	0.542208	
Cycle_f9	-0.1562415	0.4874617	-0.321	0.748578	
Cycle_f10	0.6388672	0.4897385	1.305	0.192079	
Cycle_f11	1.5759263	0.4880197	3.229	0.001244	**
Cycle_f12	2.6174012	0.4873303	5.371	7.94e-08	***
Cycle_f13	6.5788295	0.4832862	13.613	< 2e-16	***
Cycle_f14	6.1635144	0.4863876	12.672	< 2e-16	***
Cycle_f15	7.8504822	0.4849745	16.187	< 2e-16	***
Cycle_f16	8.4797269	0.4840278	17.519	< 2e-16	***
Cycle_f17	9.2873291	0.4926731	18.851	< 2e-16	***

Cycle_f18	8.4020813	0.4977888	16.879	< 2e-16	***
Cycle_f19	8.2842372	0.5014240	16.521	< 2e-16	***
Cycle_f20	7.1119499	0.5037835	14.117	< 2e-16	***
Cycle_f21	6.4217314	0.5176986	12.404	< 2e-16	***
Cycle_f22	6.6481341	0.5145465	12.920	< 2e-16	***
Cycle_f23	7.5200319	0.5176303	14.528	< 2e-16	***
Cycle_f24	7.0700504	0.5146729	13.737	< 2e-16	***
Cycle_f25	7.0273971	0.5219913	13.463	< 2e-16	***
Cycle_f26	6.5795833	0.5251524	12.529	< 2e-16	***
Cycle_f27	5.2513839	0.5203357	10.092	< 2e-16	***
Cycle_f28	6.1794259	0.5212258	11.856	< 2e-16	***
Cycle_f29	6.2699481	0.5265391	11.908	< 2e-16	***
Cycle_f30	4.8518557	0.5208945	9.314	< 2e-16	***
Cycle_f31	4.4267302	0.5195196	8.521	< 2e-16	***
Cycle_f32	3.6976751	0.5157231	7.170	7.83e-13	***
Cycle_f33	3.3088678	0.5088649	6.502	8.13e-11	***
Cycle_f34	2.5510132	0.5109267	4.993	6.01e-07	***
Cycle_f35	4.9862513	0.5068330	9.838	< 2e-16	***
Cycle_f36	8.2586058	0.5083457	16.246	< 2e-16	***
Cycle_f37	7.8190245	0.4978851	15.704	< 2e-16	***
Cycle_f38	6.0228027	0.5015898	12.007	< 2e-16	***
Cycle_f39	3.2116758	0.4941176	6.500	8.27e-11	***
Cycle_f40	3.0615896	0.4906329	6.240	4.48e-10	***
Cycle_f41	2.4814352	0.4881070	5.084	3.74e-07	***
Cycle_f42	1.8106806	0.4862013	3.724	0.000197	***
Cycle_f43	1.9132834	0.4867949	3.930	8.52e-05	***
Cycle_f44	0.7930801	0.4848359	1.636	0.101907	
Cycle_f45	0.4840959	0.4836285	1.001	0.316858	

Cycle_f46 1.3088556 0.4774544 2.741 0.006126 **

Cycle_f47 -0.6775602 0.4793571 -1.413 0.157535

Cycle_f48 -0.0984046 0.4756451 -0.207 0.836101

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table 17: Model A Results

Residual standard error:	6.326 on 16377 degrees of freedom
Multiple R-squared	0.9411
Adjusted R-squared	0.9408
F-statistic	3738 on 70 and 16377 DF
p-value	< 2.2e-16
Mean Absolute Percentage Error	3.786157 %
Mean Absolute Error	3.792842 kWh

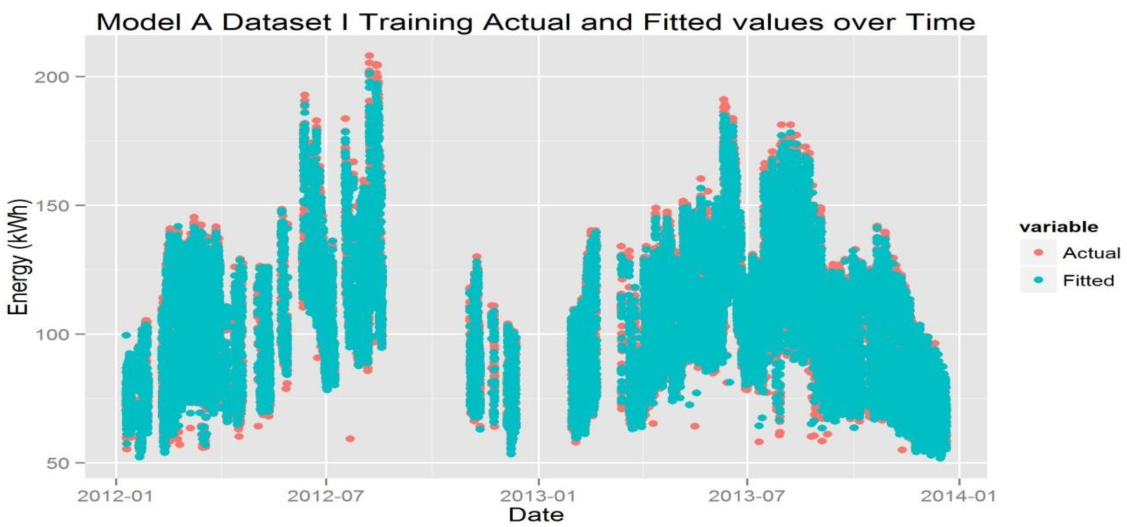

Figure 48: Model A Actual vs Forecasted values

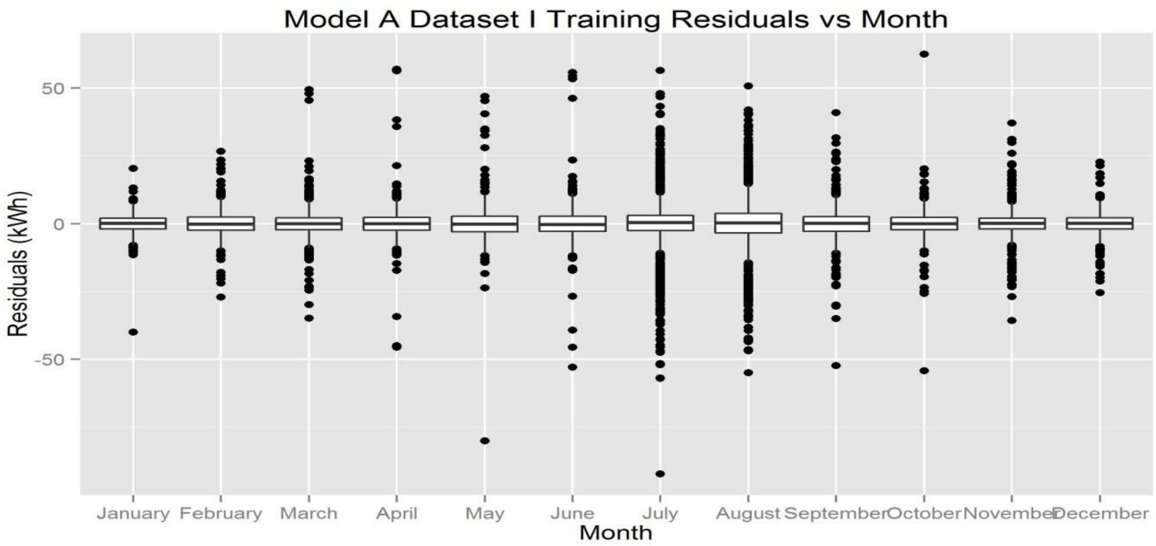

Figure 49: Model A Training residuals

4. Conclusion

This secton has detailed the analysis done on Model A. A mean absolute error of 3.78% is achieved.

Appendix D: Model B Statistical Analysis

1. Introduction

This appendix details the statistical analysis input and output of the R® statistical analysis using the inbuilt R Multiple linear regresion modelling tool.

2. R Input Model

Energy ~ PreviousPeak + Baseline + Temperature * Baseline

3. R output

```
Call:
lm(formula = Energy ~ PreviousPeak + Baseline + Temperature *
    Baseline, data = D1STB)
Coefficients:
        (Intercept)         PreviousPeak            Baseline          Temperature
          -4.946845             0.625486            0.443142             0.268347
Baseline:Temperature
          -0.003947
Call:
lm(formula = Energy ~ PreviousPeak + Baseline + Temperature *
    Baseline, data = D1STB)
Residuals:
    Min      1Q  Median      3Q     Max
-73.518  -2.387   0.110   2.670  47.186
Coefficients:
```

Estimate Std. Error t value Pr(>|t|)

(Intercept) -4.9468453 0.6781745 -7.294 3.14e-13 ***

PreviousPeak 0.6254856 0.0046091 135.708 < 2e-16 ***

Baseline 0.4431419 0.0078167 56.692 < 2e-16 ***

Temperature 0.2683467 0.0416143 6.448 1.16e-10 ***

Baseline:Temperature -0.0039467 0.0003835 -10.291 < 2e-16 ***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table 18: Model B results

Residual standard error:	5.874 on 16419 degrees of freedom
Multiple R-squared	0.9492
Adjusted R-squared	0.9491
F-statistic	7.663e+04 on 4DF
p-value	< 2.2e-16
Mean Absolute Percentage Error	3.685385 %
Mean Absolute Error	3.758275 kWh

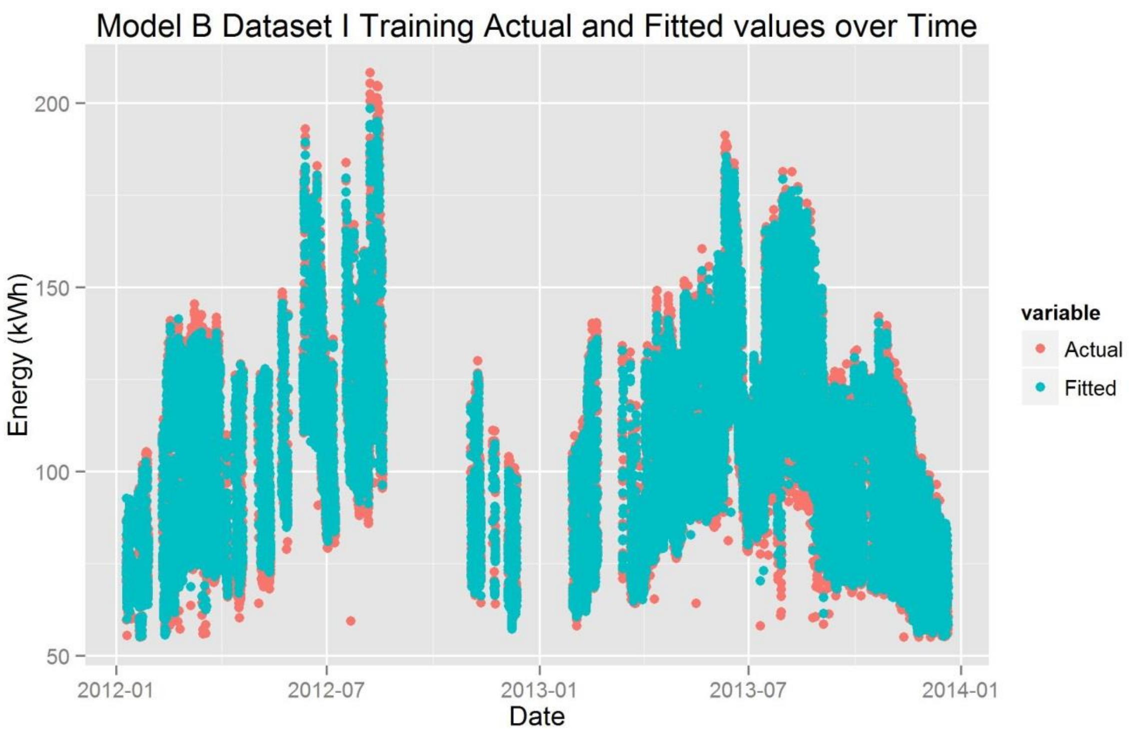

Figure 50: Model B Actual and fitted values over time

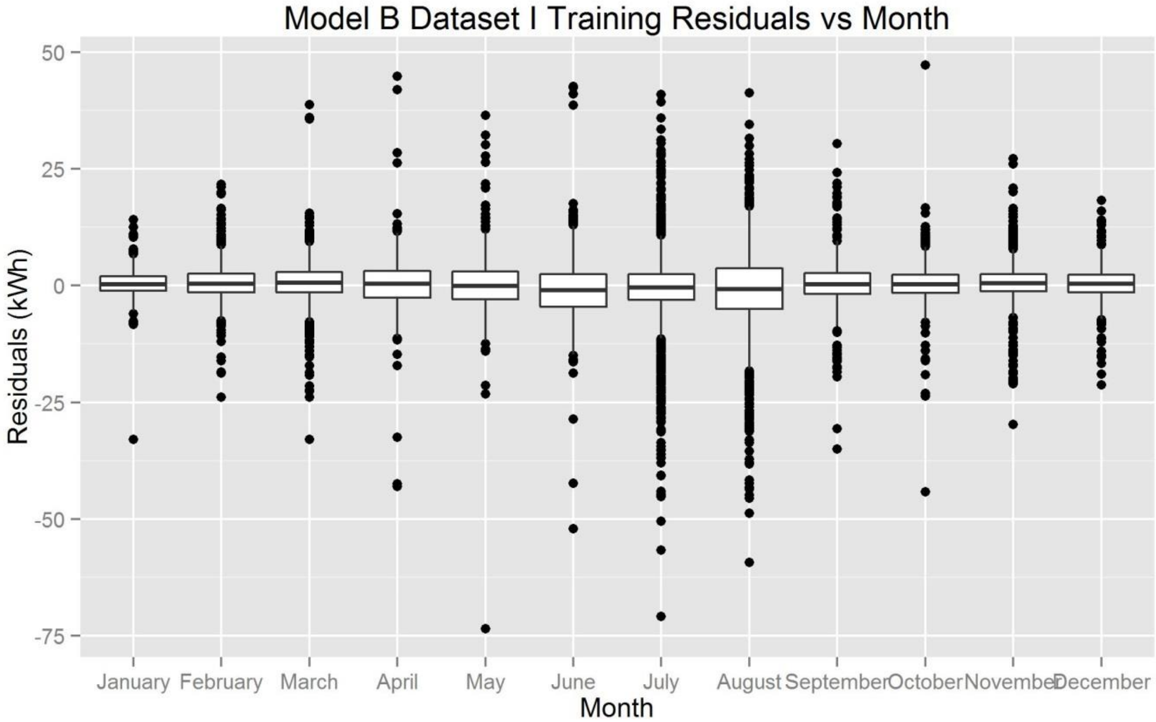

Figure 51: Model B training data residuals

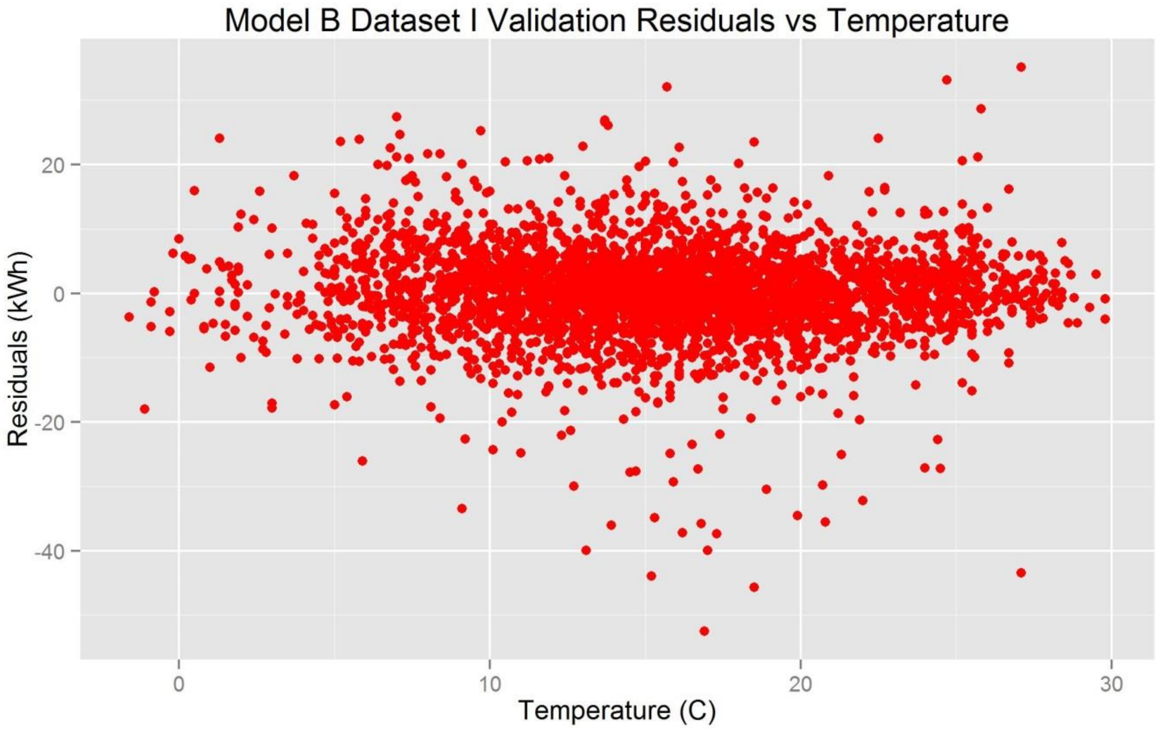

Figure 52: Model B residuals vs temperature

4. Conclusion

This secton has detailed the analysis done on Model A. A mean absolute error of 3.78% is achieved.

Appendix E: ICONIX Process Report

5. ICONIX process

As described in section 6.3 ,the ICONIX process is a Unified Modelling Language (UML) driven analysis and design of a software application[137]. It provides a step by step analysis of system objects and use cases in a bid to turn them into working code. The motivation behind this approach is that this process produces software of high quality which is maintainable, reusable, reliable and efficient. This appendix is a summary of the process followed to come up with the classes and functions used in developing the dashboard prototype.

6. Class Diagrams

The following section shows class diagrams for the different layers of the application. When the ICONIX process starts these classes are just potential object names without any properties and iteratively the properties and methods of the classes are added. The class diagrams shown here are the results of this process and they show all the properties and methods of each class.

1.1 Presentation Classes

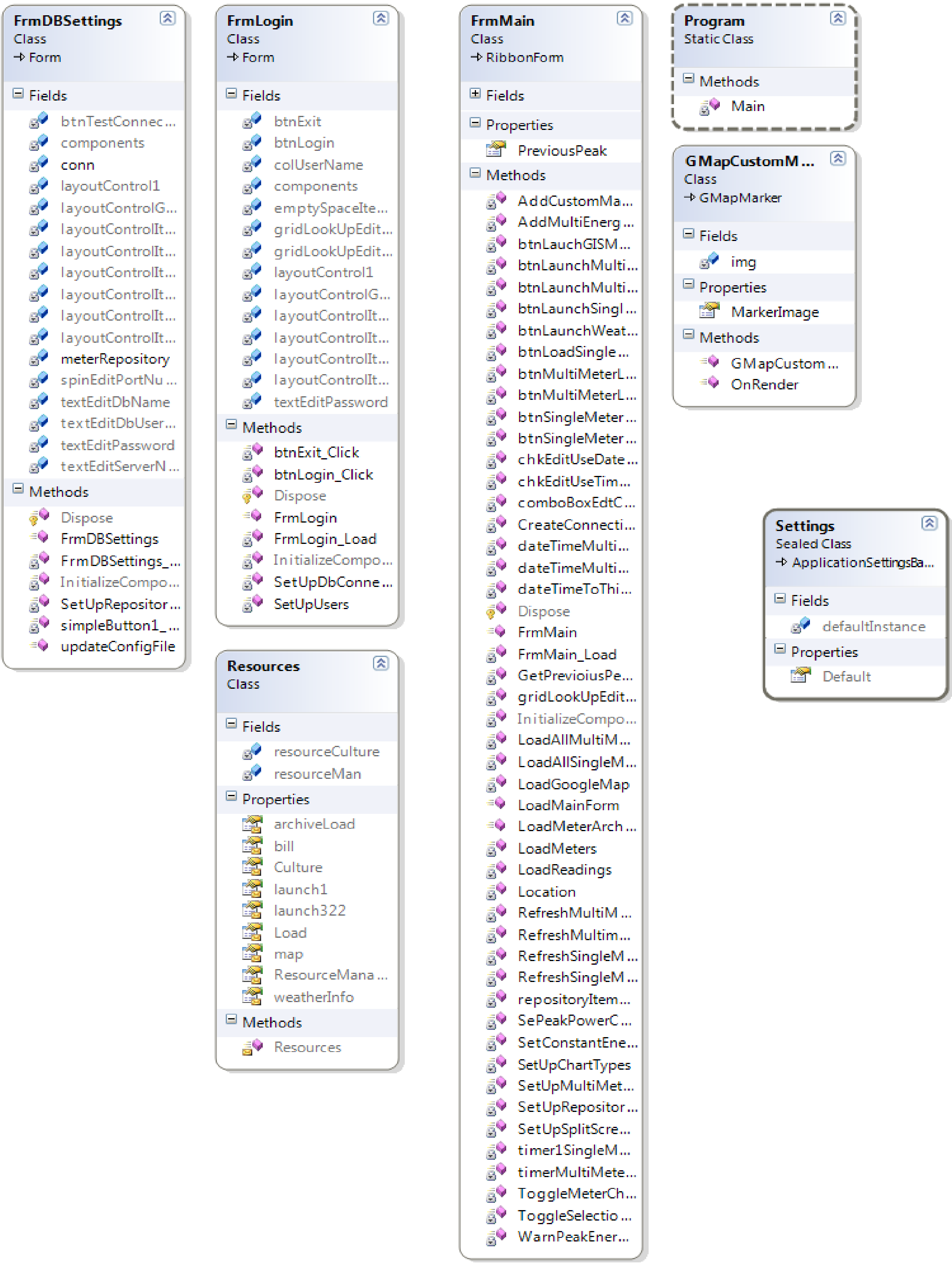

Figure 53: Presentation layer classes

1.2Data Access and Repository Classes

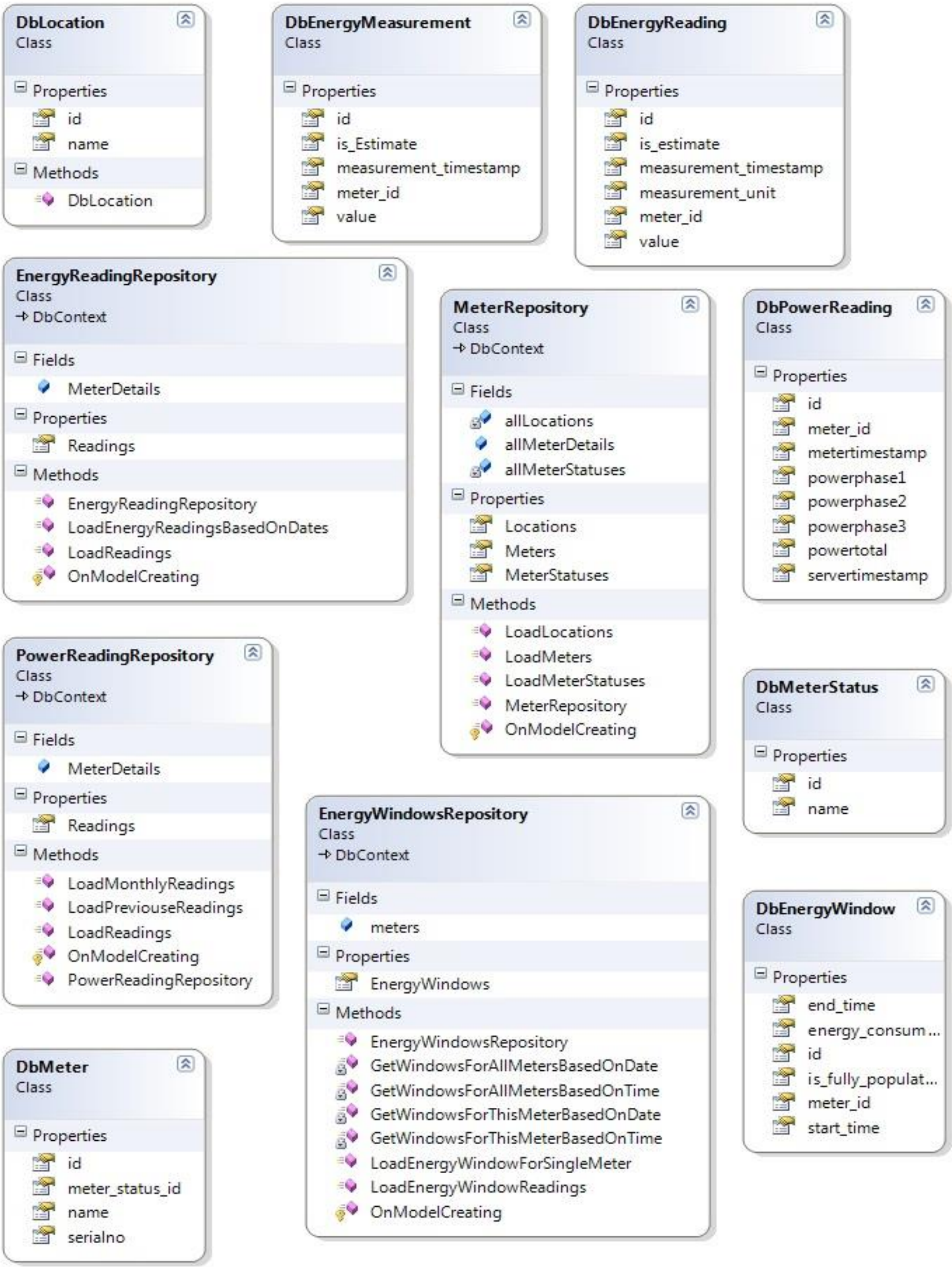

Figure 54: Data Access Layer and Repository Classes

1.3 Control and Model Classes

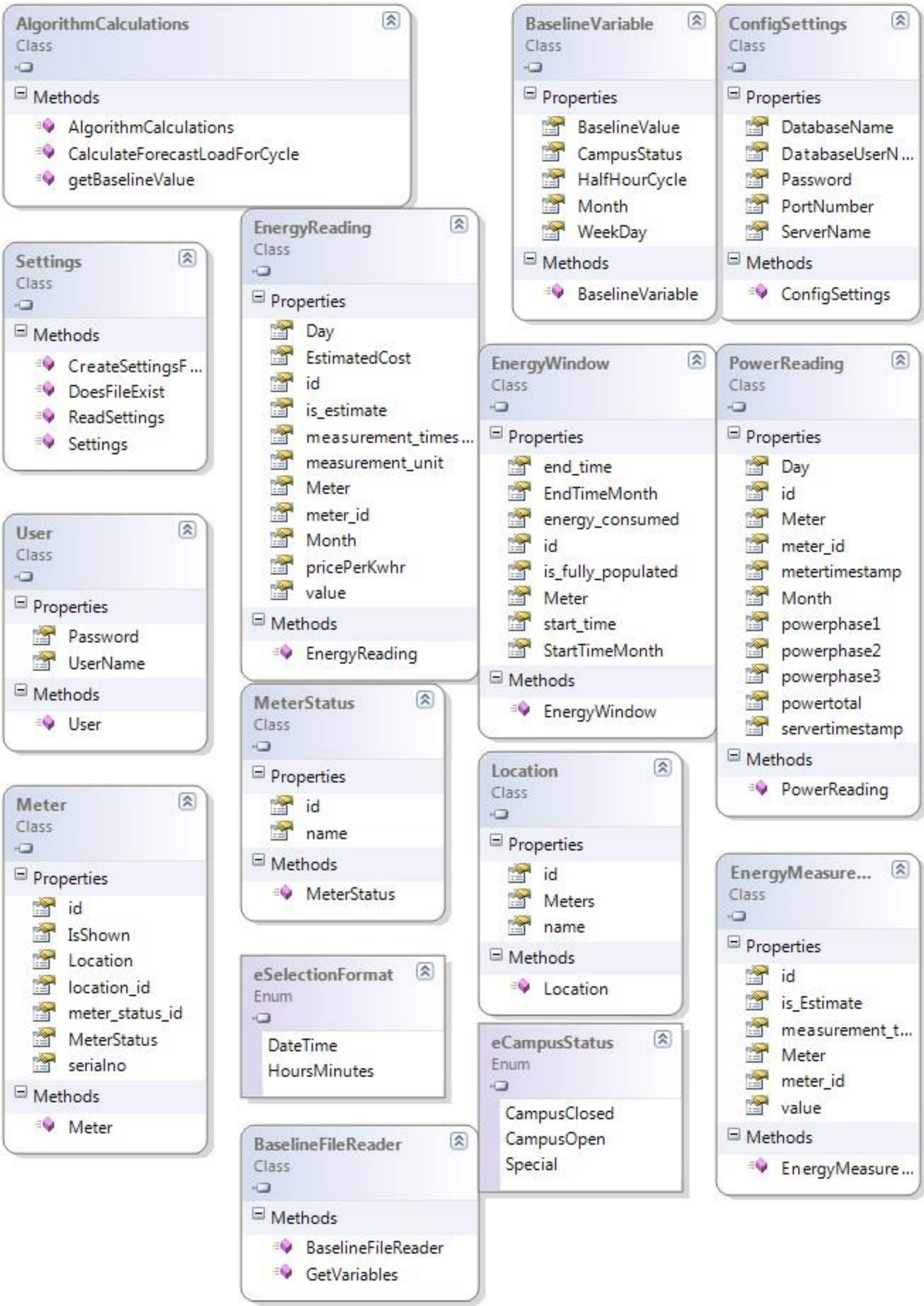

Figure 55: Control layer and Model Classes

7. Use Case Diagrams

Use case diagrams are used to show the interactions of a user with the system .They attempt to capture all the possible actions that a user could take. This section shows these use cases.

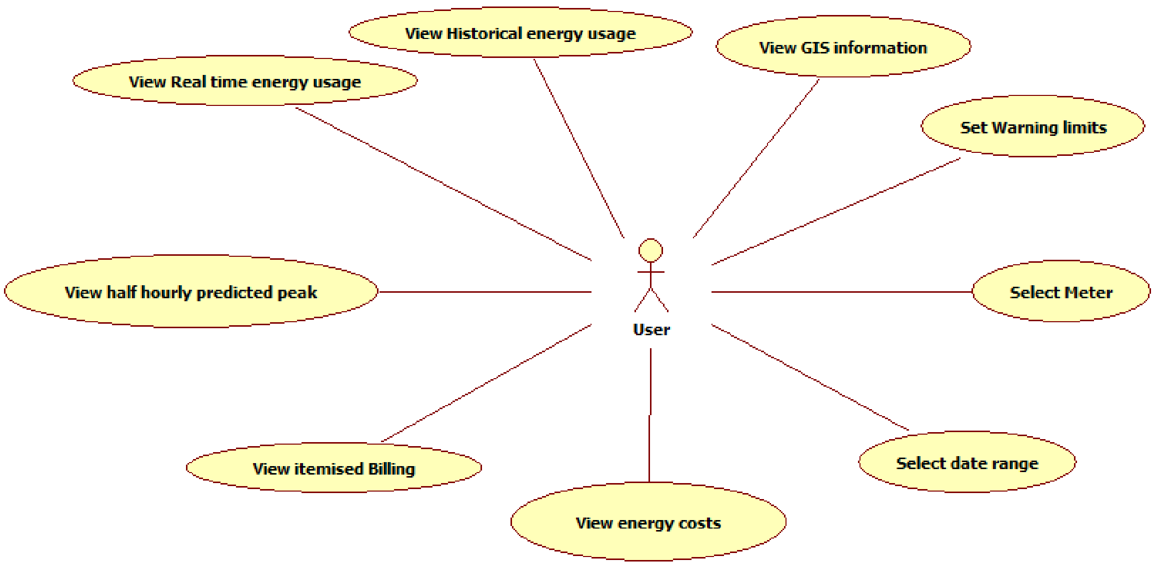

Figure 56: User System Use Case

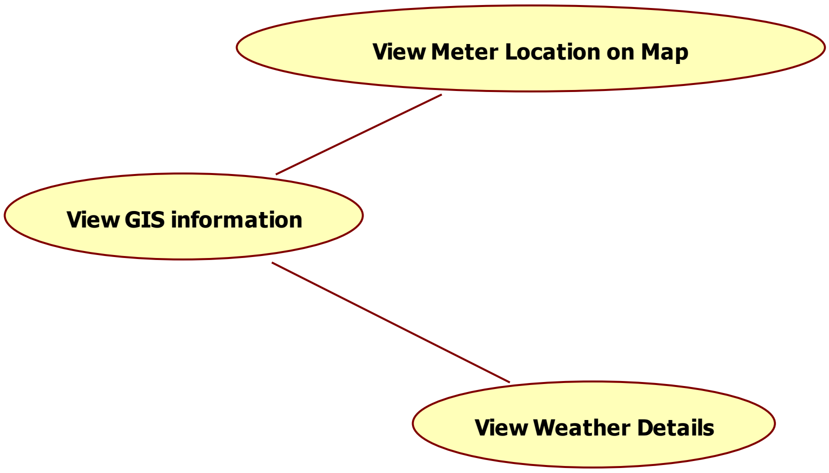

Figure 57: Expanded View for GIS viewing use case

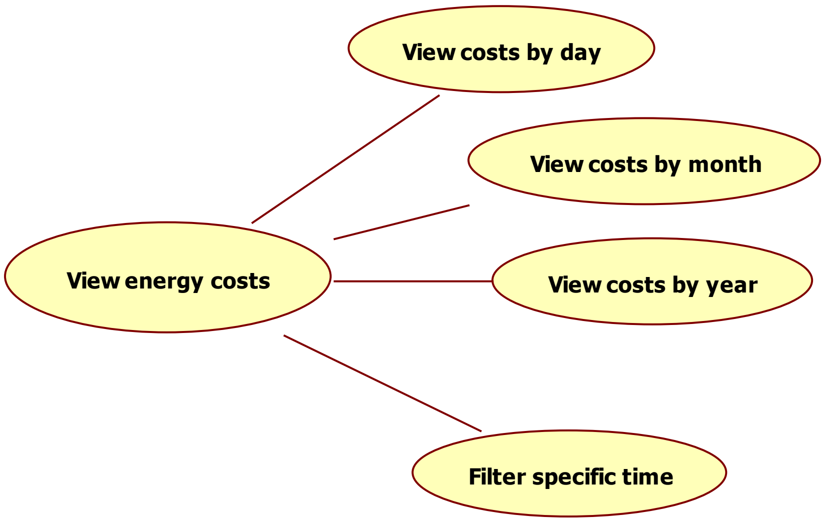

Figure 58: Expanded Energy Cost Viewing Use Case

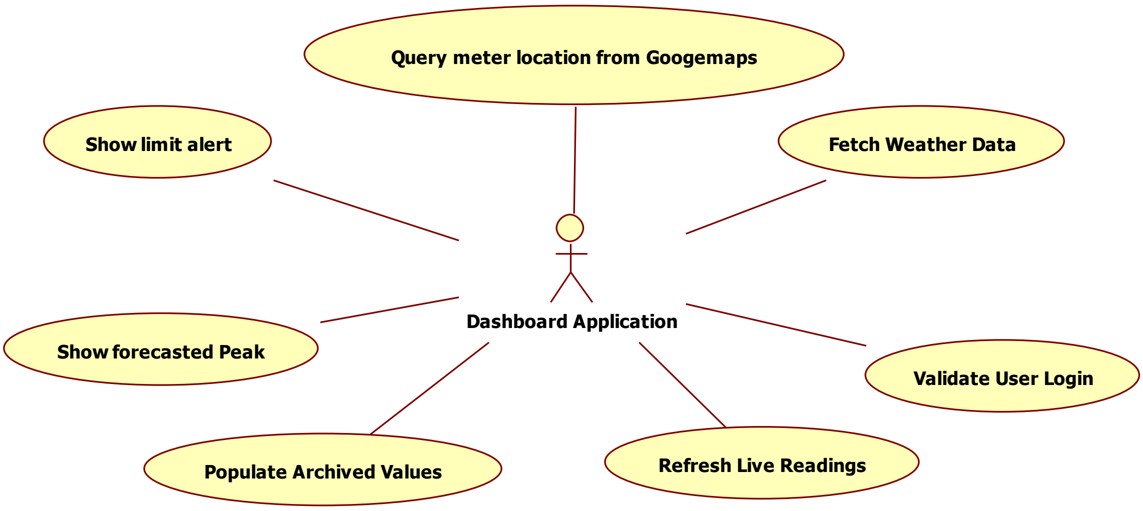

Figure 59: Application Use Case

1.4 Use case descriptions

This section gives descriptions of each of the major use cases of this application. The basic and alternate courses of action are outlined.

1.4.1 System log in use case description

Basic Course

- User logs into the system by typing user name and password
- User presses enter
- System looks up user and validates password.
- System finds user and continues with dashboard start up and data loading from the database

Alternate course

- If customer type wrong password system displays an error message and prompts user to retype password.
- If system could not load system data from the database it displays error message to user and asks them to check if connection string to database is correct.

1.4.2 Meter selection

Basic Course

- User selects meter from drop down
- System looks up meter details from database
- System uploads meter data from database

Alternate Course

- If system does not select any meter the system will continue displaying message saying please select meter
- If user selects meter but system cannot load the meter details from the database an error message is displayed.
- If system cannot load meter data an error message and reason is displayed by system.

1.4.3 View GIS information

Basic Course

- User selects meter and system fetches meter geo-coordinates from database.
- System geo-coordinates values to the Google® Maps API which displays location on map.

Alternate Course

- If the System is not able to find meter geo-coordinates from database it displays an error message.
- If system fetches geo-coordinates from database and passes them to the Google API but Google cannot display the map for any reason an error message is displayed

1.4.4 View itemised billing

Basic Course

- User selects docking panel for itemised billing
- System fetches values for the currently selected meter and displays them on the grid. User interacts with grid to see desired information

Alternate Course

- If selected panel is not able to be shown an error message is show
- If system cannot find required itemised billing values an error is shown to the user and user can try to reload data

1.4.5 View hourly predicted Peak

Basic Course

- User selects to view forecasted half hourly peak load.
- System fetches necessary values for calculating peak load.
- System displays peak load

Alternate Course

- System fails to find necessary values for load forecasting calculation. System displays error message to user.
- System retries to fetch value .If system fails on second attempt then forecasting is paused for half an hour before another retry

1.4.6 View historical usage data

Basic Course

- User selects desired date range of data and presses enter
- System fetches required data
- System displays data on grids

Alternate Course

- Selected date range is not valid. System displays error message.

- There is no data on the desired data range. System displays informative message to user.

1.4.7 View Real time usage data

Basic Course

- User selects to view live usage data from a particular meter.
- System fetches usage data every 30 seconds from database. System displays data on a graph

Alternate Course

- System fails to find data in 30 second cycle. Graph is updated with a zero value marked with a red marker to indicate missing value.

8. Robustness diagrams

This section shows a visual representation of the use cases described in the previous examples. This visual representation is shown using diagrams named Robustness or activity diagrams. These diagrams help to see any gaps in the thought process of the designer as it visually shows the connections within a system.

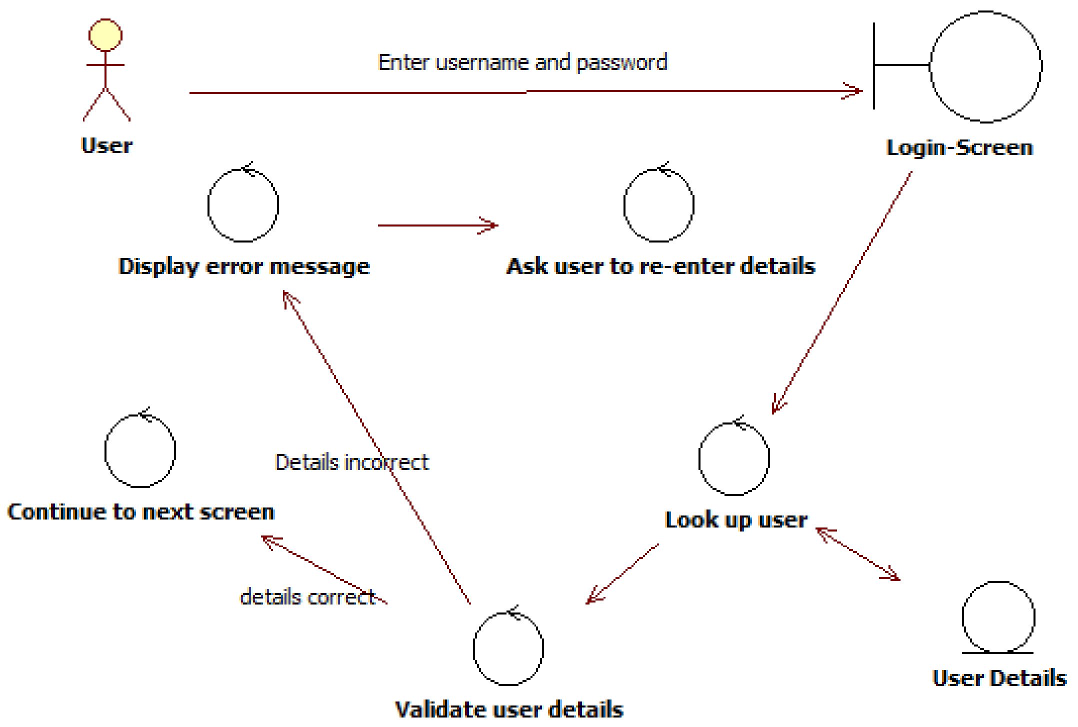

Figure 60: User login Robustness Diagram

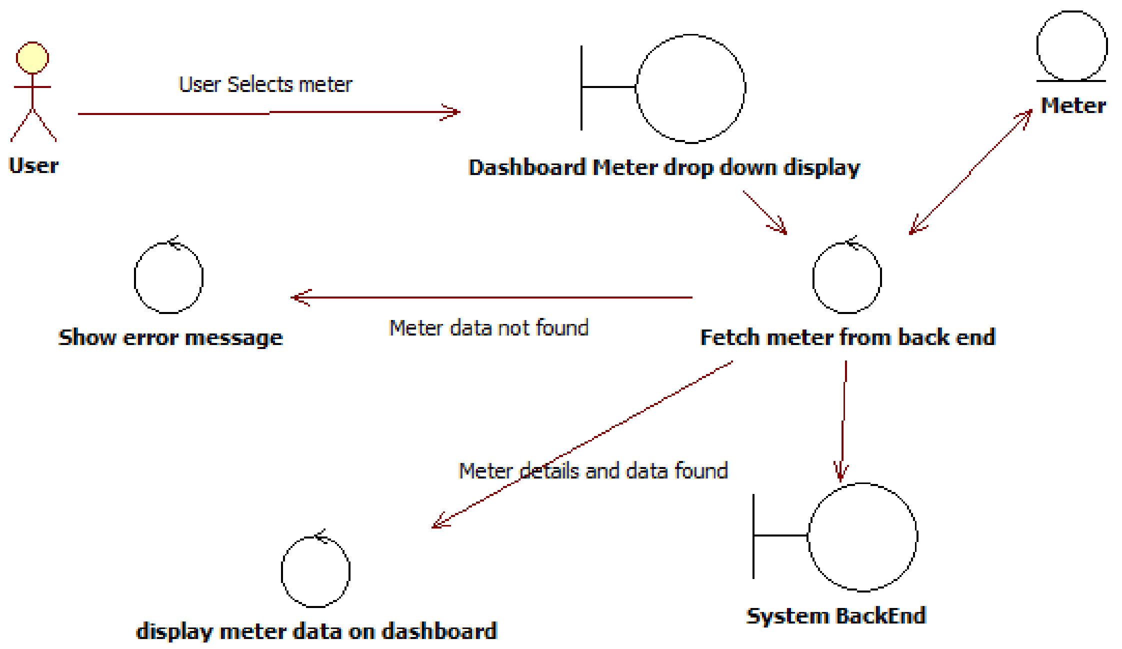

Figure 61: Meter selection Robustness Diagram

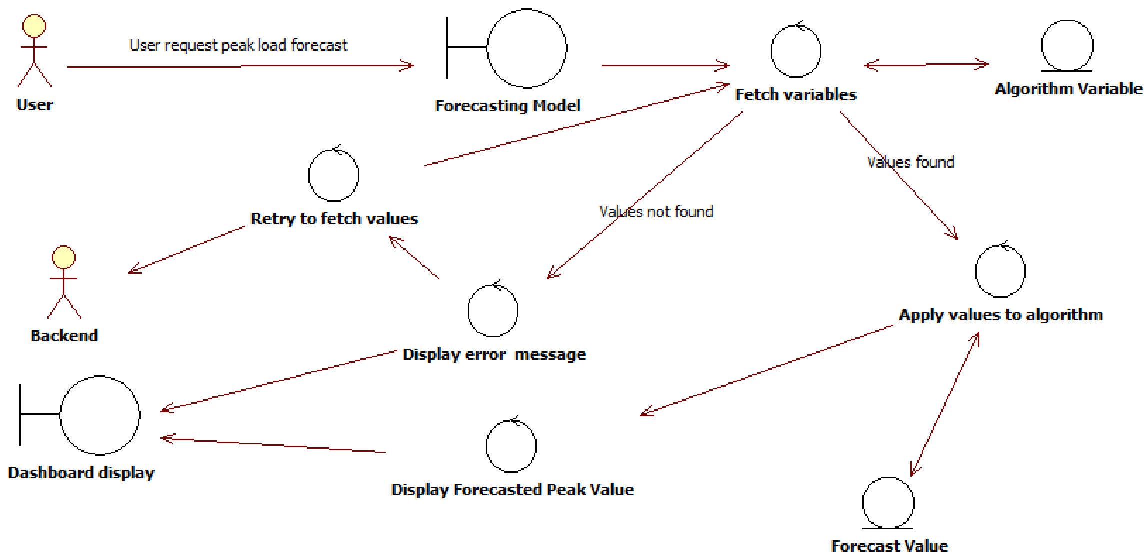

Figure 62: View forecasted Peak Load Robustness Diagram

9. Conclusion

This document gave a brief summary of the ICONIX process followed in the design of the prototype. As can be seen the breakdown of the use cases and robustness diagrams bring out the functionality of the prototype which easily translates to methods, properties and ultimately classes (objects) of the prototype.

Appendix F: Dashboard Source Code

The source code report is 102 pages so it is on the supplied disk. The actual source code is also included.

Appendix G: User Interface Screenshots

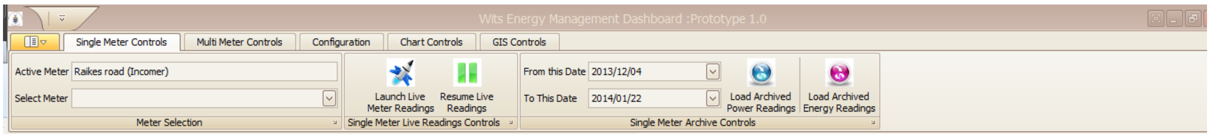

Figure 63: Easy access buttons

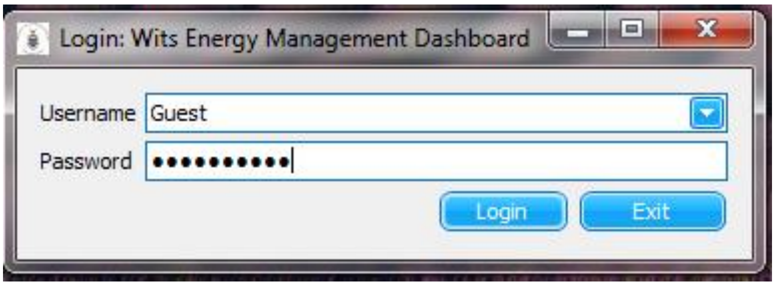

Figure 64: User Login

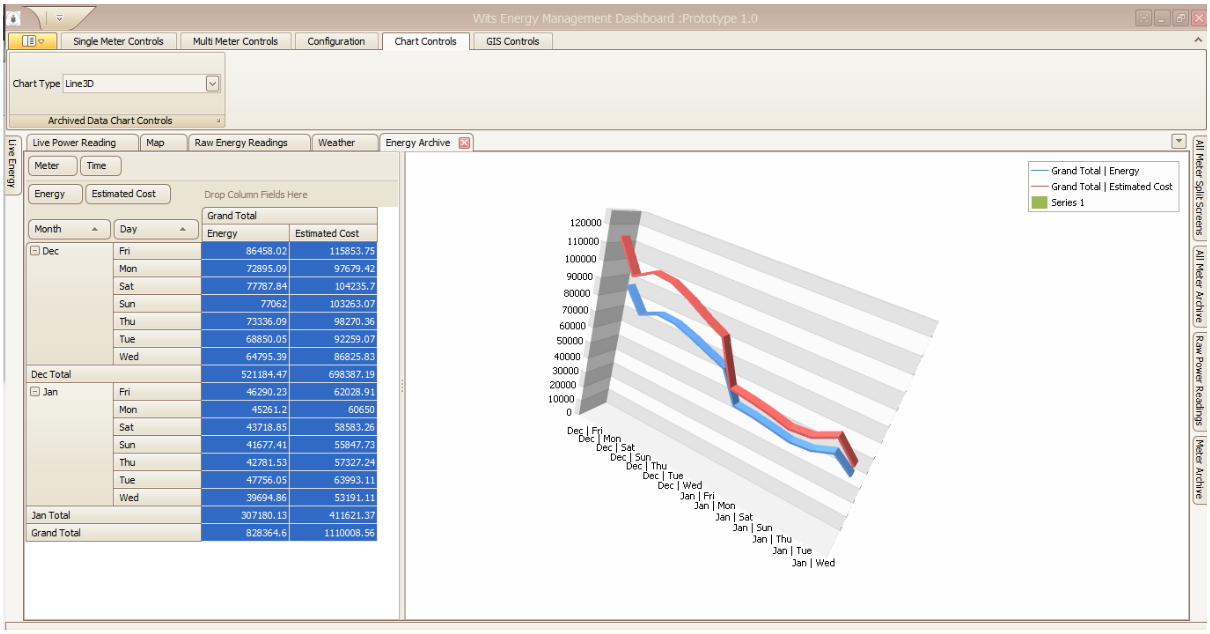

Figure 65: Graph and charting functionality demonstration

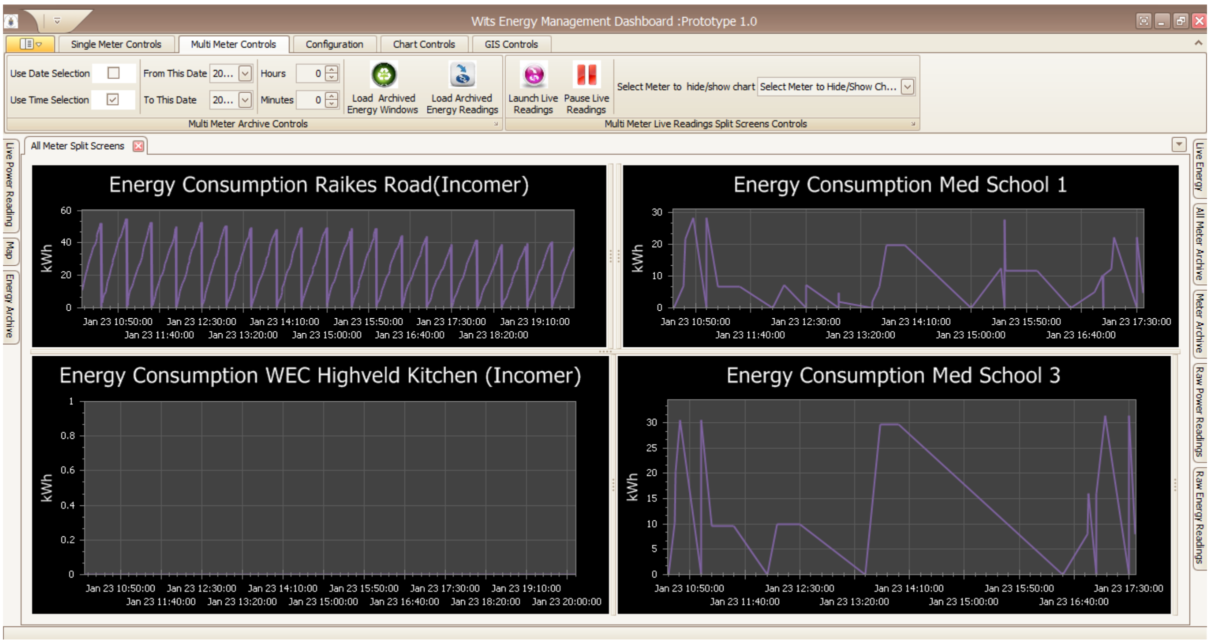

Figure 66: Multi meter live readings viewing

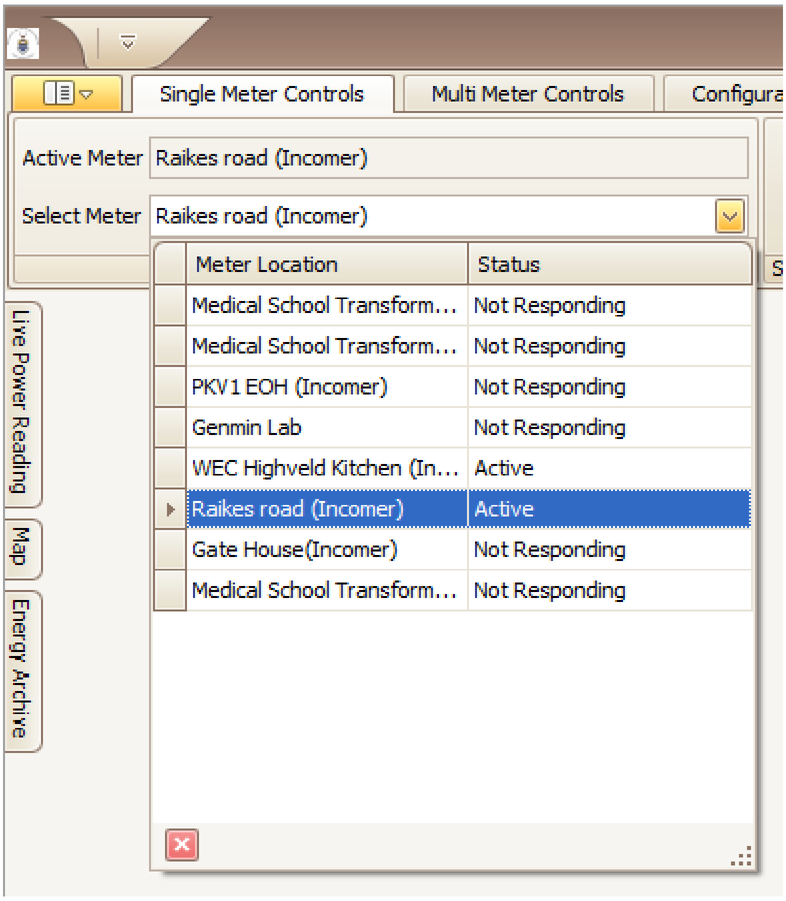

Figure 67: Meter Status and Selection

Appendix H: Usability Questionnaires and Test case feedback forms

Please find the questionnaires attached in the following pages. For each user there are 3 forms. Two of them are the usability questionnaires and one Test case feedback form. The pages are numbered 1 to 3 for each user. The results from these questionnaires are summarised in the tables below. This is the data used to create the analysis graphs.

Usability Tests Raw Data

Table 19: Overall reaction to Software

overall reaction											
users	1	2	3	4	5	6	7	8	9	10	% average
wonderful	100	90	100	80	80	90	100	100	100	100	94
easy	80	100	80	90	90	100	80	80	90	100	89
satisfying	90	100	90	80	80	100	90	90	100	100	92
stimulating	80	80	100	90	90	100	90	100	100	100	93
flexible	70	90	90	90	90	100	80	70	100	100	88

Table 20: Screen organisation

Participant	Screen Organisation														
Reading characters on the screen	94			users	1	2	3	4	5	6	7	8	9	10	% average
Organisation of information	88				100	80	100	100	90	90	100	80	100	100	94
Sequence of screens	88				100	90	80	100	90	90	100	70	80	80	88
					100	80	80	90	80	90	100	80	100	80	88

Table 21: Terminology and System Information

Terminology and System Information											
users	1	2	3	4	5	6	7	8	9	10	% average
Use of terms throughout system	90	100	80	100	100	90	80	90	100	80	91
Terminology related to task	100	100	80	100	90	90	80	100	100	90	93
Position of messages on screen	90	100	80	90	90	90	90	100	100	90	92
Prompts for input	100	90	80	100	100	80	90	100	90	100	93
Computer informs about its progress	100	90	90	100	90	90	90	100	90	80	92
Error messages	100	100	70	90	100	90	100	100	100	90	94

Table 22: Learning Difficulty

Learning Difficulty											
users	1	2	3	4	5	6	7	8	9	10	% average
Learning to operate the system	80	100	100	90	90	100	70	80	90	90	89
Exploring new features by trial and error	90	100	90	100	100	90	80	80	90	100	92
Remembering names and use of commands	90	100	90	80	90	90	80	70	90	100	88
Performing tasks is straightforward	100	100	100	90	90	90	90	80	90	80	91
Help messages on the screen	100	70	100	90	90	80	80	70	100	60	84
Supplemental reference materials	90	60	100	90	80	60	80	70	100	70	80

Table 23: System capabilities

System Capabilities											
users	1	2	3	4	5	6	7	8	9	10	% average
System speed	90	100	100	60	60	70	60	90	90	50	77
System reliability	90	90	100	80	80	80	70	90	80	70	83
Correcting your mistakes	80	100	80	80	80	80	70	80	90	100	84
Designed for all levels of user	70	100	100	80	80	100	80	90	90	100	89

Table 24: Perceived Usefulness

	Perceived Usefullness
Using the energy dashboard would increase my energy usage awareness	100
Using the energy dashboard would make it easier to manage energy usage	75
I would find the energy dashboard useful in my home/company	65
Does the dashboard serve well as a reporting tool	80

Table 25: Perceived Ease of use

	Perceived Ease Of Use
Learning to operate the energy dashboard would be easy for me	60
I would find it easy to get the energy dashboard to do what I want it to do	70
My interaction with the energy dashboard would be clear and understandable	60
I would find the energy dashboard to be flexible to interact with	55
It would be easy for me to become skilful at using the energy dashboard	90
I would find the energy dashboard easy to use	100

Test Case Feedback Form

Test case	Order	Achieved(Y/N)	Difficulty Level On a Scale 1-5
Start and log into application	1st	Y	1
Select Meter	2nd	Y	1
View live power readings graph	3rd	Y	1
View live energy readings graph	Any	Y	1
View forecasting details	Any	Y	1
Set warning limits and alerts	Any	Y	1
View itemised energy readings	Any	Y	1
view itemised bill by day	Any	Y	2
View itemised bill by month	Any	Y	1
Analyse archived readings using at least one chart	Any	Y	4
View weather forecast	Any	Y	1
View meter position in Google maps	Any	Y	1

Comments

Very relevant for homes and commercial entities focused on saving electricity and money. Its also ~~an~~ a user friendly, adaptable tool for people at various levels of education

Questionnaire on User Interface Satisfaction

	OVERALL REACTION TO THE SOFTWARE		1	2	3	4	5	6	7	8	9		N/A
1		terrible							X			wonderful	
2		difficult								X		easy	
3		frustrating							X			satisfying	
4		dull								X		stimulating	
5		rigid								X		flexible	
	SCREEN		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**		**N/A**
6	Reading characters on the screen	hard								X		easy	
7	Organization of information	confusing								X		very clear	
8	Sequence of screens	confusing								X		very clear	
	TERMINOLOGY AND SYSTEM INFORMATION		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**		**N/A**
9	Use of terms throughout system	inconsistent								X		consistent	
10	Terminology related to task	never								X		always	
12	Position of messages on screen	inconsistent								X		consistent	
13	Prompts for input	confusing							X			clear	
14	Computer informs about its progress	never								X		always	
15	Error messages	unhelpful								X		helpful	
	LEARNING		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**		**N/A**
16	Learning to operate the system	difficult								X		easy	
17	Exploring new features by trial and error	difficult									X	easy	
18	Remembering names and use of commands	difficult								X		easy	
19	Performing tasks is straightforward	never								X		always	
20	Help messages on the screen	unhelpful								X		helpful	
21	Supplemental reference materials	confusing							X			clear	
	SYSTEM CAPABILITIES		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**		**N/A**
22	System speed	too slow					X					fast enough	
23	System reliability	unreliable							X			reliable	
24	Correcting your mistakes	difficult							X			easy	
25	Designed for all levels of users	never							X			always	

List most negative aspects:

The screen was freezing from time to time and refreshing took time.

List most positive aspects

Can be used to allow saving of electricity in most households.

Attributes of Usability Questionnaire

	Perceived Usefulness		1	2	3	4	5	6	7		N/A
3	Using the energy dashboard would increase my energy usage awareness	unlikely							X	likely	
5	Using the energy dashboard would make it easier to manage my energy usage	unlikely							X	likely	
6	I would find the energy dashboard useful in my home/company	unlikely							X	likely	
7	Does the dashboard serve as well as a reporting tool	Unlikely							X	likely	

	Perceived Ease of Use		1	2	3	4	5	6	7		N/A
7	Learning to operate the energy dashboard would be easy for me	unlikely							X	likely	
8	I would find it easy to get the energy dashboard to do what I want it to do	unlikely							X	likely	
9	My interaction with the energy dashboard would be clear and understandable	unlikely							X	likely	
10	I would find the energy dashboard to be flexible to interact with	unlikely							X	likely	
11	It would be easy for me to become skilful at using the energy dashboard	unlikely							X	likely	
12	I would find the energy dashboard easy to use	unlikely							X	likely	

May you please give a brief summary of your thoughts in your own words:

This tool would be a useful tool for homes, schools and factories to save electricity while making progress and realizing profits in relevant areas of business.

Name: Wendy Chiota

Position Held: Lecturer (Midlands State University)

Email add: chiotaww@msu.ac.zw

Test Case Feedback Form

Test case	Order	Achieved(Y/N)	Difficulty Level On a Scale 1-5
Start and log into application	1st	Y	1
Select Meter	2nd	Y	1
View live power readings graph	3rd	Y	1
View live energy readings graph	Any	Y	1
View forecasting details	Any	Y	1
Set warning limits and alerts	Any	Y	2
View itemised energy readings	Any	Y	1
view itemised bill by day	Any	Y	3
View itemised bill by month	Any	Y	1
Analyse archived readings using at least one chart	Any	Y	3
View weather forecast	Any	Y	1
View meter position in Google maps	Any	Y	1

Comments

It gives a different perspective on how I view electricity bills and usage. I became more aware and alert through the use of dashboard. I like it and it is the future in a constantly changing world.

Questionnaire on User Interface Satisfaction

			1	2	3	4	5	6	7	8	9		N/A
	OVERALL REACTION TO THE SOFTWARE		1	2	3	4	5	6	7	8	9		N/A
1		terrible									✓	wonderful	
2		difficult							✓			easy	
3		frustrating								✓		satisfying	
4		dull								✓		stimulating	
5		rigid							✓			flexible	
	SCREEN		1	2	3	4	5	6	7	8	9		N/A
6	Reading characters on the screen	hard							✓			easy	
7	Organization of information	confusing						✓				very clear	
8	Sequence of screens	confusing							✓			very clear	
	TERMINOLOGY AND SYSTEM INFORMATION		1	2	3	4	5	6	7	8	9		N/A
9	Use of terms throughout system	inconsistent							✓			consistent	
10	Terminology related to task	never							✓			always	
12	Position of messages on screen	inconsistent							✓			consistent	
13	Prompts for input	confusing							✓			clear	
14	Computer informs about its progress	never								✓		always	
15	Error messages	unhelpful						✓				helpful	
	LEARNING		1	2	3	4	5	6	7	8	9		N/A
16	Learning to operate the system	difficult						✓				easy	
17	Exploring new features by trial and error	difficult							✓			easy	
18	Remembering names and use of commands	difficult							✓			easy	
19	Performing tasks is straightforward	never								✓		always	
20	Help messages on the screen	unhelpful							✓			helpful	
21	Supplemental reference materials	confusing							✓			clear	
	SYSTEM CAPABILITIES		1	2	3	4	5	6	7	8	9		N/A
22	System speed	too slow					✓					fast enough	
23	System reliability	unreliable						✓				reliable	
24	Correcting your mistakes	difficult						✓				easy	
25	Designed for all levels of users	never							✓			always	

List most negative aspects:

The dashboard speed was not satisfying

List most positive aspects

The incorporation of technology into managing electricity usage. It stimulates the mind and enjoyable.

Attributes of Usability Questionnaire

	Perceived Usefulness		1	2	3	4	5	6	7		N/A
3	Using the energy dashboard would increase my energy usage awareness	unlikely							✓	likely	
5	Using the energy dashboard would make it easier to manage my energy usage	unlikely							✓	likely	
6	I would find the energy dashboard useful in my home/company	unlikely							✓	likely	
7	Does the dashboard serve as well as a reporting tool	Unlikely							✓	likely	

	Perceived Ease of Use		1	2	3	4	5	6	7		N/A
7	Learning to operate the energy dashboard would be easy for me	unlikely							✓	likely	
8	I would find it easy to get the energy dashboard to do what I want it to do	unlikely							✓	likely	
9	My interaction with the energy dashboard would be clear and understandable	unlikely							✓	likely	
10	I would find the energy dashboard to be flexible to interact with	unlikely						✓		likely	
11	It would be easy for me to become skilful at using the energy dashboard	unlikely							✓	likely	
12	I would find the energy dashboard easy to use	unlikely							✓	likely	

May you please give a brief summary of your thoughts in your own words:

It is an interesting application and i think it would be helpful in managing electricity usage

Name: CHIEDZA MAKOTA

Position Held: STUDENT UNIVERSITY OF PRETORIA (BCOM ACCOUNTING)

Email add: chiesimz@gmail.com (u10078381@tuks.co.za

Test Case Feedback Form

Test case	Order	Achieved(Y/N)	Difficulty Level On a Scale 1-5
Start and log into application	1st	Y	1
Select Meter	2nd	Y	1
View live power readings graph	3rd	Y	1
View live energy readings graph	Any	Y	1
View forecasting details	Any	Y	1
Set warning limits and alerts	Any	Y	1
View itemised energy readings	Any	Y	1
view itemised bill by day	Any	Y	1
View itemised bill by month	Any	Y	1
Analyse archived readings using at least one chart	Any	Y	1
View weather forecast	Any	Y	2
View meter position in Google maps	Any	Y	1

Comments

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Questionnaire on User Interface Satisfaction

	OVERALL REACTION TO THE SOFTWARE		1	2	3	4	5	6	7	8	9		N/A
1		terrible									✓	wonderful	
2		difficult							✓			easy	
3		frustrating								✓		satisfying	
4		dull									✓	stimulating	
5		rigid						✓				flexible	
	SCREEN		1	2	3	4	5	6	7	8	9		N/A
6	Reading characters on the screen	hard									✓	easy	
7	Organization of information	confusing								✓		very clear	
8	Sequence of screens	confusing									✓	very clear	
	TERMINOLOGY AND SYSTEM INFORMATION		1	2	3	4	5	6	7	8	9		N/A
9	Use of terms throughout system	inconsistent									✓	consistent	
10	Terminology related to task	never									✓	always	
12	Position of messages on screen	inconsistent									✓	consistent	
13	Prompts for input	confusing								✓		clear	
14	Computer informs about its progress	never								✓		always	
15	Error messages	unhelpful									✓	helpful	
	LEARNING		1	2	3	4	5	6	7	8	9		N/A
16	Learning to operate the system	difficult							✓			easy	
17	Exploring new features by trial and error	difficult							✓			easy	
18	Remembering names and use of commands	difficult						✓				easy	
19	Performing tasks is straightforward	never							✓			always	
20	Help messages on the screen	unhelpful						✓				helpful	
21	Supplemental reference materials	confusing						✓				clear	
	SYSTEM CAPABILITIES		1	2	3	4	5	6	7	8	9		N/A
22	System speed	too slow								✓		fast enough	
23	System reliability	unreliable								✓		reliable	
24	Correcting your mistakes	difficult							✓			easy	
25	Designed for all levels of users	never								✓		always	

List most negative aspects:

User Manuals would very useful for people who do not have skills for using computers or any electronic device

List most positive aspects

The application is very much useful as it shows how much energy is being used and the users will be able to manage their energy usage.

Attributes of Usability Questionnaire

	Perceived Usefulness		1	2	3	4	5	6	7		N/A
3	Using the energy dashboard would increase my energy usage awareness	unlikely							✓	likely	
5	Using the energy dashboard would make it easier to manage my energy usage	unlikely							✓	likely	
6	I would find the energy dashboard useful in my home/company	unlikely							✓	likely	
7	Does the dashboard serve as well as a reporting tool	Unlikely							✓	likely	

	Perceived Ease of Use		1	2	3	4	5	6	7		N/A
7	Learning to operate the energy dashboard would be easy for me	unlikely						✓		likely	
8	I would find it easy to get the energy dashboard to do what I want it to do	unlikely						✓		likely	
9	My interaction with the energy dashboard would be clear and understandable	unlikely					✓			likely	
10	I would find the energy dashboard to be flexible to interact with	unlikely					✓			likely	
11	It would be easy for me to become skilful at using the energy dashboard	unlikely						✓		likely	
12	I would find the energy dashboard easy to use	unlikely					✓			likely	

May you please give a brief summary of your thoughts in your own words:

The application is very much useful but user manuals need to be provided to make the software usage easier.

Name: Senyolo Elvis

Position Held: Software developer

Email add: elvis.senyolo@opsi.co.za

Test Case Feedback Form

Test case	Order	Achieved(Y/N)	Difficulty Level On a Scale 1-5
Start and log into application	1st	Y	1
Select Meter	2nd	Y	1
View live power readings graph	3rd	Y	1
View live energy readings graph	Any	Y	1
View forecasting details	Any	Y	1
Set warning limits and alerts	Any	Y	1
View itemised energy readings	Any	Y	1
view itemised bill by day	Any	Y	1
View itemised bill by month	Any	Y	1
Analyse archived readings using at least one chart	Any	Y	2
View weather forecast	Any	Y	1
View meter position in Google maps	Any	Y	1

Comments

The application takes a while to get used to but it has an MS Office GUI it quickly starts feeling natural to use. The navigation was fairly easy to comprehend and I was impressed with the options that were offered and was not easily lost. The user friendliness in terms of getting the options I want when I want is good. I was also impressed by the ability to organise the panels to suit my needs and preferences as a consumer. I liked being able to have real time and historic data side by side. The ability to look at a specific meter is very valuable especially in an industry such as ours. This can help prevent unnecessary breaker trips as the controller can receive real time warnings on abnormal power surges. An electric utility can also use this tool to help predict demand more accurately so that it does not over generate power.

Questionnaire on User Interface Satisfaction

#	Item		1	2	3	4	5	6	7	8	9		N/A
	OVERALL REACTION TO THE SOFTWARE		1	2	3	4	5	6	7	8	9		N/A
1		terrible									X	wonderful	
2		difficult									X	easy	
3		frustrating									X	satisfying	
4		dull									X	stimulating	
5		rigid									X	flexible	
	SCREEN		1	2	3	4	5	6	7	8	9		N/A
6	Reading characters on the screen	hard									X	easy	
7	Organization of information	confusing									X	very clear	
8	Sequence of screens	confusing									X	very clear	
	TERMINOLOGY AND SYSTEM INFORMATION		1	2	3	4	5	6	7	8	9		N/A
9	Use of terms throughout system	inconsistent									X	consistent	
10	Terminology related to task	never									X	always	
12	Position of messages on screen	inconsistent								X		consistent	
13	Prompts for input	confusing								X		clear	
14	Computer informs about its progress	never					X					always	
15	Error messages	unhelpful								X		helpful	
	LEARNING		1	2	3	4	5	6	7	8	9		N/A
16	Learning to operate the system	difficult								X		easy	
17	Exploring new features by trial and error	difficult									X	easy	
18	Remembering names and use of commands	difficult									X	easy	
19	Performing tasks is straightforward	never							X			always	
20	Help messages on the screen	unhelpful					X					helpful	
21	Supplemental reference materials	confusing						X				clear	
	SYSTEM CAPABILITIES		1	2	3	4	5	6	7	8	9		N/A
22	System speed	too slow				X						fast enough	
23	System reliability	unreliable						X				reliable	
24	Correcting your mistakes	difficult									X	easy	
25	Designed for all levels of users	never									X	always	

List most negative aspects:

The availability of only one meter was a big let down for me. This led to the inability to drill down into more details about usage. The connection speeds were also not to a satisfactory level. The user interface could also do with more tool tips.

List most positive aspects:

The application has tremendous potential, utilities and consumers can both benefit from it. The ability to tell remotely how much power is being consumed in your home is a big plus. The application aligns users expectation and the supply ~~of~~ utility. Users will know what to expect on their monthly bill.

Attributes of Usability Questionnaire

	Perceived Usefulness		1	2	3	4	5	6	7		N/A
3	Using the energy dashboard would increase my energy usage awareness	unlikely							√	likely	
5	Using the energy dashboard would make it easier to manage my energy usage	unlikely							√	likely	
6	I would find the energy dashboard useful in my home/company	unlikely							√	likely	
7	Does the dashboard serve as well as a reporting tool	Unlikely							√	likely	

	Perceived Ease of Use		1	2	3	4	5	6	7		N/A
7	Learning to operate the energy dashboard would be easy for me	unlikely							√	likely	
8	I would find it easy to get the energy dashboard to do what I want it to do	unlikely							√	likely	
9	My interaction with the energy dashboard would be clear and understandable	unlikely							√	likely	
10	I would find the energy dashboard to be flexible to interact with	unlikely							√	likely	
11	It would be easy for me to become skilful at using the energy dashboard	unlikely							√	likely	
12	I would find the energy dashboard easy to use	unlikely							√	likely	

May you please give a brief summary of your thoughts in your own words: Brilliant concept and well executed. Pity the hardware fails the application but it ticks all the right boxes in terms of engineering requirements for both the electricity end user and utility.

Name: Ntsako Manyike

Position Held: Design Engineer (Eskom Distribution Limpopo Operating Unit)

Email add: ntsako.manyike@eskom.co.za

Test Case Feedback Form

Test case	Order	Achieved(Y/N)	Difficulty Level On a Scale 1-5
Start and log into application	1st	Y	1
Select Meter	2nd	Y	1
View live power readings graph	3rd	Y	1
View live energy readings graph	Any	Y	1
View forecasting details	Any	Y	1
Set warning limits and alerts	Any	Y	1
View itemised energy readings	Any	Y	1
view itemised bill by day	Any	Y	1
View itemised bill by month	Any	Y	1
Analyse archived readings using at least one chart	Any	Y	1
View weather forecast	Any	Y	1
View meter position in Google maps	Any	Y	3

Comments

The system was very user friendly it still need to be upgraded especially the meter positions that are supposed to ~~be shown~~ displayed on google Maps. If it was circles with different colours eg green for good power use, Red for above peak etc

Questionnaire on User Interface Satisfaction

	OVERALL REACTION TO THE SOFTWARE		1	2	3	4	5	6	7	8	9		N/A
1		terrible									✓	wonderful	
2		difficult								✓		easy	
3		frustrating									✓	satisfying	
4		dull									✓	stimulating	
5		rigid									✓	flexible	
	SCREEN		1	2	3	4	5	6	7	8	9		N/A
6	Reading characters on the screen	hard									✓	easy	
7	Organization of information	confusing								✓		very clear	
8	Sequence of screens	confusing								✓		very clear	
	TERMINOLOGY AND SYSTEM INFORMATION		1	2	3	4	5	6	7	8	9		N/A
9	Use of terms throughout system	inconsistent								✓		consistent	
10	Terminology related to task	never									✓	always	
12	Position of messages on screen	inconsistent								✓		consistent	
13	Prompts for input	confusing									✓	clear	
14	Computer informs about its progress	never									✓	always	
15	Error messages	unhelpful									✓	helpful	
	LEARNING		1	2	3	4	5	6	7	8	9		N/A
16	Learning to operate the system	difficult								✓		easy	
17	Exploring new features by trial and error	difficult								✓		easy	
18	Remembering names and use of commands	difficult								✓		easy	
19	Performing tasks is straightforward	never								✓		always	
20	Help messages on the screen	unhelpful									✓	helpful	
21	Supplemental reference materials	confusing									✓	clear	
	SYSTEM CAPABILITIES		1	2	3	4	5	6	7	8	9		N/A
22	System speed	too slow								✓		fast enough	
23	System reliability	unreliable							✓			reliable	
24	Correcting your mistakes	difficult								✓		easy	
25	Designed for all levels of users	never								✓		always	

List most negative aspects:

I liked the colour schemes but feel that they could be made better.

List most positive aspects

like the flexibity of the reports, one can sort any way possible.

Attributes of Usability Questionnaire

	Perceived Usefulness		1	2	3	4	5	6	7		N/A
3	Using the energy dashboard would increase my energy usage awareness	unlikely							✓	likely	
5	Using the energy dashboard would make it easier to manage my energy usage	unlikely							✓	likely	
6	I would find the energy dashboard useful in my home/company	unlikely							✓	likely	
7	Does the dashboard serve as well as a reporting tool	Unlikely							✓	likely	

	Perceived Ease of Use		1	2	3	4	5	6	7		N/A
7	Learning to operate the energy dashboard would be easy for me	unlikely							✓	likely	
8	I would find it easy to get the energy dashboard to do what I want it to do	unlikely							✓	likely	
9	My interaction with the energy dashboard would be clear and understandable	unlikely						✓		likely	
10	I would find the energy dashboard to be flexible to interact with	unlikely							✓	likely	
11	It would be easy for me to become skilful at using the energy dashboard	unlikely							✓	likely	
12	I would find the energy dashboard easy to use	unlikely							✓	likely	

May you please give a brief summary of your thoughts in your own words:

This is a very useful tool to have in once house hold or even in a Company. It will help people to save on electricity (cut down on electricity usage) I hope it becomes available for the general public.

Name: Jacob Futama

Position Held: Software Engineer

Email add: jacob.futama@opsi.co.za

Test Case Feedback Form

Test case	Order	Achieved(Y/N)	Difficulty Level On a Scale 1-5
Start and log into application	1st	y	1
Select Meter	2nd	y	1
View live power readings graph	3rd	y	1
View live energy readings graph	Any	y	1
View forecasting details	Any	y	1
Set warning limits and alerts	Any	y	1
View itemised energy readings	Any	y	1
view itemised bill by day	Any	y	2
View itemised bill by month	Any	y	2
Analyse archived readings using at least one chart	Any	y	2
View weather forecast	Any	y	2
View meter position in Google maps	Any	y	1

Comments

Works Perfectly will assist in improving consumption.

Questionnaire on User Interface Satisfaction

	OVERALL REACTION TO THE SOFTWARE		1	2	3	4	5	6	7	8	9		N/A
1		terrible									✓	wonderful	
2		difficult							✓			easy	
3		frustrating								✓		satisfying	
4		dull							✓			stimulating	
5		rigid						✓				flexible	

	SCREEN		1	2	3	4	5	6	7	8	9		N/A
6	Reading characters on the screen	hard							✓			easy	
7	Organization of information	confusing								✓		very clear	
8	Sequence of screens	confusing							✓			very clear	

	TERMINOLOGY AND SYSTEM INFORMATION		1	2	3	4	5	6	7	8	9		N/A
9	Use of terms throughout system	inconsistent							✓			consistent	
10	Terminology related to task	never								✓		always	
12	Position of messages on screen	inconsistent								✓		consistent	
13	Prompts for input	confusing									✓	clear	
14	Computer informs about its progress	never							✓			always	
15	Error messages	unhelpful								✓		helpful	

	LEARNING		1	2	3	4	5	6	7	8	9		N/A
16	Learning to operate the system	difficult							✓			easy	
17	Exploring new features by trial and error	difficult								✓		easy	
18	Remembering names and use of commands	difficult								✓		easy	
19	Performing tasks is straightforward	never									✓	always	
20	Help messages on the screen	unhelpful									✓	helpful	
21	Supplemental reference materials	confusing								✓		clear	

	SYSTEM CAPABILITIES		1	2	3	4	5	6	7	8	9		N/A
22	System speed	too slow								✓		fast enough	
23	System reliability	unreliable								✓		reliable	
24	Correcting your mistakes	difficult							✓			easy	
25	Designed for all levels of users	never						✓				always	

List most negative aspects:

N/A

List most positive aspects

Can be used to save Electricity Consumption

Attributes of Usability Questionnaire

	Perceived Usefulness		1	2	3	4	5	6	7		N/A
3	Using the energy dashboard would increase my energy usage awareness	unlikely							✓	likely	
5	Using the energy dashboard would make it easier to manage my energy usage	unlikely							✓	likely	
6	I would find the energy dashboard useful in my home/company	unlikely						✓		likely	
7	Does the dashboard serve as well as a reporting tool	Unlikely							✓	likely	

	Perceived Ease of Use		1	2	3	4	5	6	7		N/A
7	Learning to operate the energy dashboard would be easy for me	unlikely							✓	likely	
8	I would find it easy to get the energy dashboard to do what I want it to do	unlikely						✓		likely	
9	My interaction with the energy dashboard would be clear and understandable	unlikely					✓			likely	
10	I would find the energy dashboard to be flexible to interact with	unlikely						✓		likely	
11	It would be easy for me to become skilful at using the energy dashboard	unlikely					✓			likely	
12	I would find the energy dashboard easy to use	unlikely							✓	likely	

May you please give a brief summary of your thoughts in your own words:

....

....

....

....

Name: Aboo Raheman

Position Held: Solution Specialist

Email add: ab.rahman@opsi.co.za

Test Case Feedback Form

Test case	Order	Achieved(Y/N)	Difficulty Level On a Scale 1-5
Start and log into application	1st	Y	1
Select Meter	2nd	Y	1
View live power readings graph	3rd	Y	1
View live energy readings graph	Any	Y	1
View forecasting details	Any	Y	1
Set warning limits and alerts	Any	Y	1
View itemised energy readings	Any	Y	1
view itemised bill by day	Any	Y	1
View itemised bill by month	Any	Y	1
Analyse archived readings using at least one chart	Any	Y	2
View weather forecast	Any	Y	1
View meter position in Google maps	Any	Y	1

Comments

Questionnaire on User Interface Satisfaction

	OVERALL REACTION TO THE SOFTWARE		1	2	3	4	5	6	7	8	9		N/A
1		terrible								X		wonderful	
2		difficult									X	easy	
3		frustrating									X	satisfying	
4		dull							X			stimulating	
5		rigid								X		flexible	
	SCREEN		1	2	3	4	5	6	7	8	9		N/A
6	Reading characters on the screen	hard									X	easy	
7	Organization of information	confusing							X			very clear	
8	Sequence of screens	confusing							X			very clear	
	TERMINOLOGY AND SYSTEM INFORMATION		1	2	3	4	5	6	7	8	9		N/A
9	Use of terms throughout system	inconsistent									X	consistent	
10	Terminology related to task	never									X	always	
12	Position of messages on screen	inconsistent									X	consistent	
13	Prompts for input	confusing								X		clear	
14	Computer informs about its progress	never								X		always	
15	Error messages	unhelpful									X	helpful	
	LEARNING		1	2	3	4	5	6	7	8	9		N/A
16	Learning to operate the system	difficult									X	easy	
17	Exploring new features by trial and error	difficult									X	easy	
18	Remembering names and use of commands	difficult									X	easy	
19	Performing tasks is straightforward	never									X	always	
20	Help messages on the screen	unhelpful						X				helpful	
21	Supplemental reference materials	confusing					X					clear	
	SYSTEM CAPABILITIES		1	2	3	4	5	6	7	8	9		N/A
22	System speed	too slow									X	fast enough	
23	System reliability	unreliable								X		reliable	
24	Correcting your mistakes	difficult									X	easy	
25	Designed for all levels of users	never									X	always	

List most negative aspects:

....

....

....

List most positive aspects

LOOKS VERY USEFULL

INFORMATIVE DATA IS ALWAYS GOOD

....

....

....

Attributes of Usability Questionnaire

	Perceived Usefulness		1	2	3	4	5	6	7		N/A
3	Using the energy dashboard would increase my energy usage awareness	unlikely							X	likely	
5	Using the energy dashboard would make it easier to manage my energy usage	unlikely							X	likely	
6	I would find the energy dashboard useful in my home/company	unlikely							X	likely	
7	Does the dashboard serve as well as a reporting tool	Unlikely							X	likely	

	Perceived Ease of Use		1	2	3	4	5	6	7		N/A
7	Learning to operate the energy dashboard would be easy for me	unlikely							X	likely	
8	I would find it easy to get the energy dashboard to do what I want it to do	unlikely						X		likely	
9	My interaction with the energy dashboard would be clear and understandable	unlikely							X	likely	
10	I would find the energy dashboard to be flexible to interact with	unlikely					X			likely	
11	It would be easy for me to become skilful at using the energy dashboard	unlikely							X	likely	
12	I would find the energy dashboard easy to use	unlikely							X	likely	

May you please give a brief summary of your thoughts in your own words:

ADD THE MISSING SETTINGS FOR VI CUSTOMIZATION AND FINE TUNING OUTPUT, WARNINGS ETC.
ADD/CREATE CUSTOMIZED POWER INPUT PROFILES FUNCTIONALITY NEEDED. ADD FEATURE/VI TO ADD NEW INPUT/METRES VIA DASHBOARD

Name: ANDRÉ STEYN

Position Held: MOBILE SOFTWARE DEVELOPER

Email add: ANDRE.STEYN@OPSI.CO.ZA

Test Case Feedback Form

Test case	Order	Achieved(Y/N)	Difficulty Level On a Scale 1-5
Start and log into application	1st	Y	1
Select Meter	2nd	Y	1
View live power readings graph	3rd	Y	1
View live energy readings graph	Any	Y	1
View forecasting details	Any	Y	1
Set warning limits and alerts	Any	Y	1
View itemised energy readings	Any	Y	1
view itemised bill by day	Any	Y	1
View itemised bill by month	Any	Y	1
Analyse archived readings using at least one chart	Any	Y	1
View weather forecast	Any	Y	2
View meter position in Google maps	Any		2

Comments

Questionnaire on User Interface Satisfaction

#	Item		1	2	3	4	5	6	7	8	9		N/A
	OVERALL REACTION TO THE SOFTWARE		1	2	3	4	5	6	7	8	9		N/A
1		terrible									✓	wonderful	
2		difficult							✓			easy	
3		frustrating								✓		satisfying	
4		dull									✓	stimulating	
5		rigid								✓		flexible	
	SCREEN		1	2	3	4	5	6	7	8	9		N/A
6	Reading characters on the screen	hard									✓	easy	
7	Organization of information	confusing									✓	very clear	
8	Sequence of screens	confusing								✓		very clear	
	TERMINOLOGY AND SYSTEM INFORMATION		1	2	3	4	5	6	7	8	9		N/A
9	Use of terms throughout system	inconsistent								✓		consistent	
10	Terminology related to task	never									✓	always	
12	Position of messages on screen	inconsistent									✓	consistent	
13	Prompts for input	confusing									✓	clear	
14	Computer informs about its progress	never									✓	always	
15	Error messages	unhelpful									✓	helpful	
	LEARNING		1	2	3	4	5	6	7	8	9		N/A
16	Learning to operate the system	difficult									✓	easy	
17	Exploring new features by trial and error	difficult								✓		easy	
18	Remembering names and use of commands	difficult								✓		easy	
19	Performing tasks is straightforward	never									✓	always	
20	Help messages on the screen	unhelpful									✓	helpful	
21	Supplemental reference materials	confusing									✓	clear	
	SYSTEM CAPABILITIES		1	2	3	4	5	6	7	8	9		N/A
22	System speed	too slow									✓	fast enough	
23	System reliability	unreliable									✓	reliable	
24	Correcting your mistakes	difficult							✓			easy	
25	Designed for all levels of users	never									✓	always	

List most negative aspects:

Need To Improve User Understanding
Need in phone devices as well
~~pls Cost~~

List most positive aspects

Save our Electricity Bills
Help To save Energy in Country

Attributes of Usability Questionnaire

	Perceived Usefulness		1	2	3	4	5	6	7		N/A
3	Using the energy dashboard would increase my energy usage awareness	unlikely							✓	likely	
5	Using the energy dashboard would make it easier to manage my energy usage	unlikely							✓	likely	
6	I would find the energy dashboard useful in my home/company	unlikely							✓	likely	
7	Does the dashboard serve as well as a reporting tool	Unlikely							✓	likely	

	Perceived Ease of Use		1	2	3	4	5	6	7		N/A
7	Learning to operate the energy dashboard would be easy for me	unlikely						✓		likely	
8	I would find it easy to get the energy dashboard to do what I want it to do	unlikely							✓	likely	
9	My interaction with the energy dashboard would be clear and understandable	unlikely							✓	likely	
10	I would find the energy dashboard to be flexible to interact with	unlikely							✓	likely	
11	It would be easy for me to become skilful at using the energy dashboard	unlikely							✓	likely	
12	I would find the energy dashboard easy to use	unlikely							✓	likely	

May you please give a brief summary of your thoughts in your own words:

Excellent Innovation fore Each levels of Users for Knowing Consumption of electricity in House level, office level, organisation level. It's definetly Help ful to Users To save power.

Name: VeeraPrasad. Nunna

Position Held: Test Manager

Email add: Prasad.chinna@opsi.co.za

Test Case Feedback Form

Test case	Order	Achieved(Y/N)	Difficulty Level On a Scale 1-5
Start and log into application	1st	Y	1
Select Meter	2nd	Y	1
View live power readings graph	3rd	Y	1
View live energy readings graph	Any	Y	1
View forecasting details	Any	Y	1
Set warning limits and alerts	Any	Y	2
View itemised energy readings	Any	Y	1
view itemised bill by day	Any	Y	1
View itemised bill by month	Any	Y	1
Analyse archived readings using at least one chart	Any	Y	3
View weather forecast	Any	Y	1
View meter position in Google maps	Any	Y	1

Comments

Pretty easy to use - well not easy but with time one actually gets it

Questionnaire on User Interface Satisfaction

	OVERALL REACTION TO THE SOFTWARE		1	2	3	4	5	6	7	8	9		N/A
1		terrible							X			wonderful	
2		difficult								X		easy	
3		frustrating							X			satisfying	
4		dull								X		stimulating	
5		rigid								X		flexible	

	SCREEN		1	2	3	4	5	6	7	8	9		N/A
6	Reading characters on the screen	hard								X		easy	
7	Organization of information	confusing							X			very clear	
8	Sequence of screens	confusing								X		very clear	

	TERMINOLOGY AND SYSTEM INFORMATION		1	2	3	4	5	6	7	8	9		N/A
9	Use of terms throughout system	inconsistent							X			consistent	
10	Terminology related to task	never							X			always	
12	Position of messages on screen	inconsistent								X		consistent	
13	Prompts for input	confusing								X		clear	
14	Computer informs about its progress	never								X		always	
15	Error messages	unhelpful									X	helpful	

	LEARNING		1	2	3	4	5	6	7	8	9		N/A
16	Learning to operate the system	difficult								X		easy	
17	Exploring new features by trial and error	difficult									X	easy	
18	Remembering names and use of commands	difficult							X			easy	
19	Performing tasks is straightforward	never								X		always	
20	Help messages on the screen	unhelpful								X		helpful	
21	Supplemental reference materials	confusing								X		clear	

	SYSTEM CAPABILITIES		1	2	3	4	5	6	7	8	9		N/A
22	System speed	too slow					X					fast enough	
23	System reliability	unreliable							X			reliable	
24	Correcting your mistakes	difficult							X			easy	
25	Designed for all levels of users	never							X			always	

List most negative aspects:

Dependent on internet connectivity

List most positive aspects

Very insightful. I think this makes data usage real – there is power in SEEING

Attributes of Usability Questionnaire

	Perceived Usefulness		1	2	3	4	5	6	7		N/A
3	Using the energy dashboard would increase my energy usage awareness	unlikely							X	likely	
5	Using the energy dashboard would make it easier to manage my energy usage	unlikely							X	likely	
6	I would find the energy dashboard useful in my home/company	unlikely							X	likely	
7	Does the dashboard serve as well as a reporting tool	Unlikely							X	likely	

	Perceived Ease of Use		1	2	3	4	5	6	7		N/A
7	Learning to operate the energy dashboard would be easy for me	unlikely						X		likely	
8	I would find it easy to get the energy dashboard to do what I want it to do	unlikely						X		likely	
9	My interaction with the energy dashboard would be clear and understandable	unlikely						X		likely	
10	I would find the energy dashboard to be flexible to interact with	unlikely							X	likely	
11	It would be easy for me to become skilful at using the energy dashboard	unlikely							X	likely	
12	I would find the energy dashboard easy to use	unlikely							X	likely	

May you please give a brief summary of your thoughts in your own words:

The dashboard has made me change my views on what energy ~~[illegible]~~ I use seeing the energy used makes me want to control / change my energy usage - can definately use this in my home

Name: Chenai Mangisi

Position Held: Manager: Technology Assurance + Advisory

Email add: cmangisi@deloitte.co.za

Test Case Feedback Form

Test case	**Order**	**Achieved(Y/N)**	**Difficulty Level On a Scale 1-5**
Start and log into application	1st	✓	1
Select Meter	2nd	✓	1
View live power readings graph	3rd	✓	1
View live energy readings graph	Any	✓	1
View forecasting details	Any	✓	1
Set warning limits and alerts	Any	✓	1
View itemised energy readings	Any	✓	1
view itemised bill by day	Any	✓	1
View itemised bill by month	Any	✓	1
Analyse archived readings using at least one chart	Any	✓	2
View weather forecast	Any	✓	1
View meter position in Google maps	Any	✓	1

Comments

Managed to complete all the activities

Questionnaire on User Interface Satisfaction

	OVERALL REACTION TO THE SOFTWARE		1	2	3	4	5	6	7	8	9		N/A
1		terrible								✓		wonderful	
2		difficult									✓	easy	
3		frustrating									✓	satisfying	
4		dull									✓	stimulating	
5		rigid									✓	flexible	

	SCREEN		1	2	3	4	5	6	7	8	9		N/A
6	Reading characters on the screen	hard									✓	easy	
7	Organization of information	confusing									✓	very clear	
8	Sequence of screens	confusing									✓	very clear	

	TERMINOLOGY AND SYSTEM INFORMATION		1	2	3	4	5	6	7	8	9		N/A
9	Use of terms throughout system	inconsistent									✓	consistent	
10	Terminology related to task	never								✓		always	
12	Position of messages on screen	inconsistent								✓		consistent	
13	Prompts for input	confusing									✓	clear	
14	Computer informs about its progress	never								✓		always	
15	Error messages	unhelpful									✓	helpful	

	LEARNING		1	2	3	4	5	6	7	8	9		N/A
16	Learning to operate the system	difficult									✓	easy	
17	Exploring new features by trial and error	difficult								✓		easy	
18	Remembering names and use of commands	difficult								✓		easy	
19	Performing tasks is straightforward	never								✓		always	
20	Help messages on the screen	unhelpful							✓			helpful	
21	Supplemental reference materials	confusing					✓					clear	

	SYSTEM CAPABILITIES		1	2	3	4	5	6	7	8	9		N/A
22	System speed	too slow						✓				fast enough	
23	System reliability	unreliable							✓			reliable	
24	Correcting your mistakes	difficult							✓			easy	
25	Designed for all levels of users	never									✓	always	

List most negative aspects:

The graphs freeze now and again

List most positive aspects

Easy to use generally

Attributes of Usability Questionnaire

	Perceived Usefulness		1	2	3	4	5	6	7		N/A
3	Using the energy dashboard would increase my energy usage awareness	unlikely							✓	likely	
5	Using the energy dashboard would make it easier to manage my energy usage	unlikely							✓	likely	
6	I would find the energy dashboard useful in my home/company	unlikely							✓	likely	
7	Does the dashboard serve as well as a reporting tool	Unlikely						✓		likely	

	Perceived Ease of Use		1	2	3	4	5	6	7		N/A
7	Learning to operate the energy dashboard would be easy for me	unlikely							✓	likely	
8	I would find it easy to get the energy dashboard to do what I want it to do	unlikely							✓	likely	
9	My interaction with the energy dashboard would be clear and understandable	unlikely							✓	likely	
10	I would find the energy dashboard to be flexible to interact with	unlikely						✓		likely	
11	It would be easy for me to become skilful at using the energy dashboard	unlikely							✓	likely	
12	I would find the energy dashboard easy to use	unlikely							✓	likely	

May you please give a brief summary of your thoughts in your own words:

There is some good stuff here. This is something practical and it would go a long way in lowering my energy bills.

Name: Tawanda Mhuri

Position Held: Industrial Engineer at SC Junction

Email add: tmhuri@scjunction.co.za

Appendix I: Wits Energy Team Correspondence during design and development of Dashboard

Intentionally left blank

Rodwell Mangisi

From: Barney Marques <Barney.Marques@wits.ac.za>
Sent: 28 June 2012 09:47 AM
To: Rodwell Mangisi; Willie Cronje; Stephen Levitt; Mehroze Abdullah; Ken Nixon
Subject: RE: Nice capture of Raikes Road event.

Hi All
The generator contractor was on site yesterday and we tried to gradually migrate the load from City Power to the generator (to allow the machine to run on actual load), however the BMS stopped the process since we were using approximately 2,9 Mw and the generator can only handle about 2,3 Mw. However if City Power HAD gone down the BMS would have shut ALL no-essential equipment down before change-over and only allowed enough load to the generator to match its capacity.
Thank you
Barney

From: Rodwell Mangisi [mailto:rodwell.mangisi@opsi.co.za]
Sent: 28 June 2012 09:39 AM
To: Willie Cronje; Stephen Levitt; Mehroze Abdullah; Barney Marques; Ken Nixon
Subject: RE: Nice capture of Raikes Road event.

Hi prof

Do we have any idea what caused this sudden drop in consumption?

regards

RODWELL MANGISI

Systems & Software Developer
Bsc(Elec&Info Engineering) Wits

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Cel +27 72 028 0144
Fax + 27 11 880 2424
rodwell.mangisi@opsi.co.za
www.opsisystems.com

From: Willie Cronje [mailto:Willie.Cronje@wits.ac.za]
Sent: 27 June 2012 12:18
To: Stephen Levitt; Mehroze Abdullah; Barney Marques; Rodwell Mangisi; Ken Nixon
Subject: Nice capture of Raikes Road event.

Hallo everyone

This is screen grab of our Raikes meter having recorded an event on West Campus.

Regards
Willie

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Rodwell Mangisi

From: Willie Cronje <Willie.Cronje@wits.ac.za>
Sent: 12 March 2012 08:33 AM
To: Rodwell Mangisi
Subject: RE: quick question(urgent)

Rodwell

I think 90s is fine for now.

It will mean less than 30 data –points for 30 minutes.
But I think it is till acceptable.

All the best with the implementation.
Looking forward to a nice demo on Friday.

Regards
Willie

From: Rodwell Mangisi [mailto:rodwell.mangisi@opsi.co.za]
Sent: 12 March 2012 08:15 AM
To: Willie Cronje
Subject: quick question(urgent)

Hi prof

Just wanted to find out if updating the Live graph every 90seconds is acceptable to you? Apparently that is the fastest it can be because of the network. Or maybe further investigation must be carried out with respect to this?

Please let me know your thoughts . I have attached response from mandla below.

Regards

RODWELL MANGISI

Systems & Software Developer
Bsc(Elec&Info Engineering) Wits

OPSI Systems
Tel + 27 11 880 7951
Cel +27 72 028 0144
Fax + 27 11 880 2424
rodwell.mangisi@opsi.co.za
www.opsisystems.com

From: Mandla Mbuli [mailto:lm.mbuli@gmail.com]
Sent: 12 March 2012 08:09 AM
To: Rodwell Mangisi
Subject: Re: meter reading frequency

It is not configurable. It is something that just happens, I would assume it takes as long as it takes for a TCP/IP communication and I think that would be something that has to be measured. I can tell you though that the minimum time WILL (i haven't done this yet) be 1 second. As to how long it will take, I am not sure I can ever tell you because it will depend on the meter, the network speed and other factors I can't think of.

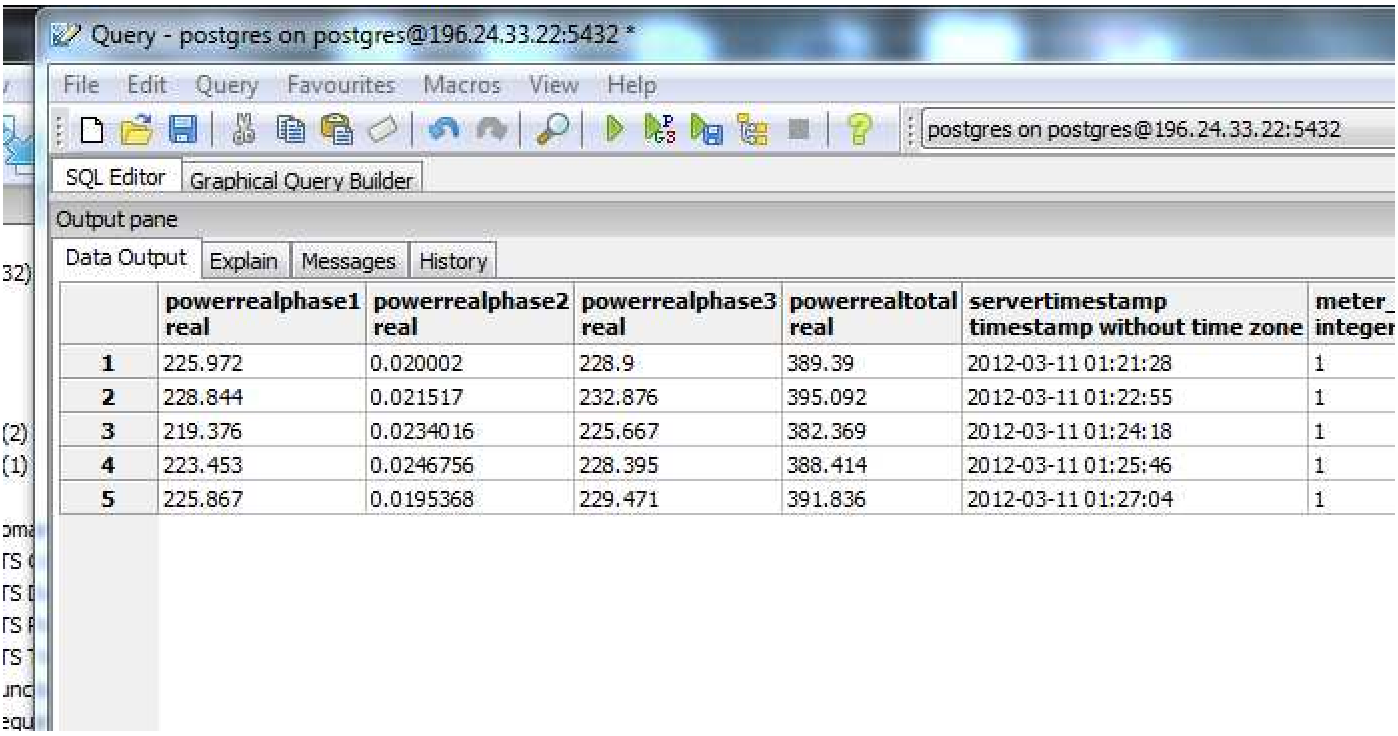
--

Leonard Mbuli
email: lm.mbuli@gmail.com
cell: 0815143468

On 11 March 2012 01:38, Rodwell Mangisi <rodwell.mangisi@opsi.co.za> wrote:

Hi guys

Can someone offer me some clarity on the frequency(number of times) a meters reading is taken per minute. From the data that I am getting on the server at IP address 196.24.33.22   the readings are coming after 90 seconds. Is this time configurable? Can I get the readings any faster?The faster the readings the nicer it would look on the live graphs. As it is I am only able to update the graphs after waiting for almost 90 seconds.I have attached a screenshot of sample readings I am receiving. Look at the servertimeStamp to see what I am talking about.



	powerrealphase1 real	powerrealphase2 real	powerrealphase3 real	powerrealtotal real	servertimestamp timestamp without time zone	meter_ integer
1	225.972	0.020002	228.9	389.39	2012-03-11 01:21:28	1
2	228.844	0.021517	232.876	395.092	2012-03-11 01:22:55	1
3	219.376	0.0234016	225.667	382.369	2012-03-11 01:24:18	1
4	223.453	0.0246756	228.395	388.414	2012-03-11 01:25:46	1
5	225.867	0.0195368	229.471	391.836	2012-03-11 01:27:04	1

Kind regards

Rodwell Mangisi

From: Willie Cronje <Willie.Cronje@wits.ac.za>
Sent: 05 June 2012 12:41 PM
To: Rodwell Mangisi
Cc: Stephen Levitt
Subject: Problem with integration
Attachments: Medschool20120605b.png

Rodwell

I attach another screenshot.
You can clearly see that the one integration period went from 11:30 to 12:30?
Even more curious the first interval on the screen was only 20 min?

Regards
Willie

Rodwell Mangisi

From:	Stephen Levitt <stephen.levitt@wits.ac.za>
Sent:	09 April 2013 11:34 AM
To:	Jake Helme; Peter Brookstein; Rodwell Mangisi; Rameez Khan; Avanindra Singh; Christopher Zumbika
Subject:	Fwd: Wits metering innitiative meeting

Title:

Wits metering innitiative

Location:

CoM prof. Cronje office

When:

12 April 2013 12:00 – 13:00

Organiser:

Willie Cronje

Description:

When: Friday, April 12, 2013 12:00 PM-1:00 PM. (UTC+02:00) Harare, Pretoria Where: CoM prof. Cronje office

-------- Original Message --------
Subject: Wits metering innitiative
Date: Tue, 9 Apr 2013 11:19:55 +0200
From: Willie Cronje <Willie.Cronje@wits.ac.za>
To: Stephen Levitt <Stephen.Levitt@wits.ac.za>, Ken Nixon
<Ken.Nixon@wits.ac.za>, Barney Marques <Barney.Marques@wits.ac.za>,
Mxolisi Dube <Mxolisi.Dube@wits.ac.za>, Mercy Shuma-Iwisi
<Mercy.Shuma-Iwisi@wits.ac.za>

<table width="100%" border="0" cellspacing="0" cellpadding="0" style="width:100%;">
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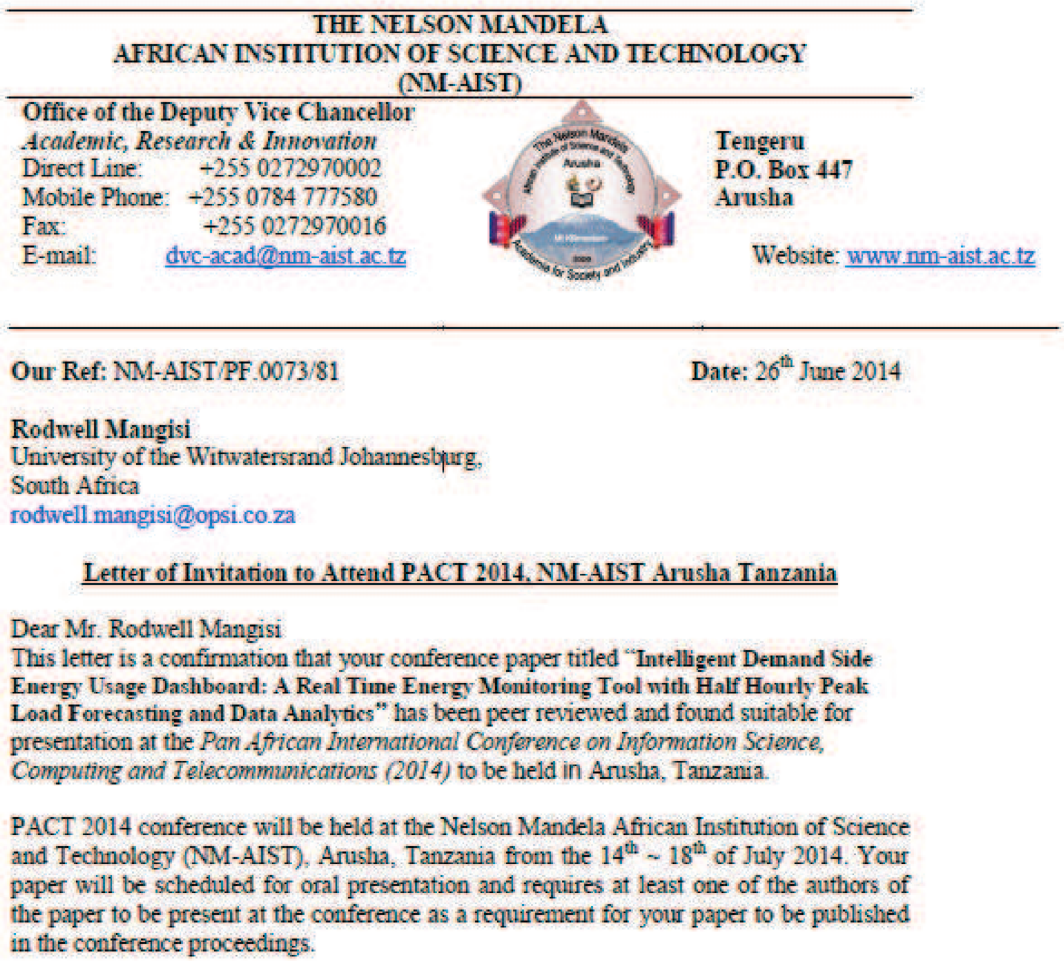
</tr>
</table

Appendix J: Conference Paper

1. Introduction

The image below shows the details of the conference to which this paper was submitted and accepted.



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Our Ref: NM-AIST/PF.0073/81

Date: 26th June 2014

Rodwell Mangisi
University of the Witwatersrand Johannesburg,
South Africa
rodwell.mangisi@opsi.co.za

Letter of Invitation to Attend PACT 2014, NM-AIST Arusha Tanzania

Dear Mr. Rodwell Mangisi
This letter is a confirmation that your conference paper titled "**Intelligent Demand Side Energy Usage Dashboard: A Real Time Energy Monitoring Tool with Half Hourly Peak Load Forecasting and Data Analytics**" has been peer reviewed and found suitable for presentation at the *Pan African International Conference on Information Science, Computing and Telecommunications (2014)* to be held in Arusha, Tanzania.

PACT 2014 conference will be held at the Nelson Mandela African Institution of Science and Technology (NM-AIST), Arusha, Tanzania from the 14th ~ 18th of July 2014. Your paper will be scheduled for oral presentation and requires at least one of the authors of the paper to be present at the conference as a requirement for your paper to be published in the conference proceedings.

Figure 68: Conference Details

Intelligent Demand Side Energy Usage Dashboard: A Real Time Energy Monitoring Tool with Half Hourly Peak Load Forecasting and Data Analytics

Rodwell Mangisi
School of Electrical and Information Engineering
University of the Witwatersrand
Johannesburg, South Africa
rodwell.mangisi@opsi.co.za

Barry Dwolatzky
Johannesburg Center for Software Engineering(JCSE)
University of the Witwatersrand
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barry.dwolatzky@wits.ac.za

***Abstract* - The smart grid, and in particular smart meters, is a growing world-wide phenomenon which has allowed for the availability of detailed real time usage data to the user in ways that were not possible in the past. This has led to the need for intelligent software applications to make use of this data in order to help consumers lower their energy consumption. This paper looks at the architecture and functionality of an intelligent demand side energy management dashboard prototype. It focuses on real time energy usage visualisation and half hourly peak load forecasting. The prototype implements real time data visualisation, as well as a Multiple Linear Regression based forecasting algorithm for half hourly peak load forecasting; using data from the University of the Witwatersrand advanced metering infrastructure. The visualisation techniques applied are shown to be suitable for consumer side energy monitoring and the forecasting algorithm is found to have a small absolute average error of 3.69%.**

Index Terms – Multiple Linear Regression, Short term load forecasting, Advanced Metering Infrastructure

A. Introduction

With the advent of smart meters a world of possibilities has been opened in the power data management and analytics arena. Smart meters and the data they provide can allow energy consumers to analyse, control, manage and forecast energy usage. Energy consumers have realised that if they take advantage of these capabilities they can save themselves a lot of money by intelligently managing their energy consumption [1]. One way consumers can reduce their energy bills is to shave their peak loads since utilities charge penalties on the highest peak achieved. In order for consumers to shave or control their peak loads one of the things they can do is to implement short term load forecasting (STLF). Load forecasting is not an easy task as the nature of a load profile is complex and depends directly or indirectly on a variety of mostly uncontrollable and uncertain factors such as the season (weather elements like temperature, humidity, wind speed etc.), day of the week, hour of the day, weekend or no weekend, holiday or no holiday and historical load profiles. To carry out this complex task forecasters use a number of algorithms implemented using various techniques notably classical statistics and Artificial Intelligence (AI) based techniques [2]–[5]. In this paper a classical statistics approach using Multiple Linear Regression (MLR) is used to offer short term load forecasting functionality to the proposed dashboard.

The problem spaces that the proposed dashboard prototype attempts to evaluate are as follows:

- Half hourly energy demand forecasting;
- Real time instantaneous power (kW) visualisation;
- Real time energy (kWh) usage visualisation;
- Real time energy billing estimations; and
- Smart grid data mining and analytics

B. Background

An Advanced Metering Infrastructure (AMI) is a network of automated two way communication between a smart meter with an IP address and a utility company or home energy management system [6]. The goal of such an infrastructure is to provide utility companies or private customers with real time and profile data about energy consumption and allow customers to make informed decisions on energy usage.

The University of the Witwatersrand School of electrical engineering energy group in collaboration with the Wits Property and Infrastructure Management Division (PIMD) set up an AMI network across all the universities campuses. There are over 150 smart meters across all the campuses and more meters continue to be added. Fig 1 below shows some of the Strike Enermax [7] smart meters that have been placed on the campuses.

Fig 1: Medical School Network Smart Meters

This AMI network is used as the laboratory for the study in this paper.

II. System Overview

A. *System Architecture*

The proposed energy management dashboard is a data driven application. The data used is real time energy consumption data that is continually collected from smart meters set up across the University of the Witwatersrand campuses. The data is stored into a PostgreSQL relational database. Since the application is driven from a database and presents information to the user via a user interface it is designed and implemented as a multi-tier software application to capture these different layers. The application is separated into three layers, namely the presentation layer (user interface), the application (business logic) layer and the data access layer as shown in Fig 2 below.

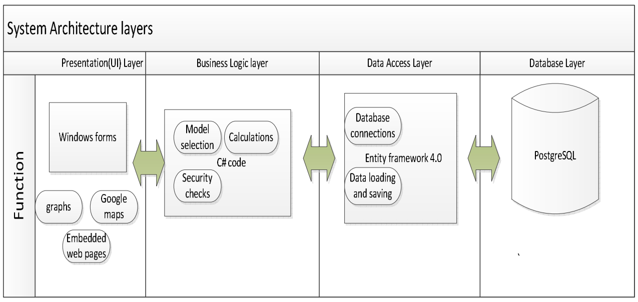


Fig 2: System Architecture

B. *Half hourly load forecasting algorithm*

Load forecasting is a major component of the dashboard. A multiple linear regression model is developed to capture the relationship between the load and the multiple variables it depends on. In order to develop the model half hourly load data for 2 years (2012-2013) from the University of the Witwatersrand west campus is used. The data is collected from the advanced metering system set up across the campus. Hourly historical temperature (^{o}C) data for Johannesburg for the same time period (2012-2013) is used with special permission from the South African weather service (SAWS). The load and temperature relations are investigated by analysing this data using built-in MLR modelling functions in R statistical package [8]. The following analysis is done before a MLR model is presented and used for STLF in the dashboard.

i. *Load-Temperature relationship*

The relationship of the load to the temperature is plotted and is shown in Fig 3 below. From the plot it can be seen that the relationship is not linear but is of some polynomial form. Table 2 below explains the trends realised in this analysis.

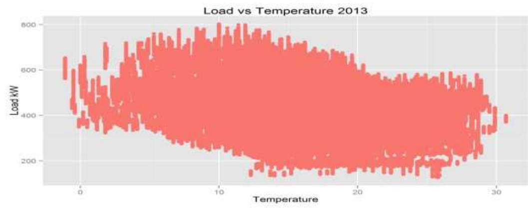


Fig 3: Load -Temperature relationship

Table 1: Load-Temperature analysis

Trend	Possible reason
As temperature reduces load increases	In low temperatures geysers use more energy to maintain hot water; People tend to switch on heaters and also stay indoors and hence have a lot of devices operational for longer.
Load decreases with increasing temperature up to a point and starts increasing again but to a lower peak than at lower temperature.	As temperature goes up people tend to switch off the heaters. But as temperature increases past comfortable levels people will start switching on air conditioners to maintain comfortable levels.

As has been shown in previous studies, a 3rd order polynomial relationship of load to temperature can be used with good results[5]. This is the relationship used to model the load-temperature relationship in the MLR model developed for the dashboard.

ii. *Load-Time of Day relationship*

Energy use depends heavily on the time of day as well as on the day of the week. In order to investigate this relationship on the available consumption data the data is plotted as shown in Fig 4.

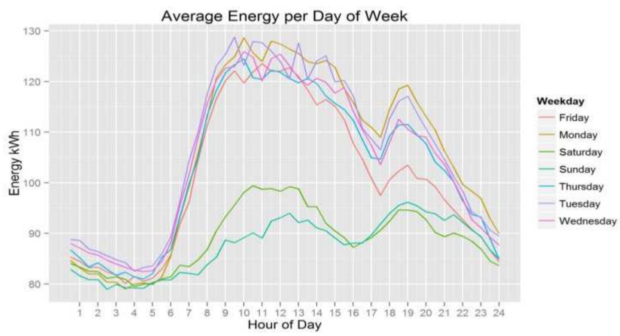


Fig 4: Load-Time of Day relationship

As can be seen energy usage is very low on Saturday and Sunday compared to the other week days. On all the days it can be seen that maximum usage occurs around midday (12pm) and is at its lowest between 3am and 4am. This plot shows that energy usage depends on the day of the week and time of day. It also shows dependability on whether the day is a weekend or week day. The plot also shows some expected trends for the hour of the day as tabulated below:

Table 2: Hourly Demand Behaviour

Trend	**Possible Reason**
Energy demand between midnight and 5am is very low	People on campus residences are sleeping , non-resident students and staff have left the campus at this time, devices and equipment not in use
Demand starts rising from around 6am till about 11am	People on campus residences start waking up, heaters, water boilers, air conditioning, cooking equipment starts being switched on. non-residents start arriving on campus
Demand starts decreasing from 11am till about 4:30pm	This period constitutes a time where water boilers are not being used to their maximum. Also from about 12pm some non-resident people start leaving campus and most equipment starts being shut down
Demand start increasing from 5pm until about 8pm	Cooking equipment starts being switched on. Resident students start switching on their devices in their rooms, part time classes also start around 6pm.
Demand starts decreasing from 8pm to midnight	Most resident students start calling it a night, devices shut down, no demand on water boilers, heaters or air conditioning.

iii. Load Dependence on Campus State

The data used in this study is for a University campus. It is important that an analysis is done to see how the load depends on the state of the campus. In this research the campus state variable is introduced and defined as the operational state of the campus broken into the following:

- Is campus closed (campus on holiday)
- Is campus open (campus fully operational)
- Special state (campus in administrative state i.e. registration period, orientation week and exam times)

The plot in Fig 5 below shows that an introduction of the campus state variable is important. It is shown that during the closed state energy usage is at its lowest. In the open state as expected the energy usage is at its maximum and it reduces slightly for the special case. This supports the introduction of this variable as the different states cannot be treated the same since they have a major impact on usage behaviour.

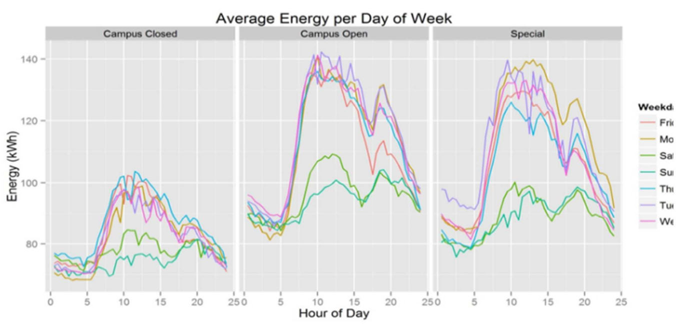


Fig 5: Load profile for different campus operational states

iv. Previous Peak

When carrying out any forecasting study it is important to think of how and if the past predicts the future [9]. In this STLF model the previous peak plays an important part as it gives a very strong indicator of what the next peak could be. The previous peak load is added as one of the independent variables in the model.

v. Independent Variable Listing

Table 3 below shows the selected varibles and indicates if the variable is either a quantitative variable or a qualitative variable.

Table 3: Independent Variable Listing

Variable	**Type of variable**	**Categories**
Temperature	Quantitative	n/a
Campus State	Qualitative	Open, Closed and Special
Day of the week	Qualitative	Sunday to Saturday
Time of day	Qualitative	1 to 48 (24 hour day divided into 48 half hour cycles)
Previous peak load	Quantitative	n/a

vi. MLR Model

A data transformation exercise is applied to the training data before an equation is formulated. The applied transformation introduces a single variable (named Baseline) to replace the half hour cycle, day of the week, month and campus state. This reduces the number of parameters required in solving the model. Time of day has 48 categories which introduces too many parameters. The transformation process is applied to the training data by first segmenting the data by half hour cycle, day of the week, month and campus status. For each segment, the mean of all peak energy values is calculated and this becomes the baseline value. Essentially the baseline variable is the expected peak energy before day of forecast and then on the day of forecast the temperature and previous peak are added to the model to give the forecast peak. The baseline variable captures the effects of half hour cycle, day of the week, month and campus status. The MLR model is modeled by the following equation:

$$\boldsymbol{Load} = \boldsymbol{\alpha_0 T(t)} + \boldsymbol{\alpha_1 L(t-0.5)} + \boldsymbol{\alpha_2 T(t)^3} + \boldsymbol{\alpha_3 B} + \boldsymbol{\alpha_5 (T(t) * B)} \quad \textbf{(1)}$$

Where:

$Load$= Forecast Peak load

$T(t)$= Temperature at time t

$L(t-0.5)$= Peak load of previous half hour cycle

$\alpha_{(0-5)}$ = Regression parameters

B= Baseline variable

vii. Forecasting Algorithm logic

As described previously, one of the functionalities of the prototype is to forecast the next half hourly peak load based on the developed MLR model. The logic that carries out this forecasting functionality is as summarised in the flow chart below.

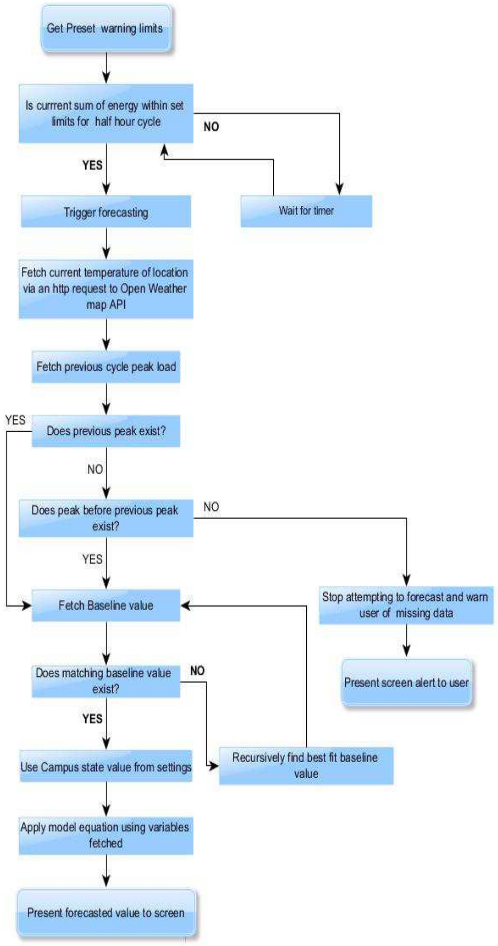


Fig 6: Peak load forecasting logic flow chart

This involves the looking up of baseline values, getting current Johannesburg temperature values from the open weather application programming interface (API)[10] , getting the campus state from the user input settings ,looking up previous peak load and applying these values to the MLR model.

viii. MLR Model Performance

Fitting this model to the training data using the 'lm' function in R [8] the equation coefficients are solved . A statistical significance testing on the results show that all the parameters chosen in this model are significant. The residuals of Model B are tabulated below. They show a small Inter quartile range of 5.057. The R-squared value is 0.9492 which indicates a strong fit of the data to the proposed model.

Table 4: Model B residuals

Min	1Q	Median	3Q	Max
-73.518	-2.387	0.110	2.670	47.186

The residuals scatter plot shown below also shows and supports the above results showing a strong fit with all points bunched around the zero value. This shows small deviations of forecast values from actual values.

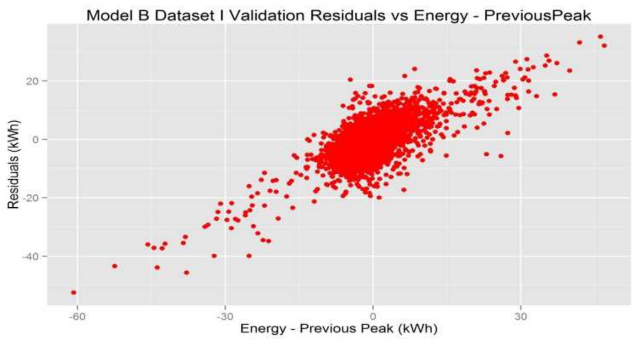


Fig 7: Forecasting Model Residuals plot

The algorithm is used to test data for a week in April (1st April-7th April 2013) and the results are plotted as shown in Fig 8 below. The plot shows a very strong fit and accuracy of the predicting algorithm. A mean absolute percentage error (MAPE) of 3.69 % is calculated for the model.

Fig 8: April week 1: Actual and forecasted half hour loads

C. User Interface

The proposed application is a dashboard hence the presentation layer is the most important layer of this system. Windows forms are used to create a configurable user interface. Users have the ability to drag and reposition different dock panels to suit their preferences. The overall interface of the dashboard looks as shown in Fig 9 below. The dashboard has a lot of panels that retreat into the sides of the screen and can be brought to the front on demand or if the user desires they can be docked to different positions on the screen. Each dock panel can also be floated across multiple screens such that on one screen the live energy graphs could be shown whilst on another the analytics screen is being shown as is the case in Fig 10 below. The different available panels show the following:

- •Real time Power and energy graphs per available meter
- •GIS panel showing meter position on a map
- •Energy readings archive that allows users to visualise past usage on graphs
- •Itemised energy values and actual Rand cost on an Excel like gridviews.
- •Settings panel for inputting cost per hour
- •Settings panel for inputting thresholds that trigger alerts
- •Embedded web page showing current and forecast weather

Fig 9: Dashboard with multiple screens docked

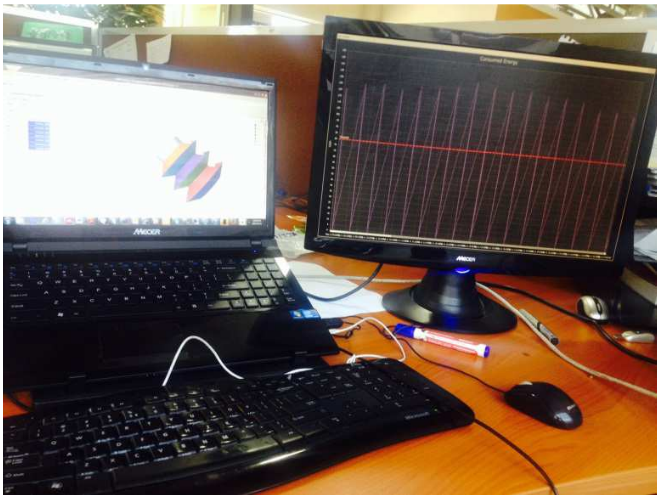


Fig 10: Dashboard panels spread across multiple screens

D. Real time load monitoring

The dashboard implements data mining techniques to populate live meter data from the smart meters. Users can select any meter they want to query from a drop down listing all the available meters and their online status as shown Fig 11below.

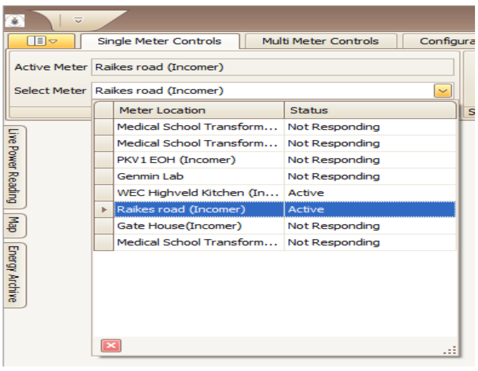


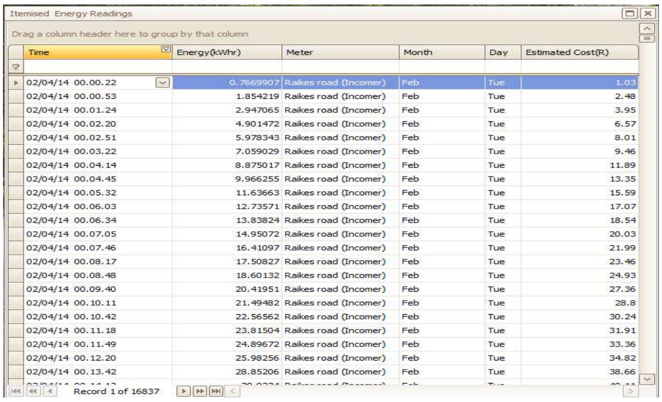
Fig 11: Meter Status and Selection

Real time data is then collected from the backend and shown on graphs as depicted in Fig 12 below. These graphs refresh every 30 seconds with current live energy and power readings.

Fig 12: Real time load graphs

F. Itemised Billing

The proposed dashboard also provides the user with itemised usage readings. These values can also include an estimated cost of the energy consumed. The cost is calculated by using the user supplied cost values that are input in the settings panel of the dashboard.



Itemised Energy Readings

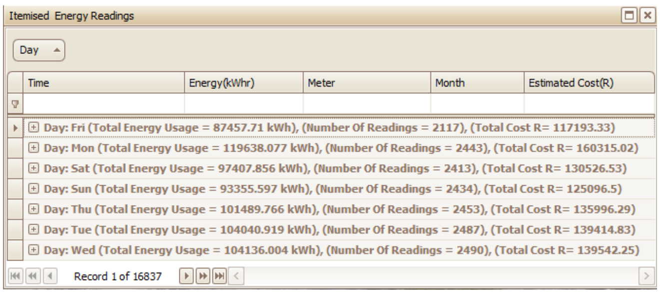
Drag a column header here to group by that column

Time	Energy(kWhr)	Meter	Month	Day	Estimated Cost(R)
02/04/14 00.00.22	0.7669907	Raikes road (Incomer)	Feb	Tue	1.03
02/04/14 00.00.53	1.854219	Raikes road (Incomer)	Feb	Tue	2.48
02/04/14 00.01.24	2.947065	Raikes road (Incomer)	Feb	Tue	3.95
02/04/14 00.02.20	4.901472	Raikes road (Incomer)	Feb	Tue	6.57
02/04/14 00.02.51	5.978343	Raikes road (Incomer)	Feb	Tue	8.01
02/04/14 00.03.22	7.059029	Raikes road (Incomer)	Feb	Tue	9.46
02/04/14 00.04.14	8.875017	Raikes road (Incomer)	Feb	Tue	11.89
02/04/14 00.04.45	9.966255	Raikes road (Incomer)	Feb	Tue	13.35
02/04/14 00.05.32	11.63663	Raikes road (Incomer)	Feb	Tue	15.59
02/04/14 00.06.03	12.73571	Raikes road (Incomer)	Feb	Tue	17.07
02/04/14 00.06.34	13.83824	Raikes road (Incomer)	Feb	Tue	18.54
02/04/14 00.07.05	14.95072	Raikes road (Incomer)	Feb	Tue	20.03
02/04/14 00.07.46	16.41097	Raikes road (Incomer)	Feb	Tue	21.99
02/04/14 00.08.17	17.50827	Raikes road (Incomer)	Feb	Tue	23.46
02/04/14 00.08.48	18.60132	Raikes road (Incomer)	Feb	Tue	24.93
02/04/14 00.09.40	20.41951	Raikes road (Incomer)	Feb	Tue	27.36
02/04/14 00.10.11	21.49482	Raikes road (Incomer)	Feb	Tue	28.8
02/04/14 00.10.42	22.56562	Raikes road (Incomer)	Feb	Tue	30.24
02/04/14 00.11.18	23.81504	Raikes road (Incomer)	Feb	Tue	31.91
02/04/14 00.11.49	24.89672	Raikes road (Incomer)	Feb	Tue	33.36
02/04/14 00.12.20	25.98256	Raikes road (Incomer)	Feb	Tue	34.82
02/04/14 00.13.42	28.85206	Raikes road (Incomer)	Feb	Tue	38.66

Record 1 of 16837

Fig 13: Itemised billing grid views

From these views users are able to group the columns into a variety of summary groups. They can view by day in order to see their consumption totals per day as shown in Fig 14 below.



Itemised Energy Readings

Day

Time	Energy(kWhr)	Meter	Month	Estimated Cost(R)

- Day: Fri (Total Energy Usage = 87457.71 kWh), (Number Of Readings = 2117), (Total Cost R= 117193.33)
- Day: Mon (Total Energy Usage = 119638.077 kWh), (Number Of Readings = 2443), (Total Cost R= 160315.02)
- Day: Sat (Total Energy Usage = 97407.856 kWh), (Number Of Readings = 2413), (Total Cost R= 130526.53)
- Day: Sun (Total Energy Usage = 93355.597 kWh), (Number Of Readings = 2434), (Total Cost R= 125096.5)
- Day: Thu (Total Energy Usage = 101489.766 kWh), (Number Of Readings = 2453), (Total Cost R= 135996.29)
- Day: Tue (Total Energy Usage = 104040.919 kWh), (Number Of Readings = 2487), (Total Cost R= 139414.83)
- Day: Wed (Total Energy Usage = 104136.004 kWh), (Number Of Readings = 2490), (Total Cost R= 139542.25)

Record 1 of 16837

Fig 14: Itemised billing view grouped by day of the week

Users can also group these columns by month and by meter if they are viewing multiple meters at the same time. These views also offer the ability of filtering and ordering the values in any user requested way.

E. Archived Data Analytics

The prototype offers users the ability to create custom pivot tables and charts and apply them to archived data. Users can select to apply any date range on a single or multiple meters and the dashboard will query the backend for this data. Figures 15 and 16 below show some of the charts available to the user. In this mode the user can do a variety of analytics such as study trends for the past day, weeks, months or years.

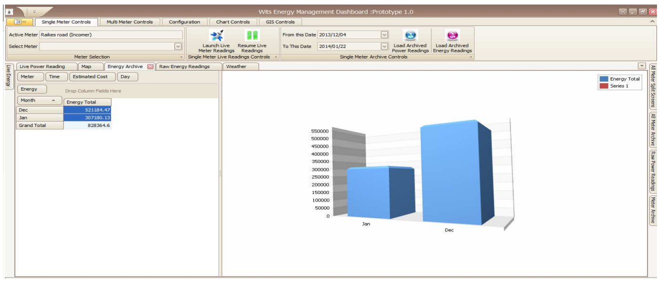


Fig 15: Archived usage data analytics (3D bar charts)

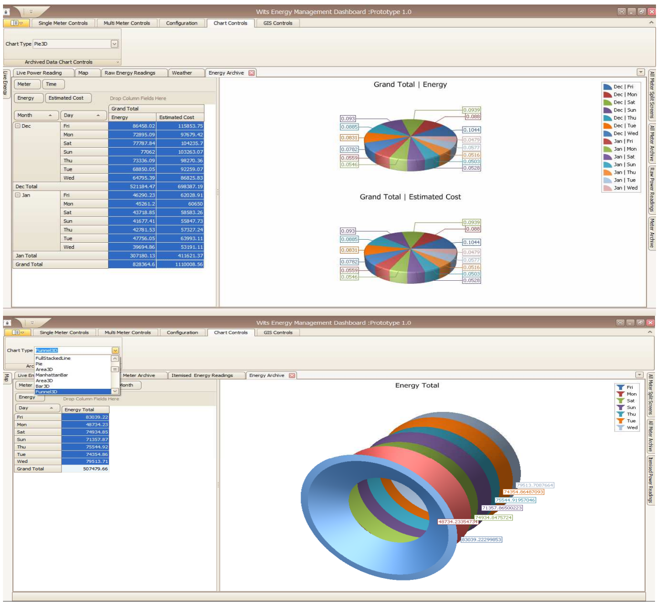


Fig 16: 3D Pie and Funnel charts applied to archive usage data

The analytics functionality also allows users to compare usage for different meters against each other.

III. User Acceptance

Ten people from different walks of life were approached to be testing participants. The approach taken in getting user feedback is to demonstrate the prototype then train the user on how to operate it. The user is then given time to interact unaided with the dashboard and thereafter asked to fill in a questionnaire. The questionnaire is based on the measurement scales discussed by Davis [11] that help in measuring perceived usefulness, learning difficulty and overall reaction to the software. The questionnaire survey gave a very positive feedback with all users who tested the application reporting that the dashboard is user friendly, intuitive and a tool they would use if it was made available to them. One of the questionnaire response analysis graphs is shown in Fig 17 below.

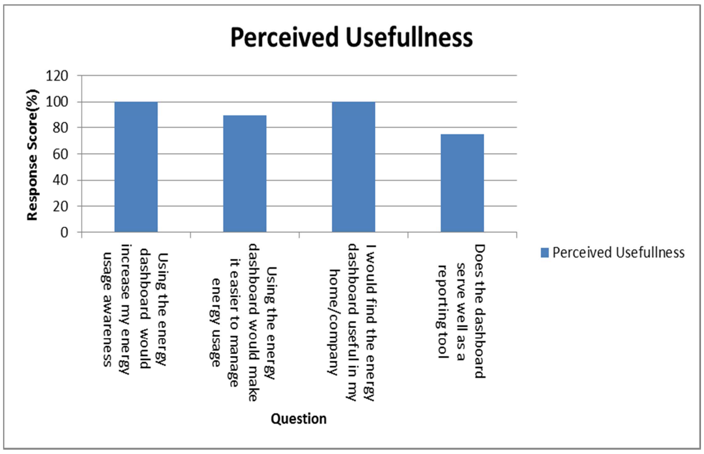


Fig 17: Perceived Usefulness questionnaire response analysis

IV. Conclusion

A load forecasting dashboard with live energy monitoring graphs has been presented. The forecasting algorithm has been shown to be accurate with a MAPE of 3.69 % .The prototype uses advanced real time smart grid data visualisation techniques which have been shown in the usability tests to have the potential to change user behaviour positively. If the dashboard is made available to consumers it can have direct financial benefits to them as they will start being energy wise and shaving their peak loads. This also benefits utilities as energy demand will be lowered and the strain on national grids reduced.

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