Non-Intrusive Load Monitoring and Identification for Energy Management Systems Using Computational Intelligence Approach

By

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Declaration

I, Ereola Johnson Aladesanmi, declare that this is my own work. All other sources used have been referenced. The dissertation has not been submitted before for any other degree at this or any other university.

Signature:

Mr. Ereola Johnson Aladesanmi

Signed at the University of Cape Town

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ABSTRACT

Electrical energy is the life line to every nation's or continent development and economic progress. Referable to the recent growth in the demand for electricity and shortage in production, it is indispensable to develop strategies for effective energy management and system delivery. Load monitoring such as intrusive load monitoring, non-intrusive load monitoring, and identification of domestic electrical appliances is proposed especially at the residential level since it is the major energy consumer. The intrusive load monitoring provides accurate results and would allow each individual appliance's energy consumption to be transmitted to a central hub. Nevertheless, there are many practical disadvantages to this method that have motivated the introduction of non-intrusive load monitoring system. The fiscal cost of manufacturing and installing enough monitoring devices to match the number of domestic appliances is considered to be a disadvantage. In addition, the installation of one meter per household appliances would lead to congestion in the house and thus cause inconvenience to the occupants of the house, therefore, non-intrusive load monitoring technique was developed to alleviate the aforementioned challenges of intrusive load monitoring. Non-intrusive load monitoring (NILM) is the process of disaggregating a household's total energy consumption into its contributing appliances. The total household load is monitored via a single monitoring device such as smart meter (SM). NILM provides cost effective and convenient means of load monitoring and identification. Several non-intrusive load monitoring and identification techniques are reviewed. However, the literature lacks a comprehensive system that can identify appliances with small energy consumption, appliances with overlapping energy consumption and a group of appliance ranges at once. This has been the major setback to most of the adopted techniques. In this dissertation, we propose techniques that overcome these setbacks by combining artificial neural networks (ANN) with a developed algorithm to identify appliances ranges that contribute to the energy consumption within a given period of time usually an hour interval.

First, the artificial neural networks (ANN) were used to model the household energy consumption for pattern recognition. The ANNs use the actual hourly household energy consumption and time of the day as inputs and the appliance energy consumptions as a target and finally, the neural network validation was carried out.

Second, an algorithm was developed to recognize a group of appliances. The algorithm use the output of the ANN compared it to the appliance energy consumption range to predict the appliances range for a specified time. The algorithm displays the time of the day that the energy was consumed by the appliances per hour, the total energy consumed and the predicted appliances as output and then plot the graphs for appliances predicted. In the graph, the appliances range with the highest probability is predicted as the appliances that are ON for that hour. The research work contributes significantly to the energy managements at the residential domain and improves efficiency of available energy resource usage. In addition, it enables real-time appliance recognition, which is a stepping-stone towards energy consumption reduction in the residential domain. Furthermore, it will allow a number of applications such as load-shifting, energy audit, energy expenditure breakdown per appliances, detection of faulty appliances and energy consumption forecast for effective energy planning.

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Nomenclature

Abbreviations

NILM	Non-Intrusive Load Monitoring
ILM	Intrusive Load Monitoring
SM	Smart Meter
ANN	Artificial Neural Network
LRN	Layered Recurrent Neural Network
MSEREG	Mean Square Error with Regularization
MLP	Multi-Layer Perception
MAPE	Mean Absolute Percentage Error
SMAPE	Symmetric Mean Absolute Error
RMSE	Root Mean Square Error
STD	Standard Deviation
AE	Absolute Error
MAE	Mean Absolute Error
MASE	Mean Absolute Scaled Error
HMES	Home energy management system
SG	Smart Grid
CI	Computational Intelligence
AMI	Advanced Metering Infrastructure
WAN	Wide-Area Network
HAN	Home Area Network

MDMS	Meter Data Management System
DR	Demand Response
EPRI	Electric Power Research Institute
SMS	Smart Metering System
AHAM	Association of Home Appliances Manufacturer
EM	Electromagnetic Meters
AMR	Automatic Meter Reading
WAMPAC	Wide-Area Monitoring Protection System
SMT	Synchronized Measurement Technology
PMU	Phasor Measurement Unit
GPS	Global Positing System
IEA	International Energy Agency
NIST	National institute of Standard and Technology
EIPP	Eastern Interconnected Phasor Project
DC	Data Collector
DSM	Demand Side Management
DLC	Direct Load Control Critical Peak Pricing
CPP	Critical Peak Pricing
TOUP	Time of Use Pricing
RTP	Real Time Pricing
CIU	Customer Interface Unit
ACD	Application Controller Device
PLC	Power line System

GSM	Global System Mobile
RF	Radio Frequency
Wi-Fi	Wireless- Fidelity
LAN	Local Area Network
MAN	Metropolitan Area Network
ANSI	American National Standards Institute
EISA	Energy Independent and Security Act
NAN	Neighbours Area Network
DAP	Data Aggregation Points
WI MAX	Worldwide Interoperability for Access
HWMP	Hybrid Wireless Mesh Protocol
ZC	ZigBee Coordinator
ZR	ZigBee Router
ZED	ZigBee End Device
SEP	Smart Energy Profile
HA	Home Automation
CBA	Commercial Building Automation
WLAN	Wireless Local Area Network
MIMO	Multiple-input multiple-out
OFDM	Orthogonal Frequency Division Multiplexing
WPA	Wi-Fi Protected Access
WPS	Wi-Fi Protected Setup
PSK	Pre-Shared Key

PIN	Personal Identification Number
PBC	Push-Button Configuration
NFC	Near-Field Communication
NB-PLC	Narrowband Power Line Communication
BB-PLC	Broadband Power Line communication
LDR	Low Data Rate
HDR	High Data Rate
SGIP	Smart Grid Interoperability Panel
OSI	Open System Interoperability
PHY	Physical Layer
HD-PLC	High Definition Power Line Communication
ITU	International Telecommunication Union
DLL	Data Line Layer
SH	Smart House
SA	Smart Appliances
ECDEM	European Committee of Domestic Equipment Manufacturer
TRV	Thermostatic Radiator Valves
EC	Electronically Commutator
ECEEE	European Council for Energy Efficiency Economy
COP	Coefficient of Performance
CDA	Conditional Demand Analysis
EPRI	Electric Power Research Institute
RMS	Root Mean Square

PR	Power Factor
STFT	Short Time Fourier Transforms
FTT	Fast Fourier Transforms
V-I	Voltage- Current
CW	Continuous Wavelet Transform
DWT	Discrete Wavelet Transform
SCADA	Supervisory Control and Data Acquisition
IS	Intelligent System
AI	Artificial Intelligence
FL	Fuzzy Logic
SI	Swarm Intelligence
AIS	Artificial Immune System
FS	Fuzzy System
EC	Evolutionary Computation
BN	Biological Neuron
ADALINE	Adaptive Linear Element
LMS	Least Means Square
FFLNN	Feed-Forward Layer Neural Network
MLFFNN	Multilayer Feed Forward Neural Network
RBF	Radial Bases Function
ART	Adaptive Resonance Theory
KBNN	Knowledge Based Neural Network
MLP	Multilayer Perceptron

MFNN	Multilayer Feed-forward Neural Network
TV	Television
AC	Air-conditioning
DSTV	Dstv-Decoder
RF	Refrigerator
WH	Water Heater
EST	Electric Stove
MIC	Microwave
SLC	Slow Cooker
EFP	Electric Frying Pan
CK	Cordless Kettle
SM	Sewing Machine
OV	Oven
INB	Incandescent Bulb
PC	Personal Computer
MO	Modem
EFE	Electric Fence
PR	Printer
EH	Electric Heater
EBL	Electric Blanket
EI	Electric Iron
VCL	Vacuum Cleaner
ECP	Electric Circulation Pump

DW	Dishwasher
EFN	Electric Fan
HI-FI	Hi-Fi Equipment
SP	Swimming Pool
TUD	Tumble Dryer
WM	Washing Machine

CHAPTER 1

Introduction

Recently, electric power sector is experiencing a major challenge in its generation and distribution systems, due to the increase in energy demand and limited energy generation resources across the globe. Also, the persistent increase in global population will continue to increase the demand for energy. In an effort to meet the increase in energy demand and ensure efficient utilization of electricity, energy conservation and effective management have therefore become an area of increase interest of research to utility across the globe. Also, In order to avoid disastrous damage to the utility infrastructure and also to the global economy, it is therefore necessary to develop techniques by which energy infrastructure can meet such an increase in energy demand. Apart from the industrial sector, which accounts for the largest energy consumption, residential buildings account for the second largest energy consumption globally. In order to reduce the load placed on national infrastructure and resources, it is essential to improve the efficiency of energy consumption in residential buildings by eliminating wasted energy. The improvements in energy consumption efficiency will contribute to a reduction in overall electricity demand. In this context, the concept of Home Energy Management System (HEMS) refers to a home environment upgraded with smart appliances for managing, improving domestic energy consumption and appropriately interacting with the end user for the aim of energy consumption management. The understanding and comprehensive energy consumption monitoring techniques in the residential sector can bring several advantages. Primarily, proper monitoring of household energy consumption is advantageous to improve the homeowners' awareness about the actual amount of energy consumed in the house and its associated cost. Energy consumption monitoring techniques if properly configured and managed can be used to detect the load profile of a specific appliance and their energy usage profiles. Therefore, customers can be made to know how much the usage of a specific appliance affects the total energy consumption of the house and decide whether to replace it with a more efficient one or just adjust its usage to off-peak hours. In addition, the analysis of an appliance load profile can also help in identifying faulty appliances and thus replace them before the appliance status further worsens. Apart from the aforementioned benefits, effective energy consumption monitoring is also beneficial to utility companies. Analysis and predictions on energy consumption of a typical household can provide information that is useful for defining and enforcing policies that can improve energy consumption management, such as demand response program. The most widely designed home energy monitoring techniques basically provide information on the whole energy consumption profile of the household. However, this information is not useful in recognizing and predicting user habits and proposing possible suggestions [1]. One way of increasing the efficiency of domestic energy usage, is to encourage positive behavioural change in consumers. This can be achieved by providing feedback to household's occupant indicating how much energy each domestic appliance has consumed. The simple and effective way of managing residential energy consumption is by monitoring the energy consumption of each appliance in the household.

This dissertation, deal with intelligence and effective technique of monitoring and identifying residential appliances using non-intrusive load monitoring and identification technique, where the whole household appliances are monitored without intruding into the customer's premises. The consumption of individual appliances is estimated using artificial neural network and an algorithm is developed to predict the actual appliance(s) that are switched ON at a giving period of time.

1.1 Aim of the Dissertation

The main aim of this dissertation is to disaggregate the total energy consumed in a household into individual appliances for the purpose of monitoring and identification.

1.2 Research Methodology

The research was conducted by analysing the energy consumption of some selected households in Johannesburg based on their hourly energy consumption. Also, energy consumption of some selected domestic appliances was analysed. Finally, artificial neural network in MATLAB was used for pattern recognition of household energy consumption for the purpose of appliances' monitoring and identification. And an algorithm was developed to identify the appliance based on the hourly energy consumption of the household using the outputs of the neural network.

1.3 Scope and Limitations of the Dissertation

This dissertation concentrates on the non-intrusive approach of load monitoring and adopts artificial neural network for energy consumption pattern recognition and developed an algorithm for the purpose of appliances monitoring and identification. The first part of this work involves the load profile analysis of some selected households. The analysis is based on different seasons (summer and winter) of the year and different days of the week (weekdays and weekend). The second part covers the identification of the appliance(s) based on the load profile analysis. The appliance(s) identified in this dissertation are limited only to the domestic appliances, the industrial appliances are not considered.

1.3.1 Limitation

There are still some limitations to the full implementation of the algorithm used in this dissertation. For instance, the algorithm cannot detect any appliance that is not in the household appliance database, which may be as a result of new appliance brought into the house.

1.4 Contribution of the Dissertation

The method employed in this dissertation overcomes the problem of monitoring and identifying energy consumption of phantom appliance since the hourly appliance energy consumption is used for the modelling.

1.5 Dissertation Structure

The remaining chapters of this dissertation are structured as follows:

Chapter 2: Overview of smart grid (SG). This provides the basic knowledge of smart grid application, smart metering system and current scenario in smart grid (smart house and smart appliances);

Chapter 3: This chapter presents an overview of energy consumption of some selected domestic smart appliances. In this section, technical description and mode of operation of these appliances as well as the factors that determined the energy consumption of each appliance are discussed.

Chapter 4: This chapter describes load monitoring and identification techniques. Also, the chapter presents appliance signatures.

Chapter5: Overview of computational intelligence (CI) techniques used for non-intrusive load monitoring was presented in the chapter. The focus was on artificial neural network (ANN)

Chapter 6: This chapter analysis time dependence of energy consumption of some selected households in Johannesburg based on different days of the week and seasons of the year. Comparisons were made on the energy consumption of the household. The energy consumption data used for the analysis were collected from six different high-income households in Johannesburg.

Chapter 7: The chapter presents energy consumption and cost analysis of some selected domestic appliances. The analysis is carried out on different days of the week (working days and weekends) and different season of the year (winter and summer) and comparisons were made for the purpose of identifying the specific appliances that contribute greatly to the monthly energy bill the household.

Chapter 8: Finally, the appliances were modelled based on the individual hourly appliance energy consumption and an algorithm was developed to identify the appliances.

Chapter 9: Presents the conclusion and recommendation for future works

CHAPTER 2

Smart Grid Overview

Introduction

The emerging of smart meters in power systems will contribute immensely to the efficient and effective energy management systems, especially in the residential sector. It will enable utility to have access to real-time information about consumers. The information ensures more reliable, secure and efficiency of energy management systems. In addition, the communication between consumer and utility aim to provide information to consumers about their energy consumption patterns for judicious use of electricity. Also information about energy consumption in the residential sector has not been accurate due to lack of real time information. With the concept of smart grid the data acquisition will become more accurate and fast. Furthermore, for effective implementation of a home energy management system, the household must be equipped with sensors or devices for collecting real-time data, smart appliances for managing and optimizing the energy consumption. Thus, in this context, the concept of a smart grid is very essential in the implementation of load monitoring and identification. Therefore, this chapter reviews the basic concept of a smart grid for effective implementation of residential energy management, load monitoring and identification. Recently, utility industries across the globe are trying to address numerous challenges, such as generation heterogeneity, demand response, reduction in overall carbon emission and energy conservation. It is evident that such critical issues cannot be addressed within the limits of the existing conventional power grid. The next-generation power grid, known as the "smart grid" or "intelligent grid," is expected to address the major deficiency of the existing conventional power grid [2].

A smart grid is a new concept in power systems, where some technologies are employed in order to automate or computerized the power grid. These automation technologies aim to improve the reliability, efficiency and security of the power grid. In this regards, smart grid aims to automatically control and monitor power system devices and communicate with the information to both the utility and the end users in real-time. Smart grid concepts were denoted as Automatic Metering Infrastructure (AMI). Basically, information is exchanged within the smart grid concept is into ways, the first way is based on the change of information between consumer's smart meters and the second way is the change of information between smart meters and the utility control centre. The information exchanges between consumer's smart meters are beneficial to consumers as well as the utility in many ways. Identification of energy household consumption, demand-side management, demand control, and energy price estimation are some of the benefits [3].

2.1 Conventional Power Grid

For a clear understanding of smart grid, it is essential to review conventional power grid, due to this, section reviews conventional power grid structure. In the conventional power grid, electrical energy is generated from the centralized power generating station locating close to the source of energy such as coal, fossil fuel, natural gas and petroleum. The step-up transformer in the station transformed the energy generated to high-voltage electrical energy that is suitable for transmission over a long distance transmission line to the consumption locations. The transmission lines are connected to a substation where the step-down transformer transformed the high voltage electrical energy into lower-voltage energy. The lower-voltage energy is then transmitted over distribution power lines to different destinations for customers' use [4]. The conventional power grid is radial in nature and was designed mainly for power flow in one direction. The control and protection scheme in the conventional power grid is minimal and the response to disturbances is slow and usually by manual means. Consequently, the conventional power grid is vulnerable to attacks and disturbances which may lead to blackout in some cases. In addition, due to the nature of sources of power generation in conventional grids, it contributes greatly to environmental pollution through the emissions of gasses such as CO2, and NO2 from the coal, fossil fuel and petroleum. Furthermore, in conventional power grids about ten percent of power generated is loss, which contributes to the high cost of electricity and global warming. For instance, in the United States, over half of the electricity generated is lost due to power generation, transmission and distribution inefficiency [5]. Also, the conventional power grid designed in the twentieth century, with poorly planned distribution networks, overloading of system components, lack of reactive power support and regulation services contribute significantly to the present poor power system performance. Electromechanical metering and billing system of conventional power grid contribute to irregularity in billing system and illegal consumption of electricity by consumers, which incur serious losses and consequently impose a high electricity price on legal consumers. Moreover, the ageing infrastructures and old technologies used in building conventional power grid has led to inadequate power generation which cannot meet the increase in the recent energy demand. In order to overcome these challenges, electric power system must move from conventional system which is characterized by the central generation system to the modern electric power grid which is characterized by decentralized generating system. This modern electric power grid (smart grid), allows the integration of different technologies for better performance. The figure 2.1 below depicts the structure of the conventional power grid from the generating station to the consumer's premises.

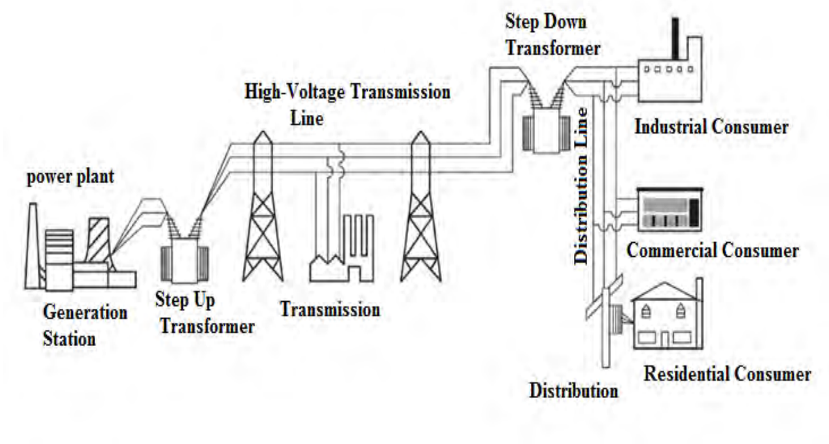


Figure 2.1: Structure of Conventional Power Grid [4]

2.2 Future Power Grid: Smart Grid (SG)

The Smart Grid is a fairly new idea, that was introduced in the late-1990s and the first practical large-scale was introduced in the early 2000s [6]. Due to the dependency of electric power systems on old infrastructures and older ideas, the grid is poorly prepared for the challenges of the 21st Century. The first Smart Grid implementation is usually attributed to Italy, where the country's largest energy provider, *Enel S.p.A.*, set up the ENEL Telegestore Project, starting in 2000. Thus far, the company has installed more than 30 million smart meters across Italy. In 2003, US, Austin, Texas, began their own Smart Grid project which now has over 200,000 devices online with another 300,000 expected to join the network in 2030. Austin was followed by Boulder, Colorado. With the moniker Smart Grid City, Boulder is considered the home of the first fully functional Smart Grid-enabled city in the US, with a network of more than 23,000 smart meters. Since then, many other jurisdictions, especially in North America and Europe, have taken steps toward embracing Smart Grid technology and transitioning from one-way systems to fully bi-directional systems [6]. Smart grid is still in its infant stage in power system, due to this there is yet no generally agreed definition of the term. Different people and countries have diverse opinion about the smart grid. According to the United State department of energy, 'SG is defined as a digital technology to improve reliability, security and efficiency (both economic and energy) of electric power system from the large generation, through the delivery system to the electricity consumers and a growing number of distributed generation and storage devices' [7].

The European technology platform defines the smart grid as an 'electricity network that can intelligently integrate the actions of all users connected to the it – generator, consumers and those that do both- in order to effectively deliver sustainable, economic and secure electricity supplies' [8].

According to International Energy Agency (IEA) [9], "smart grid is electricity network that uses digital and other advanced technologies to monitor and manage the transport of electricity from all generation sources to meet the varying electricity demand of end users. Smart grid co-ordinate the needs and capabilities of all generators, grid operators, and-user and electricity market stakeholders to operate all parts of the system as efficient as possible, minimizing costs and environmental impacts while maximizing system reliability, resilience and stability".

According to [10] *Arup Sinha, et al.*, defines "Smart Grid as the modernization of the electricity delivery system so that it monitors, protects and automatically optimizes the operation of its interconnected elements – from the central and distributed generators through the high-voltage network and distribution systems to industrial users and building automation systems, to energy storage installations and to end-users". Generally, Smart grid is a concept of transforming the electric power system from a one-way system into a network based on two-way communications channel between producers and consumers using advanced communications, automation controls, and other forms of information communication technologies. The basic structure of a smart grid is shown in the Figure 2.2.

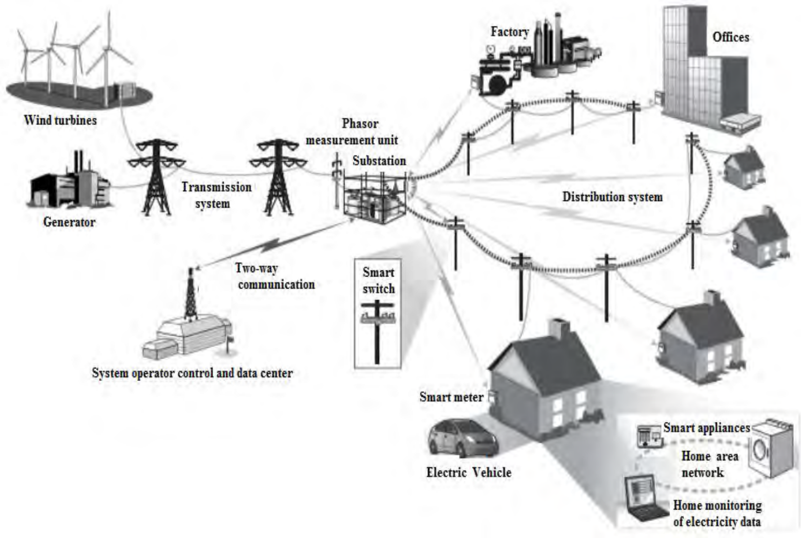


Figure 2.2: Basic structure of smart grid [11]

The main features of smart grids are self-healing, flexibility in network topology (Accommodates different distributed generations), improved power quality, resilience to disturbances and attacks, active participation of consumers and accommodation of new products, services and markets.

The comparison between conventional power grid and smart grid are presented in table 2.1.

Table 2.1: Comparison of Conventional Grids to Smart Grids

Characteristics	Conventional grid	Smart grid
Participation	Consumers are Passive	Consumers are Active
Communication	One-way communication	Two-way communication
Topology	Rigid	Flexible
Response to attacks	Manually	Self-healing
Generation	Centralized	Distributed generated
Control	Limited	Pervasive

2.3 Benefits of Smart Grid

Smart grid implementation is not only for energy security and quality of the power supply, but also to achieve sustainable energy development. In addition, Smart grid implementation offers various benefits to all electricity stakeholders (governments, energy regulatory bodies, energy providers, operators and consumers). The principal beneficiaries are the utility and the consumers. However, smart grid implementation benefits can be categorized into [12]:

- Technical benefits;
- Societal benefits;
- Economic benefits;
- Environmental benefits;
- Security benefits

Technical benefits are associated directly with the power producers and operators (generation, transmission, and distribution companies). The benefits include: reduction in operational cost, improved power grid reliability, improved operational efficiency, improved security of power equipment and reduction in power theft. Also, enhance robust transmission and distribution system and accommodate new technologies. SG also enhances electricity consumption monitoring through different programs such as demand response and demand side managements [12].

The benefits of SG to the general public include generation of high quality power, reduction in power outage, lower electricity cost, accurate billing and creation of more market for electricity retailers. Smart grid technologies help consumers to manage their electricity consumption and hence save more money [12].

Environmental benefits of a smart grid include reduction in environmental pollution due to gas emission and discharge reduction. The reduction in the gas emission is due to high integration of renewable energy sources which does not generate gases during operation. It also reduced public health hazards, through reduction in carbon dioxide (CO_2) and some other gasses that are hazardous to health [12].

Smart Grid increases the strength and resilience of the grid to both physical and cyber security, hence reduce man-made attacks and natural disasters. The self-healing technology of smart grid improves the period of restoration during disturbances. Smart grid also reduces vandalization of utility properties due to improve detection techniques through advanced control and monitoring [12].

2.4 Smart Grid Applications

According to the national institute of standard and technology (NIST), smart grid can be split into seven areas, bulk generation, transmission, distribution, customers, grid operation, service provider and market. For effective management of energy and load control in a smart grid environment, all of these seven areas must communicate effectively with each other. In order to achieve the effective communication, certain classes of applications are required. These applications include [13]:

- Advanced metering infrastructure (AMI)
- Automated demand respond
- Tele-protection
- Distribution automation
- Micro grid management.

2.4.1 Advanced Metering Infrastructure (AMI)

The integration of smart meters or electronic meters into the electric power metering system for effective billing and monitoring the system for effective performance of the power grid is referred to as Advanced Metering Infrastructure (AMI). AMI foster smooth interaction between the utility, the power system and the loads. In addition, consumers are able to respond to real time electricity pricing, monitoring and control of electricity consumption in their premises in real-time. The components of advanced metering infrastructures include Smart Meters (SM), Wide-Area Network (WAN), Home Area Network (HAN), and Meter Data Management Systems (MDMS) [14]. Smart metering is an important component of advanced metering infrastructure which is used for exchanging information and data between system networks and end-users. Smart meter collects data on energy consumption and delivers the accurate data to Meter Data Management System (MDMS) for evaluation and processing. MDMS is a database system for acquiring, processing and storing information on smart meters. Meter data management system automatically controls the affairs of the system such as turning on and off electricity, data management on fault detection and restoration, and load forecasting management. Home Area Network (HAN) is a means of communication between consumers' premises and the utility. It coordinates consumers' energy consumption pattern by connecting smart meter and other smart appliances effective load management [15].

2.4.2 Automated Demand Response (DR)

According to the association of home appliance manufacturers, demand response is defined as a situation whereby consumers, utility or designated third party can reduce electricity consumption during peak period or other critical energy situation [5]. To achieve successful load management in residential electricity use, demand response must be effectively implemented. According to electric power research institute (EPRI) in the United States in 2009, residential energy consumption account for about 38% of the total energy consumed. In this regard, home appliances such as a water heater, air-conditioning consumed more than half of the total energy used. Implementing demand response in conjunction with smart appliances will reduce residential electricity consumption in real time. Thus, improve energy efficiency and reduces greenhouse gas emission [5].

To achieve successful and effective implementation of demand response for monitoring and managing home appliance, according to association of home appliance manufacturers (AHAM), the following three factors must be considered [5]:

- Consumers privacy must be considered;
- Security and flexibility of smart grid communication standards must be considered;
- Price incentive must be provided to motivate customers [5].

2.5 Smart Metering System (SMS)

Electricity metering has been in practice since the discovery of electricity in 1752. Electricity metering was introduced for the purpose of measuring the amount of energy consumed by electrical appliances. Electricity meters are generally grouped into two categories:

- Electromechanical meters or traditional meters and
- Smart meters or electronic meters

2.5.1 Electromechanical Meters

Electromechanical or solid state meters that cumulatively measure, record and store aggregated kWh data that are periodically retrieved for use in customer billing or energy management [16]. Electromechanical meters (EM) operate by counting the rotation of an aluminum disc that is made to rotate at a speed by the application of a magnetic field, caused by the flow of electric current. The amount of rotation determines the amount of energy consumed. The reading is done monthly and manually, this made the operation to be inaccurate [17]. Electromechanical meters have been faced-off by electronic meters.

2.5.2 Smart Meters or Electronic Meters

Smart meters or electronic meters are those that have the capability to measure and record interval data (at least 30minuts intervals for electricity) and communicate the data to a remote location in a format that can be easily integrated into a smart metering system. The system that collects real-time energy usage data from smart meter via a network system either on-request or defined schedule basis. The system is capable of providing usage information on at least a daily basis and can support desired features and functionality related to energy use management, procurement, and operations [16]. Smart meters brought certain benefits to the metering system. These benefits include: improving accuracy and reliability, low cost, ability to measure parameters like power factor, reactive power, harmonic currents and maximum power. In addition, smart meters, can be used to remotely connect and disconnect consumers, detection of electricity theft, and allows active participation of consumers through demand response. It can also store information and transmit data to remote places through different communication means, advanced billing capabilities such as time of use and automatic meter reading (AMR) [17].

2.6 Application of Smart Metering System

2.6.1 Power Grid Monitoring and Control

Apart from the aforementioned benefits, smart meters are also used for monitoring and control of the power system. This functionality of smart metering is achieved through wide- area monitoring, protection and control (WAMPAC) system. Wide-area monitoring, protection and control involved the use of system wide information and communication of selected local information to a remote location to counteract the propagation of large disturbances. The concept of wide-area monitoring, control, and protection may be used as a platform for more flexibility or adaptive detection and control strategies, having a better management of disturbances and higher power transfers and operating economies. On the basis of a modern wide-area monitoring system, advanced protection and control strategies can be applied through the development and implementation of new analytical tools. The key enabling advanced monitoring technology for modern wide-area monitoring, protection and control systems is the introduction of synchronized measurement technology (SMT). Currently, phasor measurement units (PMU) are the most accurate and advanced time-synchronized technology available. They provide voltage and current phasor and frequency information, synchronized with high precision to a common time reference provided by the global positioning system (GPS). The operation of PMU is based on numerical measurement algorithms, which must be both computationally efficient and suitable for real-time applications in particular for dynamic response-type application. Utility companies need to develop a clearly defined guide for adopting SMT. This guide should include both short-term objectives and long-term objectives. The short-term objectives include enhanced visualization of the power system, post-disturbance analysis, and model validations, while long-term objectives include development of a WAMPAC system. PMU deployment is still in its infant stage in some part of the world. A number of areas that needs to be addressed while planning and designing for wide-scale deployment of PMUs are: compatibility, interoperability, flexibility of the new applications, and operation in the environment in which a number of communication protocols and communication media will be simultaneously used. It is expected that the increased use of wide-area measurements will result in a more efficient and reliable, use of corrective actions for system-wide disturbances [18]. In addition, proper implementation of WAMPAC system will reduce the number of disasters on the power networks and generally enhance the reliability and security of energy generation, transmission and distribution, especially in power networks with high penetration of renewable energy sources [18]. Figure 2.3 shows a typical WAMPAC architecture based on SMT.

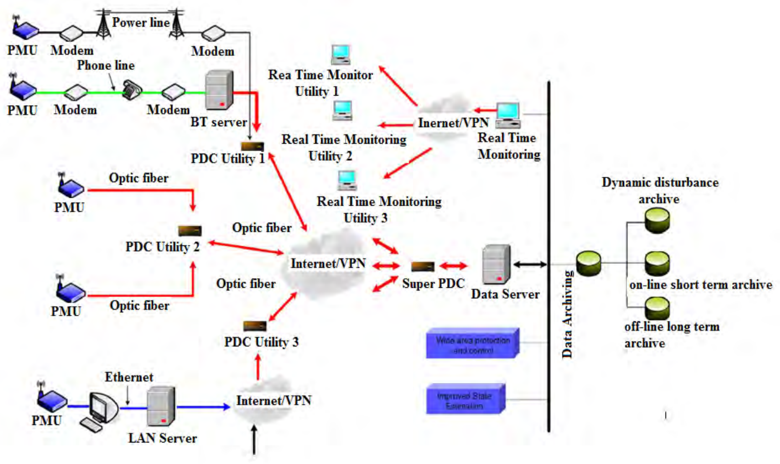


Figure 2.3: Generic Architecture of WAMPAC System [18]

The Figure 2.3 is a typical WAMPAC architecture based on SMT, the concept of this architecture has been used in the Eastern Interconnect Phasor Project (EIPP) in the United States [18]. In the WAMPAC system with several participants, each utility can have its own data collector (DC) and each data collects synchrophasors from PMUs over different communication channels such as fibre optic or power lines. The super data collector is provided to collect selected synchrophasors from the data collectors. It is anticipated that the super data collector can handle a variety of data transmission protocols. Furthermore, all the data collected in super data collector can be returned back to the data collector in each power utility, hence each power utility can understand the status of the power grid outside its regional control area [18].

2.6.2 Smart Meters for Demand Side Management

In addition to power grid monitoring and control, smart metering offers potential benefits in energy efficiency measure. Smart meters are very crucial demand side management (DSM) enabling technology as they provide information about energy usage. Demand side management (DSM) is a program employed by utility companies to control energy consumption at the end-user-side of the meter. DSM is employed to use the available energy more efficiently without installing new generation and transmission infrastructure. DSM programs include conservation and energy efficiency programs, demand response programs or load shifting, and residential or commercial load management programs. The aims of residential load management programs include the following: reducing consumption and shifting consumption. Energy consumption reduction can be achieved among the consumers by encouraging energy-aware consumption patterns and by constructing more energy efficient buildings (smart house). However, there is also a need for practical solutions to shift the high-power household appliances to off-peak hours to reduce the peak-to-average ratio (PAR) in load demand. There are many approaches for managing residential loads. One of these approaches is direct load control (DLC). DLC is a program that is based on an agreement between the utility company and the customers, the utility can remotely control the operations and energy consumption of certain appliances in a household. For example, it may control lighting, thermal comfort equipment (heating, ventilating, and air conditioning), refrigerators, and pumps. However, implementing residential load control and home automation, users' privacy must be put into consideration and it can serve as a major barrier in implementing DLC programs.

Another approach for managing residential loads is smart pricing. This is a scenario whereby consumers are required to voluntarily control their loads by reducing their consumption at peak hours. In this case, critical-peak pricing (CPP), time-of-use pricing (TOUP), and real-time pricing (RTP) are the techniques adopted. For example, in RTP tariffs, the price of electricity varies at different hours of the day. The prices are usually higher during the afternoon, on hot days in the summer, and on cold days in the winter. During this period, more of the thermal comfort equipment is used [19]. The major barrier confronting this technique is that it is usually difficult and confusing for the users to manually respond to prices that are changing every hour, another problem that RTP may face is loaded synchronization, where a large portion of the load is shifted from a typical peak hour to a typical non-peak hour, without significantly reducing the PAR [19]. The first wave of demand side management programs was limited by the availability of technology. The management and verification efforts of the technology were time consuming and expensive, thus restricted the program only to the larger customers. The next wave of demand side management programs aims at changing the face of energy saving through the global economy. Mckingsey [19] estimates that by 2020, the United State could reduce energy consumption by 9.1 quadrillion BTU, over one-fifth of its total projected demand. According to him, successful demand side management program incorporates some or all of these six levers: rate, incentive, access to information, utility controls, education and marketing, and customer insight and verification [19].

- **Rate:** Utility has already designed their tariffs in order to make electricity affordable for lower income customers to make electricity price better reflect the cost of generation.
- **Incentive:** To encourage consumers to actively participate in DSM programs, utility has found that rebate check, compensation for participating in a pilot, or free technology such as in-home display can increase customer adoption
- **Access to information**: when customers have access to real-time information they become more aggressive about managing their usage. For instance, customers reduced their electricity consumption by 6.5 percent based on information provided on an in-home display [19].
- **Utility control:** Direct load control (DLC) programs are used to curb demand such as air conditioning during critical peak periods. These controls could be integrated with programmable commodity thermostats, home energy controllers or smart appliances.
- **Education and marketing:** Educate customers on the benefits of DSM programs can be targeted to different market segments, different educational goals or different channels
- **Customer insight and verification**: to ensure effectiveness of DSM programs, it is essential to verify demand side management programs result and collect feedback from customers regardless of whether the targets are broad or narrow.

2. 6.3 Advanced Metering Infrastructure for Residential Customers

Advanced metering infrastructure is not a single technology but an integrated technology system that is used for metering, storage analysis, power consumes and operating data. NRS049 advanced metering infrastructure for residential and commercial customers, has been drafted and published to create a standard specification for AMI systems in South Africa. The functionality of the AMI system as specified in NRS049 is explained by looking at the individual requirements [20]:

- AMI master station
- AMI smart meter
- Customer Interface Unit (CIU)
- Appliance Controller Device (ACD)
- Communication network

❖ **AMI Master Station**

The AMI master station provides connectivity to back-end systems, including a billing system, connect/disconnect system, reporting, fault system, meter data management system, tamper detection system, load management system and quality of supply system, and in the case of prepayment system applications, to the vending management system. The AMI master station must be able to support the retrieval of the billing register values [20].

❖ **AMI Smart Meter**

The meter is connected to the master station through a concentrator or directly to the master station. The main function is to register active energy consumption data and sent information through to the customer interface unit for display. It supplies capacity control (load limiting) through the internal connect/disconnect connector NRS049 specifies that active energy consumption data must be stored on the meter as total register values (normal cumulative energy data) as well as half-hourly data. The meter must be able to support a time-of- use tariff structure. Apart from billing, the meter must be able to record different events such as tampering event identified, supply outages, under and over voltage conditions, It performs disconnect and connect commands send by the master station during events such as load limiting and control. The meter will typically be installed in a secure cabinet where the customer will not have access to it to prevent tampering or bypassing. Customers will have access to billing and other information through the customer interface unit [20].

❖ Customer Interface Unit (CIU)

CIU display energy information to the customers. It is installed in the customer's premises where they can have access to their energy consumption data and energy information such as energy cost, status of the appliance control devices, status of load limiting and all event alarms [20].

❖ Appliance Control Device (ACD)

The appliance control device will connect and disconnect loads from the supply depending on the signal sent from the meter and master station. Under normal operating conditions, the appliance control devices will be switched by the meter according to the time-of-use daily pattern. Loads will be switched off during peak time-of-use periods. The appliance control devices can also be operated from the master station in situations where there is a severe strain on the capacity of the electricity supply system. The status of the appliance control devices will be controlled by the meter and this information will in turn be sent from the meter to the customer interface unit. The "turn-on" times of the appliance control devices will be scattered through a predetermined and randomized time maintained from the meter to avoid the creation of another peak loading condition at "turn-on".

The benefits of appliance control devices are to both the utility and the consumers. The utility will experience less loading during peak consumption periods and the customers that are agreed to have certain appliance control automatically in their house will have such load removed automatically from the peak periods which will save them energy cost.

❖ Smart Grid Communication Network

Information and communication technology is the backbone of smart grids. The communications network is a medium of transferring data and sharing information within the functionalities of the AMI system. Communication networks in smart metering system can be power line communication (PLC), global system for mobile communication (GSM), radio frequency (RF), ZigBee, Bluetooth, and wireless fidelity (Wi-Fi). Others include local area network (LAN) at utility data centre, wide area network (WAN) for backhaul communication, metropolitan area network (MAN) of smart meters at commercial and residential areas and home area network (HAN) within customers' premises. For proper and smooth communication within the aforementioned component of AMI, standardization of communication technologies plays a vital role. The standardization of components enables interoperability between components from different vendors. Several standard proposed by the American National Standards Institute (ANSI) includes ANSI C12.22 defined application layer messaging services that are applicable for enterprise and end device component of an AMI for smart grid. It provides both session and session's communications that help to reduce the complexity of handling communication links on both sides with less signalling overhead. Also, ANSI C12.19, IEEE P1377/D1 and MC1219 (Measurement Canada) collaborated to develop a standard known as Utility Industry End Device Data Tables. This standard uses AES encryption to enable strong, secure communications, including confidentiality and data integrity. Other standards developed by ANSI include C12.18 and C12.21protocols which only supports session's oriented communication [21]. Furthermore, National Institute of Standards and Technology (NIST) under the Energy Independence and Security Act (EISA) of 2007 developed a standard that the primary responsibility to coordinate the development of a framework which includes protocols and model standards for information management to achieve interoperability of smart grid devices and systems [22]. Figure 2.4 depicts an AMI system using direct communication to the meter.

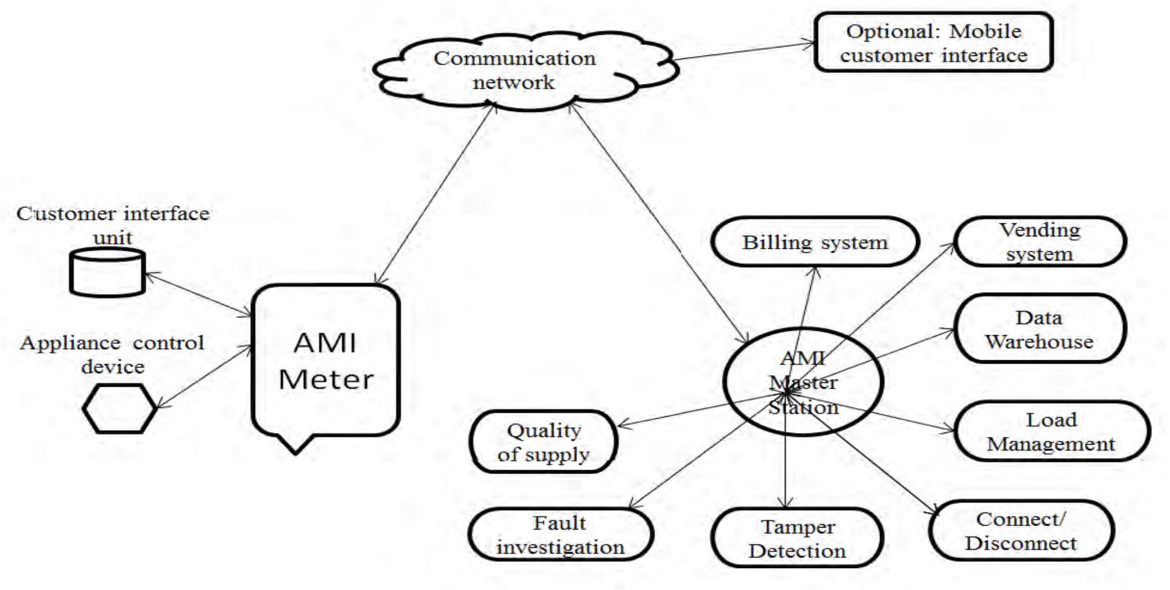


Figure 2.4: AMI Systems Using Direct Communication to the Meter [22].

2.7 Data Communication and Network Technologies

Communication networks play a vital role in smart grid system since it is concerned with transfer and information within the power system. Smart grids distribute electricity between generators and end users using bi-directional information flow to control intelligent appliances at consumers' premises saving energy consumption and reducing the consequent expense, meanwhile increasing system reliability and operation transparency. With a communication infrastructure, the smart metering, monitoring techniques can provide the real-time energy consumption as a feedback and correspond to the demand to and from utilities. Network operation centre can retrieve those customer power usage data and the on-line market pricing from data centres to optimize the electricity generation, distribution according to the energy consumption. The cornerstone of a smart grid is it's the ability to interact via a communication infrastructure. It follows that the development of a reliable and pervasive communication infrastructure represents crucial issues in both structure and operation of smart grid communication systems. In this connection, a strategic requirement in supporting this process is the development of a reliable communication infrastructure for establishing robust real-time data transportation through Wide Area Networks (WANs) to the distribution feeder and customer level [23]. Some of the factors to be considered when choosing a communication channel or technology for smart metering system include: cost effectiveness, throughput, easy interoperability, reliability and long lifespan, maintenance, low power consumption, security, range, latency and bandwidth

Cost Effectiveness: Smart metering communications technologies must be designed to minimize cost and provide excellent value.

Throughput: is the rate at which data packets or data is successfully transmitted over the communication link or path. It is also called data speeds. This rate is usually presented in bits per second (bit/s).

Easy Interoperability: Communication network infrastructures for a smart metering system must be able to communicate with other communication infrastructures from different vendors.

Reliability and Long Life Span: Smart meter communication network should be able to stay longer in use without replacement of components. Smart metering communication technologies must be reliable and designed with industry standard and specification to meet different environmental conditions such as temperature, humidity and corrosion.

Maintenance: Communication network for smart metering system must be easy to maintain without replacing the entire meter. Software must be easy to upgrade, manage, configured, and validate remotely

Low Power Consumption: In most cases, the network will depend on the power produced by the meter; hence the networks must be designed to meet the supply of current the meter can provide. Vendors need to ensure that communication networks are extremely power efficient for cost reasons.

Security: Information technologies and control system involve in smart metering system calls for adequate security. These include consumer privacy, data integrity and ensure continuous system operation.

Low Cost of Installation: Smart metering communication network must be simple to install and reduce the cost of training expertise for installation.

Range: Range describes the length in which the data communication path can travel with low dB loss in the signal. When the range is too long in distance, the reliability of the data transmission can be poor.

Latency: is an expression of how much time it takes for a packet of data to move from one destination point to another. It varies from network to network.

Bandwidth: Is the measure of data carrying capabilities when transmitted over a communication channel.

There are many ranges of networking technologies that may be considered for smart grid applications for each of the different areas of the network; due to this selection of right communication technologies for the smart metering is a big challenge. Nevertheless, three types of communication network to be considered for advanced meter infrastructure (AMI) are: Home Area Network (HAN), Neighbourhood Area Network (NAN) and Wide Area Network (WAN) [24]:

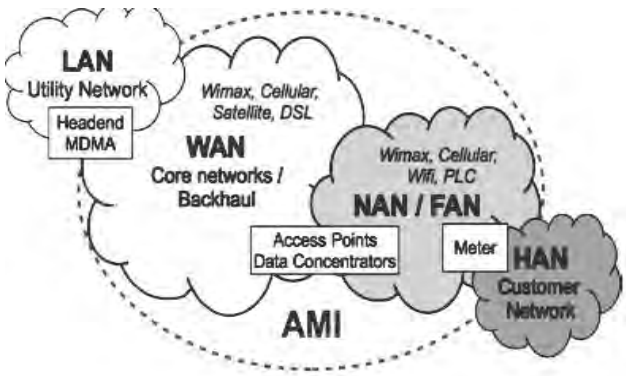


Figure 2.5: Advanced Metering Communication Networks [25]

2.7.1 Wide Area Network (WAN) for Smart Grid Applications

Wide area network is a communication link between head ends in the local utility network and either concentrators or smart meters. It aggregates data from multiple NANs and conveys it to utility companies' private networks. It also enables the long-haul communications among different data aggregation points (DAPs) of power generation plants, distribute energy resource stations, substations, transmission and distribution grids and control centres. The utility company's Wide Area Network (WAN) is also responsible for providing the two-way network needed for substation communications, distribution automation, and power quality monitoring, while also supporting data aggregation and backhaul for NANs. WANs may cover a wide range area and could aggregate many supported devices that needs up to 100 Mb/s of data transmission [26]. WAN uses long-range and high bandwidth communication technologies such as WiMAX, GPRS and cellular 3G. In this research work only WiMAX will be considered.

WiMAX

Worldwide Interoperability for Microwave Access (WiMAX) is a 4G telecommunication based on IEEE802.16 standards standard for Wireless Metropolitan Area Network (WMAN). WIMAX technology enables the delivery of last mile wireless broadband access as an alternative to cable and DSL. It is also implemented as a backbone network, which will build up the internet connection for a wide range of area.

The transmission range of WiMAX can reach 31 miles and data rate of about 70Mbps. The first IEEE802.16 standard was drafted in 2001 with an operating range of 10-66 GHz for communication infrastructure. Currently, WiMAX has two main categories: fixed WiMAX and mobile WiMAX. The fixed WiMAX (IEEE-802.16-2004 standard) is for fixed wireless applications, it has a frequency band 3.5 and 5.8 GHz. The mobile WiMAX (IEEE-802.16e standard) is for mobile wireless services. It has frequency bands 2.3, 2.5, 3.5 GHz [27]. The IEEE802.16 standards were developed to support wireless access in the long distance range using point-to-multipoint link. The main feature of the WiMAX standard that made it suitable for smart grid communications are: the orthogonal frequency division multiplexing (OFDM) based physical layer, interoperability of equipment, time and frequency division duplexing supported, per subscriber based adaptive modulation and coding, multiple quality of service (QoS) classes supported including security characteristic [28]. The role of WiMAX within different smart grid implementation varies depending on the utility's requirements and existing infrastructure, the availability of wire line connectivity, and the overall environment in which the utility operates. The roles within the smart grid include: backhaul, last-mile connectivity to offices and mobility workforce, including mobile access for field workers and broadband connectivity from the office location, emergency connectivity through mobile base stations during emergencies, and remote control capability [29]. WiMAX for smart grid application offer the following advantages, wireless automatic meter reading (WAMR). Large distance coverage and sufficiently high data rates make WiMAX technology more suitable for wireless automatic meter reading as a part of utility automatic metering infrastructure (AMI). Also, WiMAX enables electricity real-time pricing based on real-time electricity consumption of the consumers. The real-time pricing capability of WMAR systems allows customers to shift their loads during off-peak period. In addition, with WiMAX technology, faster outage detection and restoration can be implemented. However, WiMAX is confronting challenges for instances, radio frequency hardware for WiMAX tower is comparatively expensive, hence the placement of a WiMAX tower should be done optimally to reduce infrastructure costs and meet the quality of service (QoS). Also, WiMAX frequency above 10GHz cannot penetrate through obstacle due to these low frequencies are the most practical for AM applications especially in urban areas. The lower frequency bands are already licensed and hence the most likely way of utilizing WiMAX is by leasing it from the third party [27].

2.7.2 Neighbourhood Area Network (NAN) for Smart Grid Applications

In smart gird, neighbourhood area network (NAN) refers to a network of smart meters that are connected to each other in order to send/rely metering data to concentrating nodes, collectors, which in return, send the data over a wide area network (WAN) to the utility centre. Smart grid NAN is deployed within the distribution domain of the grid. The distribution domain dispatches power to households in the customer domain through the electrical and communication architectures between the transmission and customer domains. Smart grid NANs offer distribution domain with the capability of monitoring and controlling electricity delivery to each household, according to user demands and energy availability. NANs directly connect all the end users in regional areas, forming the most important segment in the power grid that can determine the efficiency of the whole grid. Coverage of a NAN would be around 1–10 square miles. The data rate would be higher than that of HANs, approximately around 10–1000 Kbps. In a neighbourhood area, smart meters send their data through single or multi-hop communication to collectors. In the NAN, smart meters can perform routing and find their best path to collectors. Each smart meter maintains a list of peers, so that in case of failure of one peer, it can switch to the next available peer. Hence, redundant paths make the network more reliable. A fully redundant routing requires each smart meter to discover the best single or multi-hop possible collector in its vicinity and establish a connection with it. In case of detecting loss of connectivity, smart meters are able to re-configure themselves to re-establish the connection to the network. NAN should provide scalable, secure access and device management for mesh-connected AMI devices such as water, electric and gas meters with instantaneous enterprise-to-gateway connectivity to residential and commercial locations. Information is available on-schedule, on-demand, or on-event from virtually anywhere via these wireless communication devices. Generally, a NAN can consist of several smaller NANs where each NAN is defined by a set of smart meters that communicate with one collector. Each NAN can have an ID (mesh ID) which can be identified by its collector. A NAN consists of different components which are mainly classified into follow: Collector, smart meter, and advanced meter reading application.

Collector: is a communications gateway that coordinates communication within the NAN. It operates as the intermediary data concentrators, collecting and filtering data from groups of mesh-enabled meters, and economically sharing wide area network resources making communication more affordable while ensuring high performance.

Smart Meter*:* Smart meters automatically establish a connection with the collectors based on application performance settings to ensure timely and secure data delivery to utility for generating customer bills and also automatically control the consumption of electricity through the delivery of load control messages to the smart meters.

Advanced Meter Reading Application: is the most important application in the advanced metering infrastructure that records customer consumption and transmits the measurements over the NAN to collectors hourly or at a faster pace.

In addition to reading functionality, NAN might include capabilities such as remote meter management (connecting/disconnecting smart meters), recording and transferring event logs, security logs and outage reporting [30]

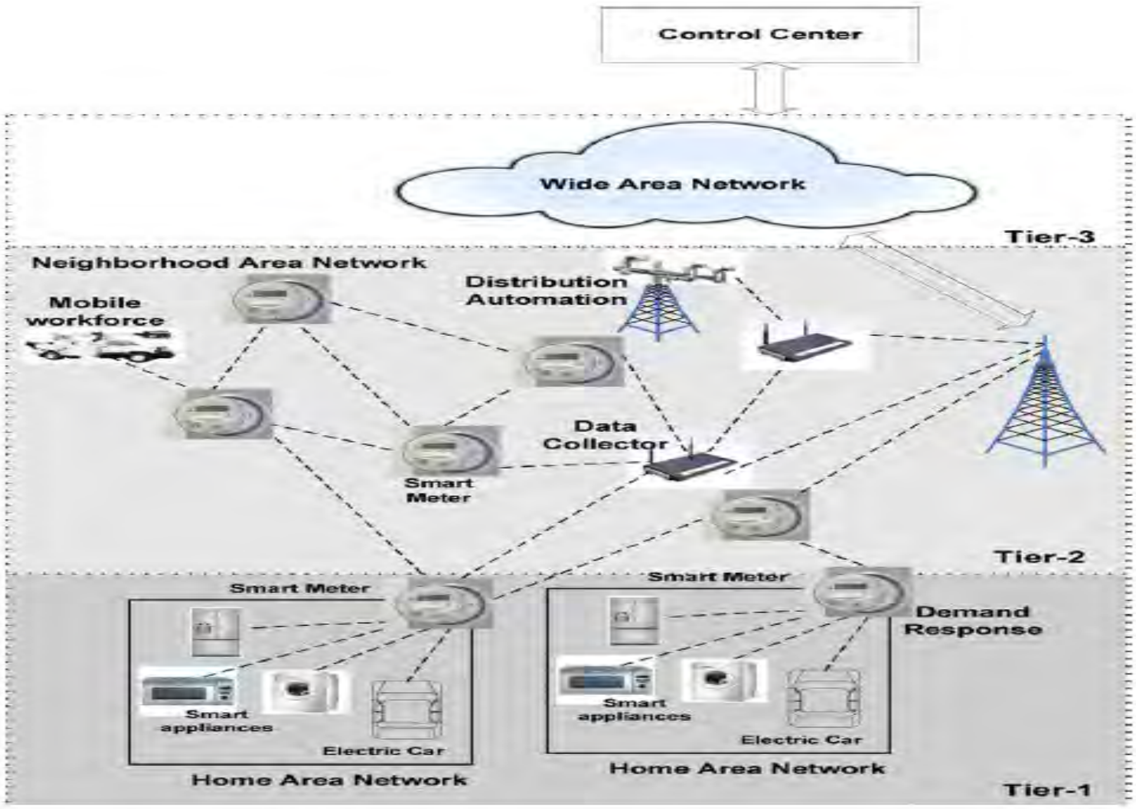


Figure 2.6: Neighbourhood Area Network (NAN) (Tier 2) **[30]**

2.7.3 Home Area Network (HAN)

Home area network is a dedicated network that completely connects the smart appliances in the home into the overall smart metering system. Home area network is now emerging with the smart grid sector to serve home with a digital application solution and energy management. According to IMS Research [32], the installed base of smart home meter networks will increase from 1.5million homes in 2009 to 14.7million in 2014 globally. Home area network has high applications for homeowners, utilities and smart grid operators, as utilities are seeking means of implementing demand side management programs. The latest application of home area networks is installation of smart meters with an in-home display to monitor and manage the power consumption within the networked area. It also allows remote monitoring and control of smart appliances. Smart meters have the capacity to connect wirelessly with the home appliances that contain RF antennas on the same frequency. The meters can thus control appliance and generate detailed data on power consumption of each appliance. Home area network empowers the consumers and allows the smart grid infrastructure to benefit the homeowners directly, thus assisting the utility in managing peak electric demand. In addition, HAN can effectively manage grid load by automatically controlling high energy consuming systems with HAN and smart grid infrastructure. This results in stress free electric grid avoiding potential blackout. The key calling in implementing a HAN solution is to connect the entire house network to the wide area network for remote monitoring and control- and simultaneously to connect objects inside house to offer smart interoperability features. The challenge of HAN from a consumer perspective is remote controlling and monitoring for utility companies, while the challenge from the service provider's perspective is remote metering for utility companies. In achieving the vision of the smart grid program at the consumer level to allow homeowners to better understand and manage their energy consumption will require many new types of devices with lower bandwidth but regular and consistent data stream requirements. Home appliances will be networked and communicating information that allows the homeowner to better understand and manage energy usage. Generally, challenges of implementing HAN are to interconnect different technologies to offer smart services for comfort, automation, security, and energy management. Thus, it is in the consumers and manufactures best interest to identify the most worthy networks that will serve the purpose of interoperability, economies of scale and easy adoption. In the context of this research two HAN technologies will be examined. ZigBee and power line communication or power line carrier (Home Plug) [32], [33].

ZigBee for Smart Grid Applications

ZigBee is a wireless protocol developed specifically for low power and low data-rate communications. It is designed for monitoring and control of devices. ZigBee utilizes the IEEE 802.15.4 standard for the physical and MAC layers. The ZigBee radio operates on the ISM bands. ZigBee end devices are intended to be battery operated for up to five years on one charge. ZigBee attains this power savings through a number of design decisions, namely: a simplified protocol stack, low data-rate transfers, short-range transmissions, and wall powered networking devices. The data rate of ZigBee varies depending on the ISM frequency used. ZigBee has three types of equipment, ZigBee Coordinator (ZC), ZigBee Router (ZR), ZigBee and End Devices (ZED). The ZC is a fully functional device that holds the network coordinator to form one network. It does manage connection to other networks. It provides dual communication of information within the network they are well powered. ZR is also an FFD that routes data between ZigBee devices within a network. It does not manage connection to other networks they are well powered. ZED is a reduced function devices, it cannot relay data from other devices. The reduced feature of ZED allows it to save a significant of amount of time thereby increasing battery life span. They are battery powered. ZigBee network's topology can be star, cluster and mesh network. ZigBee has a wide area of application which includes load control, energy management consoles, remote control, building and home automation and smart energy. ZigBee house and home automation based on enabling smart home and buildings that can control appliances, lighting, environment, energy management and security as well as expanding connectivity to other ZigBee networks. ZigBee smart energy focuses on interoperable products that monitor, control, inform and automate the delivery and use of energy. Apart from the ZigBee specification the ZigBee alliance develops and makes available ZigBee profile. These profiles define the functionality of the devices and interoperability requirements. The smart energy profiles (SEP), home automation (HA), commercial building automation (CBA) are a few of the available profiles. The devices are designed and certified to meet specific profiles allowing the devices to be tailored to specific industries. The major limitation to the use of ZigBee network is short bandwidth [33].

Power Line Communications for Smart Grid Applications

The idea of using power lines communication for the purposes of remote metering and load control has been for decades. Power line communications (PLCs), uses the existing electrical infrastructure to transfer data from one device to another. Power line communications technology enhances intelligence and reliability across a broad range of smart grid applications, including smart electrical meters, lighting, solar, electric car charging, smart appliances, home automation, intelligent building control, and networking. Suited for applications such as smart metering and control applications. Power line technologies can be grouped into: narrowband PLC (NB-PLC) and broadband PLC (BB-PLC).

- **Narrowband PLC (NB-PLC)**

Narrowband power line communication systems usually operate in the frequency range from 3 kHz to 500 kHz. NB-PLCs can be also divided into low data rate (LDR) and high data rate (HDR) systems. LDR systems have throughputs of a few Kbit/s and usually are based on single carrier technology. Example standards, listed in the NIST Smart Grid Interoperability Panel (SGIP) catalogue of the Standards are ISO/IEC 14908-3 (LON, ANSI/EIA 709.2) and ISO/IEC 14543-3-5 (KNX, EN 50090). These standards span all layers of the open systems interconnection (OSI) model and can, also be used over other media such as twisted pair and in some cases even wirelessly. Their main area of application has been industrial and building automation. Another protocol is BACnet (ISO 16484-5). HDR, however, focus on the physical layer (PHY) with throughputs of up to 1Mbit/s NB-PLC. Orthogonal frequency division multiplexing (OFDM) is the modulation scheme for HDR NB-PLC. Example of HDR NB-PLC systems are G3-PLC and PRIME. Due to the ongoing standardization projects HDR NB-PLC has developed a new standard IEEE 1901.2 and ITU-T G.hnem [34].

- **Broadband PLC**

In the last decade, BB-PLC chips from semiconductor vendors; such as Intellon, DS2, Gigle, and Panasonic came to market that operate in the band from around 1 MHz to 300 MHz The chips are mainly based on three consortia backed specifications developed within the frameworks of the Home Plug Power line Alliance (Home Plug), the Universal Power line Association (UPA) and the High Definition Power Line Communication (HD-PLC) Alliance. Related products allow data rates around 200Mbit/s and are not interoperable. However, to make PLC systems a broad success, an internationally adopted BP-PLC standard became essential. The International Telecommunications Union (ITU) as well as the Institute of Electrical and Electronics Engineers (IEEE) commenced work on such next generation standards, namely, ITU-T G.hn and IEEE 1901. At the end of 2008, the physical layer and the overall architecture were consented in ITU-T Recommendation G.9960. The Data Link Layer (DLL) Recommendation G.9961 was approved in June 2010, and a MIMO transceiver extension G.9963 was consented in September 2011. Alongside, the Home Grid Forum was founded to promote the ITU-T G.hn standard and to address certification and interoperability issues. Simultaneously, IEEE P1901 was working on the “Draft Standard for Broadband over Power Line Networks: Medium Access Control and Physical Layer Specifications”. It covers the aspects Access, In-Home, and coexistence of Access-In-Home and In-Home-In-Home networks, and the official IEEE Std 1901–2010 was published in December, 30, 2010, with the HomePlug Power line Alliance is a certifying body for IEEE 1901 compliant products. In analogy to the introduction of multiple-input and multiple-output (MIMO) to ITU G.hn, the Home Plug Alliance introduced the HomePlug AV2 specification in January 2012. The Home Plug AV2 specification includes features like multiple-input and multiple-output with beam forming, an extended frequency range of up to 86 MHz, efficient notching, several transmit power optimization techniques, 4096-QAM, power save modes, short delimiter, and delayed acknowledgement, boosting the maximum physical layer (PHY) rate to around 2Gbit/s. Further, to cover multiple homes networking media less than one umbrella, IEEE P1905.1 is working on a standard for a converged digital home network for heterogeneous technologies. It defines an abstraction layer for multiple home networking technologies like IEEE 1901, IEEE 802.11 (Wi-Fi), IEEE 802.3 (Ethernet), and MoCA 1.1 and is extendable to work with other home networking technologies.

Generally, power line communications (PLCs) will fulfil various communication tasks in Smart Grid deployments as PLC provides the natural upgrade from simple electricity conductors to hybrid and bidirectional electrical and data communication solutions. From the utility point of view, one of the main advantages of the PLC is the full control over the physical medium, without the need to depend on third party providers like telecommunication companies or cellular operators [34].

2.8 Smart House (SH) and Smart Appliance

The energy consumption management goal has generated significant interest in greatly increasing the deployment of energy efficiency measures. Previous studies have shown that residential electricity consumption can be reduced up to 15% when using better energy management processes [35]. Smart Grid implementation associated with home automation network has the possibility of becoming the most powerful tools for the residential energy consumption management and control. However, there are two challenges for implementing home automation network interconnected with a smart grid. The first challenge is that customers' acceptance of home automation is still very low, and the second challenge is that home automation network required a two-way communication with each household appliances due to this, the old appliances would have to be modified to suit this purpose, while the new appliances could be manufactured with the necessary communication and control means [35]. The Integration of smart energy-efficiency appliances into the smart grid will significantly accelerate energy conversation and thus alleviating global carbon dioxide emission.

Smart energy-efficient appliances are no longer passive devices that drive emission, but an active participant in the electrical infrastructure that can be effectively used to reduce energy consumption of residential homes. Apart from the energy reduction and energy storage, smart energy-efficient appliances can also optimized electrical grid for greater compatibility with its greenest energy generation sources such as wind solar power which are inherently variable in supply [5].

2.8.1 Smart House (SH)

The issue of energy management and saving is of great concerns to utilities globally, due to this, they are looking means of addressing the issue in order to achieve sustainable energy system. One of the proposed solutions the issue is a widespread use of the smart house technologies which allows residential energy consumption, saving up or above 40 % [36]. Smart house (SH) is the integration of information communication technologies to residential and commercial building environments with the aim of achieving improved safety, comfort communication and power saving with little or without human interface. The hierarchical in designing smart house include system levels, subsystem levels and element levels. To ensure maximum performance of the smart house, the subsystem level should include climate control subsystem, lighting and domestic appliances subsystem, safety and security subsystem and monitoring subsystem. Achieving effective coordination among the main subsystems, components and the user, the smart house system should include the remote controls, the inner smart house control module, the central control module, and smart house subsystem controllers. Connecting the intranet in the smart house with internet by joining smart house and tele-action, controlling the smart house remotely will be very easy. Tele-action is the ability to control devices remotely. In addition, data exchange between the major functional components of the smart house will be very easy since it is done through internet. The modes of operation of smart house include automatic mode, user mode, and standby mode. The initial operating condition of the system is referred to as automatic operating mode. In this mode, the input parameter references to their area subsystems situation are set. The use mode is a situation in which the system requires certain information from the user. In this case the user performs the required task. The last mode of operation is the standby mode in which the system switched to its starting state expecting the next event. The principal benefit of SH is power management and saving. Other benefits include safety, comfort and effective monitoring and communication between consumers and utility. The technical requirements for proper implementation of smart house are low cost, and easy to install devices, plug -and- play devices, flexibility system, and reliability [36], [37]. The figure 6 depicts a schematic block diagram of smart house system.

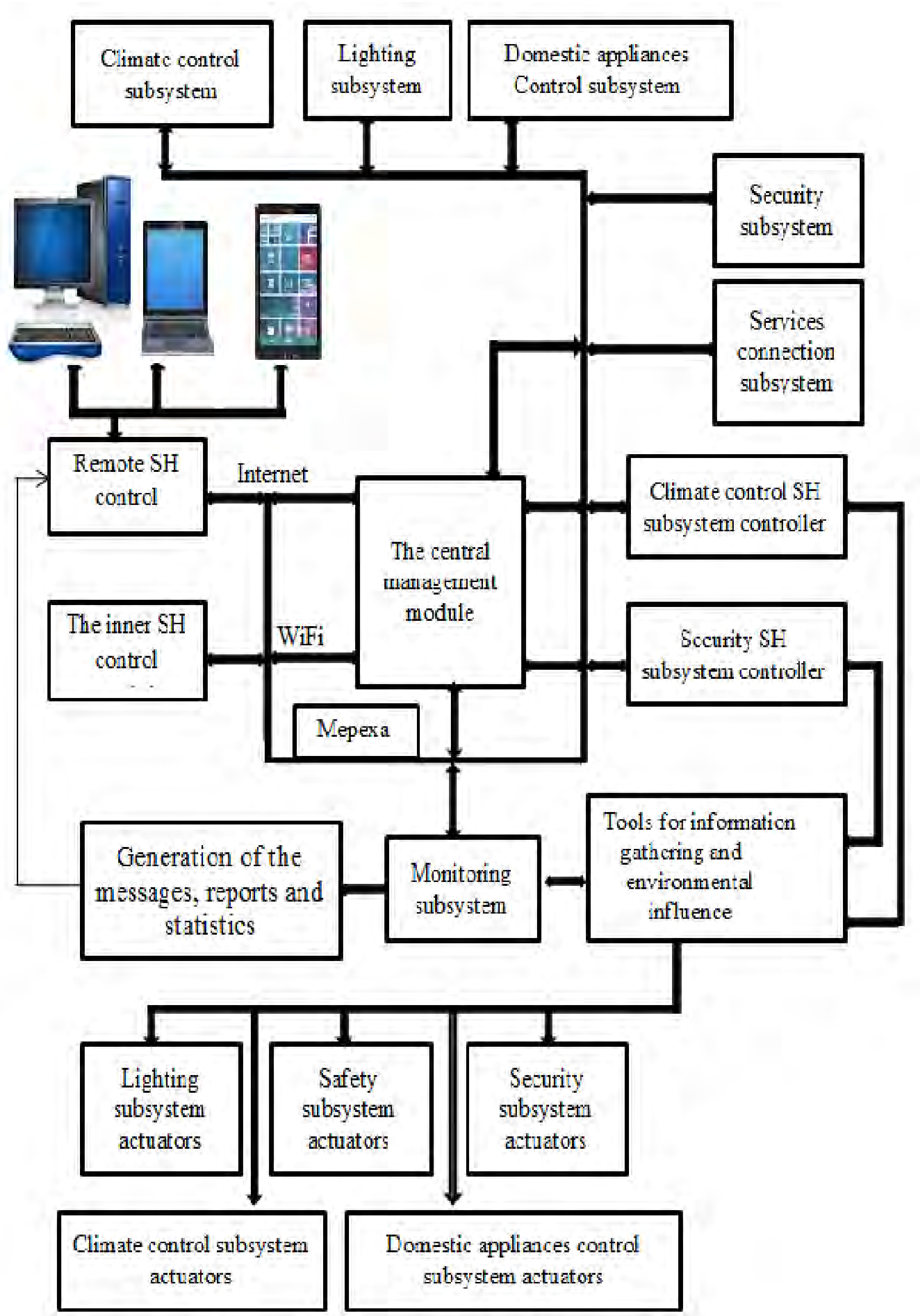


Figure 2.7: Schematic Diagram of a Smart House System **[37]**

2.8.1.1 Smart House Data and storage pattern

The housing data are data collected from smart house. There are two types of smart house data [38].

- House logs data and
- House configuration data

House Log Data: is a type of data that dynamically change with time. It is the record of the power usage of smart appliances via smart meter deployed in the smart house. House log data include energy consumption, appliance status, such as TV channel set temperature air conditioner, and environmental log such as room temperature and humidity. They are normally recorded with time and date. Energy consumption log consists of the history of energy consumed within a given period of time. It is recorded and stored as shown in the following example: "2014-04-06 10:30:46 Power of TV is 600W". In this example, 2014-04-06 is the date of consumption, 10:30:46 is the time and 600W is the total unit of power consumed by the appliance that is TV. Appliances status log, this type of house log records the appliances history and conditions of operations. Example; "2014-04-06 10:30:46 TV is off" – is an example of appliance log generated from the appliance status. Also, "2014-04-06 10:50:00 TV is turned ON" is a device generated from the appliance operation. Environmental log is taken from sensor it recorded the environmental context of the smart house. For example, "2014-04-06 10:30:46 temperature is 25 degrees" is an event taken from the temperature sensor. Similarly, "2014-04-06 10:30:46 number of is 15" is log taken from the counter is the total number of appliances in the smart house [38].

House Configuration Data: These types of data are static or fixed. House configuration consists of all the information about the smart house. House configuration data includes address of the house, names and types of appliance, inhabitant information, and floor plan and the number of rooms. It is stored in structural entities. The appliances information is characterized by two entities: appliances name and appliances class. The appliance's name represents examples of the appliances, while appliances class represents a class of appliances, manufacturer, model number, types and appliance specification. Appliances class can also include miscellaneous information like date of purchase, price of purchase and the room where the appliance is installed for the purpose of location identification. Inhabitant information is characterized by two entities, inhabitant and household. Inhabitant information described an individual living in the smart house by their personal identities like name, and age. Each person living in smart house is bound with a household. The situation will be changed if the household relocate to another house. Generally, since house log data is heterogeneous, it is in practical to determine a strict data plan in ahead. Thus, the schematic data management with a simple key value in the database is used in the storing house log as depicted in table 2.2.

Table 2.2: House Logs Data Storage Format

Key	Value
2014-04-06T10:30:46.cs7.energy.tv01	{Value: 600, unit: w}
2014-04-06T10:30:46.cs7.Device.tv01	{Status: power: off}
2014-04-06T10:50:00.cs7.Device.tv01	{Operation: on}
2014-04-06T10:30:46.cs7.Env.temp2	{Value 25.0 unit: Celsius}
2014-04-06T10:30:46.cs7.Env.apcount3	{Value 3: unit: appliances}

In the table 2.2, key is a concatenation of (date, time, house ID, log type, appliance ID) which forms a unique string of every house log. As for the value, each log defines own hash to describe the content. The key-value storage can receive benefits of high scalability and easy duplication [38].

2.8.2 Challenges of Managing House Data

The purpose of smart house is to gather date of the house in-real time and use the data to provide appropriate service based on the data. The data involved varieties of information about the inhabitant of the house and all appliances in the house. Thus, the size of the gathered data becomes very huge and managing the data is now a challenge to utility. According to *Yamamoto Shintaro et al* in literature [37], two challenges confronting smart house data management are examined. The challenges are:

- Storage and process large-scale heterogeneous house log
- Smart house data modelling

Data Storage and Process Large-Scale Heterogeneous House Log

Smart house send the house log periodically via smart meter. Although, the data is small in size, when accumulated over a long period of time it becomes a big amount of log data, and the data needs to be processed and stored for the appropriate purposes. In this case, there is a need for a scalable data platform that can store and process large-scale and heterogeneous house log data [37].

Smart House Data Modelling

Smart house data logs are used for various purposes. As all possible future inquiries are unimaginable, there is a need to define a solid data model for the house data, which is independent of a specific services or applications. The data model of house configuration must be handled with care, since the inquiry is always specified with constant features [37].

2.9 Summary

This chapter has described the general concept of smart grid and its applications. Smart metering and its applications were also reviewed. The correct choice of communication technologies is very crucial to the effective operation of smart grid and smart metering system since they involved the dual exchange of information and data between the end-users and the utility. For this reason, data communication and different communication network technologies were are also reviewed. Wireless communication technologies are more preferred to wire communication technologies due to their low cost of installation, high level of scalability and wide area coverage. Though, the choice of communication technology to employ depends on the agreement between the country concern and the utility. However, wireless communications are vulnerable to cyber-attack and it signal can be affected by attenuation due to the distance. Finally, smart house (SH) - the current scenario in power system through the implementation of smart grid is reviewed. For effective management and conservation of energy in residential sector, home appliances must be made smarter (smart appliance) and the total energy consumption of each appliance must be monitored. This will also help in identifying the individual appliances in the household, thus the next chapter examines the energy consumption of some selected domestic appliances.

CHAPTER 3

Overview of Energy Consumption of Some Selected Household Smart Appliances

Introduction

In the recent years, utility companies around the globe are facing challenges on how to meet the drastic increase in energy demand of their customers. Different strategies are being employed in order to ensure adequate supply of electricity to the end-users. One of the strategies of ensuring energy conservation is by monitoring energy consumption in the residential sector. For effective energy monitoring and conservation, both utility and consumer must be well familiar with the energy consumption of each domestic smart appliance at any given time. The aims and objectives of domestic smart appliances include the reduction of energy losses as a result of reduced peak load, thus increasing energy efficiency and reducing system cost. The information can also be used for load control for specific devices; utility can also use the information for planning electricity distribution system and optimal production capacity. In addition, accurate knowledge of household electricity consumption of appliances is very crucial when planning, integrating or installing of standalone renewable energies into the grid and residential areas respectively. In this chapter the selected smart appliances are electric water heater, washing machine, refrigeration (refrigerator and freezer), electric cooking appliances (oven and stove), swimming pool and heating circulation pump. Technical description with regards to mode of operation, energy consumption rate, factors influencing their energy consumption rate and power demand curve is examined.

3.1 Smart Appliances (SA)

Household appliances account for the significant percentage of energy consumption across the globe. For instance, in 2007, about 28.8 % of the total energy consumed in Europe was accounted for residential sector and it is increasing with more than 2 % annually [39]. Also, in Belgium household electricity consumption was accounted for approximately 25 % of the total energy consumed, the largest part of the energy is used for heating of the house, while the rest was used for electric appliances like water heating. Also, in South Africa the largest user of energy in the residential building is water heating, which was estimated to be around 40 % to 50

% of the monthly electricity use of an average middle to upper income household. Therefore, energy efficiency measures regarding the use of smart appliances will become increasingly important in the residential sector [40]. Smart appliances (SA) are appliances that combine sensing and control algorithm to automatically control or adjust its operation in response to the signal received from the electrical network for the purpose of energy demand management and saving. Smart appliances can be categorized into three based on the signal they response to, from the utility, thus the three groups are not mutually exclusive:

- Appliances which automatically respond to basic changes in electricity network properties. These appliances react to change in electrical signal without customers' intervention. They can operate without smart meter or smart grid devices. Examples are: A dynamic demand controller whereby software within the appliance's control unit measures signals from the electricity supply and adjusts power consumption automatically and voltage controllers that respond to network voltage fluctuations and maintain an optimum voltage level into the household, which can lead to energy savings in certain appliances.
- Appliances with inbuilt dual communication device automatically provide information to consumers, suppliers and network operators. These appliances use smart meter and smart grid (SG) technology to integrate the communication signals within the network [41].
- Appliances which use demand response technology to control customer's electricity consumption through time-of-use (TOU) and critical peak pricing (CPP) programs. Time-of-use (TOU) and critical peak price (CPP) programs are two common techniques used by utility to encourage consumers to shift their loads from on-peak period to off-peak period. The major aim of these programs is to reduce utility demand during on-peak period and thus reduces overall costs. Smart appliances have been designed to support time-of-use and critical peak pricing to reduce demand. Price signals to reduce demand, building automation and consumer feedbacks are directed into the appliance interface to make their usage easy for the consumers. With the interface, consumers are able to access the appliances setting through a set of pre-configured automated responses which translate the time-of-use and critical peak pricing signals into control signals, such as Low, Normal, High, and Critical. The pre-configured setting can also be modified as required, such as disregard the utility price signal and continue normal operation. These settings make it very easy for the consumers to participate actively in the process, thus reducing energy bills and improving the efficiency of the system. However, the biggest challenge in this system is how long and actively would the consumers embrace the process [42].

3.2 Benefits of Smart Appliances

Smart appliances have the capability to adjust their operation according to the dynamic electricity tariff of smart grid. The cost of electricity consumption can be reduced through peak load management. Smart appliances also bring the benefits of reliability improvement of utility grid by their load management feature at the granularity level of individual appliances. The household smart appliances aimed at minimizing overall daily electricity consumption of household and thus reduce electricity cost and customer's bills. In addition, smart appliances increased competition in the energy market and improve energy supply

3.3 Barriers to the Development of Smart Appliances

The development of Smart Appliances is complementary to the ongoing work on smart meters and smart grids. In many respects the successful deployment of Smart Appliances is essential for smart grids and smart metering to deliver the full range of anticipated benefits, particularly those in relation to energy management efficiency at customers' level. Some of the factors responsible for the developments of smart appliances are: United Kingdom energy policy goals, international regulations, electricity price, maintenance cost and customer demand for increasing functionality in their new appliances. Some of the barriers to the development of Smart Appliances are listed below [41]:

- High capital cost of production;
- Energy companies not yet agreeing on how they want to integrate the appliances;
- Lack of government policy and regulation for Smart Appliances, including the impact of building regulations on the promotion of electric heating;
- Customer reaction to Smart Appliances;
- Lack of consistent appliance Standards;
- Lack of interoperability due to different communication platforms from different vendors;
- The obligation for the countermand function to make Smart Appliances acceptable to consumers;
- Lack of consumer confidence in the operation of the appliances.

3.4 Mitigation Technique

Some of the measures suggested by the experts for overcoming the potential barriers of developing smart appliances include:

- Consistent international and national appliance standards;
- Trials to prove the business case for Smart Appliances;
- Greater awareness of the consequences of personal energy use,
- Consumer awareness of countermand functions;
- Ensuring easy to use smart appliances.

3.5 Overview of Selected Appliances

In this section, an overview of the technical operation and functionality, and power demand curves of some household smart appliances are investigated. In addition, energy consumption, as well as the time of the day the household appliances are usually operated is also reviewed. Electric water heater, washing machine, swimming pool pump, refrigeration (refrigerator and freezer), oven and stove, heating circulation pump are some of the appliances to be considered.

3.5.1 Electric Water Heater

Water heating is a thermodynamic process that uses an energy source to heat water above its initial temperature of 10°C. Domestically, appliances that continual supply hot water is called hot water heater, hot water boiler, heat exchanger or geyser. The name depends on the manufacturer or the country that concerns. Electric heater is any electrical appliances that convert electric energy into heat energy. Thus, any appliance that uses electric energy to heat or boil water is referred to as an electric water heater. Electric water heater can be categorized into two: electric instantaneous water heaters and electric water heater with storage. Instantaneous water heaters heat up the needed volume of water on demand. According to the water flow a pressure difference sensor communicates the energy demand. The flowing water is directly heated by a heater rod. Instantaneous water heaters use high voltage current and usually vary between 18 kW and 27 kW of power demand. The water temperature can be set to about 60°C. A sensor controls the flow of water into the instantaneous water heater and then an element heats the water that flows through the unit. The heating process stops working immediately when the hot water tap is turned off. Instantaneous water heaters are available in single-point and multi-point units. The single point units serve only one pint such as shower, while multi-point units can serve up to two points such as a shower, bath and basin. Instantaneous water heater saves electricity usage up to 30 % to 40 %, and thus minimized customers' electricity consumption bills [43], [44]. Electric water heater with storage is a type of water heaters which preheat and store the water in a tank for future use. Electric water heaters with storage are heated by an electric resistance heating element near the bottom of the storage tank. Cold water flows into the insulated tank and is heated up by the heater. The warm water flow from the bottom to the top of the tank and flow through the insulated pipes as soon as hot water is needed on any of the connected taps**.** The time of heating up the water depends on the set temperature, the volume of water and the electric power. For instance, water heaters with storage capacity of about 30 litres, with an electric power of about 2 kW connected to the normal residential voltage supply can take 2 to 15 minutes for 0.5 and 5 litres respectively to boil up to the require temperature of 65°C [43]. Domestic hot water can be supplied either by the centralized or decentralized system. Centralized system is a system whereby the water is heated in a centrally located device and distributed through pipes to different places of tapping points. The major setback to centralized systems is the loss of energy due to long distribution distances. Electric water heater with storage will provide a lasting solution to the setback in a centralized system, since there is no need for connecting the electric device to a pipe. Due to the water storage capacity, the water can be heated during off-peak period and store for use in on-peak period, depending on the insulated materials used in the cylinder, the system can store water for two days. The decentralized heating system is a system whereby the water is heated close to where it is needed either by instantaneous water heater or by appliances with water storage tank.

Power Consumption of Electric Water Heater

Energy used for water heating is a significant portion of the total energy demand in the residential sectors [43]. For instance, according to the European commission, a total of 65-75 TWh of electricity was accounted for electricity consumption on water heating and storage in 2003 to 2004 in European countries which was amounted to about 9 % of the total energy consumption of households [43]. In addition, in 2004, water heating in the residential sector consumed about 23 % of all residential natural gas use, 8 % of all residential electricity use, about 12 % of total residential energy expenditures, and about 8 % of all end-use natural gas are used to heat water in residential buildings in United State [45]. Due to the mild climate of South Africa, hot water consumption is the largest user of energy in the domestic sector. It was estimated to be up to 40-50 % of monthly electricity consumption of an average middle-to-upper income household having been quoted in South African energy policy discussion document [46]. In Australia, 40 % of the total energy consumption in the average home is associated with water heating. The sources of energy for water heating are: electricity 79 % and natural gas 16 %, while the remaining 5 % are renewable energy sources like solar [47]. In addition, an average 34 % of New Zealand household electricity consumption is used for water heating [48]. A

Norwegian comparison of engineering and econometric methods of estimating end use based on 1990 energy survey data found that electricity consumption for water heating varied between 14 and 24 % of the total residential electricity consumption [49]. The use of the water heater for boiling water depends on certain factors like size of family, time of use and purpose of use (kitchen use and bathroom use). For instance, according to the Bavarian Ministry of Economics (BME) an average warm water demand per person in a day in Germany is about 35 litres. In Switzerland a consumption of 45 litres per Person has been published in 2007 and 48.5 litres were published in 1993. An increase of up to 33% in consumption of hot water has been recognized, depending on season, weekday and daytime. The seasonal variation in hot water consumption in Switzerland is shown in Figure 3.1. From the Figure 3.1, the consumption of hot water during the summer time is obviously lower than consumption during the winter period due to the use of heating appliances. On weekends the hot water consumption per person is obviously higher than on weekdays, especially in autumn and winter since the occupants will be at home on weekends than weekdays. The average consumption per person is 48.51 litres per day.

Figure 3.1: Daily Hot Water Consumption by Season and Weekday in Switzerland **[43]**

The power demand of large electric storage water heaters can be distinguished between two devices: storage water heaters which heat during night time and storage water heaters which heat continuously even during day time. The former operates at times of high availability of power. These devices are controlled by external signals from the electricity provider. Regardless of the type of the devices and the period of use, power demand is a function of the following factors: electrical capacity of the device, the volume of the water to be heated, desired temperature and the heating duration [45]. The average energy consumption of electric water heater in some countries is shown in the Figure 3.2.

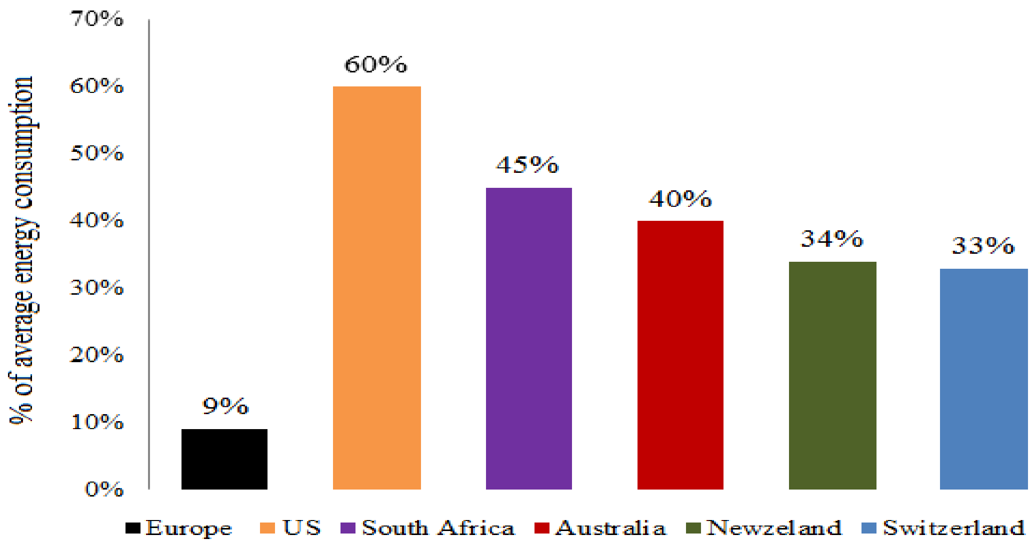


Figure 3.2: Electricity Consumption of Electric Water Heater in Some Countries

3.5.2 Washing Machine

The washing machine is an electronic device that is designed to wash laundry like clothes, sheets and towels. The washing machine has come a long way and passed through several phases since the first patent under the category of washing and wringing machine was evolved in Britain in 1691 [50]. Modern washing machines can be classified based on the loading methods top loading washing machines and front loading washing machines [50]. In top loading washing machines, laundries are placed in a vertically-mounted cylinder that is contained within a water retaining tub with a finned water pumping agitator in the centre of the bottom of the cylinder. During the wash cycle, the outer tub is filled with enough water to fully immerse and suspend the clothing freely in the cylinder. The agitator in the bottom of the machine performs the washing action, by the rotating back and forth, rolling the laundry from the top to the bottom continuously. These machines use more water, and hence more energy to heat the water. So its energy costs are more and it takes longer to dry clothes. However, the process of loading clothes and adding items mid-cycle is easier in these machines. Top loading washing machines take less cycle time and perform very well even without putting detergent. It is very common in, Canada, the United States, and Latin America

Front loading washing machines or horizontal-axis clothes washer is very common in Europe, the Middle East, Asia, and Africa [50]. Front loading washing machines are commonly used in industries and in commercial clothes washers. It is only recently that is gaining popularity in homes. It consists of a tub and a drum rotating around a horizontal axis. Water is filled into the tub up to a certain low level, which is maintained throughout the main cleaning process. The laundry is only partially immersed in the water, but mainly soaks up the water needed for the cleaning process. This cleaning is done at various temperatures depending on the garments to be washed. Front loading washing machines operate in a way different from top loading machines. The only similarity between them is that both uses detergent and water and spin at the end of the wash to remove water. In front loading washing machines, the tube spins horizontally, it has no agitator to move the clothes through the water the movement of the tube causes the clothes to be lifted out of and plunged back in the water again and again. The whole process is controlled by a step timer or an electronic control device and lasts between about 15 minutes and up to 3 hours, depending on the set program and temperature. Time delay functions are incorporated in some machines and allow either to shift the starting time by a defined number of hours or to end the process at a predefined time. Front loading washing machines have several advantages over top loading machines. Front loading machines can save a lot of energy, and can prolong the life of the clothes washed in them. They also do not make much noise and have larger capacities. Due to its special wash mechanism, a front loading washing machine uses a much less quantity of water than top loading machines. Use of less water means using less energy, hence less energy bills. However, front loading washing machines are more expensive to buy and available in fewer models [50].

Power Consumption of Washing Machine

Washing machines are common home appliances that most people use to clean their clothes and they only operate on consumer demand, therefore energy consumption during the operation is determined by the following factors, ambient conditions e.g. temperature, frequency of operation, machine efficiency under real use condition, load size used, time period in low power mode (start delay and standby). The frequency of operation depends mainly on the size of the household, since it determines the amount of load to be treated. For instance, a recent metering study in Germany has measured the total energy consumption washing machine in 100 households for one month to be at 1045,5 kWh and the average consumption per cycle at 0,89 kWh with an average load of 5 kg [43]. This leads to an annual electricity consumption of 125 kWh and 141 wash cycles per household. Also, according to the Green Book on Energy Efficiency published by the European commission in 2003, the total electricity consumption of washing machines of 26 TWh for 160 million households per year was 170 kWh per household owning a washing machine [43].

3.5.3 Refrigeration

Refrigeration is the process by which the temperature of an item is generally kept below room temperature. The refrigerating system is made up of a compressor; evaporator, fan, condenser and expansion device. Refrigeration includes both refrigerator and freezer.

3.5.3.1 Refrigerator

Refrigerators consist of an insulated inner compartment which is cooled by an attached heat pump. The cooling device is mostly situated on the backside of the box. The compressor cooling machine is the main technology behind Refrigerators. The evaporation of the liquid refrigerant generates the cold in the evaporator, which then absorbs heat from the refrigerated inner space. After its full evaporation the refrigerant vapour is compressed by the compressor and then condensed while releasing the heat in proportion to the one absorbed at evaporator level. After condensing, the refrigerant is expanded by an expansion valve which is used to regulate the refrigerant fluid back to the evaporator and to control the refrigerant flow. In this appliance the circulation of the refrigerant is driven by a compressor, which demands a motor and electrical energy. The absorber cooling process uses ammoniac as refrigerant. A mixture of ammonia gas and hydrogen flows from the evaporator into the absorber, where the ammonia vapour is suspended in water. The insoluble hydrogen flows back into the evaporator. The mixture of ammonia and water is then heated by the boiler while the refrigerant vaporizes by absorbing heat from the box. The refrigerant vapour gets into the condenser and the water flows back into the absorber. The ammoniac vapour is condensed while removing the heat. Then the ammoniac streams back to the hydrogen containing in the evaporator. The whole process of cooling is controlled by an electronic thermostat control device according to the thermostat setting within the appliance. The motor switch on when the upper thermostat setting is reached and remaining until the temperature reaches a lower setting. The setting length depends on the refrigerator contents. Beside the ambient temperature, which affects the efficiency of the heat pump, frequent door openings during the day also affect the load curve increasing the total power demand.

3.5.3.2 Freezer

Freezers operate on the same principle as refrigerators. According to European committees of domestic equipment manufacturers, the total amount of energy consumed by freezers alone is about 33.3 TWh in 2005. Currently, in about 154, 55 million households that make up of EU-15 with a penetration of freezers of 52 %, the annual energy consumption per household owning a freezer is about 414 kWh. The power demand of freezers depends on the size and the range of power rating [43]

The door-openings scenario in freezer is different from that from that of a refrigerator, the opening and closing of the freezer may be once or twice a day. The frequency of placing new items to be frozen in the freezer may be one to three times per week. Hence opening the door of a freezer for taking out something won't have a significant effect on the power demand of a freezer because of the large coolant capacity inside. In case of putting a new thing to be cooled down and frozen the period of operation of compressor will increase [43].

Power Consumption of Refrigeration (refrigerator and freezer)

Refrigeration (refrigerator and freezer) is a domestic appliances owning virtually by all households globally. It operates 24 hours of the day due to the nature of its purpose of preserving perishable items like foodstuffs, thus, it consumes a lot of energy. Refrigerator is an appliance that operates as long as they are connected to the supply.

According to European committees of domestic equipment manufacturers (ECDEM), the total amount of energy consumed by refrigeration (refrigerator) in 2005 is about 66.1TWh [51]. The EU-15 which consists of about 154, 55 million households, the annual energy consumption per household owning a refrigerator is about 403, 5 kWh.

The consumption of energy within the period of use is determined by the following factors: ambient conditions such as temperature, place of installation in the kitchen, frequency of door opening, temperature setting, capacity, exchange of cool load by warm load and machine efficiency under real use conditions.

Refrigerators in average households vary largely in terms of the casing size, inside temperature and the main ambient temperature in the kitchen or installation room. The actual power demand of a refrigerator varies according to their size in a range from 50 W to 300 W. With an average energy consumption of 403.5 kWh per household owning a refrigerator per year and a power using-factor of 33.3 %, an average power demand of 138.2 W per appliance can be estimated. The frequency of door opening in the refrigerator is another factor that affects its energy consumption. The energy-consumption is related to the frequency of door openings because of the heat-input of exchanging air as well as the items to be cooled [43].

3.5.4 Heating Circulation Pump

Heating circulation pumps or simply circulators are used mainly in the household to circulate hot water in central heating system. The central heating system comprises the following elements: a heater (boiler), a circulator, pipe and heat-emitters (radiators) as shown in the simplified diagram in Figure 3.3 [52]

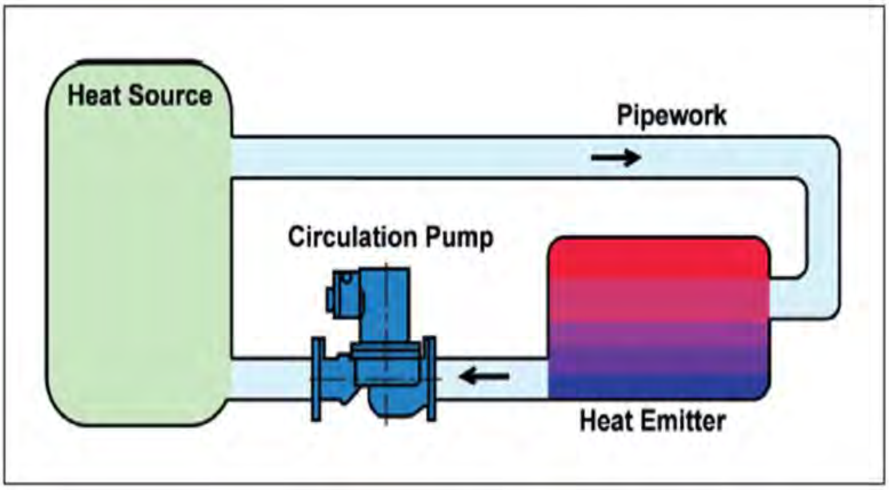


Figure 3.3: Simplified Diagram of a Typical Heating System with a Circulation Pump **[52]**

The water is heated up in a boiler and then pumped through the pipes to (heat emitters) radiators within the house for heating up the rooms. The cooled down water flows back to the boiler where it is being re-heated and start the process again. The pump is running as long as warmth is needed in the house.

The efficiency of the heating system and how the components are controlled have a considerable influence on the energy efficiency of the device. Thus, heating controls are required to ensure that heating systems operate efficiently. The purpose of heating control is to operate the system only when it is necessary and to the minimum acceptable temperature. The heat control in a wet system can be categorized into: boiler control, time control, and temperature control [53].

- **Boiler Control**: The principal aim of most boiler controls is to maintain the require temperature of water that flows from the boiler. This is achieved by controlling the firing of the burner inside the boiler. At the basic level, these controls simply turn the system on and off or provide a high or low setting. The aim of boiler firing control is to regulate the burner to maintain the require boiler flow temperature. Boiler firing controls are normally packaged with the boiler [53].

- **Time Control**: Time controls are fundamental to any efficient heating system. They stipulate when the heating should start and duration. Most modern heating systems have different types of time control and understanding their mode of operations is vital in order to achieve significant energy saving [53].

- **Temperature Control:** Temperature controls help heating systems to supply the right temperatures to maintain comfort without wasting energy. The two basic and common types of building temperature control are wall thermostats (central room thermostat) and thermostatic radiator valves (TRVs). Room thermostats are commonly used for control of heating systems. Thermostats control the operation of the boiler or pump, switching it on or off when the space temperature limits are reached. It is common in small systems for the thermostat to control only the heat pump, however, greater energy savings can be achieved by controlling the boiler as well as the pump. Thermostatic radiator valves (TRVs) are simple control valve with an air temperature sensor, used to control the heat output from the radiator by adjusting water flow. TRVs can provide very efficient control when properly installed and operate [53]. In addition, energy saving can also be achieved by replacing or upgrading the old pumps with high efficiency circulation pumps. These pumps are electronically commutated (EC), due to their efficiency there is about 60 % reduction in circulator annual electricity consumption [54].

Power Consumption of Heating Circulation Pump

The circulator is one of the largest electricity consumers in the household. Particularly in the middle and northern European climate zone, the electricity consumption of a circulator in a heating system may be as high as 500 to 600 kWh compared to the electricity consumption of the fridge or freezer [55]. According to an ECEEE 2007 summer study, the electricity consumed by circulators for heating purposes in households in EU-27 amounted to about 50 TWh per year. This is caused by over 100million circulators, most of them with power input below 250 W. This means that about 2 % of total electricity consumption in Europe is consumed by circulators in all types of buildings [54]. The consumption of energy by heating circulation pumps in the period of use is determined by following factors:

- Type of pump
- Duration of the heating process
- Hydraulic adjustment of the heating system

Based on the recent study in Germany the power demand of a circulator in a three-person household in a single family house varies depending on the type and age of the pump they are using [43]. For an old pump, the consumption varies between 520 kWh and 800 kWh and from 60 to 150 kWh for a new pump with an estimated amount of 6000 working hours per heating period in a year. The average amount of working hours for circulators depends on the need for warmth in the households which in turn depends on the heating days in different countries. Due to different climate zones, the demand for room heating varies from country to country. When the average temperature of the day is below the heating limit temperature of 15^{oC} the day is said to be heating day. The number of heating days is calculated by the following formula:

$$Z_d = \frac{G}{(ti - tz)} \tag{3.1}$$

where

Z_d represents the number of heating days, *G* is the number of cooling degree days, ti is the base temperature, and *tz* is the average outside temperature during the process of cooling. According to [54], if the hydraulic balance were properly adjusted in a heating system, a conventional technology circulator with small input power of about 10 W to 35 W would be sufficient to secure the same heat supply to all radiators Also by introducing more efficient pumps and control strategies, it is possible to reduce electricity consumption considerably [43], [54].

3.5.5 Electric Cooking Appliances: Oven and Stove

Electric hobs also known as called stoves are either fitted with hot plates or with glass ceramics. The conventional model in stock is a sealed hob with usually four hot plates made of cast iron. The heat is being transferred through thermal conduction. In comparison to them ceramic stove tops using up to 20% less energy depending on the cooking process. The heat is transferred from the heating element to the cookware via thermal radiation and conduction. In an induction cooker, a coil of copper wire is placed underneath the cooking pot. Instead of a heating element this copper coil is being used which induces turbulent electrical flow in the bottom of the cookware and thereby heats it up. The ceramic stove top is here not being heated up. As soon as the cooking pot is removed the heat input will stop and only a little residual heat will remain. When compared to other technologies of electrical cooking the induction hob is the most energy efficient of all cooking appliances.

Ovens consist of enamelled steel sheet which are insulated from the inside to the outside of the casing. The temperature can vary between 50°C and 300°C and the heating systems range from top and bottom heat with fan, heating, grill or combinations of some of them. The heat is transferred through radiation and to a small amount through natural convection. The use of a fan, heating system strengthening the convection which speeds up the cooking process enables the use of a lower temperature and therefore reduced the consumption of energy. The energy consumed depends on the cooking time and on the chosen heating process which can reach a total power input of up to 3000 W.

Beside an oven or hob as a single device combined devices called electric cookers are also available on the market. They are old-fashioned open-coil elements, slow to heat up and difficult to clean, but fairly efficient at transferring electric energy to the pot [43].

Energy Consumption of Electric Cooking Appliances

Cooking appliances consume a lot of energy when they are used, but the total use depends upon how often and how long the appliances are in use and the type of cooking appliances. According to the carried out in in French, the consumers power demand and energy consumption of domestic cooking appliances, was about 50 % of the total cooking related energy consumption was attributed to electric hobs and approximately 42 % of the total energy consumed was attributed to ovens. The combined cooking related energy consumption accounted for 14 % of the total electricity consumption of the households' considered. The average annual energy consumption of all electric cooking appliances is the 568 kWh/year. The Figure 3.4 shows the annual average electricity consumption of electric cooking of different appliances in Europe

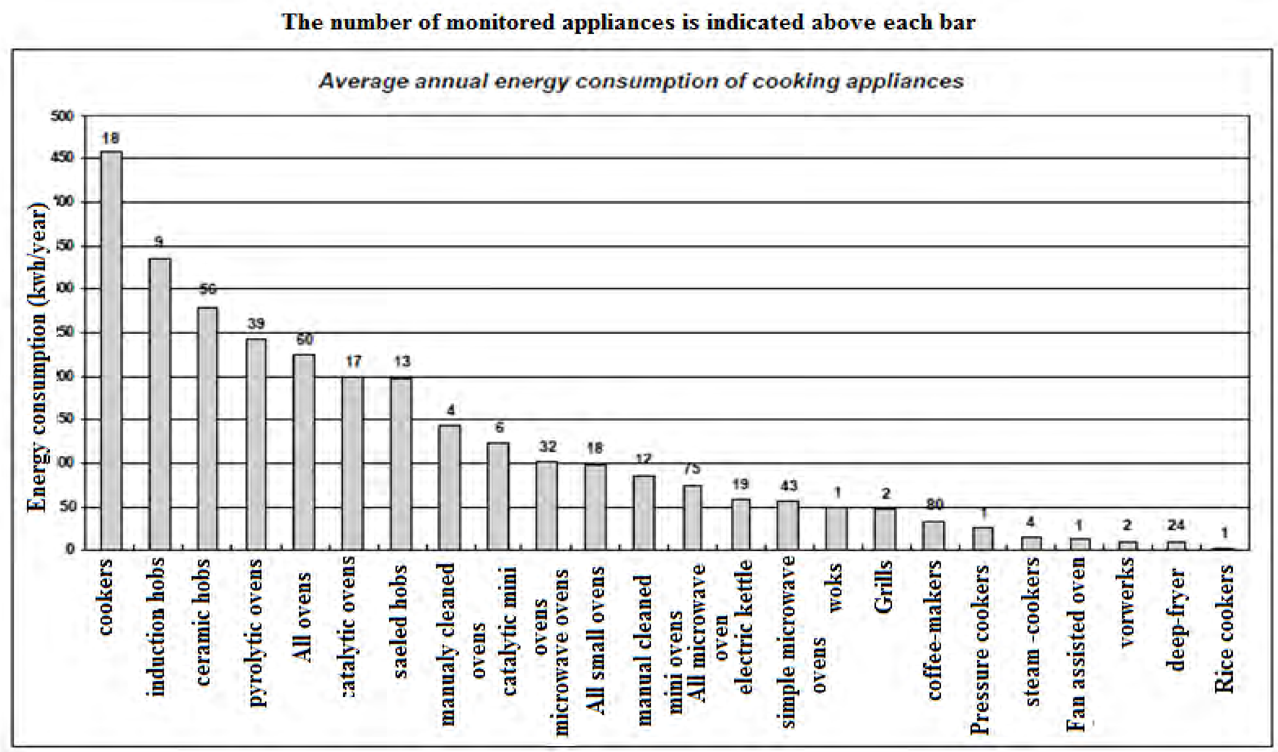


Figure 3.4: European Annual Average Monthly Energy Consumption of Electric Cooking Appliances **[56]**

Induction hobs used the most energy compared with other models due to their standby power demand of 30 % of the total power consumption and their heavy daily use. In respect of the energy consumption per hour of use induction hobs are the most energy efficient one with a relative energy efficiency of about 82 % and energy consumption of 588 W/h. Ceramic hobs with a consumption of 999 Wh and relative energy efficiency of up to 70 % is ext to induction hobs in term of efficient while the least efficient hobs are sealed hob with the relative energy efficiency of about 50 % and 1161 Wh consumption [56]. In addition, the total electricity consumed in EU-15 for electric cooking is estimated to be 52 TWh in which 37 TWh was accounted for electric hobs and 15 TWh for electric ovens [57].

The average energy consumption per household of ovens was accounted to be 224 kWh/year. The value recorded for convection ovens was 233 kWh/year and fan-assisted ovens were 219 kWh/year. The average energy consumption of a cooking period of an oven was 889 Wh. Catalytic-ovens used 199 kWh/year, pyrolytic-ovens used 243 kWh/year and manually cleaned ovens used 224 kWh/year. The average cleaning cycle of a pyrolytic-oven used 3490 Wh, although the device was not commonly use, it accounts only for 11 % of the total energy consumed by the ovens. This level of energy consumption could be reduced by improving the quality of the insulation of the oven. From the energy saving point of view, the most efficient electric oven is the one with the highest overall energy consumption levels. This was due to the relatively heavier use of these appliances. The power demand of an oven is high for the period of about 2 hours in the morning. Cooking appliances are devices which are operated in the moderately small period of time during the day and based on consumer need. Thus, the energy consumption in the period of use depends on the frequency of operation, cooking process and its performance, type of hob (ceramic or induction), device efficiency under real use conditions, cooking temperature, the amount of hot plates heating option of the oven and frequency of oven door opening [43].

3.5.6 Tumble Dryer

Tumble dryer or Clothes dryer is a household appliance that is used to remove moisture from a load of clothing and other textiles. Many dryers consist of a rotating drum called a "tumbler" through which heated air is circulated to evaporate the moisture, while the tumbler is rotated to maintain an air space between the articles.

Tumbler dryers continuously draw in the cool, dry, ambient air around them and heat it before passing it through the tumbler. The resulting hot, humid air is usually vented outside to make room for more dry air to continue the drying process. This design makes no effort to recycle the heat put into the load, and thus is considered environmentally wasteful. Also, using these machines may cause clothes to shrink or become less soft due to loss of short soft fibers. A simpler non-rotating machine called a "drying cabinet" may be used for delicate fabrics and other items not suitable for a tumble dryer. For these items, as well as to save energy, many people use open air methods such as a clothesline and clotheshorse. Nevertheless, it is simple and reliable, and therefore has been widely used. As an alternative for heating the air with an electrical heater a gas fired heater is possible. Gadgets following this approach are available on the market, but have a very low acceptance among the consumers. Another alternative is to regain the energy contained in the humid air flow after the drum by the use of a heat pump. If this energy is extracted, it can immediately be used to heat up the air flow of the air going into the drum. In such machines, e.g. no electrical heating element is necessary and a saving of about 40 to 50% of the total energy consumption is possible. The drying process is controlled either manually or automatically. Manually controlled drying process uses a timer-function where the consumer has to set a predefined drying time. The Automatic drying process uses a control device which detects the humidity of the load and can therefore be used to target a specific final humidity. Time delay functions are incorporated in some machines and allow either to shift the starting time by a defined number of hours or to end the process at a predefined time. To avoid damping, some kind of drum rotation or pre-drying is recommended for the time waiting for the start of the process [45].

Energy Consumption of Tumble Dryer

Tumble dryer is a home appliance that is used most often in winter period than in summertime. The energy consumption during the operation depends on the following factors: ambient conditions, frequency of operation, selected program, machine efficiency under real use conditions, load size used and time span in low power mode. The frequency of operation mainly depends on the household size, as this defines the amount of load to be treated. The power demand may vary from program to program and between machines. When the spinning efficiency of the drying machine or the desired final humidity is higher or the amount of textiles loaded is lower the curve will finish earlier and if the textile loaded is higher, the curve will finish late. Only if the consumer has activated at start time delay function the power demand is shifted by a defined number of hours. According to European Green Book on Energy Efficiency, the total electricity consumed by tumble dryer is 13.8 TWh for the EU-15 in 2003. The total energy consumed per household owning tumble dryer per annual in EU-15 is about 251 kWh [43].

3.5.7 Dishwasher

A dishwasher is a mechanical device for cleaning dishes and eating- utensils. Dishwashers can be found in private homes and restaurants. The mechanical dishwasher cleans by spraying hot water at the dishes. A mix of water and detergent is circulated by a pump. Water is pumped to one or more rotating spray arms, which blast the dishes with the cleaning mixture. Once the wash is finished, the water is drained, more hot water is pumped in and a rinse cycle starts. After the rinse cycle finishes and the water is drained, a heating element in the bottom of the tub heats the air to dry the dishes. Sometimes a rinse aid is used to eliminate water spots for streak-free dishes. The cleaning is done at various temperatures (mainly 50/55°C, 60/65°C or 70/75°C), depending on the program selected by the consumer and the nature of the dishes. The water is heated up to the desired temperature by a resistant heating system of between 1800 W and 2500 W rated power. The whole process is controlled by a step timer or an electronic control device and lasts between about 15 minutes and up to 3 hours, depending on the program and temperature chosen. Time delay functions are incorporated in some machines and allow either to shift the starting time by a defined number of hours or to end the process at a predefined time [43].

Energy Consumption of Dishwasher

Electrical energy is used mainly for heating up the water to the desired temperature, thus also heating up the dishes and the tub. Additional electrical energy is used for driving the circulation pump motor and for the other electronic devices, including the user interface. But also after the end of the program electricity is used by many machines (to a very small extend) to keep some safety functions alive, like water protection sensor systems or remote control systems. Therefore the energy consumption in the period of use depends on the following, factors: ambient conditions, frequency of operation, selected program and temperature, amount and type of detergent used, the additional rinse option chosen, machine efficiency under real use conditions, load size used and Low power mode

The frequency of operation depends on the size of household, which determine the amount of dishes to be washed. Low power mode such as start delay or pre-select function also determines the amount of energy consumed by the machine. This function allows shifting the starting time to any hour of the day or night when maybe cheaper tariffs are offered. Currently, most of the available products of dishwashing machines are equipped with such an option, depending on the country concerned. However, this function also has a negative effect on the energy consumption, as the machine will consume a small amount of energy when waiting for the start time [43].

3.5.8 Air-conditioning

Air conditioning is the process of altering the properties of air mainly temperature and humidity to more favourable conditions, typically with the aim of distributing the conditioned air to an occupied space to improve comfort. In the most general sense, air conditioning can refer to any form of technology, heating, cooling, de-humidification, humidification, cleaning, ventilation, or air movement that modifies the condition of air. In common use, an air conditioner is a device commonly used at home or automobile system that lowers the air temperature. The cooling is typically done using a simple refrigeration cycle, but sometimes evaporation is used, commonly for comfort cooling in buildings and motor vehicles. The main designs available on the market are portable single duct room air conditioners, single package room air conditioners for window or through-wall mounting, single-split package room air conditioners with indoor and outdoor unit and multi-split package room air conditioners consisting of one outdoor unit and a variable number of indoor units [43].

Energy Consumption of Air-conditioning

As room air conditioners in the residential sector are operated on consumer demand only, the electricity consumption for room air conditioning is determined by following mainly consumer driven factors: ambient conditions, frequency of operation, temperature settings, appliance efficiency under real use conditions, maintenance, additional functions like high or low airflow, air purifiers and timer settings. The operating hours and desired temperature are influenced by the favourite of the user and the local climate. The physical characteristics of the room such as insulation or heat gain and by the design of the unit, the way it is installed and the measures taken to prevent warm air entering the room also affect the energy consumption. The electricity consumption for room conditioning varies from time to time during daytime, the peak consumption occurs at 17 O'clock [43]

3.5.9 Electric Heating

Electric heating is any process in which electrical energy is converted to heat. Common applications include space heating, water heating and industrial processes. An electric heater is an electrical appliance that converts electrical energy into heat. The heating element inside every electric heater is simply an electrical resistor, and works on the principle of joule heating: an electric current through a resistor converts electrical energy into heat energy. Most modern electric heating devices use nichrome wire as the active element. The heating element, depicted on the right, uses nichrome wire supported by heat resistant, refractory, electrically insulating ceramic. Although all electric heaters use the same physical principle to generate heat, they differ in the way they deliver that heat to the environment, based on this, electric heating can be grouped into two:

- Direct heating systems;
- Storage heating systems.

Direct Heating Systems

There are different types of direct heating systems on the market with technologies like convection heater, radiative heater, and fan heater. In these systems the heating energy is immediately available as soon as the electrical current is led through the resistance wire. The way of heat transmission is different in the various technologies.

In a convection heater, the heating element heats the air in contact with it by thermal conduction. Hot air is less dense than cool air, so it rises due to buoyancy, allowing more cool air to flow in to take its place. This sets up a convection current of hot air that rises from the heater, heats up the surrounding space, cools and then repeats the cycle. These heaters are sometimes filled with oil, which functions as an effective heat reservoir. They are ideally suited for heating a closed space. They operate silently and have a lower risk of ignition hazard if they make unintended contact with furnishings compared to radiant electric heaters. This is a good choice for long periods of time, or if left unattended

Radiative heaters contain a heating element that reaches a high temperature, the element is usually packaged inside a glass envelope resembling a light bulb and with a reflector to direct the energy output away from the body of the heater. The element emits infrared radiation that travels through air or space until it hits an absorbing surface, where it is partially converted to heat and partially reflected. This heat directly warms people and objects in the room, rather than warming the air. This style of heater is particularly useful in areas which unheated air flows through. They are also ideal for basements and garages where spot heating is desired.

A fan heater, also called a forced convection heater, is a variety of convection heater that includes an electric fan to speed up the airflow. This reduces the thermal resistance between the heating element and the surroundings faster than passive convection, allowing heat to be transferred more quickly. They operate with considerable noise caused by the fan. They have a moderate risk of ignition hazard if they make unintended contact with furnishings. This type of heater is a good choice for quick heating of enclosed spaces. Electric space heating is useful in places where air-handling is difficult, such as in laboratories

Storage Heating Systems

Storage heater is an electrical heater, which stores thermal energy during the evening or at night, when base load electricity is available at lower cost, and releases the heat during the day as required. The inside of a standard storage heater contains a storage core (ceramic or other material) with a high heat retention capacity. Heating elements within the storage core convert electrical energy into heat almost without loss. The core is being heated up to temperatures between 600°C and 700°C and is surrounded by a high-grade insulating material which reduces the heat losses. A connected room temperature controller comes into play when the actual room temperature falls below the required level. In that event a fan is started to absorb compartment air, which is being heated up on its way through the hot storage core of the heating element and then blown into the entire room. The temperature of the expelled air is regulated by a thermally controlled mixing valve. The power input depends on the size of the heating unit and ranges up to 7 kW.

Electric under floor heating is available as direct and storage heating system. The heating power of a direct underfloor heating varies between 80 W/m^2 and about 180 W/m^2.

The floor is used as storage material for the heat in a storage underfloor heating system.

For a room temperature of 27°C a power input of 70 W/m^2 is needed [43].

Compared to other types of heating system, storage heaters, are cheaper than running the same amount of electrical heating using electricity at regular daytime rates. Storage heaters allow houses to be sited in areas where natural-gas distribution systems are not available, without requiring the homeowners to pay higher daytime electrical-heating bills. In addition, the capital cost of night storage heating is relatively low, and installation is far easier than the initial installation of gas-fired boilers, piping and radiators. This is an important advantage when renovating old buildings without existing central heating. It has low maintenance costs.

However, the storage heater can only heat with the energy stored the night before. Thus, if the system was switched off or if the charge control was set too low, there may not be sufficient energy to heat the rooms, and this can only be corrected for the next day. This is a problem for example, when the weather turns cold unexpectedly, or when returning from a vacation late at night, or the users simply not thinking to change the settings because they are at a comfortable temperature. Some heaters alleviate this problem by also allowing heating during the day, but this is typically expensive (because the electricity is charged at full rate). Even under the best of circumstances, it can be difficult to accurately judge how to set the thermostats as setting them too low overnight can cause the heater to be having no perceived effect while setting them at maximum will increase the cost of running them. Similarly, in systems where every heater must be set individually, incorrectly setting one room’s heater can make the whole house feel too cold. Another demerit of storage heater is that, the heat stored during the night is automatically released into the living area during the next day, regardless of need due to the inevitable heat transfer through the storage heater insulation. Thus, if the homeowner is unexpectedly absent that day and therefore does not need the house to be warmed or is only at home for a small part of the day, the heat has already been purchased and is already there, and eventually comes out.

<u>Energy Consumption of Electric Heater</u>

Electric heating units are appliances which are operated usually automatically and on the demand for warmth in the home of the consumer. Therefore the consumption of energy in the period of use is determined by the following factors: type and size of storage heater, duration of the heating period, adjustment of the heating system, outside temperature

The energy consumption of electrical heating systems also depends on the personal sense of the warmth of the consumer which determines the duration of the heating period in one year. Storage heaters usually operate at off-peak periods, the time of their energy consumption ranges usually from 22:00 until 6:00 and sometimes periods during the day are also possible depending on the offers of the supplier.

3.5.10 Swimming Pool Pump

Swimming pool, paddling pool or simply a pool, is a container filled with water intended for swimming or water-based recreation. A pool can be built either above or in the ground, and from materials such as metal, concrete, plastic or fibreglass. A typical swimming pool consists of four major components [58]:

- A tank (basin, shell)
- A circulation system – pumps, inlets and outlets, pipe work
- Filtration and
- A dosing system for treatment chemicals.

The basic idea is to pump water in a continual cycle, from the pool via filtration and chemical treatment and back to the pool again. By this circulation, the water in the pool is kept relatively free of dirt, debris and microorganisms (bacteria and viruses). Other processes included – heaters, for example. And it must be possible to make up water lost by evaporation, backwashing the filters and bathers carrying it out of the pool on costumes etc. The main difference between pools is how the tank is constructed. There are several pool styles, each with advantages and disadvantages. Concrete pools are usually finished with tiles. As these are not flexible, the pool tank must be reinforced concrete, designed as a monolithic structure to fit into the geological conditions of the site chosen. The standard for reinforced concrete structures is British Standard 8110-1: 1997 Structural use of concrete. British Standard 8007: 1987 design of concrete structures for retaining aqueous liquids is an adjunct to BS8110 [58]. Generally speaking the vast majority of commercially built swimming pools and a small percentage of domestic pool tanks are built to BS 8007. This requires that the pool tank is inherently watertight (strictly, up to 10mm loss per week). It does not rely on waterproof renders or applied finishes to stop leaking. It must be water tested after construction and before the internal finishes are applied to confirm this. The commonest leakage problem in small pools is when pipework and run through the walls and floor of the pool tank. Hence, great care needs to be taken to ensure a good watertight joint at these interfaces.

The circulation system consists of pumps, inlets and outlet, pipe work. Outlets and inlets

During normal operation, pool water is removed at the bottom of the pool through two or more main drain outlets and from the surface perimeter of the pool into a deck-level transfer channels, skimmers or overflow channels. The bottom outlets are usually at the lowest point in the pool, so that the entire pool floor surface slopes toward them. Most of the dirt and debris, heavier than water, will sink and leave the pool through these outlets. Inlets and outlets also need to be safely designed, with a safe water flow rate. The designer specifies the number and arrangement needed to achieve the recommended flow rates. To keep people from getting their hair or limbs caught in the pipe work, the outlets are covered with grilles or special covers. Water is drawn out of the pool by circulation pumps through the pool outlets, and is returned to the pool via the filtration and treatment systems, through the pool inlets. The heart of the pool system is the water circulation pump. In a typical pool one or more electric pump will draw water from the pool, pull it through a strainer and push it through the filtration system and back into the pool [58], [59]. Other appliances considered in this dissertation include slow cooker, electric blanket television, personal computer, modem, hi-fi equipment, electric fence, electric fan, electric frying pan and electric sewing machine.

3.6 Summary

This chapter serves as a prior investigation into the identification of residential appliances using smart meter data. Technical characteristic with regards to the operation of some selected household appliances are reviewed. Also the rate of energy consumption of these appliances was examined and the following conclusions are drawn up from the energy consumption point of view. Among the appliances considered in this chapter, heating circulation pumps consumed considerably large amount of electricity followed by electric water heater while refrigeration (freezer and refrigerator) consumed moderate electricity. Washing machines and electric cooking appliances consume the least electricity

CHAPTER 4

Overview of Load Monitoring and Identification Techniques

Introduction

Due to the recent increase in energy demand and limited energy generation resources, energy conservation is becoming utility priority globally. Globally, residential energy consumption accounts for the significant portion of the total energy consumption and is envisaged to increase in the near future. For instance, in the European Union, residential energy consumption accounts for about 40 % of the total generation and it is predicted that global energy demand will double by the end of year 2030 [60]. Also, in the United State, residential energy accounts for about 35 % of the total energy consumption and is likely to increase by 15 % by 20030 [61]. Apart from the increase in energy prices and climatic change, increase in energy consumption will have direct impacts on the economy of a country. Therefore, significant reduction in energy consumption, especially ate the residential sector is very essential and this can be achieved through residential energy consumption monitoring and relay the information back to the consumers [60]. According to [61], maximum energy conservation can be achieved using feedback mechanisms. Feedback mechanism can be direct or indirect feedbacks. Indirect feedback mechanisms involve standard monthly billing, improved billing, and daily or weekly activities on energy usage while direct feedback mechanisms involve real-time in home display information such as price signalling capability appliances disaggregation or control. Generally, feedback mechanisms have reduced individual household electricity consumption by 4 to 12 % throughout the United States and many other developed countries [61]. It is estimated that feedback programs for household might generate electricity saving that range from as little as 0.4 % to more than 6 % of total residential electricity consumption. Feedback programs could provide the equivalent of 100 billion (kWh) of electricity saving annually by 2030 in the United States [61]. The Figure 4.1 shows the summary of the types and energy saving of feedback programs.

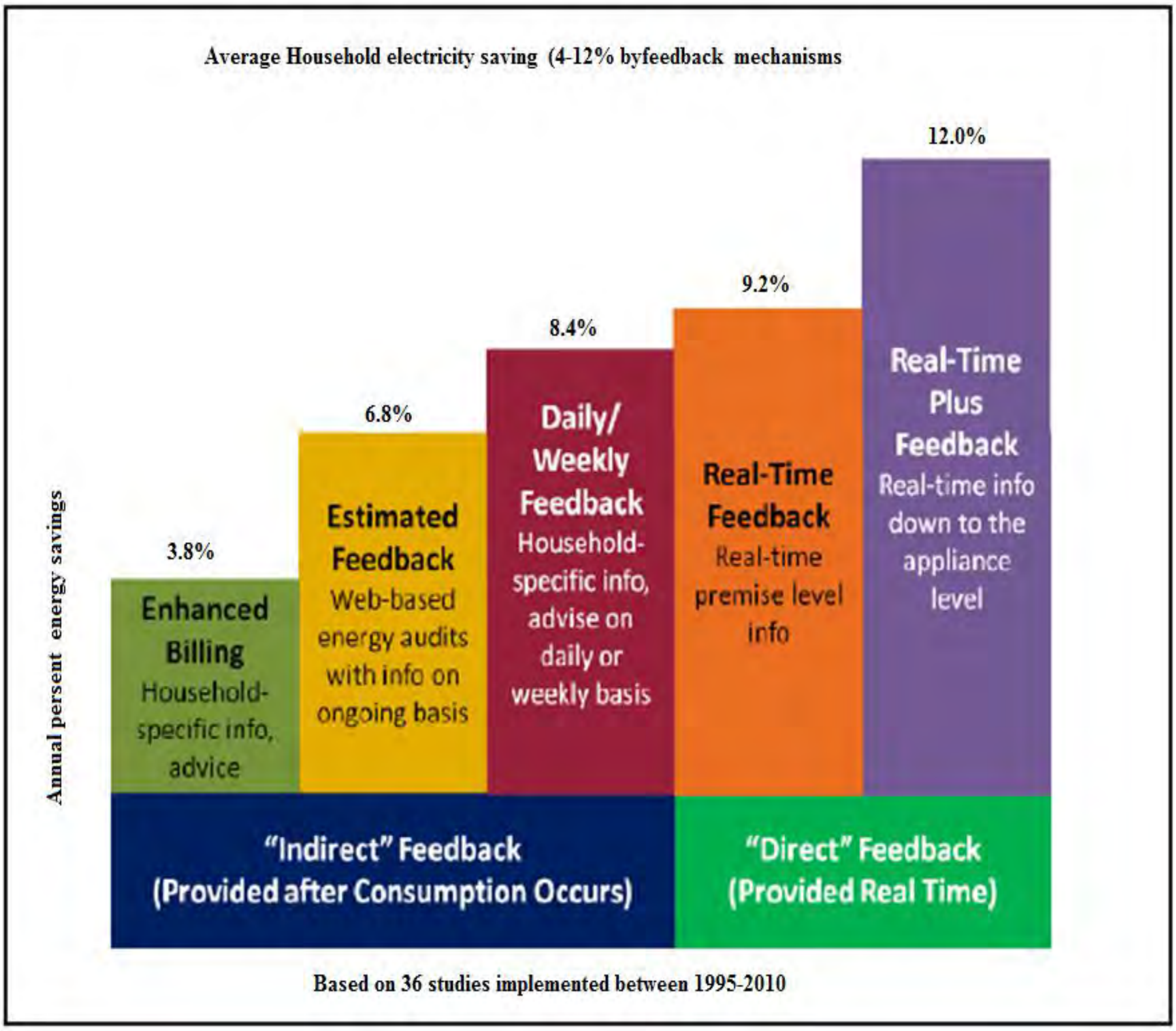


Figure 4.1: Summaries of the Types and Energy Saving of Feedback Programs **[61]**

To ensure real-time energy information dissemination in feedback programs, smart meters will play an important role. However, these smart meters provide little information on the breakdown of energy consumption of each household appliance. In order to achieve disaggregation of energy consumed by each appliance effort has led to the development of Appliance Load Monitoring (ALM) methods.

ALM aimed at performing detail energy sensing and supply detailed information about energy consumption of each domestic appliances to consumers for the purpose of energy conservation system at domestic level. ALM is not only a condition for precise energy feedback, but it is equally applicable for other applications such as fault detection, and remote load monitoring systems [61].

4.1 Conventional Load Monitoring Techniques

The conventional method of monitoring appliances is based on supervisory control and data acquisition (SCADA). Sensors are installed for each appliance to be monitored, once the appliance recorder receives a sensor message, it immediately records the load data and delivers them to the data centre for further analyses. The traditional load monitoring system is comprehensive, systematic, and convenient method of load monitoring. However, the measuring devices (meters or sensors) may incur significant time and costs to install and maintain. Furthermore, increasing numbers of meters may affect the system reliability. In addition, the traditional load monitoring technique is too complicated to implement in an ordinary household. This method of load-monitoring has been queried by load-monitoring system practitioners because of too many monitoring devices involved. Due to this the future current load-monitoring systems is based on more significant issues, such as strategies for minimizing the number of monitoring devices are being developed. Besides minimizing the number of devices used in monitoring, cost effectiveness of the monitoring techniques is another factor to be considered [62], [63]. Generally, there are two types of load monitoring systems, intrusive load monitoring (ILM) and non-intrusive load monitoring (NILM) systems [64].

4.2 Intrusive Load Monitoring, System

The Intrusive load monitoring system is a common metering system that measures the energy consumption of an appliance by connecting power meters to each appliance in the household. Therefore, it requires entering the house the system is referred to as intrusive. It provides accurate result, however, imposing high costs and a complex installation which usually requires wiring and data storage units for the house households concerned [64]. Intrusive load monitoring techniques can be divided into direct and indirect monitoring techniques [65].

4.2.1 Direct Intrusive Load Monitoring Techniques

Direct intrusive monitoring techniques measure the electrical characteristics of each appliance power demand. There are three types of direct intrusive load monitoring: electrical sub-metering, smart appliances and electrical probing

- **Electrical Sub-Metering**

Electrical sub-metering is a technique of monitoring electrical appliance in which individual appliances are monitored using separate meter. The appliance meters may be a plug-in meter or a clamp-on meter. The Plug-in meters are installed by plugging the appliance into the meter, and then plug the meter into an electrical outlet. This allows the meter to both monitor the appliance and control the flow of electricity between the mains circuit and the appliance. The clamp-on meters can be installed without breaking the electrical circuit, by attaching a clamp around the lightly insulated positive or neutral wire. The power drawn by the appliance can be calculated by measuring the electromagnetic field generated by the flow of current through the wire. This technique provides accurate measurement, but it is not cost effective [65]

- **Smart Appliances**

In this measuring technique, the appliances themselves measure, record and report their energy consumption to a central hub without installing additional monitoring equipment. Smart appliances use wireless communication technology to monitor and report their consumption. Conventional or old appliances must be replaced or upgraded to smart appliance in order to self-report their consumption. The major setback to this technique is the high cost of upgrading or replacing conventional appliance. In addition, it may take longer time to replace old appliances with new ones (smart appliances) [65].

- **Electrical Probing**

Electrical probing is the process of transmitting a signal into a household electrical circuit and using features extracted from the returned signal to classify the loads currently in use. Electrical probing inherently adds interference to the electrical circuit, which can adversely affect the power quality delivered to each appliance. As a result, energy disaggregation by electrical probing has not been reported in the literature since it was first suggested by Hart [65].

4.2.2 Indirect Intrusive Load Monitoring Techniques

Indirect techniques measure non-electrical characteristics, from which each appliance's power demand is inferred. There are three types of indirect intrusive load monitoring: appliance tagging, ambient sensors and conditional demand analysis.

- **Appliance Tagging**

Appliance tagging refers to the modification of an appliance such that a tag emits a unique signal when the appliance turns on or off. These signals are detected by a central hub which estimates each appliance's energy consumption. The approach requires the customisation of each individual appliance in addition to the installation of a central signature detector. The major setback to this technique is the installation time and the cost per household [65].

- **Ambient Sensors**

Multiple wireless sensors could be used to monitor feeds other than electricity in order to disaggregate total household power consumption into individual appliances. Examples of such sensors include audio, temperature and light sensors, which could be used to monitor both human behaviour and appliance operation. This approach requires the intrusive installation of multiple sensors throughout each household [65].

- **Conditional Demand Analysis (CDA)**

Conditional Demand Analysis can then be used estimate the energy consumption of domestic appliances. Unlike other approaches requiring the installation of additional meters, CDA uses only a household's billed energy consumption. In addition, CDA also requires information about the consumer, household and weather. Such data from many households are analyzed using a multivariate regression technique to learn the typical contribution of individual appliances. CDA requires a large participant base, in which each participant must complete a detailed questionnaire. Furthermore, CDA does not capture unusual cases which do not account for by such questionnaires, such as a day when the washing machine has been run three times [65].

4.3. Non-Intrusive Load Monitoring (NILM) Systems

Nonintrusive load monitoring (NILM) is a process for analyzing changes in the voltage and current going into a house and deducing what appliances are used in the house as well as their individual energy consumption. It is non-intrusive because it does not require intruding into the house when measuring the power consumption of different appliances. Smart meters with NILM technology are used by utility companies to survey the specific uses of electric power in different homes. NILM is considered a low cost alternative to attaching individual monitors on each appliance. The overall scheme of NILM system is shown Figure 4.2. Three-phase or one-phase electricity powered the loads. A meter data management system connects to the NILM system monitor the operation of each load using a wire or wireless sensor network. The results of the monitoring are used to analyze and identify the appliance status and then to estimate the electric power demand of different loads from the time of use [62].

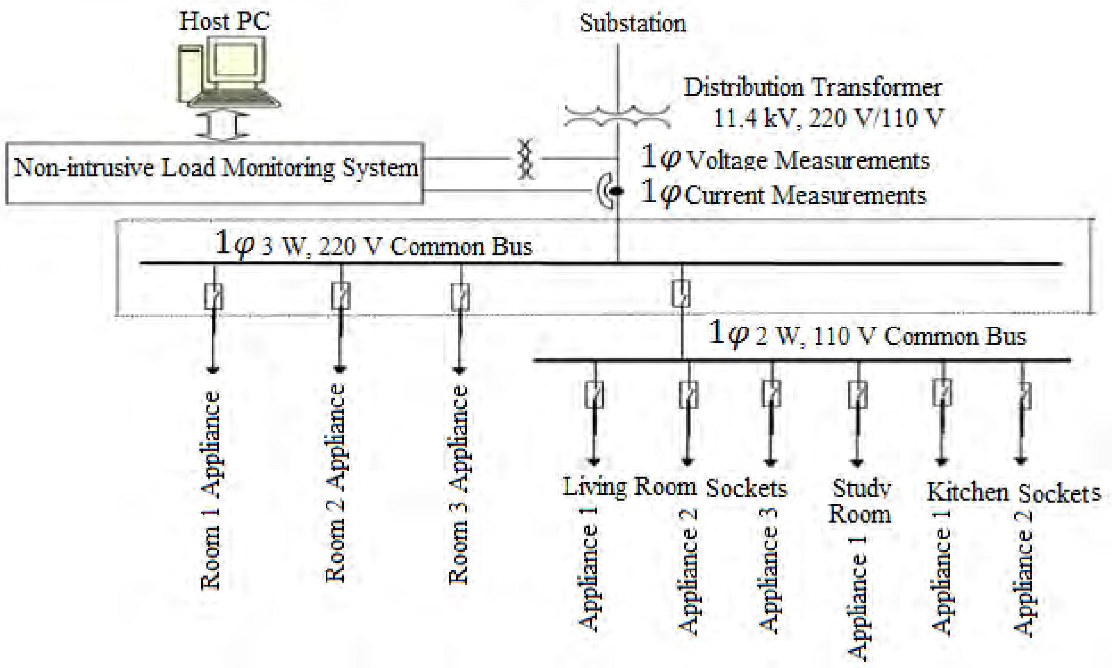


Figure 4.2: Non-Intrusive Load Monitoring and Identification System [62].

The concept of Non-intrusive Load Monitoring was invented by George W. Hart of Massachusetts institute of technology (USA) in the early 1982 with funding from the electric power research institute (EPRI) [66]. The idea of analyzing the power flow to determine household appliances and report on their on and off event started when George W. Hart was collecting and analyzing load data as part of a residential photo-voltaic systems study. After monitoring the electricity consumption of homes at 5 second intervals, he discovered that he could analyze the plot visually and tell what was happening in the monitored homes. As a result, of the collaboration with the MIT Energy Laboratory Staff, he realized that this kind of system could have significant value to utilities and they stated formalize the steps to write a computer program which made a similar analysis. This was the start to developing a fully new monitoring system for household appliances. Several research and development projects have started in other countries like French Japan, Finland and Denmark [67]. In French, Electricitee de France (EDF) has embarked on some studies since 1990 whose aim is to recognize domestic electrical appliances. The basic monitoring principle is to recognize active and reactive step changes in the total load produced by the starting and stopping of the different appliances of the customer. A digital prototype of a recorder was built within the period of 1989-1992 with the support of Schlumberger Industries [67]. The device, named ACNI, fed by the currents and voltages of a single phase customer records change in active and reactive power each time a variation of the load is detected. Software developed by EDF for an off-line PC, reads the recordings and is able to classify them in different categories using a customization technique. Recently, EDF has developed a new approach which consists of Hidden Markov Model (HMM) in an attempt to recognize the logical and chronological switch-on and switch-off of different appliances. An HMM consists of states and transitions between appliances switched on and off [67].

4.4 Applications of NILM Systems

Non-intrusive load monitoring system offers different applications from residential to industrial. Some of these applications are:

- NALM techniques are especially useful for utility monitoring of residential loads. The ease of installation will allow more appliances to be monitored in more homes, providing broader data and in many cases more accurate data than has been feasible with current technology. Lower cost, finer resolution and ease of installation, removal and maintenance (without requiring an appointment with the residents to gain entry is very valuable features from the utility perspective).
- Monitoring of individual utility customers for the purpose of the energy audit is another related application of NILM system. A NILM a can be installed temporarily at the customer's request in order to analyze the characteristic of the appliances which can be used in suggesting ways of reducing consumption and costs. A second audit is often valuable to confirm the savings resulting from conservation measures.
- Another important application of NILM is a power monitoring for failure analysis or security purposes. Failed appliances can often be detected by their unusual power consumption or duty cycles. For instance, a refrigerator which was on almost all of the time was detected and replaced. In term of security, a vacation home which is un-occupied for long periods can be monitored at a single point. The monitor could be programmed to automatically generate and report appliances usage above or below the specified thresholds and send notification to the owner automatically via phone message.
- Another application of NILM involves the verification of demand side management control many electric utilities install appliance controller on deferrable load throughout their customer base, to shed them during the period of peak power usage. NILM can verify that the system is in fact operational, and has not been defeated by radio or customer inference. Apart from the

aforementioned applications, applications of NILM system include load forecasting, and rate forecasting [68].

4.5 Advantages of NILM

The NILM has a number of important advantages compared to intrusive load monitoring (ILM), some of these advantages are: lower equipment and manpower costs due to fewer components to install and maintain, greater reliability and smaller space requirements. In addition, unlike traditional systems which are usually limited to four or eight appliances, NILM system is not constrained in the number of channels of data which can be recorded and hence can decompose the total load finely. Also, being less expensive, it can be placed at many sites, thereby reducing the biases that result from small samples. Furthermore, being non-intrusive it can be used by customers who would not allow the intrusion of utility workers to install, maintain, and remove the conventional load monitoring equipment in their house. This reduces the possibility of a customer sample skewed toward energy-conscious users [68].

4.6 Disadvantages of NILM

The NILM cannot be used to detect appliance under 100 W, continuously variable appliance such as light dimmers or appliances which operate constantly like clocks. Also, it cannot distinguish between electrically identical appliances such as two burners of the same size on an electric stove. However, harmonic current signatures and tags may be a cost-effective means for alleviating these limitations. Another disadvantage of NILM is that the system may have a greater potential for undetected error. There is a greater potential for the reported data to contain significant errors since the total load is disaggregated in software rather than the hardware of separate sensors and communication channels. More so, the software may not recognize unusual appliances not encountered in the database. Also, the method has not yet been fully specified or field tested for multistate appliances such as dishwashers, washing machines, and heat pumps. It has not been specified at all for continuously variable appliances [68].

4.7 Challenges of NILM

There are numerous challenges that need to be addressed in order to make NILM a practically viable solution. Developing a solution that could identify all types of appliances regardless of their category, make, size and the manufacturer are still a challenge. In addition, forming generic appliance models is difficult due to the high interclass variety of features within each load category, whereas the power draw pattern by most of the multi-state appliances is dependent on user-specific settings. Furthermore, appliances with low power consumption have similar power consumption characteristics which make the recognition more difficult and challenging. Also, any subtle change in energy supply by utility companies (power factor correction) at the main circuit line can cause a mismatch of appliance profile since NILM based on supervised learning process which needs each appliance to be profiled during the training phase. Aside the aforementioned challenges, it is difficult to update NILM appliance signature database [60].

4.8 Load Identification Techniques

Nowadays, the majority of loads connected to residential buildings remain unknown due to lack of intelligent load identification and monitoring capability, as well as communication between the loads and the building management system. Vital information that enables effective energy management and consumption at residential areas are provided through accurate and reliable domestic appliance identification and monitoring techniques. However, apart from the lack of effective coordination system between the loads and the building management system, inefficient and feeble intelligent load identification and monitoring techniques has made it difficult in recent time to identify and recognize the majority of the electrical load that are connected to residential buildings. By identifying different types of loads and their power consumption from the current and voltage signatures, can provide useful information for load management system and therefore improve the system efficiency. Electrical appliances often present unique characteristic in the electrical signals (voltage, current and power). Such these characteristic provides a viable means of identifying the type of appliances and its operational condition by analyzing the electrical signals [69]. Residential load monitoring and identification was first proposed in 1980s by George Hart, the operating schedules of individual loads or groups of loads are determined by identifying times at which electrical power measurement change from one steady-state value to another. This steady-state change is known as events. The event is a step change in power or the transition of appliance's operating condition from one condition to another. In this regards, the transition condition of appliances corresponding to the appliance either the turning ON or OFF are denoted by the appliances magnitude and sign in real and reactive power [70] and since then many load monitoring and identification techniques have been proposed by researchers. The general framework of non-intrusive load monitoring and identification consists of four basic steps as shown in the Figure 4.3

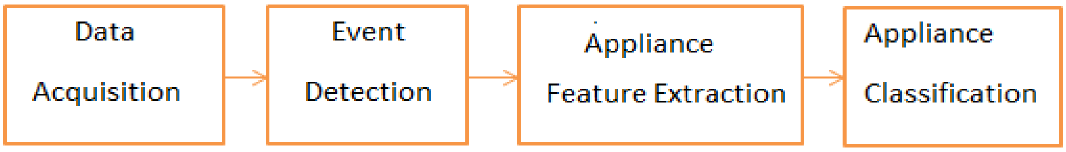


Figure 4.3: The Four Stages of NILM Approach

Data acquisition stage is a stage of obtaining aggregated load measurements from the household, such as voltage and current and process it to produce power metrics (real and reactive power). The event detection stage is a stage that corresponds to sudden change in the individual appliance operation. It is characterized by ON and OFF transition of the appliance by analyzing the change in the power consumption level of the appliance. In order to characterize the detected events, steady-state and transient event-based feature extraction methods are developed. Steady state methods identify devices based on variations in their steady state signatures, for example a change of steady state active power measurement from a high to low value can identify whether the appliance is being turned ON or OFF. The transient methods, on the other hand make use of transient signatures that uniquely define appliance state transitions by extracting features like shape, size, duration and harmonics of the transient waveforms to identify the specific appliance. Finally, these features also known as the appliance signature of the state transition, uses algorithms to classify the appliances [60].

4.8.1 Appliance Signatures for Energy Disaggregation

Most appliances are identified by their distinctive characteristics under certain condition. Appliance signature is said to be a significant parameter of the total load that provides information about the nature and operating condition of an individual appliance in the load. Nonintrusive load monitoring system (NILMS) infers individual loads of ON or OFF by checking signatures that supply information on their activities. Event signature can be fundamental frequency or harmonic frequency signatures [66].

4.8.1.2 Fundamental Frequency Signatures*:*

At the utility, fundamental frequency can be sued as appliances signature by measuring the power, current or admittance of the total load and consider the step change as signatures. The utility voltage varies over time and the actual voltage can vary within ± 10 % of the nominal voltage supply. A linear appliance plugged into the varying voltage source will also draw a current within the varying voltage. The power consumption will then vary by over $\pm 20\%$. Fundamentally, in NILM, changes detected in the total load must provide information about the events within the load. Thus, the varying in power consumption does not provide an ideal signature of the connected appliance for reasons external to the load. Consequently, to abrogate the alteration of voltage, the linear model suggests that admittance is better to power and current as a signature. Admittances depends on the voltage of a linear appliances and is additive when appliances are wired in parallel. The load admittance Y (t) is given in equation 4.1

$$Y(t) = \frac{P(t)}{V^2(t)} \tag{4.1}$$

where $P(t)$ and $V(t)$ are measured power and RMS voltage respectively. However, proper admittance is not the best choice for appliances signature, since it lacks engineering intuition about the values to expect and their units. Therefore, admittance in normalized power is preferred. The admittance in normalized power is given by equation 4.2

$$P_{normal}\,(t) = 120^2 Y\,(t) = \left(\frac{120}{V(t)}\right)^2 P(t) \tag{4.2}$$

The equation 4.2 depicts the power if the utility provides a steady voltage and the load obey a linear model [66].

4.8.1.3 Harmonic Frequency Signatures:

Harmonic currents produced by the appliance can be used as a signature to identify the appliance. A linear model suggests that the utility voltage waveform is directly proportional to the current response. For instance, if the voltage waveform is sinusoidal, the current response will also be sinusoidal, although many appliances are obviously nonlinear in this respect. At higher frequencies, notable current are generated by many power electronics devices**.** Apart from the resistive heaters and incandescent lights, virtually all appliances produce mixed harmonic current. Harmonic current signatures might be very useful in identifying certain appliance which is too similar to distinguish using real and reactive power [66]. Signatures for Appliance Identification can generally be grouped into: steady-state signature and transient-state signature [69]. The classification of appliance signature is described in the Figure 4.4

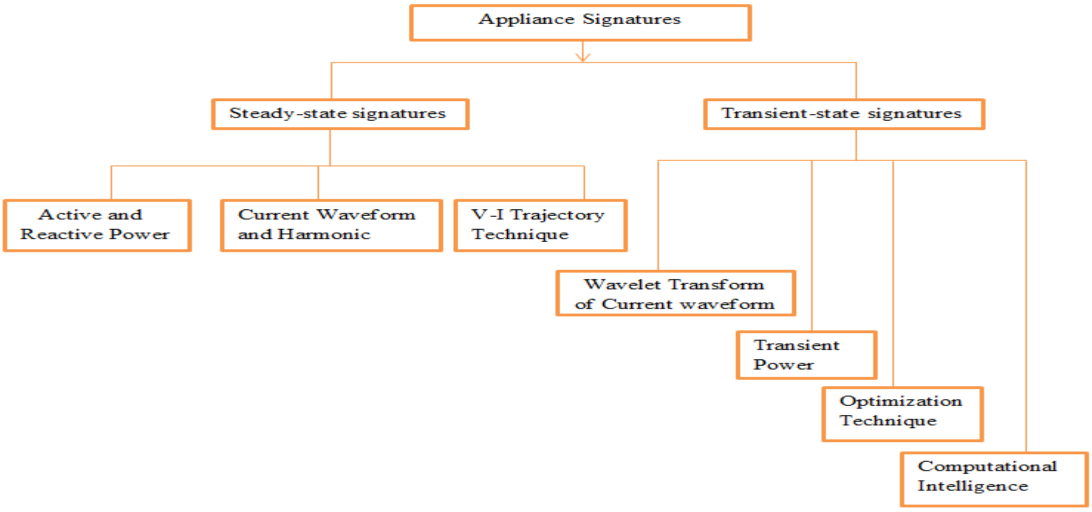


Figure 4.4: Classification of Signatures for Appliance Identification.

4.9 Steady-State Signatures

According to [66], stead-state signatures of appliance are obtained from the difference between steady-state properties of the appliance operating conditions, estimated as the difference between the operating levels of the connected state. Also, steady-state signatures are said to be the point at which the corresponding power consumption measurements change from one state to another. These changes are characterized by the magnitude and sign of active and reactive power, and they usually correspond to an appliance turning ON or OFF [68]. It is considered to be the most commonly used signature owing to its easy computation from metering devices and it does not require fast sampling rates [68]. The steady-state based technique includes [66], [69]:

- Techniques based on the active and reactive power;
- Technique based on the current waveform characteristic and harmonics;
- Techniques based on V-I Trajectory.

4.9.1 Techniques Based on Active and Reactive power

Active power is also called real power. It is the power capable of performing useful work. It is also said to be the conversion of electrical energy into another form of energy such as mechanical work or heat. It is motivated by resistive loads where current and voltage components are in phase.

$$P = V_{rms} I_{rms} \cos(\theta) \tag{4.3}$$

V_{rms} is the root mean square voltage, I_{rms} root mean square current and θ is power factor angle.

Reactive loads such as coils and capacitors consume no electrical energy as they store it and dump it back into the source. This power is called reactive power and it generates magnetic and electric fields. Reactive is consumed due to presence of reactance in a circuit such as motors, transformers, or solenoids [68].

$$Q = V_{rms} I_{rms} \sin(\theta) \tag{4.4}$$

The real power and the reactive power are measured and recorded. The variation in active and reactive power can be used to identify different types of loads. As the condition of the appliance changes, the magnitude of active and reactive power, also changes. The value is then compared with the predefined database of load power. The Load can be identified through the position in P-Q plane as shown in Figure 4.5.

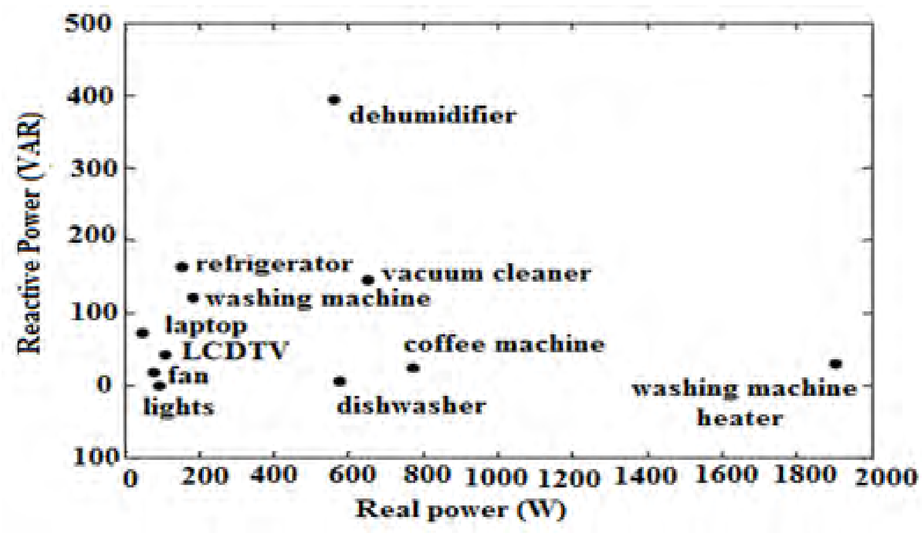


Figure 4.5: Real and Reactive Power of domestic appliances in the P-Q plane [68]

From Figure 4.5, it can be seen that many appliances are located around the horizontal axis. The loads that are far from each other in the plot can be identified only by using reactive and active power. The success rate of loads identification of large residential loads can be greater than 80 % [69]. However, there are some limitations to the use of active and reactive power based techniques. Firstly, some appliances with the same power consumption or low power appliances cannot be identified by this technique. However, according to [69], the efficiency of load identification using active and reactive power based technique can be improved using rule-based method. The algorithm uses meter data (measured energy consumption data), with assumptions about the consumer attitude. In a scenario where two or more loads have similar power demand levels, the algorithm uses decision analysis approach to distinguish between them, based on the assumptions regarding the usage of these appliances, such as the time of day or the length of usage. Beside the aforementioned limitation, another limitation to load identification based on real and reactive power is that the technique is based on steady-state power consumption. Thus, it cannot be used in real-time. However, some loads in residential buildings do not yield reliable steady-state measurements [69].

4.9.3 Technique Based on Current Waveform Characteristic and Harmonics

The best sets of information to identify appliances include current and voltage, although it is not practically viable to compare the waveforms because of computation limitation and sensitivity issues. Also, abstracting features from the waveform for appliance identification is a challenge, thus, Peak current, average current and RMS current, current timing have been selected for identification [69]. The current features in the appliance database are transmitted to a home server, which compares the feature of known appliances with the received feature to identify an appliance's model and activity. However, the method is generally affected by noise, calculation timing and variation in voltage. Also, the technique cannot identify correctly the appliances with the same power level [71]. Current waveforms are easy to be calculated and represented, thus, order to improve the identification efficiency and accuracy, they are often combined with P-Q plane methods and transient power methods for load identification. Fast Fourier Transform (FFT) or Short-time Fourier Transform (STFT) of current waveforms are used to analyze time-varying harmonic current. In addition, power factor (PF) and harmonic distortion in the current can also be used to identify loads in its steady-state signature. PF can distinctly identify a purely resistive loads, motor driving load and power electronic load. Many power electronic connected loads are non-linear and generate current harmonic, thus, current harmonics are suggested to be used to identify such loads [69], [71].

4.9.4 Techniques Based on V-I Trajectory

Load signature created by the instantaneous voltage-current (V-I) trajectory, is suggested for characterizing the loads. According to [69], the front-end power electronic circuits and the mechanical characteristics of some electromechanical loads play vital roles in signature of electrical loads. To identify different loads, the shape features of the trajectory, such as asymmetry, looping direction, area, curvature of mean line, self-intersection, and slope of the middle segment, area of segments and peak of middle segment are used for the pattern recognition. A hierarchical clustering method is employed to classify the appliances and construct the signature of the appliances. However, the method is computationally intensive [69].

4.9.5 Advantages of Using Steady-State Signatures for Appliance Identification

The steady state condition of operation of appliances is easier to detect than a momentary or transient condition of operation. For instance, the sampling rate and processing condition necessary to identify a step change in power are less demanding than those required to capture and analyze a transient current. Another advantage of steady-state appliances signature is that the detector for steady-state signatures provides information about a large number of appliances condition changes than a detector for the transients-state. Finally, Steady-state signatures are additive, which allow simultaneous events to be properly analysed [66].

4.9.5 Limitations of Steady-State Signature

The up-to date experiment in different buildings, according to [70] have revealed a number of limitations to the of steady-state signature technique in load identification. Some of these limitations are well established, while others are relatively new. The operation of V-I Trajectory based technique (two-dimensional signature-space technique) is based on some assumptions which limit its effectiveness. For instance, different appliances display unique signatures in the ΔP-ΔQ plane and they may not if the technique is applied in commercial and industrial facilities where the number and different loads is greater than residential buildings. Also, the technique may become overfilled with identical appliances as the number and the same type of appliances increases. In addition, a building may have overlap appliances in the ΔP-ΔQ plan. Another limitation is that steady-state power consumption cannot be measured in real-time. It requires waiting until transient behaviour settles out before the steady-state power consumption values can be measured. The longer waiting period prevents the monitor from tracking rapid sequences of load activation, thus, some loads will be missed and these may not be caught in the anomaly resolution phase. Also, short waiting period may prompt measurements in the middle of load transients, resulting in invalid events in the cluster analysis phase. In addition, if the differences in power consumption are large enough, some could prevent the monitor from finding a steady-state consumption level or recording any events. In addition, steady-state techniques process data in aggregation using a day or more of stored data. This is does not conform to the five-steps of disaggregation procedure, but is based on the assumption that near-real-time identification of load operation is not necessary. This restricts the monitoring to load survey and power stored data applications.

4.10 Transient-State Signatures

Advanced load monitor identifies each load based on special load transient shapes. The transient feature of a load is the physical task the load performs. For instance, the turn-on transients associated with a personal computer and with an incandescent lamp are different due to the charging capacitors on the computer power supply which is fundamentally different from heating a lamp filament. Transient-based identification allows real-time identification of appliance operation, especially turn-on events. Transients are identified by matching events in the incoming aggregate power stream to previously defined transient signatures [70]. Appliance transient signatures are more difficult to identify and provide less information compare to steady-state signatures. Nevertheless, they are worth investigating if they provide useful information to enhance steady-state signatures information. In a situation where two or more appliances consume the same amount of energy, analysis of appliances transient signature could use to identify the actual appliances that present in total load since the appliances may have different turn-on current. This would be more suitable when only one of the appliance types was present in the load. If the load contained one of each, the transient could also determine which of the two turned on when the common steady-state signature was observed. Consequently, two appliances that are on when one turns off cannot be distinguished using turn-on transient signature. Transients in the consumer appliance come in different shapes, corresponding to the generating mechanism. The other parameters for categorizing transients are their size, duration, time constants or parametric variables in models which can be fitted to the observed waveforms. Resistive appliances have no transient when switching on for a short time. Pump-appliances such as electric motors driving a pump generate a long on-transient. Other motor driven appliances such as fans, washing machine differ from pump-operated appliances by generally less substantial switching on-transient. The transient-state based technique includes [67], [68]:

- Techniques based on transient power;
- Techniques based on wavelet transform of the current waveform;
- Techniques based on optimization;
- Techniques based on intelligent learning.

4.10.1 Techniques Based on Transient Power

Advanced load monitor recognizes individual loads based on distinctive load transient shapes. The transient behaviour of a typical load is intimately related to the physical task that the load performs. For example, the turn-on transients associated with a personal computer and with an incandescent lamp are distinct because charging capacitors in the computer power supply are fundamentally different from heating a lamp filament. Overall transient profiles tend to be preserved even in loads that use active wave shaping or power factor correction. Most loads observed in the field have repeatable transient profiles, or at least sections of the transient profile that are repeatable. Transient-based recognition permits near-real-time identification of load operation, especially turn-on events. Transient harmonic power can provide extra information for variable loads, besides the transient power. It is very useful to identify variable drive connected loads, since the drive start-up is generally repeatable, controlled by a microprocessor. In order to analyze the transient power, continuous monitoring and high sampling rate are required [69], [70].

4.10.2 Techniques Based on Wavelet Transform of Current Waveform

The concept of wavelet transforms (WT) was proposed by Morlet and Grossman to overcome the problems of the short-time Fourier transform (STFT). Wavelets are mathematical functions for investigating signals with transient signature. Wavelet analysis is based on the decomposition of a signal according to scale rather than frequency, using basis functions with adaptable scaling properties. This method is generally referred to as multi-resolution analysis (MRA). A multi-resolution representation provides a hierarchical framework for interpreting signal structure and involves a coarse-to-fine transformation of the discrete-time data. The wavelet function is localized in time and frequency yielding wavelet coefficients at different scales. The time-frequency localization property means that more energetic wavelet coefficients are localized in the transform domain, thus providing a basis for data compression. This property is also useful for feature extraction [72]. The wavelet transform can be achieved in two ways depending on what information is required out of this transformation process. The two processes of wavelength transform are: continuous wavelet transforms (CWT) and discrete wavelet transforms (DWT). A continuous Wavelets transform (CWT) have two independent variables *‘a’* and *‘b’*. Where *‘a’* is the scaling factor and *‘b’* is the shift or translation factor. The magnitude of the wavelet coefficients provides information on how close the scaled and translated wavelets are to the original signal. The Continuous Wavelet Transform of a continuous signal *x (t)* is defined as:

$$CWT_{(a,b)} = \frac{1}{\sqrt{a}} \int_{-} x(t)\varphi^{*} \frac{t-b}{a} dt \tag{4.5}$$

The discrete wavelet transform (DWT) is used for computer implementation. The scale and translation variables are discredited. Any wavelet coefficient can be described by two integers, *m* and *n*. If *and* a_o and b_o are the segmentation step sizes for the scale and translation respectively, the scale and translation in terms of these parameters will be $a = a_o^m$ and $b = nb_o a_o^m$. Thus, discrete wavelet coefficients are given in the equation 4.6:

$$DWT_{m,n} = a_o^{-\frac{m}{2} \int_{-} x(t)\varphi^{*}(a_o^{-m}t - nb_o)dt} \tag{4.6}$$

For simplicity a_o and b_o are chosen to be 2 and 1, respectively [72].

Generally, loads can be represented by multiple levels of wavelet decomposition, and the energy at different levels of wavelet decomposition is used to identify loads.

4.10.3 Techniques Based on Optimization

Efficiency of load identification techniques varies because residential loads display different electrical characteristics. Thus, it is suggested that different techniques should be combined together as an optimization technique. The objective function is defined as the minimum residue while comparing the unknown loads with a set of data extracted from the know database, as given below [69]:

$$minobj_j = \sum_{k=1}^{N} w_k (\hat{y}_{k,j} - y_{k,j})^2 \tag{4.7}$$

where $\hat{y}_{k,j}$ is the feature *k* extracted from the known feature-database of load *j,* $y_{k,j}$ is the feature *k* extracted from the unknown load, w_k is the weight of feature *k, N* is the number of total features. One-to- one contrast with the known database can be performed if the load features are extracted from a single load. The left over between the unknown and the known individual load signatures are noted and the known load with the smallest leftover can be considered as the target. The technique becomes complex if the unknown load is a composite load. Composite loads are loads that have multiple signatures. Thus, other methods propose to overcome the problems of loads having multiple signature includes genetic algorithms, dynamic programming approaches, particle swarm optimization, fuzzy logic and multi-algorithm framework [69]. However, the major limitation to optimization technique is that all features of loads are assumed to be known and it is based on large database. In addition, some loads have multiple operating states and they consume different levels of energy in different states. Generally, optimization techniques are yet to be used in some cases [69].

4.10.4 Techniques Based on Computational Intelligent Learning

Computational intelligence, for instance artificial neural networks (ANN) can be used to identify loads by training the artificial neural network to learn specific features of different appliances. Through the training process, the structure and parameters of the ANN are built to capture different features of loads. It is suggested that a number of neural networks should be trained in cascade, for pattern classifiers to identify various loads. Steady-state appliance signatures, such as fundamental frequency quantities, current, power and harmonic frequency current information and distortion power are considered as the inputs of neural networks [69].

4.11 Summary

Electrical energy is the major source energy and plays an important role in the economic development of any national. Due to the recent increase in the demand for electrical energy and shortage in production, it is essential to develop strategies for effective energy management. In order to achieve effective management and ensure effective system delivery, load monitoring and identification is proposed especially at the residential level since it is the major energy consumer. Load identification systems can determine the type of the load, provide the detailed electricity consumption and running state of equipment for supply-side and the user. In this chapter, various load monitoring systems, appliance signatures and its forms were reviewed. Furthermore, different techniques for load identification were also examined. The Intrusive load monitoring provides accurate results and would allow each individual appliance's energy consumption to be communicated to a central hub. However, there are many practical disadvantages to this method that have prompted the introduction of non-intrusive load monitoring system. The financial cost of manufacturing and installing enough meters to match the number of domestic appliances would be considerable. In addition, the installation of one meter per household appliance would cause inconvenience to the occupants of the house and finally, the system would require additional meters to be deployed should the set of appliances. Therefore, the intrusive load monitoring technique should not be considered as a practical or scalable solution to the appliance energy monitoring problem. Furthermore, no single method can identify all types of the loads in households, and the success rate of identification decreases dramatically as the load feature database is increased. Based on the reviewed, it is suggested that computational intelligence, learning techniques will yield accurate result due to their ability to incorporate in their learning, temporal as well as appliance state transition information. For adequate understanding of the suggested technique, the following chapter summarizes the characteristics of the computational intelligence technique employed in this dissertation and compare it with the conventional techniques.

CHAPTER 5

Overview of Computational Intelligence Techniques Used for NILM

Introduction

Intelligent systems (IS) provide a standardized methodological approach to solve important and fairly complex problems and obtain coherent and reliable results over time. The definition of intelligent systems is a difficult problem and is subject to a great deal of debate. From the perspective of computation, the intelligence of a system can be characterized by its flexibility, adaptability, memory, learning, temporal dynamics, reasoning, and the ability to manage uncertain and imprecise information. In general, an intelligent system is a system that imitates some aspects of intelligence exhibited by nature. These include learning, adaptability, enhancing efficiency, information compression and extrapolated reasoning.

The development of digital computers made possible the invention of human engineered systems that display intelligent behaviour or features. The branch of knowledge and science that emanate from such systems is called artificial intelligence (AI). The computational environment used in such an analytical approach may be too definite and inflexible in order to cope with the intricacy and the complexity of the real world industrial systems. It turns out that in dealing with such systems, one has to face a high degree of uncertainty and tolerate imprecision and trying to increase precision may be very costly. In the face of the aforementioned difficulties, fuzzy logic (FL), artificial neural networks (NN) and evolutionary computation were combined under the name computational intelligence (CI) as a hybrid system to alleviate the difficulties [73].

5.1 Definition of Computational Intelligence (CI)

Notwithstanding the extent or the prevalent use of the term computational intelligence, there is still no generally agreed definition to describe it. However, some of the interesting definitions of computational intelligence given by different literatures are summarized below. According to [73] a system is said to be computational intelligence when it deals with numerical data, has a pattern recognition component, and uses knowledge in an artificially intelligent manner. In additionally, a system is said to be computational intelligence when it exhibits the following attributes computational adaptively, computational fault tolerance, speed approaching human-like turn around, and error rates that are estimated to be close to human performance. Computational intelligence can also be defined as a methodology involving computing that exhibits an ability to learn and deal with new situations such that the system is perceived to possess one or more attributes of reason, such as generalization, discovery, association, and abstraction. Generally, computational intelligence can be summarized as systems that possess the characteristics of computational adaptation, fault tolerance, high computational speed and less error prone to noisy information.

5.2 Computational Intelligence Paradigms

The five main paradigms of Computation Intelligence (CI) are [74]:

- Artificial Neural Networks (ANN),
- Swarm Intelligence (SI),
- Artificial Immune Systems (AIS),
- Fuzzy Systems (FS).
- Evolutionary Computation (EC).

Each of the CI paradigms has its origin in biological systems. Artificial neural network model biological neural systems, Evolutionary Computation models natural evolution (including genetic and behavioural evolution), swarm intelligence (SI) models the social behaviour of organisms living in swarms or colonies, artificial immune system (AIS) models the human immune system, and fuzzy system (FS) emanated from investigating of how organisms interact with their environment [74].

These approaches, except for fuzzy sets, are capable of the autonomous acquisition and combination of knowledge, and can be used in either supervised or unsupervised learning mode.

5.3 Artificial Neural Networks (ANNs)

These days, there is a new area of computation science that integrates the different technique of solving problem without focusing on traditional algorithm. The origin of these techniques can be linked to the intelligence of the behaviours of the biological system. It is a new way of computing denominated artificial intelligence, which through different methods is capable of managing the imprecision and uncertainties that appear when trying to solve problems related to the real world, offering strong solution and easy to implement. An artificial neural network (ANNs) is one of the most commonly used artificial intelligence techniques that are generally employed virtually in all areas of life. A neural network is a powerful data-modelling tool that is able to capture and represent complex input and output relationships. The driven force behind the widely development of neural network technology arise from the desire to develop an artificial system that could perform "intelligent" tasks similar to those performed by the human brain. Artificial neural networks can be compared with a human brain in the following ways; neural network attains knowledge through learning and also, neural network store knowledge within inter-neuron connection strengths known as synaptic weights. Generally, artificial neural networks are massively interconnected networks in parallel of simple elements (usually adaptable), with hierarchic organization, which try to interact with the objects of the real world in the same way that the biological nervous system does [75]. An Artificial Neural Networks (ANNs) consist of a collection of processing units called neurons that are highly interconnected according to a given topology. It has the ability to perform tasks such as pattern recognition, perception and control much faster than any computer. In addition to these characteristics, others, such as the ability to learn, memorize and still generalize, prompted research in algorithmic modelling of biological neural systems called artificial neural networks (ANN).

The recent development in neural modelling is due to the fact that artificial neural networks are capable and aimed at solving a specific task. Problems with a single objective can be solved easily with moderate-sized neural networks as constrained by the capabilities of modern computing power and storage space. Artificial neural networks have the ability to solve several problems concurrently using distributed parts of the brain. An artificial neuron (AN) is a model of a biological neuron (BN). Each Artificial neuron receives signals from the environment, or other artificial neurons, gathers these signals, and when fired, transmits a signal to all connected neurons. The Figure 5.1 depicts of an artificial neural network. The input signals are inhibited or exited through negative and positive numerical weights associated with each connection to the ANN. The firing of an artificial network and the strength of the exiting signal are controlled via a function, referred to as the activation function. The artificial neuron collects all incoming signals, and computes a net input signal as a function of the respective weights. The net input signal serves as input to the activation function which calculates the output signal of the ANN.

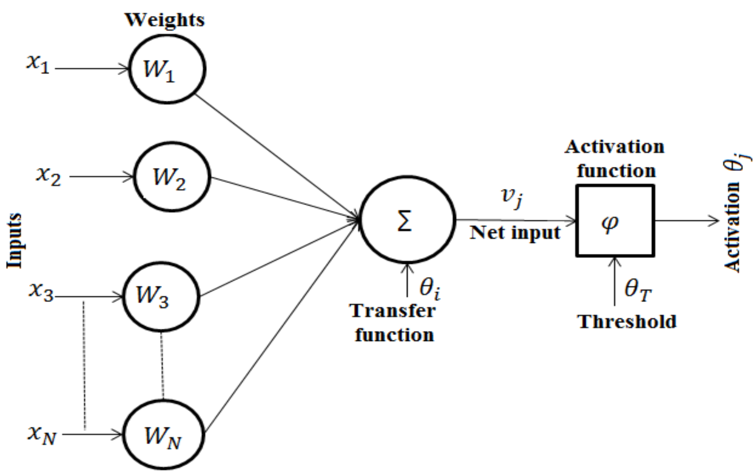


Figure 5.1: Artificial Neuron [76]

Figure 5.1 shows the structural representation of a simple artificial neuron model and the interconnection between its various network elements. The single neural model has a number of input units where each of the input signals (x_1, x_2, x_3….x_N) is fed into the model via the synaptic weights (W_1, W_2, W_3……..W_N). W_T is the summation of all the weighted input signals as expressed in equation 5.1. The summation of the weight input makes the input of the activation function produce an output signal θ_j the output of the neural model is expressed in equation 5.2.

$$W_T = W_1X_1 + W_2X_2 + W_3X_3 \cdots\cdots\cdots\cdots W_NX_N \tag{5.1}$$

$$\theta_j = \varphi(W_T + \theta_i) \tag{5.2}$$

Where N is the number of elements in the input vector, W_N is the associated synaptic weights, θ_i is the fixed bias factor which is applied externally to change the net weighted inputs of the activation function, θ_T is the threshold, and φ is the activation function [76]. The arrangement of neurons into layers and how they are connected is referred to as network architecture. An artificial neural network (ANN) is a layered network of artificial neurons. A Neural network may consist of an input layer, hidden layers, and an output layer. Through the input layer, the input stimulus is introduced to the network. The hidden layers are the internal layers of the networks while the output layer is where the output is displayed. Such a network structure is commonly referred to as multi-layer neural network [76]. A typical neural network structure is depicted in Figure 5.2.

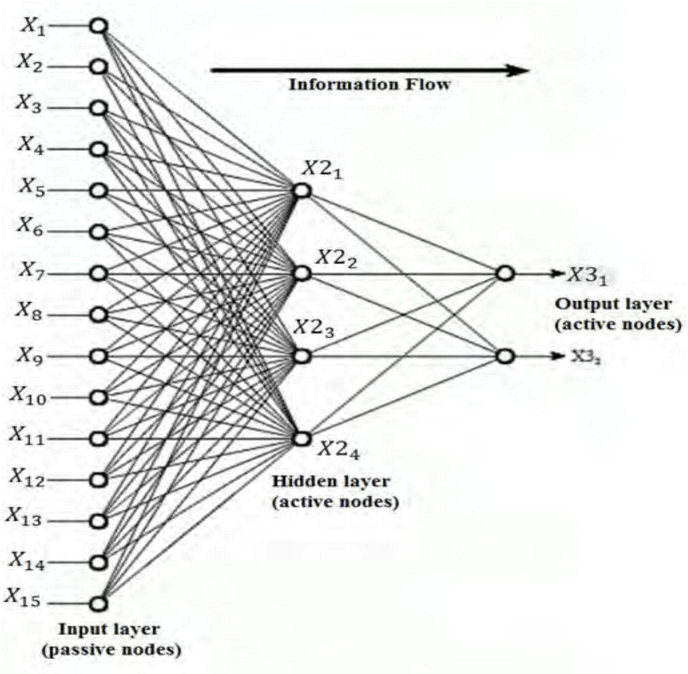


Figure 5.2: Artificial Neural Networks [77]

Each layer consists of one or more nodes, represented in the figure above by the small circles. The lines between the nodes indicate the flow of information from one node to another. In this type of neural network, the information flows only from the input to the output other types of neural networks have more complex connections, such as feedback paths. The nodes of the input layer are passive, that is they do not adjust the data. They receive a single value on their input, and duplicate the value of their multiple outputs. In contrast, the nodes of the hidden and output layer are active. This means they adjust the data. Each value from the input layer is duplicated and sent to all of the hidden nodes. This is called a fully interconnected structure. As shown in Figure 5.3, the values entering a hidden node are multiplied by weights, a set of predetermined numbers stored in the program. The weighted inputs are then added to produce a single number. This is indicated in the figure by the symbol, $\sum$. Before leaving the node, this number is passed through a nonlinear mathematical function called a sigmoid. The outputs from the hidden layer are represented in the flow diagram by the variables $X2_1$, $X2_2$, $X2_3$ and $X2_4$. Just as before, each of these values is duplicated and applied to the next layer. The active nodes of the output layer integrate and adjust the data to produce the two outputs ($X3_1$ and $X3_2$) values of the network. Neural networks can have any number of layers, and any number of nodes per layer. Most applications use the three layer structure with a maximum of a few hundred input nodes. The hidden layer is usually about 10% the size of the input layer. In the case of target detection, the output layer only needs a single node. The output of this node is threshold to provide a positive or negative indication of the target's presence or absence in the input data [77].

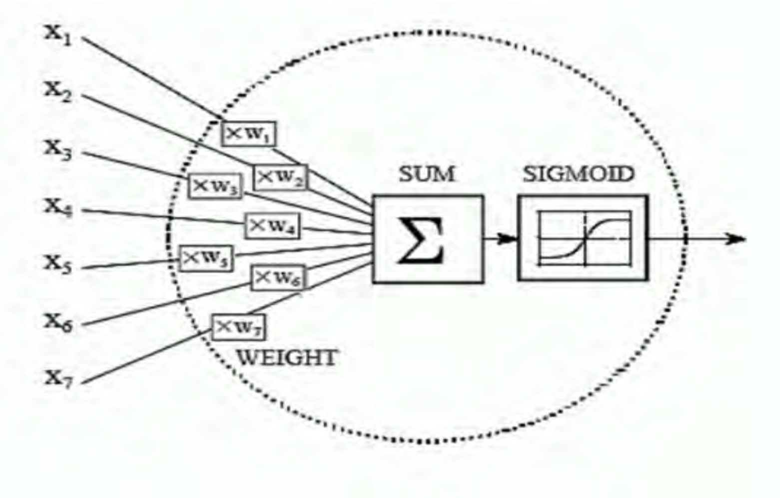


Figure 5.3: Neural network active nodes [77]

The behaviour of an artificial neural network is determined by its connection links (weights) and the activation functions. The process where the weights are tuned in a manner that the artificial neural network generates a good result is called training. Once the network is trained, it is assumed that the network stored the knowledge supplied to it. However, the knowledge in a neural network is not stored in a particular location. It depends on its topology and the magnitude of the weights in the input layer. The generalization of an artificial neural network is the capacity to reproduce desired signals for different input signals that have not been used during the network training or either, that it is able to catch the dynamics of the system being emulated [76]. The power and usefulness of artificial neural networks have been confirmed in several applications including speech synthesis, diagnostic problems, medicine, business and finance, robotic control, signal processing, computer vision and many other problems that fall under the category of pattern recognition. For some application areas, neural models show promise in achieving human-like performance over more traditional artificial intelligence techniques.

5.4 Advantages of ANNs

Artificial neural networks, with their extraordinary ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. This expert can then be used to provide projections given new situations of interest and answer. Other advantages are [78]:

- **Adaptive***:* they have the ability to learn from data. Thus, they deduce solutions from the data presented to them, often capturing quite slight relationships. This ability differs radically from standard software techniques because it does not depend on the programmer's prior knowledge of the rules. ANNs can reduce development time by learning underlying relationships, even if they are difficult to find and describe. They can also solve problems that lack existing solutions.

- **ANNs can be Generalize:** they can correctly process data that only broadly resembles the data they were trained on originally. Similarly, they can handle imperfect or incomplete data, providing a measure of fault tolerance. Generalization is particularly useful in practical applications because real world data are noisy.

- **The Networks are Nonlinear***:* they can capture complex interactions among the input variables in a system. In a linear system, changing a single input produces a proportional change in the input, and the input's effect depends only on its own value. In a nonlinear system, the effect depends on the values of other inputs, and the relationship, is a higher-order function. In this respect, systems in the real world are often non-linear.
- **Real Time Operation***:* ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured, which take advantage of this capability [79].

5.5 Disadvantages of ANNs

- Training methods are imperfectly understood. Few definite rules exist for choosing the optimum architecture and there is no definite way of finding the best solutions which also depend in practice on the accuracy of the training data used. However, continuing research should improve our understanding of how to optimally design and train neural networks.
- ANNs is time consuming. It can consume large amounts of computer time, especially during training; it is not unusual for a neural network to take many days to train even when using a high-powered workstation. However, continuing research into new training algorithms should significantly reduce training times [79].

5.6 Comparison between Human and Artificial Neurons

5.6.1 Human and Artificial Neurons

In human body neural networks are the basis of the nervous system which controls and coordinates the activities of the human system. In the human brain, a typical neuron collects signals from others through a host of fine structures called dendrites.

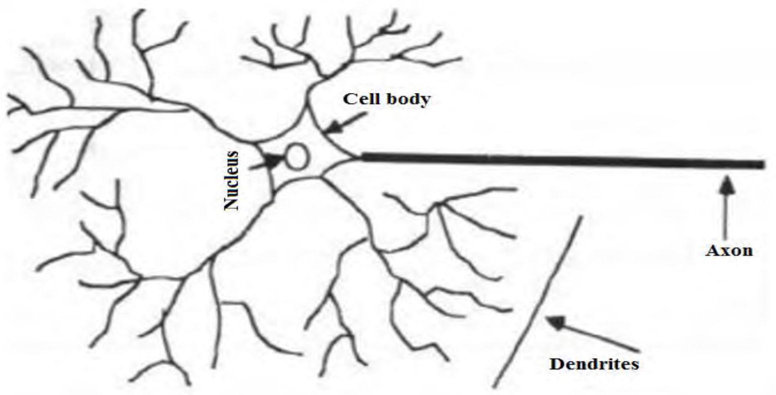


Fig 5.4: Brain Neuron [80]

The neuron sends out spikes of electrical activity through a long, thin strand know as an axon, which splits into thousands of branches. At the end of each branch, a structure called a synapse converts the activity from the axon into electrical effects that inhibit or excite activity in the connected neurons. When a neuron receives excitatory input that is sufficiently large compared with its inhibitory input, it sends a spike of electrical activity down its axon. Learning occurs by changing the effectiveness of the synapses so that the influence of one neuron on other changes [80].

5.6.2 Human Neurons to Artificial Neurons

Artificial Neural Networks (ANNs) have been developed based on the similar working principle of Human Neural Networks. Artificial Neurons are similar to their biological counterparts. The input connections of the artificial neurons are added up to determine the strength of their output, which is the result of the sum being fed into an activation function, the most common being the Sigmoid Activation Function which gives an output varying between 0 for low input values and 1 for high input values. The resultant of this function is then passed as an input to other neurons through more connections, each of which is weighted which determine the behaviours of the network. An Artificial Neural Network (ANN) is basically an information processing system composed of a large number of interconnected processing elements (neurons) working in an integrated manner to solve specific problems. An ANN is devised for specific applications, such as pattern recognition or data classification, through a learning process [81].

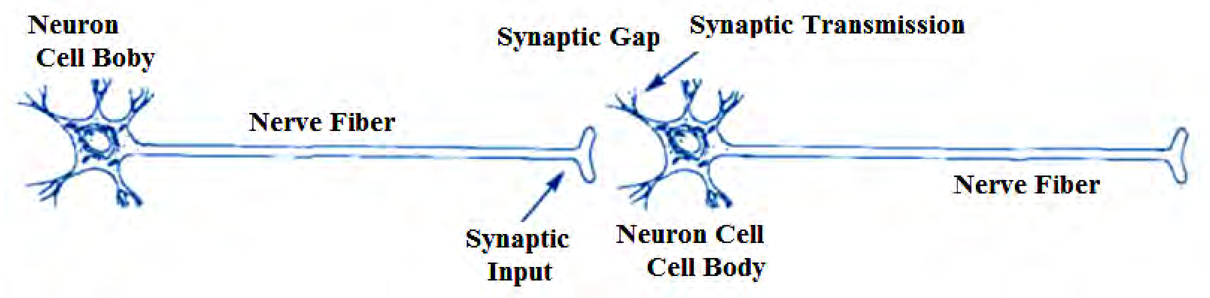


Figure 5.5: Human Neurons to Artificial Neurons [81]

5.7 Engineering Approach

5.7.1 A Simple Neuron

An artificial neuron is a device with many inputs and one output. The neuron has two modes of operation, the training mode and the using mode. In the training mode, the neuron can be trained to fire or not, for particular input patterns. In the using mode, when a taught input pattern is detected at the input, its associated output becomes the current output. If the input pattern does not belong in the taught list of input patterns, the firing rule is used to determine whether to fire or not [78].

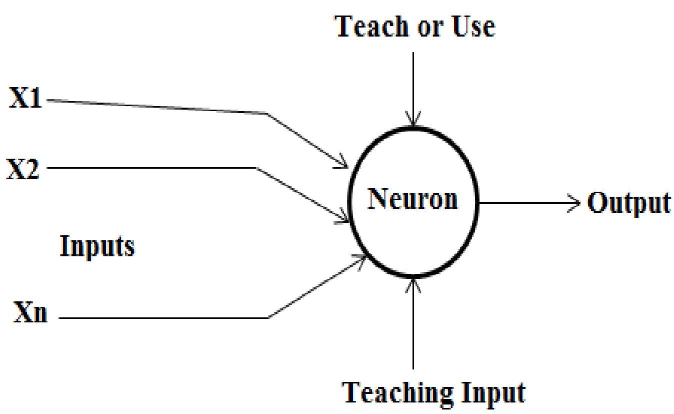


Figure 5.6: Simple Neuron [78]

5.7.2 Pattern Recognition

An important application of neural networks is pattern recognition. Pattern recognition can be implemented by using a feed-forward structure as shown in Figure 5.7. During training, the network is trained to associate outputs with input patterns. When the network is used, it identifies the input pattern and tries to output the associated output pattern. The power of neural networks comes to life when a pattern that has no output associated with it, is given as an input. In this case, the network gives the output that corresponds to a taught input pattern that is least different from the given pattern.

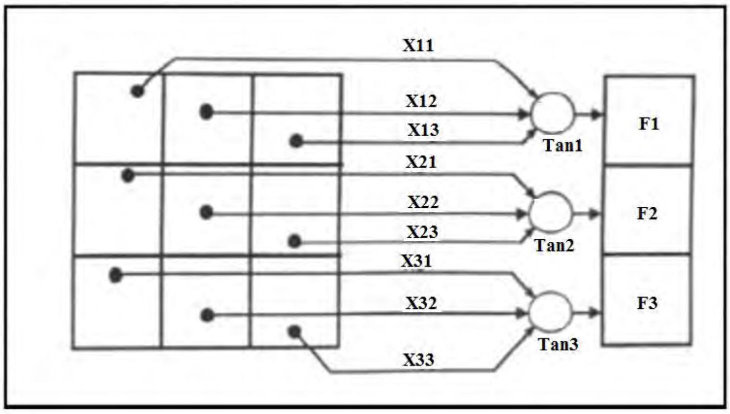


Figure 5.7: Feed-Forward Neural Network **[78]**

5.7.3 Firing Rules

The firing rule is an important concept in neural networks and accounts for their high flexibility. A firing rule determines how one calculates whether a neuron should fire for any input pattern. It relates to all the input patterns, not only the node was trained. A simple firing can be implemented by using the Hamming distance technique. Take a collection of training patterns for a node, some of which cause it to fire (the 1- taught set of patterns) and other which prevent it from doing so (the 0- taught set). Then the patterns not in the collection cause the node to fire if, no comparison, they have more input elements in common with the nearest pattern in the 1-taught set than with the nearest pattern in the 0-taught set. If there is a tie, the pattern remains in the undefined state. For a 3- input neuron is taught to output 1 when the input (X1, X2, and X3) is 111 or 101 and to output 0 when the input is 000 or 001. Then, before applying the firing rule the truth table is shown in table 5.1.

Table 5.1: Truth Table before Applying Firing Rule [78]

X1		0	0	0	0	1	1	1	1
X2		0	0	1	1	0	0	1	1
X3		0	1	0	1	0	1	0	1
Output		0	0	0/1	0/1	0/1	1	0/1	1

As an example of the way the firing rule is applied, take the pattern 010. It differs from 000 in 1 element, from 001 in 2 elements from 101 in 3 elements and from 111 in 2 elements. Therefore, the nearest pattern is 000 which belongs in the 0-taught set. Thus the firing rule requires that the neuron should not fire when the input is 001. On the other hand 001 is equally from two taught patterns that have different outputs and thus the output stays undefined (0/1). By applying the firing in every column the following truth table is obtained.

Table 5.2: Truth Table after Applying Firing Rule [78]

X1		0	0	0	0	1	1	1	1
X2		0	0	1	1	0	0	1	1
X3		0	1	0	1	0	1	0	1
Output		0	0	0	0/1	0/1	1	1	1

The difference between the two truth tables is called generalization of the neuron. Hence the firing rule gives the neuron a sense of similarity and enables it to respond sensibly to a pattern not seen during training [78].

5.8 Architectural Overview of Neural Networks

5.8.1 Network Layers

The commonest type of artificial neural network consists of layers, of units: a layer of "input" units is connected to a layer of "hidden" units, which is connected to a layer of "output" units.

- The activity of the input units represents the raw information that is fed into the network.

- The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units.
- The behaviour of the output units depends on the activity of the hidden units and the weights between the hidden and output units.

This simple type of network is interesting because the hidden units are free to construct their own representations of the input. The weights between the input and hidden units determine when each hidden unit is active, and so by adjusting these weights, a hidden unit can choose what it represents. We also distinguish single-layer and multi-layer architectures. The single-layer organization, in which all units are connected to one another, constitutes the most general case and is of more potential computational power than hierarchically structured multi-layer organizations. On multi-layer networks, units are often numbered by layer, instead of following a global numbering [78].

In network architectures Neurons are connected to form networks with different structures to perform certain functions. The manner in which the neurons of a neural network are structured is closely related to the learning abilities and functions that we want to achieve. In general, we can identify three types of network architectures based on the commonly used neural networks [79].

- Feed-forward layered networks;
- Recurrent networks;
- Lattice structure

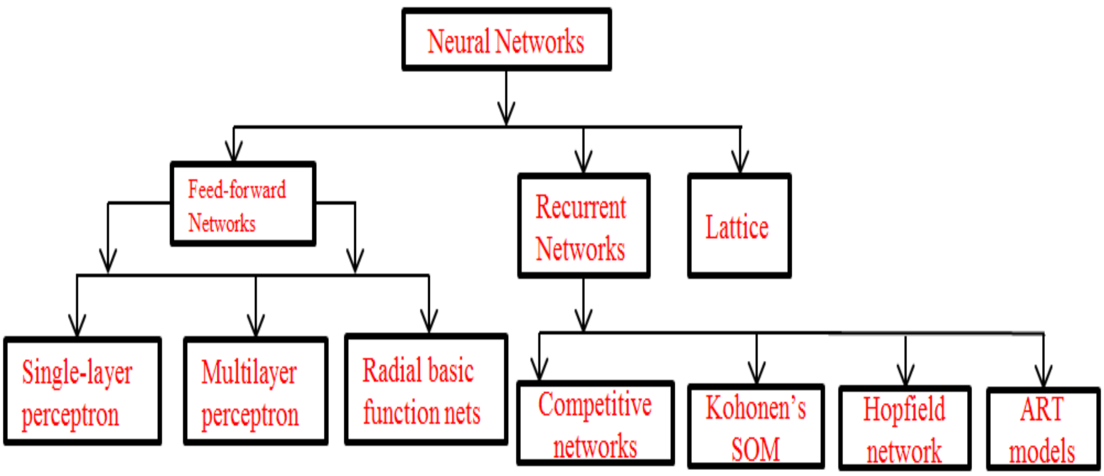


Figure 5.8: Artificial Network Architecture [79]

5.8.2 Feed-Forward Layered Neural Networks (FFLNN)

A layered neural network is a network of neurons organized in the form of layers. A standard feed-forward neural network (FFNN) consisting of three layers: an input layer, a hidden layer and output layer. A FFNN can have more than one hidden layer. A FFNN can also have direct (linear) connections between the input layer and the output layer. The information is projected from the input layer towards the output layer, but not vice versa, that is, the network is strictly of a feed-forward type. A single layer perceptron where only the output layer has neurons is the most influential work done in the development of neural networks in the mid-1960s. It generated much interest when initially developed because of its ability to learn to recognize simple patterns. However, there are limitations to the capabilities of perceptions. A single-layer perceptron cannot solve any problem that is linearly inseparable. In this respect, multilayers feed-forward (MLFF) networks have been proposed with the presence of one or more hidden layers, whose computation nodes are correspondingly called hidden neurons. The function of the hidden neurons is to intervene between the external input and the network output. By adding one or more hidden layers, the network is enabled to extract higher nonlinear relationships. Radial basis function (RBF) networks perform classification by measuring the distance between input and the centres of the RBF hidden neurons. They are faster and more suitable for problems with large sample size. In theory, a three layer network, illustrated in the Figure 5.9 can form arbitrarily complex shapes, and is capable of separating any classes. The neural network can be fully connected in the sense that every neuron in each layer of the network is connected to every other neuron in the adjacent forwarding layer, or can be partially connected where some connections are missing [79].

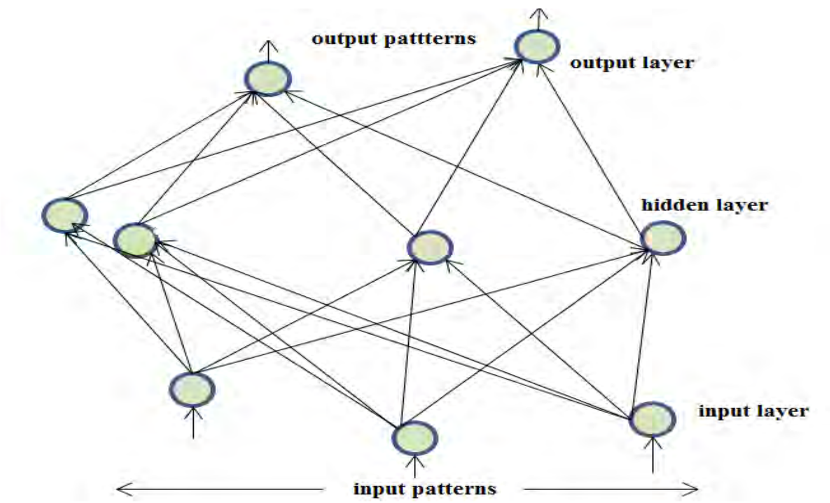


Figure 5.9: Three-Layer Feed-Forward Network **[79]**

5.8.3 Recurrent Networks

Figure 5.10 depicts the structure of recurrent neural network with hidden neurons. Recurrent neural network is distinguished from a feed-forward neural network in that it has at least one feedback loop. The presence of feedback loops has a profound impact on the learning capability of the network, and on its performance. Moreover, the feedback loops involve the use of particular branches composed of unit-delay elements, which result in a nonlinear dynamical behaviour by virtue of the nonlinear nature of the neurons. Nonlinear dynamics play a key role in the storage function of a recurrent network. Recurrent network can be grouped into Kohonen's SOM, Hopfield network and ART models [79].

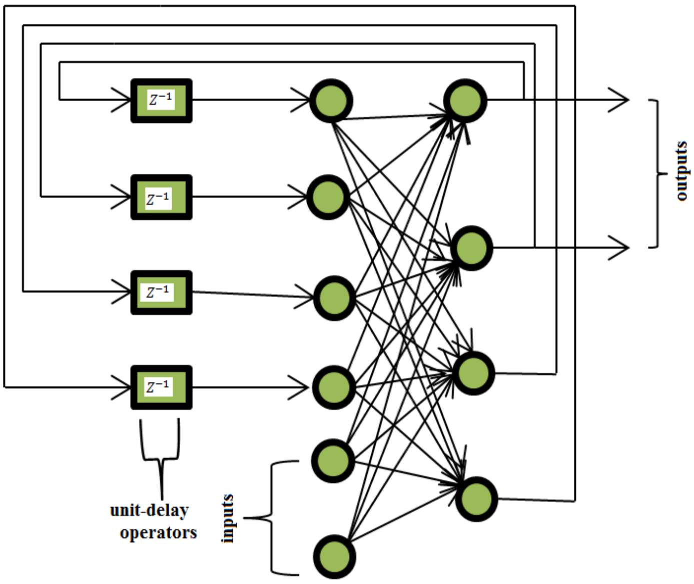


Figure 5.10: Recurrent Networks with Hidden Neurons [79]

5.8.4 Kohonen's SOM

In contrast to the feed forward neural network, Kohonen neural network contains only two layers (an input and output layer) of neurons. There is no hidden layer in a Kohonen neural network. The input to a Kohonen neural network is given to the neural network using the input neurons. These input neurons are each given the floating point numbers that make up the input pattern to the network. A Kohonen neural network requires that these inputs be normalized to the range between -1 and 1. Presenting an input pattern to the network will cause a reaction from the output neurons. The output of a Kohonen neural network is very different from the output of other neural networks. Ideally, in neural network if we have five output neurons, we would give an output that consisted of five values. This is not the case with the Kohonen neural network. In a Kohonen neural network only one of the output neurons actually produces a value. Moreover, the single value is either true or false. When the pattern is presented to the Kohonen neural network, one single output neuron is chosen as the output neuron. Therefore, the output of the Kohonen neural network is usually the index of the neuron that fired. The structure of a typical Kohonen neural network is shown in the Figure 5.11.

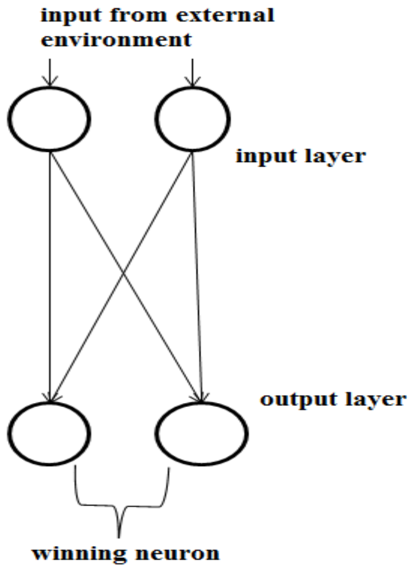


Figure 5.11: Simple Kohonen Neural Network [80]

The Kohonen neural network requires that its input should be normalized. The requirements that the Kohonen neural network places on its input data is one of the most severe limitations of the Kohonen neural network. Input to the Kohonen neural network should be between the values -1 and 1. In addition, each of the inputs should fully use the range. If one, or more, of the input neurons were to use only the numbers between 0 and 1, the performance of the neural network would suffer. To normalize the input we must first calculate the "vector length" of the input data, or vector. This is done by summing the squares of the input vector. If the length becomes too small, say less than the length is set to that same arbitrarily small value. In this case the "vector length" is a sufficiently large number. Using this length we can now determine the normalization factor. The normalization factor is the reciprocal of the square root of the length. For our value the normalization factor is calculated as follows. This result in a normalization factor is used to calculate output layer. To calculate the output, the input vector and neuron connection weights must both be considered. First the "dot product" of the input neurons and their connection weights must be calculated. To calculate the dot product between two vectors, each of the elements in the two vectors must be multiplied. The Kohonen algorithm specifies that the dot product of the input vector and the weights between the input neurons and the output neurons must be taken. The calculation will be performed for the first output neuron and the calculation must be done for each of the output neurons. Also the output must be normalized by multiplying it by the normalization factor. After the normalization of the outputs, the network has to be trained for the task. There several steps involved in this training process. Overall the process of training a Kohonen neural network involves stepping through several epochs until the error of the Kohonen neural network is below acceptable levels. The training process for the Kohonen neural network is competitive. For each training set one neuron will "win". This winning neuron will have its weight adjusted so that it will react even more strongly to the input the next time. As different neurons win for different patterns, their ability to recognize that particular pattern will be increased. The learning rate is a constant that will be used by the learning algorithm. The learning rate must be a positive number less than 1. The learning rate is just a variable that is used as part of the algorithm used to adjust the weights of the neurons. Generally, setting the learning rate to a larger value will cause the training to be faster. Though setting the learning rate to too large a number could cause the network to never converge. This is because the oscillations of the weight vectors will be too great for the classification patterns to ever emerge. Another technique is to start with a relatively high learning rate and decrease this rate as training progresses. This allows initial rapid training of the neural network that will be "fine-tuned" as training progresses. The entire memory of the Kohonen neural network is stored inside of the weighted connections between the input and output layer. The weights are adjusted in each epoch. An epoch occurs when training data are presented to the Kohonen neural network and the weights are adjusted based on the results of this item of training data. The adjustments to the weights should produce a network that will yield more favourable results the next time the same training data is presented. Epochs continue as more and more data is presented to the network and the weights are adjusted. Eventually the return on these weight adjustments will diminish to the point that it is no longer valuable to continue with this particular set of weights. When this happens the entire weight matrix is reset to new random values. This forms a new cycle. The final weight matrix that will be used will be the best weight matrix determined from each of the cycles. Additive method is the original method proposes by Kohonen to calculate changes to weights. This method uses the following equation.

$$\omega^{i+1} = \frac{\omega^i + x}{\|\omega^i + x\|} \tag{5.3}$$

The variable x is the training vector that was presented to the network. The variable ω^i is the weight of the winning neuron, and the variable ω^{i+1} is the new weight. The double vertical bars represent the vector length. The additive method generally works well for Kohonen neural networks. Though in cases where the additive method shows excessive instability, and fails to converge, an alternate method can be used. This method is called the subtractive method. The subtractive method uses the following equations.

$$e = x - w^i \tag{5.4}$$

$$w^{i+1} = w^i + x \tag{5.5}$$

The two equations show the basic transformation that will occur on the weights of the network. The purpose of the Kohonen neural network is to classify the input into several sets. The error of the Kohonen neural network, therefore, must be able to measure how well the network is classifying these items. There is no agreed way of calculating error in the Kohonen neural network. The error is just a percent number that gives an idea of how well the Kohonen network is classifying the input into the output groups. The error itself is not used to modify the weights, as in case of back propagation algorithm [82]

5.8.5 Hopfield Network

Hopfield network, which was described by J. J. Hopfield in 1982 [85], has a simple topology, the neurons are all interconnected. The network is able to recognize unclear picture correctly. However, only one picture can be stored at a time. In practical applications, it is assumed that many pictures will be given, which have to be stored and then classified. The Hopfield network is a fully interconnected neural network with each unit connected to every other unit. The network has symmetric weights with no self-connection that is all the diagonal elements of the weight matrix of a Hopfield network are zero. The main difference between Hopfield network and iterative associative network is that, in Hopfield network, only one unit updates its activation at a time and also each unit continue to receive an external signal in addition to the signal from the other units in the network, whereas iterative associative networks can have signals travel in both directions by introducing loops in the network. The asynchronous discrete time updating of the units allows a function known as energy function or Lyapunov function to be found in the network. This function proves that the network will converge to a stable set of activations. The topology of Hopfield network is shown in Figure 5.12. The topology consists of *n* number of *x* inputs neurons and *y* outputs neurons. Apart from receiving a signal from input y_1, neuron receives signal from its other output neuron also. This is the same for all other output neurons. Thus, there exists a feedback output being returned to each neuron. Hence Hopfield network is called a feedback network [83]. Figure 5.12 depicts the architecture of the discrete Hopfield neural network.

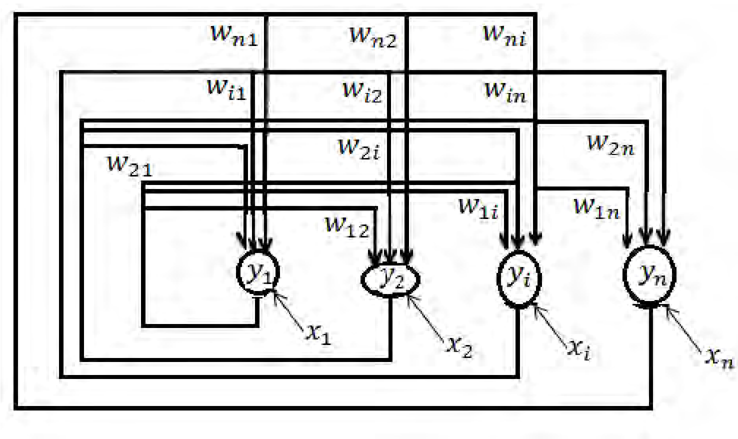


Figure 5.12: Structure of Hopfield Network **[83]**

5.8.6 Adaptive Resonance Theory (ART) Models

In an attempt to retain existing information when storing new ones in the memory of artificial neural networks and to prevent memory corruption carpenter and Grossberg's adaptive resonance theory models (ART, ART2 and ART Map) were developed. The network has a sufficient supply of output units, but they are not used until deemed necessary. A unit is said to be committed if it is being used and is said to be uncommitted if it is not being used. The learning algorithm updates the stored prototypes of a category only if the input vector is sufficiently similar to them. An input vector and a stored prototype are said to resonate when they are sufficiently similar. The extent of similarity is controlled by vigilance parameter p with 0<p<1, which also determines the number of categories. When the input vector is not sufficiently similar to any existing prototype in the network, a new category is created, and an uncommitted unit is assigned to it with the input vector as the initial prototype. If no such uncommitted unit exists, a novel input generates no response. The Figure 5.13 depicts the a simplified diagram of ART1 architecture.

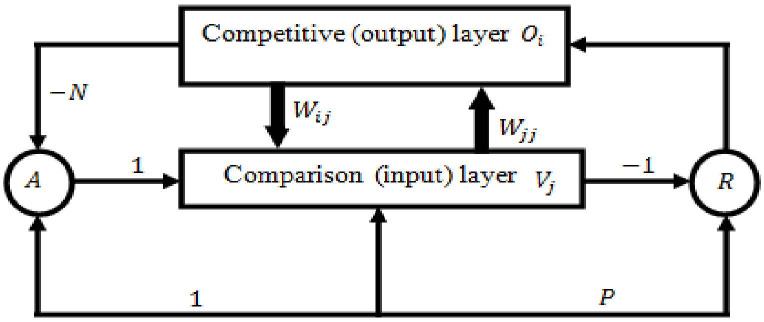


Figure 5.13: ART Network [83]

It consist of two layers of fully connected units. A top-down weight vector W_j is associated with unit j in the input layer and bottom-up weight vector is $\overline{w}_i$ is associated with output unit *i,* $\overline{w}_i$ is the normalizesd version of w_i.

$$\overline{w}_i = \frac{w_i}{\varepsilon + \sum_j w_{ji}} \qquad (5.6)$$

where ε is the small number used to break the ties selecting the winner.

The role of normalization is to prevent prototypes with a long vector length from dominating prototype with a short one. The output of the axiliary unit A is given as

$$A = sgn_{0/1}(\sum_j x_j - n\sum_i o_i - 0.5) \qquad (5.7)$$

where $sgn_{0/1}$ is the Signum function that produce +1, if x greater or less than 0 and 0 otherwise, and the output of an input unit is given by

$$v_j = sgn_{0/1}(x_j + \sum_I w_{ji}o_i + A - 1.5) \qquad (5.8)$$

If no output is on, otherwise.

$$V_j = f(x) = \begin{cases} X_j \\ x_j \wedge \sum_i w_{ji}o_i , \end{cases} \qquad (5.9)$$

5.8.7 Lattice Structures

A lattice consists of a one-dimensional, two-dimensional, or higher-dimensional array of neurons with a corresponding set of source nodes that supply the input signals to the arrays; the dimension of the lattice refers to the number of dimensions of the space in which the graph lies.

Figure 5.14 depicts a two-dimensional lattice of 4 * 4 neurons. In essence, a lattice network is a feed-forward network with the output neurons arranged in rows and columns [79]

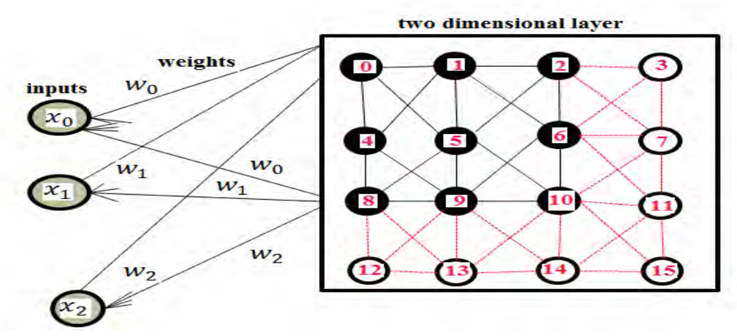


Figure 5.14: Two-Dimensional Lattices of 4*4 Neurons **[79]**

5.9 Activation Functions or Transfer Function

The activation function is used to calculate the output response of a neuron. The sum of the weighted input signal is applied with an activation to obtain the response. Activation function may be linear or nonlinear activation functions. The nonlinear activation functions are used in a multilayer network. The linear activation function is used in performing linear transformation of the input vectors. This type of function is widely used by the multilayer neural network where the output of the function produces any value outside the range of -1 to +1. Binary step functions are used mostly by single layer networks for calculating the output from the network input. It is also called threshold function or Heaviside function. It is given as [83].

$$f(x) = \begin{cases} 1, & f(x) \geq 0 \\ 0, & f(x) < 0 \end{cases} \tag{5.10}$$

Activation functions for hidden units are needed to introduce non-linearity into the networks. The reason is that a composition of linear functions is again a linear function. However, it is the non-linearity that makes multi-layer networks so powerful. For back propagation learning non-linear function must be differentiable and it helps if the function is bounded. For the output units, activation function should be chosen to be suited to the distribution of the target values.

❖ Sigmoid Functions

They are used in multilayer networks such as back propagation network and radial basis function networks. There are two main types of signal functions [83]:

- Binary sigmoid function and

- Bipolar sigmoid function.

The binary sigmoid function is also known as logistic function. It is mostly used to train data that is between 0 and1.

$$f_x = \frac{1}{1+\exp(-\sigma x)} \tag{5.11}$$

σ is the steepness parameter. Differentiating equation 5.11 above

$$f\ (x) = \sigma f(x)[1 - f(x)] \tag{5.12}$$

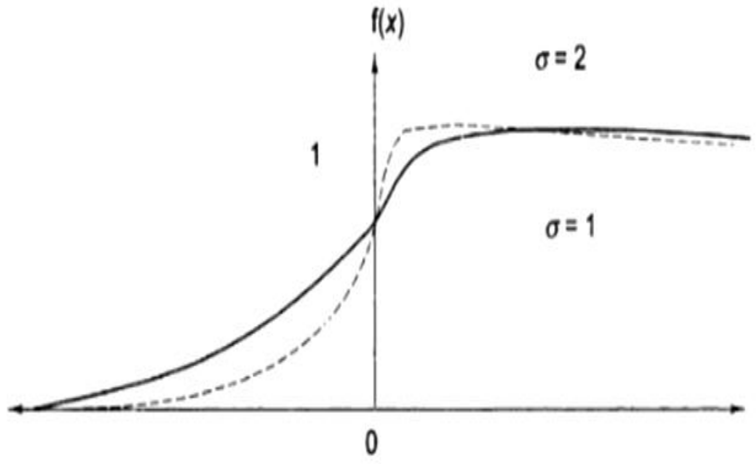


Figure 5.15: Binary Sigmoid Functions [83]

❖ **Bipolar Sigmoid Function**

The desired range is between +1 to -1. The bipolar sigmoid is represented as

$$b\ (x) = \frac{1-\exp(-\sigma x)}{1+\exp(-\sigma x)} \tag{5.13}$$

Mostly it is found that bipolar data is used, hence this activation function is widely used.

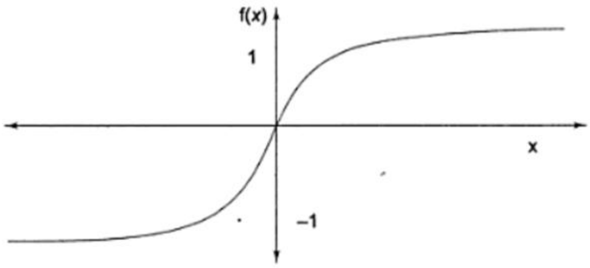


Figure 5.16: Bipolar Sigmoid Functions [83]

❖ **Bias**

Bias acts exactly as a weight on a connection from a unit, whose activation is always one, increasing the bias increase the net input to the unit. The bias improves the performance of the neural network. It should be initialized either to 0 or to any specified values, based on the neural net [83].

5.10 Neural Network Training or Learning

To achieve a desirable set of synaptic weights to pre-defined network architecture, a training process is needed. A training process is generally based on an optimization scheme to adjust the network parameters (mainly, the weights) in relation to a set of input-to-output to be matched by the neural network model. Although, a precise definition of learning is difficult to formulate, a learning process in ANN context can be viewed as the problem of updating network architecture and connection weights so that a network can effectively perform a specific task. The network usually must learn the connection weights from the available training pattern. Performance is improved over time by iteratively updating the weights in the network. ANN ability to automatically learn from examples makes them attractive and exciting. Instead of following a set of rules specified by human experts, ANNs appear to learn the underlying rules (like input-output relationships) from the given collection of representative examples. This is one of the major advantages of neural network over traditional expert systems. To understand or design a learning process, you must first have a model of the environment in which a NN operates that is you must know what information is available to the network. We referred to this model as a learning paradigm. Secondly, we must understand how network weights are updated that is learning rules govern the updating process. A learning algorithm rules are referred to as procedure in which learning rules are used for adjusting the weights [84].

As it can be anticipated, there is not a unique learning algorithm for the design of the neural networks. However, learning paradigms can be grouped into three categories [84]:

- Supervised learning
- Unsupervised learning
- Hybrid learning.

5.10.1 Supervised Learning

In a supervised learning the network is provided with a correct (output) for every input pattern. Weigh are determined to allow the network to produce answers as closed as possible to the known correct answers for every input pattern. Weights are determined to allow the network to produce answers as closed as possible to the known correct answers. Learning theory must be addressed three fundamental and practical issues associated with learning from sample: capacity, sample complexity, and computational complexity. Capacity concerns with how many patterns can be stored and what functions and decision boundary a network can form. Sample complexity determines the number of training patterns needed to train the network to guarantee a valid generation. Too few patterns may cause over-fitting wherein the network performs well on the training data set, but poorly on independent test patterns drawn from the same distribution as the training patterns. Computational complexity referred to the time required for a learning algorithm to estimate a solution from training patterns. Many existing learning algorithms have high computational complexity [84]. Supervised learning can be done through two paradigms [75],

- Error correction learning;
- Stochastic learning;
- Reinforcement learning.

❖ **Error Correction Learning**

Error correction learning uses the error between the desire output and the actual output for a given input pattern to adjust the weight. These are supervised law leaning laws, as they depend on the availability of the desires output for a given input. Let *(a, b)* be a sample of the input-output pair of vectors for which a network has to be designed by adjusting its weights so as to obtain minimum error between the desire and actual inputs. Let E be the error function and $\varepsilon(E)$ be the expected value of the error function for all the training data consisting of several input-output pairs. Since the joint probability density function of the pairs of random input-output vectors is not known, it is not possible to obtain the desired expectation $\varepsilon(E)$. Most error correction learning methods use the instantaneous error to adjust the weights, where $b^{'}$ is the actual output vector of the network for the input vector *a.* Rosenblatt's perceptron learning uses the instantaneous misclassification error to adjust the weights. It is given as:

$$\omega_{\iota J}\dot{(t)} = \eta(b_i - S_i)a_j \tag{5.14}$$

Where b_i is the desired output from the ith output for an input pattern a = $(a_1, a_{2\ldots}\ a_n)$, a_j is the *jth* component of the input, Pattern to the *ith* unit and n is a small positive learning constant. S_i is the actual output of the *ith* unit given by

$S_i = sgn(\sum_j \omega_{ij} a_j)$. Perceptron learning for a bipolar (± 1) output unit produces an error value $b_i - S_i = \pm 2$. Note that $b_i - S_i = 0$ when there is no error. Thus the discrete perceptron learning adjusts weights only when there is misclassification.

Continuous perceptron learning is error correction learning. It uses a monotonically increasing nonlinear output function $\dot{f}(x)$ for each unit. The weights are adjusted so as to minimize the squared error between the desired and actual output at every instant. The corresponding learning equation is given as:

$$\omega_{\iota J}\dot{(t)} = \eta(b_i - S_i)f(\dot{x_\iota})\ a_J \tag{5.15}$$

where

$$S_i = f_i(x_i) \text{ and } (\dot{x_\iota}) = \sum_{j=1}^{M} \omega_{ij} a_j \tag{5.16}$$

Continuous perceptron learning is also called delta learning, and it can be generalized for a network consisting of several layers of feed forward units. The resulting learning method is called generalized delta rule.

Widrow's least squared error (LMS) algorithm uses the instantaneous squared error between the desired and the actual output of a unit, assuming a linear output function for each unit. The corresponding learning equation is given below.

$$\omega_{\iota J}\dot{(t)} = \eta(b_i - x_i)a_j \tag{5.17}$$

The aforementioned error correction learning methods, discussed above assumed that the passive decay term is zero. The learning constant N should also be made smaller. The training samples must also be applied several times to the network until the weights lead to a minimum error. Although the results weights may not correspond to a global minimum of the expected error function [85].

❖ **Stochastic Learning**

Stochastic involves adjustment of weights of a neural network in a probabilistic manner. The adjustment uses a probability law, which in turn depends on the error. The error for a network is a positive scale defined in term of the external input, desired output and the weights connecting the units. In the learning process, a random weight change is made and the resulting change in the error is determined. If the resulting error is lower, then accept the random weight change. But if is not lower, and then accepting the random weight change with a predicated probability distribution. The acceptance of random change of weights despite an increase in the error from the network allows the network to escape local minima in the search for the global minimum of the error surface.

Boltzmann learning uses stochastic learning along with simulated annealing to determine the weights of a feedback network to store a given set of pattern. Stochastic learning is also used in determining the optimum weights of a multilayer feed forward neural network to arrive at asset of weight values corresponding to the global minimum of the error surface, since stochastic learning helps to overcome the local minima problems. However, all stochastic learning methods are slow in convergence and hence are times consuming [85].

❖ **Reinforcement Learning**

Reinforcement learning is a form of supervised learning because the network gets some feedback from its environment. The feedback signal (yes/no reinforcement signal) is only evaluative, not instructive, that is if the reinforcement signal says that a particular output is wrong and it gives no hint as to what the right answer should be. It is therefore important in a reinforcement learning network to implement some source of randomness in the network, so that the space of possible outputs can be explored until a correct value is found. In reinforcement learning problems it is common to think explicitly of a network functioning in an environment [86]. The environment supplies the inputs to the network, receives its output and then provides the reinforcement signal.

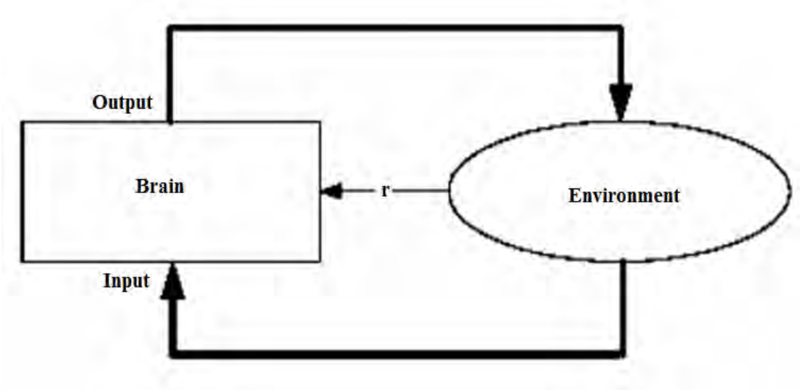


Figure 5.17: Principle Layouts for a Reinforcement-Learning Agent [86]

5.10.2 Unsupervised Learning

The artificial neural network with unsupervised learning, also known as self-supervised does not require any external element to adjust the weight of the communication link to their neurons. They do not receive any information from the environment that indicates if the generated output in response to determined input is or not correct that is why it is said that artificial neuron networks that are not supervised are capable of self-organization.

The main problem in the unsupervised classification is to divide the space where the objects are in group or categories. For which intuitively closeness criteria are used, an object belongs to a group if it is similar to the element that integrate that group. Since, there is no supervisor to indicate to the network the answer that should be generated in a concrete input. This kind of networks should find by themselves the characteristics, regularities, correlations or categories which can establish between the data that was presented in their input. There are many different interpretations of the output of the supervised networks, which depend on their structure and the learning algorithm used. In some cases the output represents a degree of familiarity or similarity between the signal that is being introduced in the network and the displayed information until then. Under other circumstance can make the grouping of the information (clustering), generating a category structure, the network detects the categories from the correlations between the presented information. In such situation, the output of the network permits realizing a codification of the input data, keeping the relevant information. Finally, some networks with unsupervised learning make a mapping of the characteristics which is called feature mapping, generates in the output neurons a geometric disposition that represents a topographic map of the characteristic of the input data, presenting to the network similar information that will always affect output neurons close to each other, in the same mapping zone. In general, there two types of unsupervised learning [75]:

- Hebbian learning,
- Competitive learning.

❖ **Hebbian Learning**

The Hebbian learning rule, named after the neuropsychologist Hebb, is the oldest and the simplest learning rule. Hebb based it on the following observation from neurobiological experiments: if neurons on both sides of a synapse are activated synchronously and repeatedly, the synapse's strength is selectively increased. Mathematically, the Hebbian rule can be described as

$$w_{ij}(t+1) = w_{ij}(t) + \eta y_j(t) x_i(t) \tag{5.18}$$

Where x_i and y_j are the output values of neurons and j, respectively, which are connected by the synapse [77]. The four important properties of Habbian process are [75]:

- Depending on the time. This refers that the link reinforce of communication is made when it is presented the activation of the two computational neurons.
- Local. For the effect described by Hebb to take place, the nodes have to be continuous to the space. The modification that is produced only affect locally.
- Interactive. The modification is done when is proved that both units are activated, because it is not possible to predict the activation.
- Correlated. Given the co-occurrence of the activation that has to be produced in very short periods of time, the effect described by the Hebb is also known as compound synapse. On the other hand, for the activation of the computational neurons to take place, it has been related to the activation of one or many previous nodes for nodes for which is called correlated synapse [75].

❖ **Competitive Learning**

Unlike Hebbian learning in which multiple output units can be fired simultaneously, competitive learning output units compete among themselves for activation. As a result, only one output unit is activated at any given time. This phenomenon is known as winner-take-all. Competitive learning often cluster or categorize the input data. A Similar pattern is grouped by the network and represented by a single unit. This grouping is done automatically based on data correlations.

The simplest competitive learning network consists of a single layer of output units. Each output unit in the network connects to all the input units X_j's via weights W_{ij}. Each output unit also connects to all other output units via inhibitory weight, but has a self-feedback with an executory weight. As a result of competition, only the unit with the largest or the smallest net input becomes the winner. When all the weight vectors are normalized these two inequalities are equivalent. A simple competitive learning rule can be stated as.

$$\Delta w_{ij} = \begin{cases} \eta(x_j^u - w_{ij}^*), i=i^*, \\ 0, i \neq i^* \end{cases} \tag{5.19}$$

Note that only the weights of the winner units get updated. The effect of this learning rule is to move the stored pattern into the winner unit (weights) a little bit closer to the input pattern. In competitive learning rule the network will not stop learning (updating weights) unless the learning rate η is 0. A particular input pattern can fire different output units at different iterations during learning. This brings up the stability issue of a learning system. The system is said to be stable if no pattern in the training data changes it category after a finite number of learning iterations. One way to achieve stability is to force the learning rate to decrease gradually as the learning process proceeds towards 0. However, plasticity is a problem arises as a result of competitive learning, is the ability to adapt to new data. This is known as Grossberg's stability-plasticity dilemma in competitive learning. The most well-know example of competitive learning is vector quantization for data compression. It has been widely used in speech and image processing for efficient storage, transmission and modelling [81].

5.10.3 Hybrid Learning

Computationally speaking, the model behind neural networks needs heavy efforts and therefore researchers are always trying to find a way to perform the neural process efficiently. One valid attempt to improve this process consists of hybridizing other techniques of computational intelligence with neural networks.

5.11 Classification of Hybrid Neural Networks

There are several possible ways of describing the features of hybrid systems based upon functionality and the degree of inter-connectivity. Thus, hybrid neural network can be classified as follows [87]:

- Unified hybrid neural network system
- Transformation hybrid neural network system
- Modular hybrid neural network system

A unified hybrid system consists of those systems that have all processing activities implemented by neural network elements as shown in the Figure 5.18. The systems have had only limited impact upon real world applications, due to the complexity of implementation, issues of model scalability and rather limited knowledge representation capability. The unified systems create levels of hierarchy. A local representation employs individual neurons to represent a concept or feature while the distributed representation stores knowledge over a number of units. In addition, a network based upon local representations is affected less by the catastrophic interference phenomena and therefore can learn incrementally. However, a distributed representation is more robust in the presence of noise because several neurons contribute to the overall classification accuracy, while in a localized scheme any error may lead to an overall classification failure. Unified hybrid systems often have their symbols encoded within a global lexicon which enables them to be created dynamically during training. A process called symbolic recirculation may occur within a unified network through the activity of learning [87].

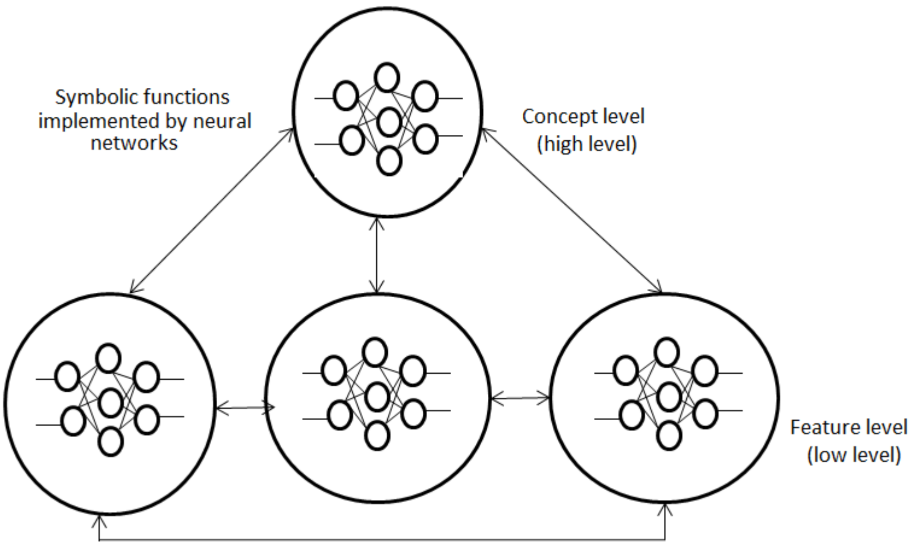


Figure 5.18: Unified Hybrid Neural Network Systems [87]

The transformational models are able to convert an initial symbolic domain into a modified neural network architecture or vice-versa. The transfer process can be a complete compilation of all information from one form into another or it may create intermediate stages. The transformational process creates special opportunities for building hybrid systems that can operate between the two levels of neural or symbolic knowledge representation. Such bi-directional flows of information enable an iterative process of knowledge insertion, extraction, and refinement to be carried out upon symbolic data that resides within neural network architecture. An important capability of transformational hybrid systems is the possibility to build architectures that confer the benefits of both symbolic and neural processing in a single system. Such hybrid systems are essentially neural networks, but are generally sparsely connected and the neurons correspond to high level concepts. The networks are able to learn in a process that is similar to supervised networks by means of training examples and often use gradient descent algorithms. In addition, these systems are also able to manipulate the initial architecture and domain knowledge of the neural network; hence they are often described as knowledge-based neural networks. These transformational architectures possess a number of interesting high level features that enable neural networks to perform the following functions:

- The possibility of incremental learning, which means that the neural network need not be retrained with all previous training data in addition to newly, acquired data. New classes may also be included in addition to new training samples for existing classes.
- The inclusion of prior knowledge will have the effect of speeding up the learning process and will be useful in those situations where training examples are scarce. This is called the knowledge insertion, extraction and refinement stage in many systems.
- A more deterministic architecture is possible, rather than the empirical process that must occur with multi-layer perceptron networks in order to discover a very good architecture. The reasoning and classification operations are rendered more transparent, although some knowledge based neural network architectures (KBNN) require a further process of symbolic rule extraction.

The experimental work carried out by number researchers on different knowledge-based neural network architectures has produced some impressive results. They show good performance in terms of classification accuracy, speed of training, reasoning with noise and missing data and good generalization capability with small training sets. Figure 5.20 illustrates the knowledge insertion, extraction and refinement phase that are incorporated in many transformational hybrid systems. The use of prior domain knowledge in the form of rules can be used to define the architecture of an initial neural network. The network can be refined by inductive learning when supplied with examples. This may entail changes to the original topology, weights and biases.

The learning algorithm may be a gradient descent type such as back propagation with modifications to account for the sparse number of connections found in the Knowledge Based Artificial Neural Networks (KBNNs). The improved performance of the neural network can be used to refine the initial rule base by a process of knowledge extraction from the neural network. The nodes and connections of the KBNN correspond to the symbolic meaning of the initial domain knowledge and are easily converted back into a symbolic format. The entire process can be repeated several times until the system shows an overall improved performance. A direct way of converting neural to symbolic knowledge is through rule extraction. This process provides a limited form of an explanation facility of how a neural network may classify any given input pattern. Rule extraction is a process that discovers the hyper plane positions of the input-to-hidden units and the hidden to- output units of a neural network. These positions are then formulated as IF.THEN rules with the most important input unit labels acting as the rule antecedents. The discovery of the hyper plane positions can be found by a number of techniques that analyze the weights and biases of the neural network. Rule extraction can be carried out with a variety of neural network types such as multi-layer perceptions Kohonen networks, radial basis functions and recurrent networks. In recent years there has been a great deal of interest in exploring techniques for extracting symbolic rules from neural networks. The benefits of extracting rules from neural networks are:

- Provision of an explanation facility by examining extracted rules for various input configurations.
- Deficiencies in the original training set may be identified, thus the generalization of the network may be improved by the addition/enhancement of new classes.
- Analysis of previously unknown relationships in the data. This feature has a huge potential for data discovery or mining and possibilities may exist for scientific induction.

Once having extracted rules from a neural network, we have a rule base that has the potential to be inserted back into a new network with a similar problem domain. This is similar to the heuristics given to expert systems. Also like the heuristics the extracted or inserted rules may be refined, as more information becomes available about the problem. This process may be a step in the right direction towards alleviating the so-called knowledge acquisition bottleneck

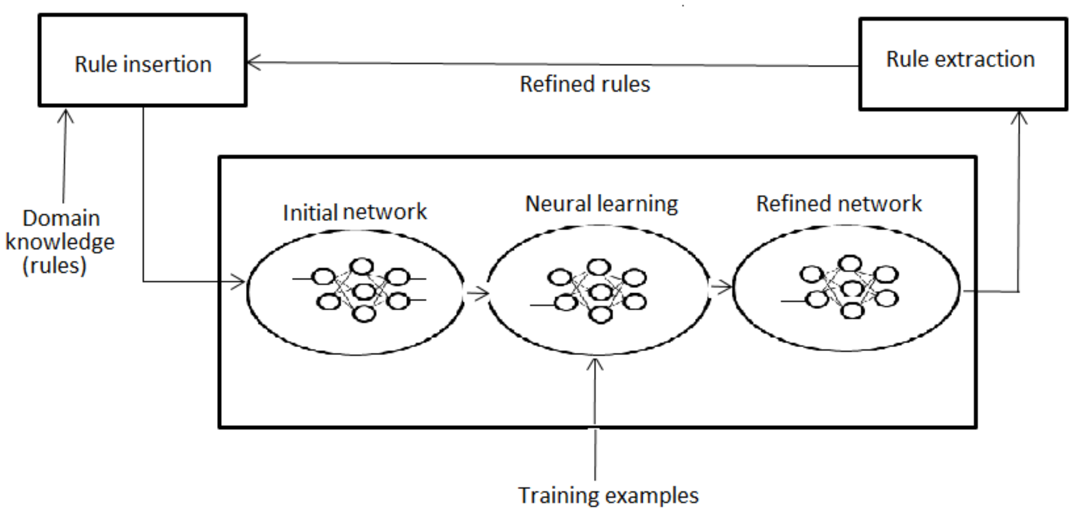


Figure 5.19: Cyclic Rule Extraction, Insertion and Refinement [87]

A modular hybrid system covers those hybrid systems that are modular in nature that is they are comprised of several neural networks and rule-based modules which can have different degrees of coupling and integration. An important aspect is that they do not involve any changes regarding the conceptual operation of either the neural network or rule-based elements. The vast majority of hybrid systems are under this category. The main reason is that they are powerful processors of information and are relatively easy to implement. Several features characterize modular hybrid systems. The most obvious characteristics are the hierarchy of module configuration. The configuration determines the complexity of information flow between the modules. Sequential flow implies that one process must be completed before data may be passed on to the next module. Parallel flow may involve simultaneous operation upon data or even feedback between the modules that can influence the course of future processing. Depending on the particular task the complexity of modular systems can vary greatly. Some systems consist of only a few modules with simple coupling and limited information flow between them. Some modular hybrid systems are more complex and are composed of many modules. As hybrid systems technology has matured, more complicated and sophisticated systems are beginning to be developed. Complexity can be measured in terms of information flow between the modules, which can be unidirectional or bidirectional. Another characteristic is the degree of coupling between the modules. This is again determined by how the modules are configured. Coupling can be identified as loosely coupled, tightly coupled or interleaved. Module configurations depend on the processing requirements. A hybrid system may take a number of architectures. The neural network and rule-based components are used to implement the various functions required. Some of the newer and larger hybrid systems have many neural and symbolic modules connected in different configurations. The configuration may be Sequential configuration and Parallel configuration.

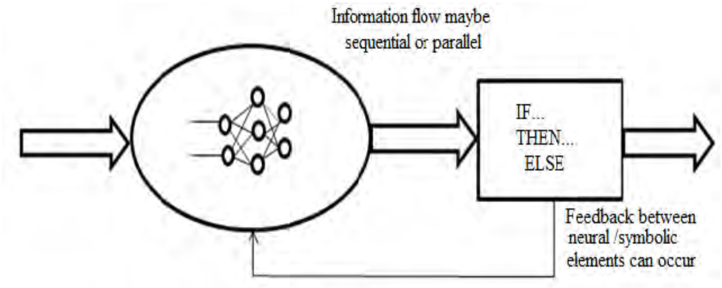


Figure 5.20: Modular Hybrid Systems [87]

5.11.1 Sequential Configuration

The main feature of this configuration is the serial processing of data as it is passed from one module to the next. One module acts as a pre-processor of data extracting the required features into a form suitable for the next module. A neural network could act as a pre-processor for a rule-based system by converting signal level information into a form more suitable for symbolic level decision making. It is also the case that a rule-based module can pre-process data for a neural network by identifying the relevant parameters for the appropriate input units.

5.11.2 Parallel Configuration

In this configuration a neural network and rule-based system operate in parallel on some common data. The reason for this approach is to compare the classifications obtained for greater confidence and reliability. Another possibility for parallel operation is where the neural network and rule-based elements operate on different data, but combines their results for an overall classification. Parallel configurations have the capability to use feedback of information from the output of one module into the input of another, enabling a more sophisticated degree of control to be implemented. Time or sequence dependent information may be used to change the operation of the system [87].

5.12 Back-Propagation Algorithm

A back propagation neural network uses a feed-forward topology, supervised learning, and back propagation learning algorithm. This algorithm was responsible in large part for the re-emergence of neural networks in the mid-1980s. Back propagation is a general purpose learning algorithm. It is powerful but also expensive in terms of computational requirements for training.

A back propagation network with a single hidden layer of processing elements can model any continuous function to any degree of accuracy (given enough processing elements in the hidden layer). Back propagation is the most widely used variant. Its two primary virtues are that it is simple and easy to understand, and it works for a wide range of problems. The basic back propagation algorithm consists of three steps.

- The input pattern is presented to the input layer of the network. These inputs are propagated through the network until they reach the output units. This forward pass produces the actual or predicted output pattern.
- Because back propagation is a supervised learning algorithm, the desired outputs are given as part of the training vector. The actual network outputs are subtracted from the desired outputs and an error signal is produced.
- This error signal is then the basis for the back propagation step, whereby the errors are passed back through the neural network by computing the contribution of each hidden processing unit and deriving the corresponding adjustment needed to produce the correct output. The connection weights are then adjusted and the neural network has just "learned" from an experience. Two major learning parameters are used to control the training process of a back propagation network. The learning rate is used to specify whether the neural network is going to make major adjustments after each learning trial or if it is only going to make minor adjustments. Momentum is used to control possible oscillations in the weights, which could be caused by alternately signed error signals. While most commercial back propagation tools provide anywhere from 1 to 10 or more parameters for you to set, these two will usually produce the most impact on the neural network training time and performance [76].

5.12.1 Drawbacks of Back-Propagation Algorithm

Although widely used, the back propagation algorithm has not escaped criticism. The method of backwards-calculating weights does not seem to be biologically plausible; neurons do not seem to work backward to adjust the efficacy of their synaptic weights. Thus, the back propagation-learning algorithm is not viewed by many as a learning process that emulates the biological world but as a method to design a network with learning. Also, the algorithm uses a digital computer to calculate the weights. When the final network is implemented in hardware, however, it has lost its plasticity. This loss is in contrast to the initial motivation to develop neural networks that emulate brain like networks and are adaptable (plastic) enough to learn new patterns. If changes are necessary, a computer calculates anew the weight values and updates them. This means that the neural network implementation still depends on a digital computer.

The algorithm suffers from extensive calculations and, hence, slows training speed. The time required to calculate the error derivatives and to update the weights on a given training exemplar is proportional to the size of the network. The amount of computation is proportional to the number of weights. In large networks, increasing the number of training patterns cause the learning time to increase faster that the network. The computational speed inefficiency of this algorithm has triggered an effort to explore techniques that accelerated the learning time by at least a factor of 2. Even these accelerated techniques, however, do not make the back propagation learning algorithm suitable in many real time applications. In addition, despite its wide applicability, the error back propagation algorithm cannot be applied to all neural network systems which can be imagined. In particular, the algorithm requires that the activation functions of each of the neurons in the network are both continuous and differentiable. Several historically important neural network architectures use activation functions which do not satisfy this condition. These include the discontinuous linear threshold activation function of the original perceptron of Rosenblatt and the continuous but non-differentiable linear ramp activation function of the units in the brain-state-in-box model of *Anderson et al* [86].

5.13 Application of Artificial Neural Networks in Load Monitoring and Identification

Artificial neural networks are widely used in monitoring and identification of residential load appliances, some of the different techniques employed by researchers in monitoring and identification of residential loads using ANNs are reviewed in this section. *Yoshimoto. K. et. al.,* [88] proposed non-intrusive appliance monitoring system using neural networks for residential customers, the system disaggregate the total electric load to individual loads of each appliance by perceiving the pattern of harmonics flowing out of a house. The system of using current harmonic signature is very effective and accurate for inverter-driven appliances that often change their mode of operation. The method does not require the detection of the step change. Reference [89], uses a method similar to the one described in reference [88]. The authors use attribute selector and artificial neural network to identify residential loads. Multilayer Perceptron (MLP) artificial neural networks that are usually applied in pattern recognition, functional approximation, identification and control were used. According to the authors, MLP architecture is adequate to recognize patterns concerning to consumer load profile. With the intention to improve the identification process, one ANN was created for each load type; all of the ANNs were configured in the same form. The Levenberg-Marquardt training algorithm that consists in an approximation of the Newton method was employed in the training process. It is very easy to adjust synaptic weights in the algorithm and it has a quick convergence when compared with conventional back propagation algorithms. Each one of the neural networks was trained to identify a specific load. The attribute selector was used as an attribute subset responsible to generalize the information contained in the database, according to the response desired. Attribute selection algorithms are usually employed when classifiers do not reach a pattern generalization without anyone pre-processing. Also, the algorithms are used where the classifiers are impracticable due to the higher number of attributes used as inputs. In addition, the work reported in the reference [63] uses artificial neural networks to identify residential loads in an exact way reference [89] presents it, but with different number of neurons in the first hidden layer and second hidden layer. The author uses back propagation algorithms to train the ANNs; the main characteristic of this algorithm is the computation of the decent gradient. Figure 5.21 depicts the residential consumer and the intelligent system used by the consumer.

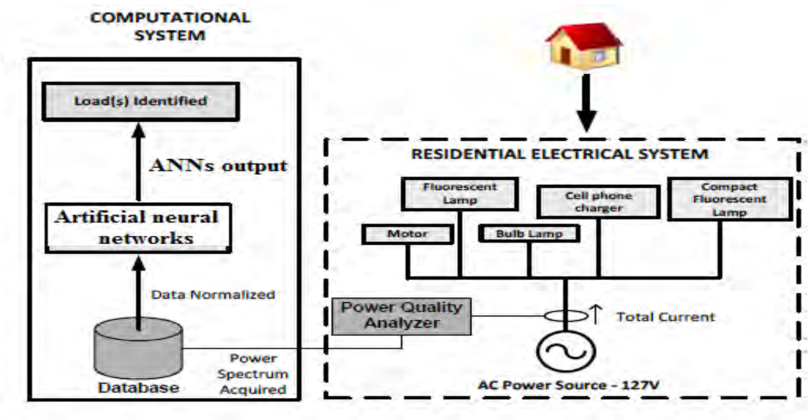


Figure 5.21: Residential Consumer and Computational System Used By the Consumer [63]

Furthermore, the author in [62] uses ANN in conjunction with turn-on transient energy analysis to identify loads. The author adopted multi-layer feed-forward neural network (MFFNN) based on the back propagation algorithm. The method can identify the similarity between giving data and known data. The input layer is the power signature information (active power, reactive power or turn on transient energy). The output layer identified individual appliances while the single hidden layer is used.

5.14 Summary

This chapter has described various computational intelligence techniques. Artificial intelligence (ANNs) was described in detailed due to its outstanding application in non- intrusive load appliances monitoring and recognition. Also, due to the ever progressing e- world has a lot to procure and gain from neural networks. Their ability to learn by situation counts for their flexibility and power. The neural Networks also don't need any specific algorithm to do a specific task. They are also well suited for real time systems because of their fast response and computational times which are as a result of their parallel architecture. They are regularly used to model residential appliances for recognition or identification. So these networks play a very significant role in the technological advancements and problem solving approaches. The outstanding features of ANNs to perform appliances recognition include ability to handle any type of data, unnecessary prior understanding of appliances behaviours, ability to extend to the higher number of inputs, ability to work with many types of values or dissimilar kind of data, and also, ANNs can learn a process that can be automated control. For example sensor that can turn on or off appliances remotely. In addition, ANNs have the ability to learn while running through mechanisms of error feedback from the user; it has the ability to handle multiple states of appliances at the same time. Furthermore, artificial neural network consumed low energy; it has a high fault tolerant rate, and inherent contextual information processing. However, ANNs have some drawback which includes a lengthy training process that take a few minutes, especially in case of appliances with a multi-signature. In this dissertation, multi-layer feed backward neural network also known as multi-layer perception (MLP) with a Levenberg -Marquardt back propagation algorithm was found suitable for the proposed task. The following chapter analyzes the energy consumption of six selected households.

CHAPTER 6

Energy Consumption Analysis of Some Selected Households in Johannesburg

Introduction

Residential energy consumption is the total amount of energy used or consumed by the appliances in a household. The amount of energy used per household varies widely depending on the standard of living of the country, climate, age and size of the household. Information on the customer’s consumption pattern in both regulated and deregulated energy environment is becoming critical for distribution companies. In the regulated environment such information is used for demand-side management system planning and better tariff design. While in the deregulated environment the information has considerable impact on the settlement price between customers and their suppliers. By knowing customer's energy consumption pattern, distribution companies or other suppliers such as independent power producer (IPP) can easily determine the price of the customer's demand. Thus, they can provide better marketing strategies and improve energy efficiency [90]. Reducing building energy consumption and shifting in energy consumption are the two general approaches for residential energy consumption management. Reducing residential energy consumption can be achieved through raising awareness among the consumers for efficient consumption patterns and constructing smart house with smart appliances. Shifting energy consumption is the process of postponing the use of certain appliances from on peak period (high tariff period) to off peak period (low tariff period). Shiftability in building energy consumption depends on customer’s needs or convenience and also on the functionality of the appliances, technical characteristics and surrounding environment (including building construction). Consumers can postpone the usage of some appliances for the purpose of energy cost reduction and consumption balancing. Appliances with shiftable consumption include water heater, washing machine. The analysis was conducted on different days of the week (weekday and weekends) and different seasons of the year (summer and winter). The data used for the consumption analysis was collected from high-income households in Johannesburg. The data were recorded at 5 minutes interval for a period of one year in six different houses. For easy analysis, the 5 minute data were converted to hourly data. The analysis and comparison were carried out on different days of the week (weekdays and weekends) and on different season of the year (winter and summer). During the course of this research, the information about the households, such as the total number of appliances in each household, the type of appliances, total number of occupants, their ages and their health conditions were not known. Therefore, the investigation in this chapter is based on hypothetical assumptions.

6.1 Factors Influencing Residential Energy Consumption

When analyzing energy consumption, it is essential to consider some factors that contribute to the total energy consumption, especially in the residential sector since they account for the second most consuming sectors after industrial sector. The key factors that influence residential energy consumption are: time of the day, economic developments of the country, the size of the household, weather conditions and appliance types. Better analysis of these factors can help in better understanding of the relationship between energy consumption and efficiency trends in the residential sector. For instance, a decrease of total energy consumption could be due to decrease in the total number of the occupants in the household concern and not by a more efficient use of energy [91]

❖ **Time of the Day**

Customer’s total energy consumption varies from time to time. The amounts of energy use during the weekdays are different from the energy used during the weekends. For example, many residential consumers use more energy on weekends than they do during the weekdays. This is because the occupants are at home on weekends (Saturday and Sunday) to use electrical appliances for a longer period of time than weekdays when they away foe work and switched off some appliances. Also, appliance load profile analysis can provide more information on the pattern of average customer energy consumption over different hours of the day and different days of the week.

❖ **Economic Development**

Another factor that can influence energy consumption is the economic development and economic situation of a country. This has dual effects on energy consumption level of residential buildings. Economic growth can be accompanied by a more efficient way of using energy in the household since more energy-efficient appliances such as efficient heating and cooling appliance and better insulated building material will be available for use, resulting in lower energy consumption levels. On the other hand, higher gross domestic product (GDP) levels may lead to buying more electrical appliances at home, thus increasing the energy consumption level of the household [91]

❖ Size of the Household

Energy consumption is also influenced by the number of people living together in one household. In large family, most electrical appliances are shared by the people living together in one household, especially heating and cooling appliance, entertainment appliances like television and cooking appliances. Besides the number of people per household the actual size in square meters is another factor that influences the energy consumption level of a household. Large households in terms of size in square metres generally have a higher heating and cooling demand and higher energy consumption by lighting appliances [92].

❖ Weather Conditions

Weather condition has significant influence on residential energy consumption, Changes in electricity consumption in residential buildings are associated with changes in weather conditions and they often cause undesirable peaks in the total energy consumption. During winter residential energy consumption normally increases because there is a need for additional heating appliances. The amount of electrical power consumed for additional heating depends on a number of factors such as intensity of external temperature variations, the length of strong cold spells or the length of warm spells also influences the electric power consumption and construction characteristics of the buildings. In addition, during extremely hot weather in summer, residential energy consumption is significantly increased due to the use of cooling appliances such as air conditioners. It is observed that there are high peaks in energy consumption associated with high summer and low winter temperature. Apart from the aforementioned factors, electricity consumption also depends on the characteristics of the residential building size, the quality of the windows, occupants' behaviour, and position of the appliance in the house and geographical location of the house [92].

❖ Types Appliances

The types of appliances used in a household have significant impacts on the total energy consumption of the household. Appliances can be categorized into energy-inefficient and energy-efficient appliances. Energy- efficient appliances are those appliances that consumed high energy such as incandescent bulbs and phantom appliances. Energy-efficient appliances are energy saving appliances such as fluorescent light and efficient refrigerator. The effectiveness of the energy-efficient appliances in driving reduction in residential energy consumption depends on two factors; consumer awareness and their readiness to purchase it. Some of the reasons for adopting energy-efficient appliances in the household include minimizing the residential energy consumption, thus reducing monthly energy bills, compatibility in appliance size, lower emissions of local and global pollutant and reduction in environmental degradation. Also the duration and period of usage of the appliance have significant influence on the total energy consumption of the household.

6.2 Techniques of Analyzing Residential Energy Consumption

Residential building energy consumption analysis is the method of evaluating energy consuming patterns of a building. Recently, three techniques are commonly used in analyzing residential energy consumption, the techniques includes [93]:

- Single measurement techniques;
- Simplified multiple measurement technique;
- Detailed multiple measurement techniques.

Single Measurement Techniques: These techniques use annual or seasonal energy usage. This technique estimates building energy consumption by combining one degree-day (A variation above or below of the mean daily temperature from a given standard value) weather value with a load value to obtain seasonal or annual energy consumption.

Simplified Multiple Measurement Techniques: These techniques involve estimations of energy consume at various conditions. The techniques estimate the energy use of different appliances in the household, according to the number of hours each appliance is expected to be used and then summed up the result to compute the annual energy consumption of the household.

Detail Multiple Measurement Techniques*:* These techniques compute energy consumption on an hourly basis. **T**he method uses 24-hour profile of average energy consumed in the household. The method employed in this dissertation is based on this technique.

6.3 Analysis of Energy Consumption Patterns

The load profile analysis shows when and how much electricity is used over a period of time. It depicts the how the time of use period of the tariff are designed and the charges associated to the different time of the day. There are two peak periods of usage during the day, one in the morning and the other in the evening. The time of usage period is grouped into ON peak and OFF-peak time of the day. The cost of electricity is usually higher during the ON peak periods when the demand for electricity is high. During the OFF peak periods the demand for electricity is lower. Usually, in residential buildings there are almost five ON peak hours in a day, the peak hours are 7 O‘clock to 10 O’clock in the morning and 18 O’clock and 20 O’clock in the evening. Generally, the total energy consumption of a household is determined mainly by the appliances in the house and the period of their usage. The time of usage applied to all days of a year, either in the summer or winter, weekday or weekend. Hence, in this analysis, summer, winter weekday and weekend energy consumption will be considered and comparisons will be made. For the analysis, six different high-income households in Johannesburg are considered. In this analysis, information about the household appliances as well as the occupants such as total number of occupants, age and their health conditions were considered.

6.3.1 Summer Energy Consumption Analysis

Summer is a season of the year that is characterized with hot weather thus increase the demand for electricity for cooling appliances. For the purpose of accuracy, both weekdays and weekends energy consumption analysis will be considered separately in the analysis. The average energy consumption profiles provided in these sections reflect the effects of the most recent weather conditions.

6.3.2 Weekdays Energy Consumption Analysis in summer

Energy consumption on workdays is comparable lower compare to energy consumption on weekends. This is due to the fact that occupants are not at home to use more electrical appliances for a long period of time. The analyses are based on hourly energy consumption of each household. It is assumed in this dissertation that what happened in one day during the week applied to all other days of the week, thus only one day of the week is being considered for the analysis. Figures 6.1 to 6.6 depict the daily energy consumption profiles of the six different selected high-income households in Johannesburg.

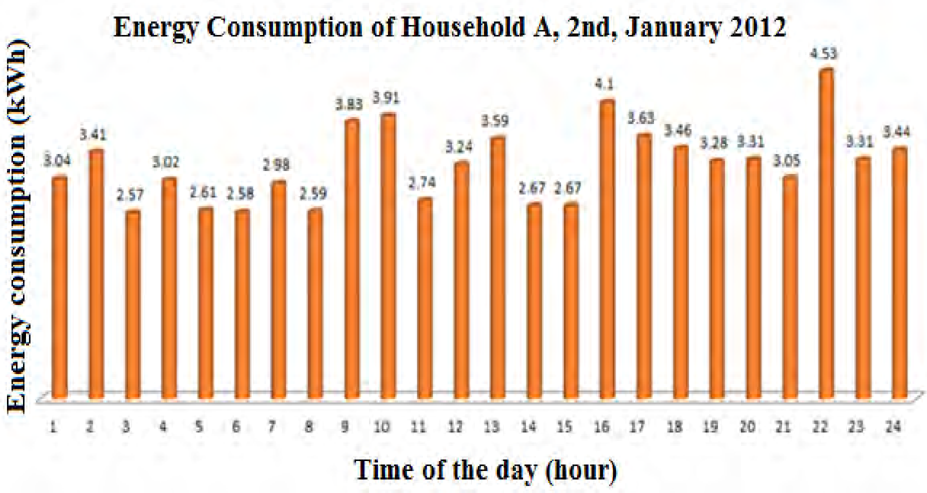


Figure 6.1: Household 'A' Weekday Energy Consumption Profile (summer)

The 24 hour energy consumption of household A is shown in Figure 6.1. In the household, the ON peak hours noticed is 16 O'clock in the afternoon and 22 O'clock in the night. The periods are high tariff period during the weekdays and are likely affected by appliances such as water heater, air-conditioning, cooking appliances, lighting and entertainment appliances. The main consumption time of water heater is 7 O'clock in the morning and 16 to 18 O'clock in the evening. The consumption time of cooking appliances is 17 to 22 O'clock. For the purpose of customers' comfort, reduction in energy consumption cost and consumption balancing, it is advisable to shift the half of the high tariff consumption of water heater to the low tariff period between 5 O'clock and 6 O'clock, which is the off peak hour and another half high tariff consumption from 18 O'clock to 23 or 24 O'clock. The energy consumption of cooking appliances, entertainment appliances and cooling appliances are considered as non-shift able appliances. The energy consumption profile of household H is shown in Figure 6.2. The consumption is different from that of households A. This may be due to the number of the occupants in the house and the type of appliances use in the house.

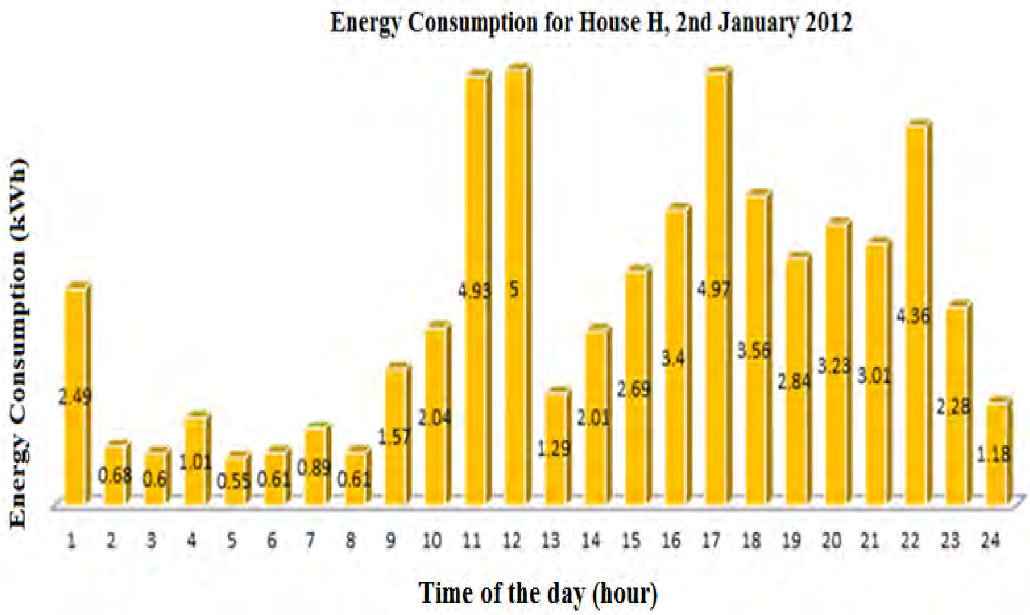


Figure 6.2: Household 'H' Weekday Energy Consumption Profile (summer)

The energy consumption profile of household H is shown in Figure 6.2. The ON peak hours in the household are: 11 O'clock, 12 O'clock, 17 O'clock and 22 O'clock respectively. The high energy consumption at 11 O'clock and 12 O'clock may be due to the use of cooking appliances, cooling appliances such as air-conditioning and entertainment appliances. The 17 O'clock and 22 O'clock consumption may be allotted to the use of cooking appliances, office appliances (personal computer) and air-conditioning. The energy consumption profile of household N is shown in Figure 6.3.

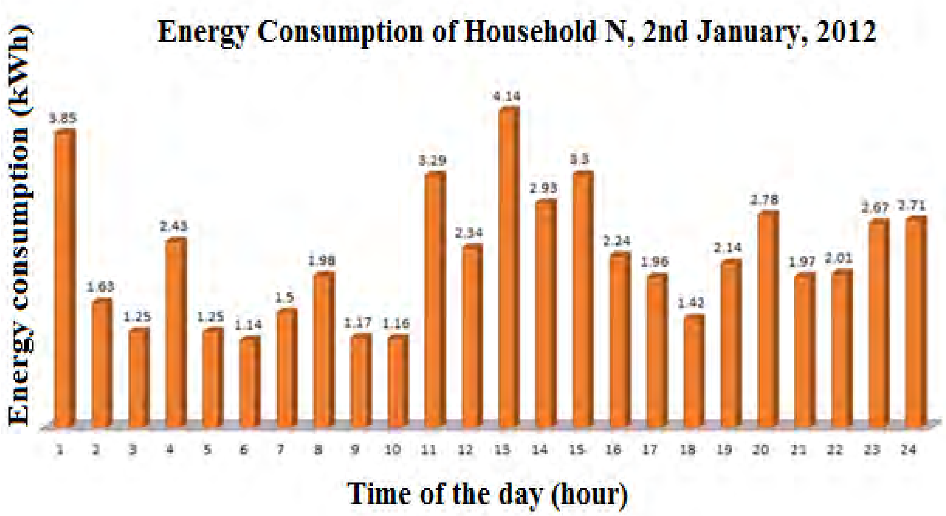


Figure 6.3: Household 'N' Weekday Energy Consumption Profile (summer)

The energy consumption of household N is shown in Figure 6.3. In the household, the ON peak periods are: 1 O'clock in the midnight, 11 O'clock, 13 O'clock and 15 O'clock. The high consumption at 1 O'clock in the midnight may probably due to the use of air-conditioning, oven, electric fence or lighting appliance. The consumptions at 11 O'clock and 13 O'clock can be allotted to the use of cleaning appliances, entertainment appliances, cooking appliances and air-conditioning. At 15 O'clock, the energy consumption may be due to the use of the water heater, cooking appliances and air-conditioning. Figure 6.4 depicts the energy consumption profile of household Z.

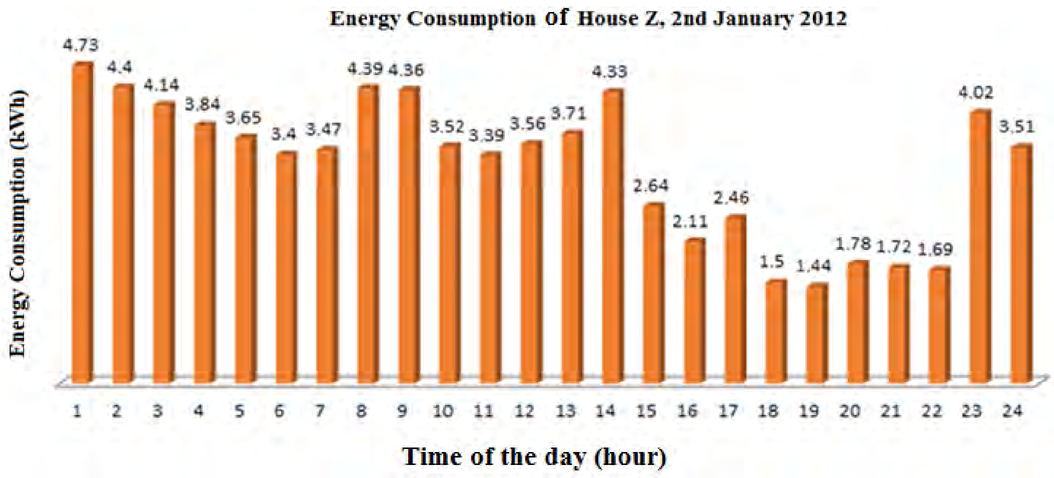


Figure 6.4: Household 'Z' Weekday Energy Consumption Profile (summer)

From the Figure 6.4, the energy consumption of the household is completely different from the household previously described. There are four ON peak periods in the household, 1 O'clock to 3 O'clock, 8 O'clock to 9 O'clock, 14 O'clock and 23 O'clock to 24 O'clock respectively. The 1 O'clock to 3 O'clock peak periods are located at the low tariff period; the 8 O'clock to 9 O'clock peak periods are located in a high tariff period, while 14 O' clock and 23 O'clock peak period are located at high tariff periods. The energy consumption at 8 to 9 O'clock may be allotted to the use of cleaning appliances, office appliances and cooking appliances, while the consumption at 14 O'clock may due to the use of air-conditioning, swimming pool and water heater. Beside the use of electric fence, lighting and refrigerator, the consumption within the hours of 1 O'clock and 3 O'clock may be due to the use of oven depending on the occupants of the household. The energy consumption at 23 O'clock and 24 O'clock may be due to lighting, electric fence, cooling appliances, and probably office appliances. Figure 6.5 depicts the energy consumption profile of household AH.

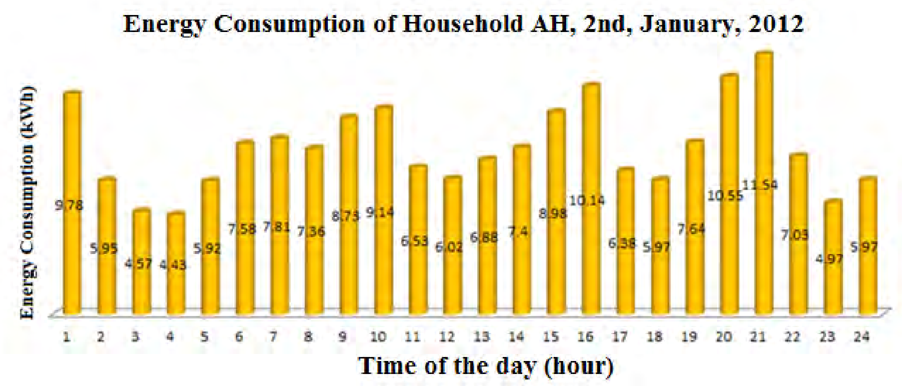


Figure 6.5: Household ‘AH’ Weekday Energy Consumption Profile (summer)

Figure 6.5 shows the detail of hourly energy consumption of household AH. The energy consumption of the house is high almost throughout the day. However, three ON peak hours are noticed. The hours are; 16 O’clock, 20 O’clock and 21 O’clock. The energy consumption at 16 O’clock may be allotted to the use of air conditioning, entertainment appliances, swimming pool and probably cooking appliances. The consumption at 21 O’clock and 22 O’clock may probably due to the use of cooking appliances, lighting, water heater and air-conditioning. Figure 6.6 depicts the energy consumption profile of household QA.

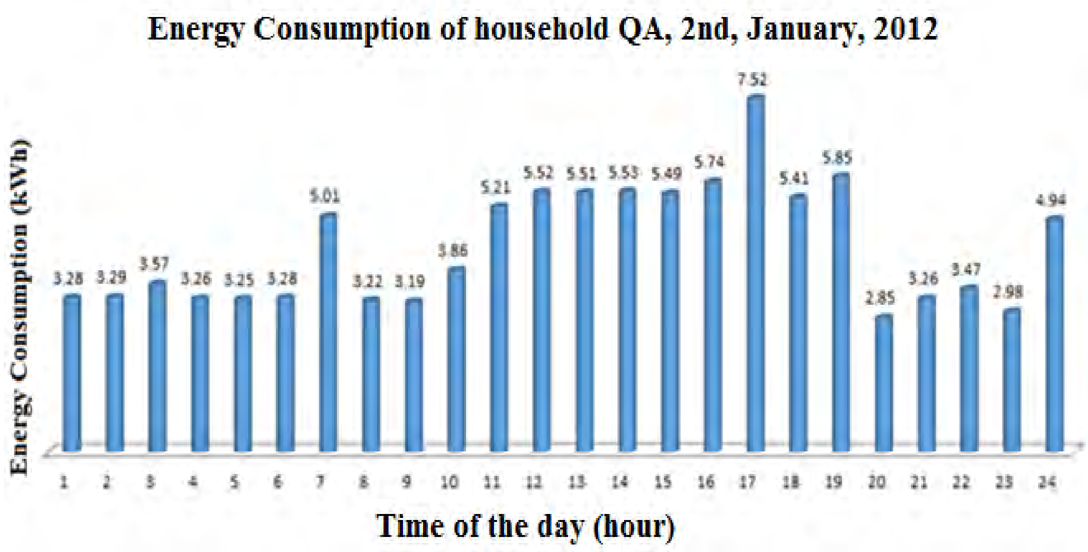


Figure 6.6: Household ‘QA’ Weekday Energy Consumption Profile (summer)

The energy consumption of household QA is shown in Figure 6.6. The ON peak hour of the household is at 17 O’clock and is located at the high tariff period of the week. The energy consumption at this hour may probably due to cooking appliances, air-conditioning, water heater and entertainment appliances. The energy consumption between the hour of 11 O’clock and 16

O'clock can be considered to be linear. This may be due to the fact that similar energy consuming appliance(s) are on for that period of times. The consumption between the hour of 18 O'clock and 19 O'clock may be allotted to the use of cooking appliances, cooling appliances and office appliances (personal computer, modem, printer etc.). The 24 O'clock energy consumption may due to the use of lighting appliance, electric fence and probably air-conditioning. The 7 O'clock energy consumption may be allotted to the use of cooking appliances, electric kettle, water heater and probably electric iron. The consumption within the hour of 8 O'clock to 10 O'clock may be due to the use of entertainment appliances (TV, Dstv decoder etc.) or cleaning appliances (vacuum cleaner, washing machine, tumble dryer, etc.). The consumption within the hour of 1 O'clock to 6 O'clock is almost linear due to some appliances that are ON at night hours. During these period the energy consumption may be due to the electric fence, lighting, electric fan, office appliances (personal computer, modem, printer etc.) and air-conditioning.

6.3.3 Weekends Energy Consumption Analysis in summer

Fundamentally the total energy consumed during the weekdays is comparatively lower compared to the total energy consumed during the weekends and this is due to the consumer's activities on weekends. Energy consumption on Saturday is normally different from Sunday energy consumption. Therefore, it is essential to analysis, energy consumption on weekends separately. This section analyses Saturday and Sunday energy consumption in summer.

6.3.3.1. Saturday- Energy Consumption Profiles

The energy consumption profiles in Figure 6.7 to 6.12 shows the hourly energy consumption profile of the six different selected households on Saturday.

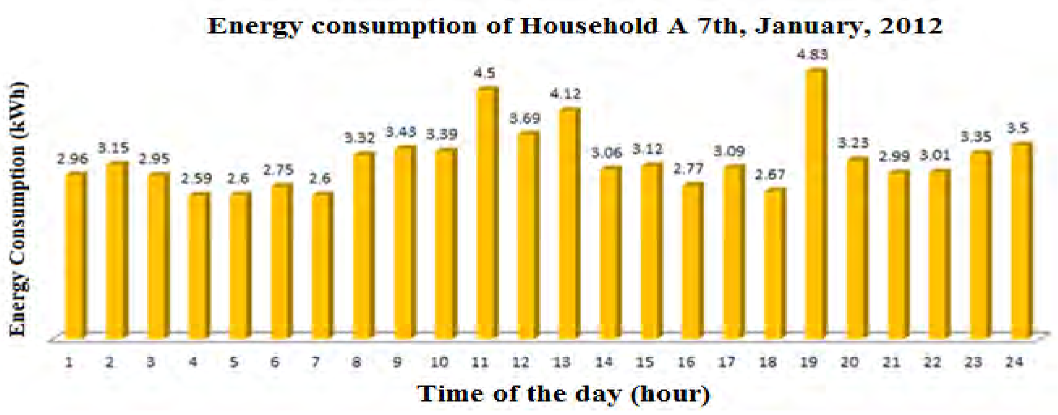


Figure 6.7: Household 'A' Saturday Energy Consumption Profile (summer)

Saturday energy consumption of household A is depicted in figure 6.7. On this day, three ON peak hours are noticed. 11 O'clock in the morning, 13 O'clock in the afternoon and 19 O'clock in the evening. The 11 O'clock and 13 O'clock ON peak hours are located in low tariff hours while the 19 O'clock ON peak hour is located at a high tariff hour. The energy consumption at 11 O'clock may probably due to the use of cooking appliances, cleaning appliances and entertainment appliances. The 12 O'clock and 13 O'clock energy consumption may be due to entertainment appliances, office appliances, air-conditioning and swimming pool. Air-conditioning, cooking appliances and office appliances may be due to the energy consumption at 19 O'clock. The energy consumption within the hours of 8 O'clock and 10 O'clock may be allotted the use of cleaning appliances, washing machine and tumble dryer. The 14 O'clock and 15 O'clock consumption may be due to entertainment appliances, office appliances, air-conditioning, and swimming pool. The 20 O'clock to 22 O'clock consumption may be due to cooking appliances, entertainment appliances, air- conditioning and office appliances. 23 O'clock and 24 O'clock energy consumption may be due to lighting appliance, electric fence, refrigerators, air-conditioning and probably office appliances. The 1 O'clock to 7 O'clock energy consumption may be due to electric fence, lighting appliance, water heater and cooking appliances. Figure 6.8 depicts the energy consumption profile of household H.

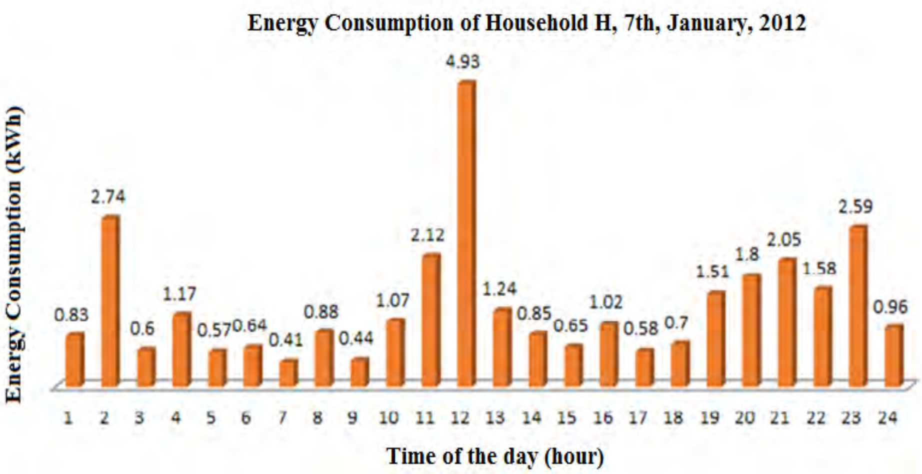


Figure 6.8: Household 'H' Saturday Energy Consumption Profile (summer)

The energy consumption of the household is completely different from the energy consumption of household A analyzed in Figure 6.7. The energy consumption of the household with the hour of 3 O'clock and 9 O'clock show that the occupant(s) switched OFF certain high consuming appliances and leave only lighting appliance and probably refrigerator. However the household ON peak hour is at 12 O'clock. The energy consumption at this hour may probably due to the use of air-conditioning, office appliances, entertainment appliances, washing machine and tumble dryer. The 14 O'clock to 18 O'clock consumption may be due to the use of refrigerator, office appliance or entertainment appliances. The 19 O'clock to 22 O'clock energy consumption may be due to cooking and entertainment appliances. The energy consumption at 23 O'clock may be allotted to the use of air-conditioning, entertainment appliances and lighting appliance. 24 O'clock and 1 O'clock energy consumption may be allotted to the use of electric fence, refrigerator and lighting appliances. The 2 O'clock consumption may be due to oven, lighting appliance and electric fence. The hourly energy consumption profile of household N is depicted in Figure 6.9.

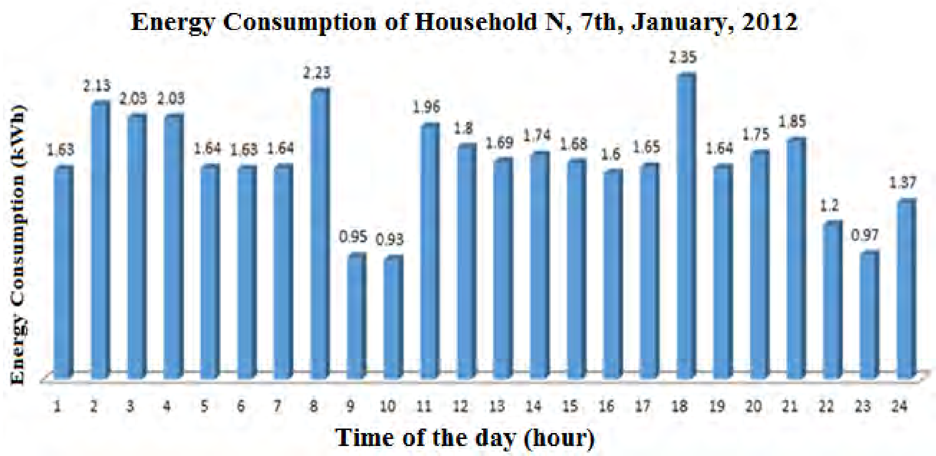


Figure 6.9: Household 'N' Saturday Energy Consumption Profile (summer)

The ON peak hours of the household are at 2 O'clock, 8 O'clock and 18 O'clock respectively. The main appliances, which affect the household energy consumption at 2 O'clock, may include refrigerator, lighting appliance and electric fence. The 8 O'clock energy consumption may be allotted to cleaning appliances, electric kettle and cooking appliances. 18 O'clock energy consumption in the household may be due to cooking appliances, refrigerator, entertainment appliances and probably Swimming pool. The 5 O'clock to 7 O'clock energy consumption of the household may be due to refrigerator, lighting and washing machine. The energy consumption of 2 O'clock to 4 O'clock may be allotted to electric fence, lighting appliance, electric fan, and probably electric oven. The 19 O'clock to 21 O'clock consumption may be due to cooking appliances, lighting, entertainment appliances and office appliances. The 11 O'clock to 17 O'clock energy consumption in the household may be due to entertainment appliances, office appliances and electric fan. The consumption at 9 O'clock to 10 O'clock may be allotted to refrigerators and electric fence probably the occupants are not around at these hours.

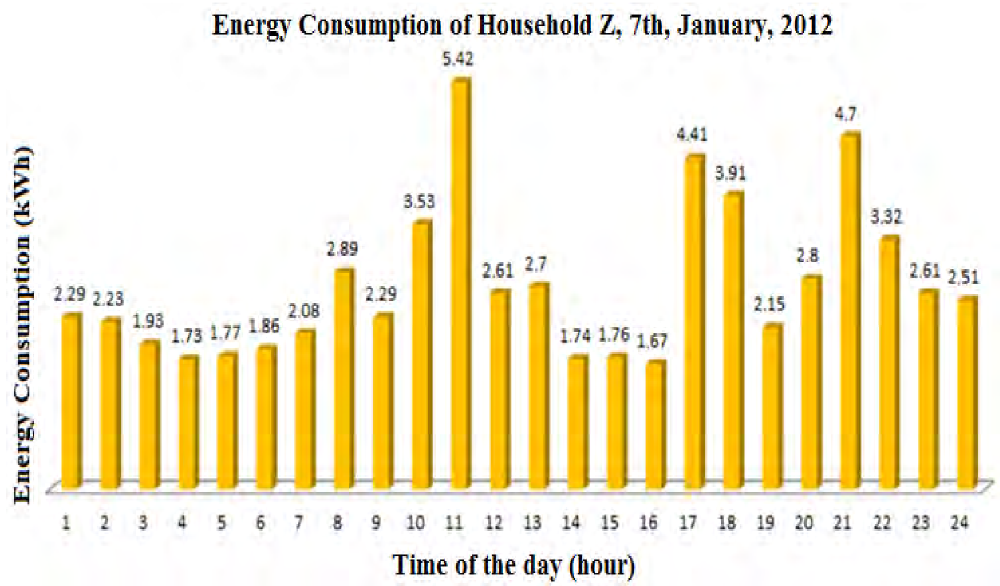


Figure 6.10: Household 'Z' Saturday Energy Consumption Profile (summer)

The energy consumption profile in Figure 6.10 represents household Z hourly energy consumption for 24 hours. In the household, three ON peak hours are noticed. 11 O'clock in the morning, 17 O'clock in the evening and 21 O'clock in the night. The 11 O'clock ON peak hour is located in a low tariff hour and is probably due to the use of washing machine, tumble dryer, cleaning appliances or swimming pool, while the 17 O'clock and 21 O'clock peak hours are located at a high tariff hours and are probably caused by the refrigerator, cooking appliances, water heater and air-conditioning respectively. The 23 O'clock to 2 O'clock energy consumption in the household may be due to electric fence, lighting appliances, electric fan and electric oven. The consumption at 3 O'clock to 6 O'clock may be due to electric fence, electric fan and lighting appliance. 7 O'clock to 9 O'clock consumption may be due to cooking appliances, refrigerators and entertainment appliances. The consumption at 10 O'clock may be due to water heater and cooking appliances. The 14 O'clock to 16 O'clock may probably due to entertainment appliances, office appliances and electric fan. The 18 O'clock consumption may be due to cooking appliances, air-conditioning, entertainment appliances or swimming pool. The 19 O'clock to 20 O'clock may be allotted to cooking appliances, entertainment and office appliances. The energy consumption of household AH is shown in Figure 6.11

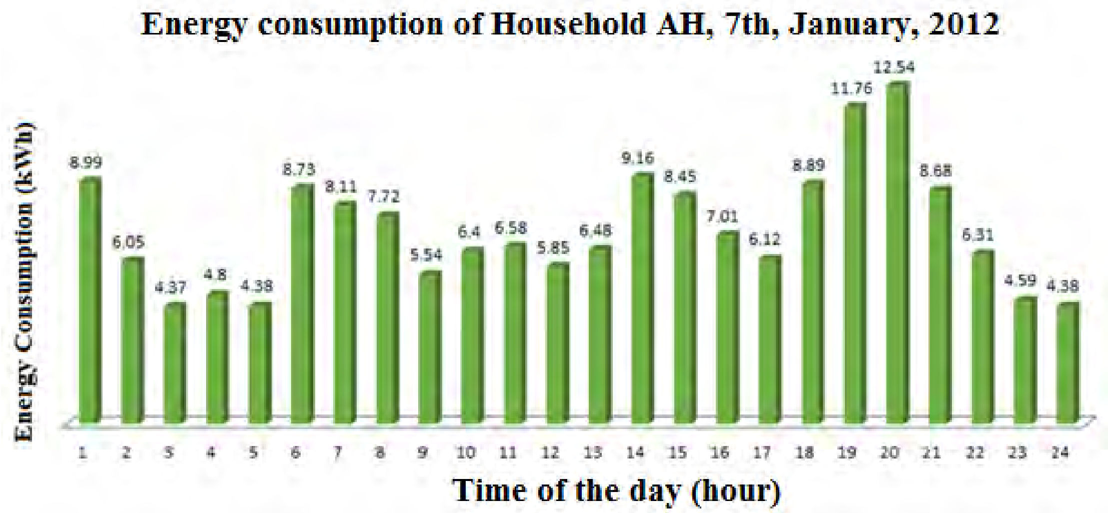


Figure 6.11: Household ‘AH’ Saturday Energy Consumption Profile (summer)

From Figure 6.11 it can be seen that in the household, four peak hours can be detected: the morning (6 to 8 O’clock), afternoon (14 to 16 O’clock), the night (19 to 21 O’clock) and the midnight (1o’clock). The morning peak hours are located in the low tariff period in the weekends and are mostly caused by water heater, washing machine, tumbler dryer and probably swimming pool pump. The afternoon peak hours are located in high tariff hours on both weekdays and weekends and are mostly caused by cooking appliances, electric kettle, and probably air-conditioning. The peak hours in the evening are located in high tariff hours both on weekdays and on weekends. They are mainly caused by cooking appliances, water heater or air-conditioning. The midnight peak hour is located at low tariff period and is probably caused by oven, air-conditioning, security (security light, electric fence). The energy consumption of household QA is analyzed in the figure 6.12.

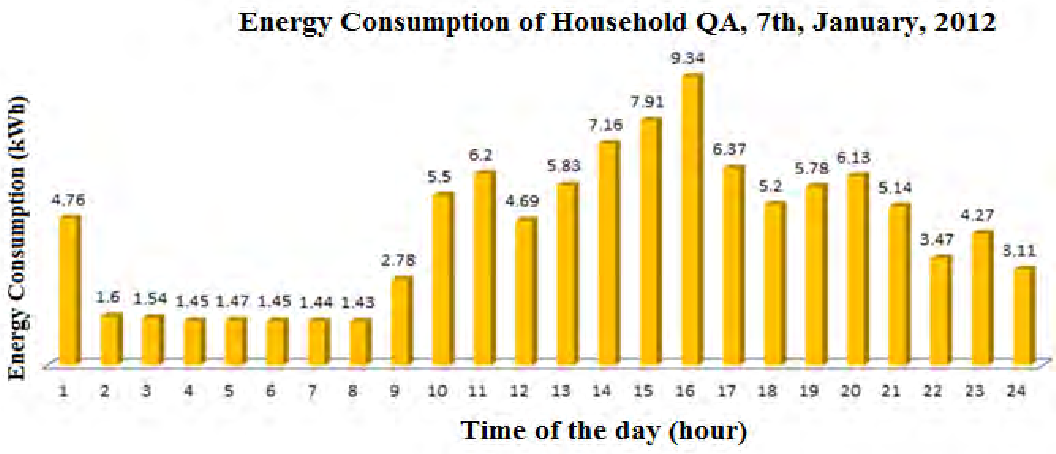


Figure 6.12: Household ‘QA’ Saturday Energy Consumption Profile (summer)

From the energy consumption profile, one can notice that the occupants switched off high energy consuming appliances and leave probably lighting appliance, electric fence and refrigerator within the hours of 2 O'clock to 8 O'clock. However the household peak consumption is at 16 O'clock and may probably due to the use of cooking appliances, air-conditioning and entertainment appliances. The consumptions at 10 and 11 O'clock may be allotted to the use of cleaning appliances, cooking appliances, or electric kettle. The 12 to 15 O'clock consumption may be as a result of using air-conditioning, entertainment appliances, office appliances (personal computer, modem, printer and hi-fi equipment), washing machine or tumble dryer. The consumption at 17 to 23 O'clock may be allotted to the use of the water heater, cooking appliances, swimming pool pump, lighting or oven.

6.3.3.2 Sunday Energy Consumption Profiles

Sunday energy consumption profiles of the six selected high-income households in Johannesburg are shown in Figure 6.13 to 6.18. The Figure 6.13 depicts the energy consumption of household A on Sunday in summer.

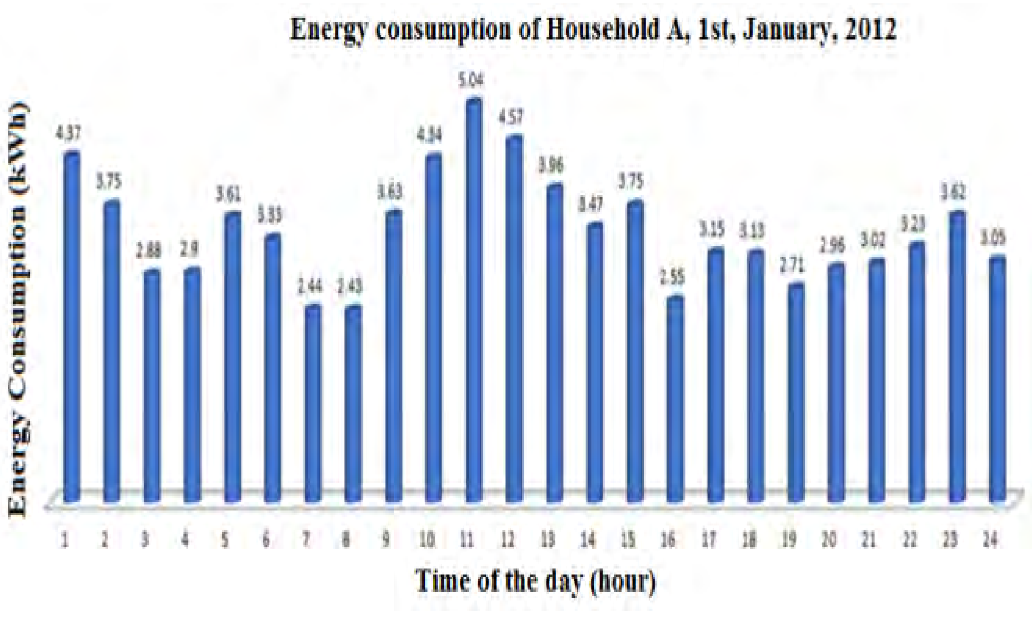


Figure 6.13: Household 'A' Sunday Energy Consumption Profile (summer)

In the household, two on peak periods are noticed. The on peak periods are 10 O'clock to 12 O'clock and 1 O'clock to 2 O'clock respectively. The peak hours are located in both high and low tariff hours on weekends. The on peak consumptions at 10 O'clock to 12 O'clock may probably due to cleaning appliances, air-conditioning, entertainment appliances, swimming pool and cooking appliances. While the on peak hours at 1 O'clock to 2 O'clock at midnight may probably due the use of appliances such as washing machine, lighting, electric fence or tumble dryer. The 5 O'clock and 6 O'clock consumption may be allotted to the use of cooking appliances, electric iron and probably water heater. The 14 O'clock to 15 O'clock energy consumption may be due to the use of air-conditioning, cooking and entertainment appliances. The energy consumption at 17 to 18 O'clock may mainly due to the cooking appliances, air-conditioning and electric kettle. Energy consumption at 19 O'clock to 20 O'clock may be due to cooking appliances, entertainment appliances, or electric kettle. The 21 O'clock to 24 O'clock energy consumption in the household may be allotted to electric fence, air-conditioning and office appliances (personal computer, modem, printer and hi-fi equipment). The consumption at 3 O'clock to 4 O'clock may be due to electric fence, lighting and refrigerator. The 5 O'clock and 6 O'clock consumption may be allotted to water heater, refrigerator and lighting appliance, while the energy consumption at 7 O'clock to 8 O'clock may due to cooking, appliances, electric kettle and entertainment appliances. The 9 O'clock energy consumption may be allotted to cooking appliances, cleaning appliances and washing machine or tumble dryer. Figure 6.14 depicts the hourly energy consumption of household H

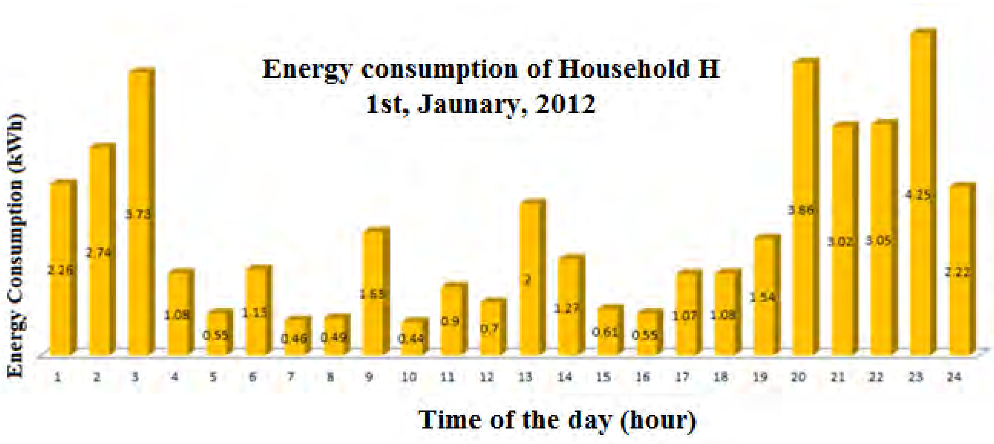


Figure 6.14: Household 'H' Sunday Energy Consumption Profile (summer)

The on peak periods noticed in the household are at 20 O'clock to 23 O'clock and 3 O'clock respectively. The 20 O'clock to 23 O'clock on peak hours are located in the high tariff hours and probably affected by cooking appliances, entertainment appliances, water heater, air-conditioning and office appliances (personal computer, modem, printer and hi-fi equipment). The 3 O'clock on peak consumption may be allotted to the use of washing machine, tumble dryer, lighting and electric fan. The consumption at 17 O'clock to 19 O'clock may be due to entertainment appliances, office appliance and electric fan. The consumption at 10 O'clock to O'clock may be due to refrigerator, lighting appliance or electric fence. The 24 O'clock to 2

O'clock energy consumption may be due to electric fence, lighting appliance, office appliances and refrigerator. Figure 6.15 shows energy consumption of household N on Sunday in summer

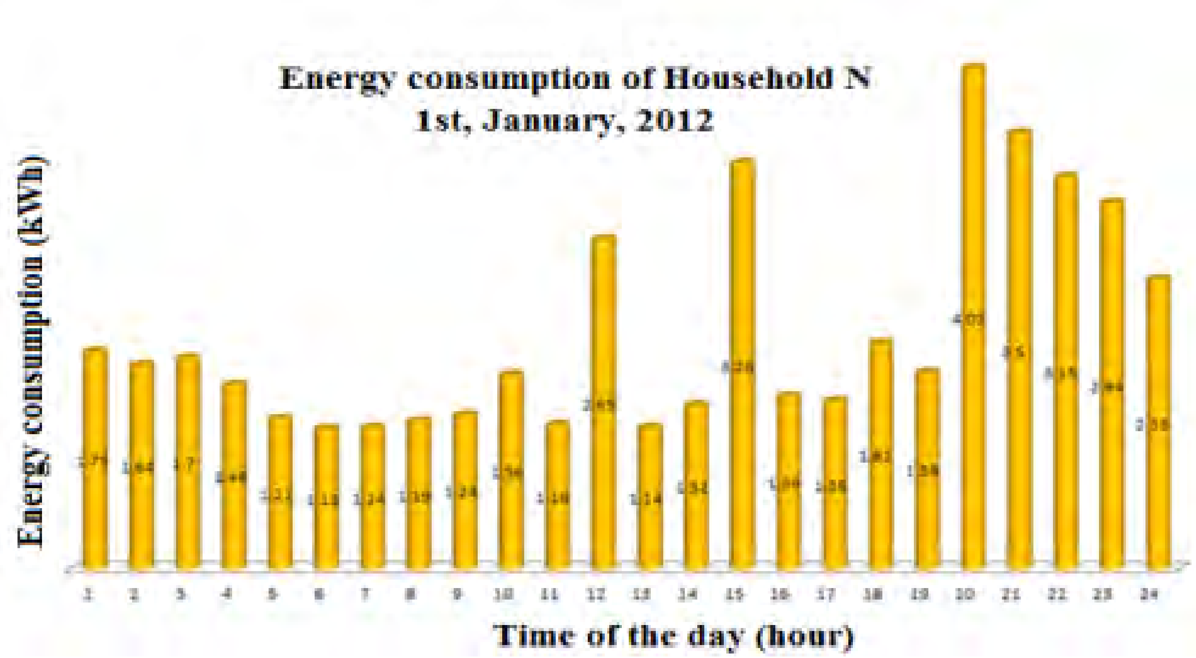


Figure 6.15: Household 'N' Sunday Energy Consumption Profile (summer)

In the household energy consumption recorded two ON peak periods. The ON peak periods are at 15 O'clock and 20 O'clock to 22 O'clock respectively. The 15 O'clock on peak consumption is located at high tariff hour on weekdays and the consumption at this hour may probably due to air-conditioning, swimming pool, entertainment appliances or office appliances (personal computer, modem, printer and hi-fi equipment). The on peak period at 20 O'clock to 22 O'clock, are located at high tariff hours and the consumption at the hour may be allotted to cooking appliances, swimming pool pump, air-conditioning and oven. The consumption at 12 O'clock may be due to electric fan, entertainment appliances and office appliances. The 13 O'clock to 14 O'clock energy consumption may be due to electric fan, entertainment appliances and office appliances. The 16 O'clock to 19 O'clock energy consumption may probably due to refrigerator, electric fan entertainment appliances and office appliances. Also, the 1 O'clock to 11 O'clock may probably due to lighting, refrigerator, electric fence and electric fan. Figure 6.16 shows the household Z energy consumption on Sunday in summer.

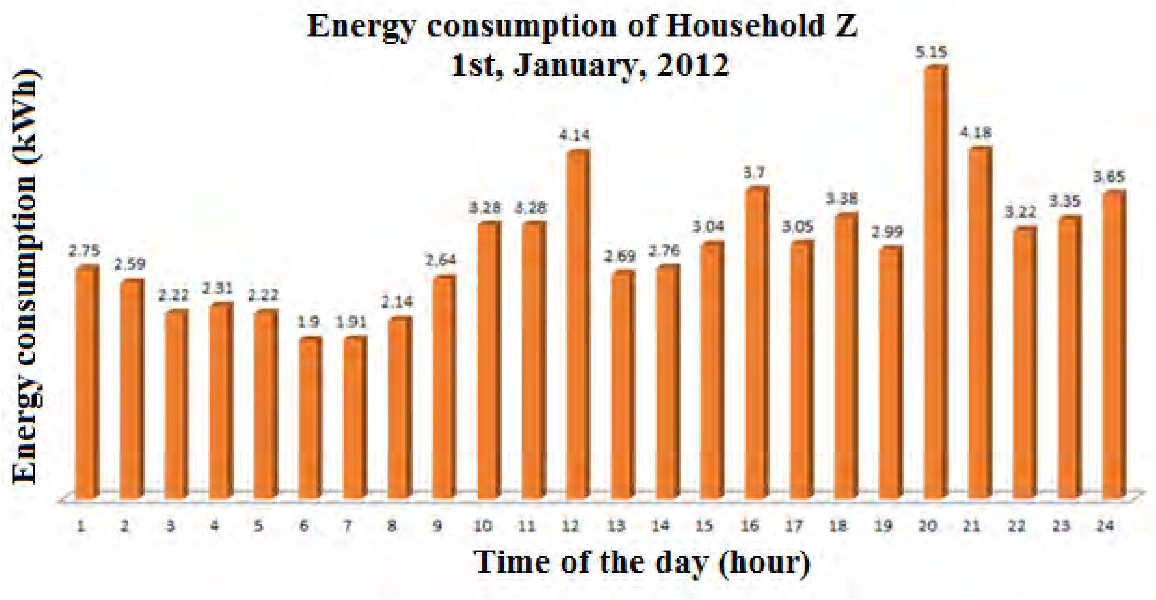


Figure 6.16: Household 'Z' Sunday Energy Consumption Profile (summer)

From the above energy consumption profile, the household recorded four on peak periods. The peak periods are 10 O'clock to 12 O'clock, 15 O'clock to 18 O'clock, 20 O'clock to 21'O'clock and 22 O'clock to 24 O'clock. The on peak period at 10 O'clock to 12 O'clock is located at high tariff hours, on weekends and the consumption may be affected by washing machine, tumble dryer, entertainment appliances and cooking appliances. The 15 O'clock to 18 O'clock on peak periods are located at high tariff hours; the consumption at these hours may be due to entertainment appliances, office appliances, swimming pool and air-conditioning. The 20 O'clock and 21 O'clock on peak periods are located at high tariff hours on weekends. The energy consumption at these hours may be due to cooking appliances, entertainment appliances, air-conditioning and probably office appliances. The 22 O'clock to 24 O'clock on peak periods are located at low tariff hours and the consumption at these hours may be due to lighting appliance, air-conditioning, office appliances and electric fence. The energy consumption at 1 O'clock to 5 O'clock may be allotted the use of lighting, appliance, refrigerator, electric fence and electric fan. The 6 O'clock and 7 O'clock energy consumption may be affected from refrigerator, electric kettle, entertainment appliances and office appliances. The 8 O'clock and 9 O'clock energy consumption may be due to cleaning appliances, cooking appliance, and entertainment appliances. The consumption at 13 O'clock and 14 O'clock may be affected from swimming pool, entertainment appliances and probably office appliances (personal computer, modem, printer and hi-fi equipment). Figure 6.17 depicts the household AH energy consumption on Sunday in summer.

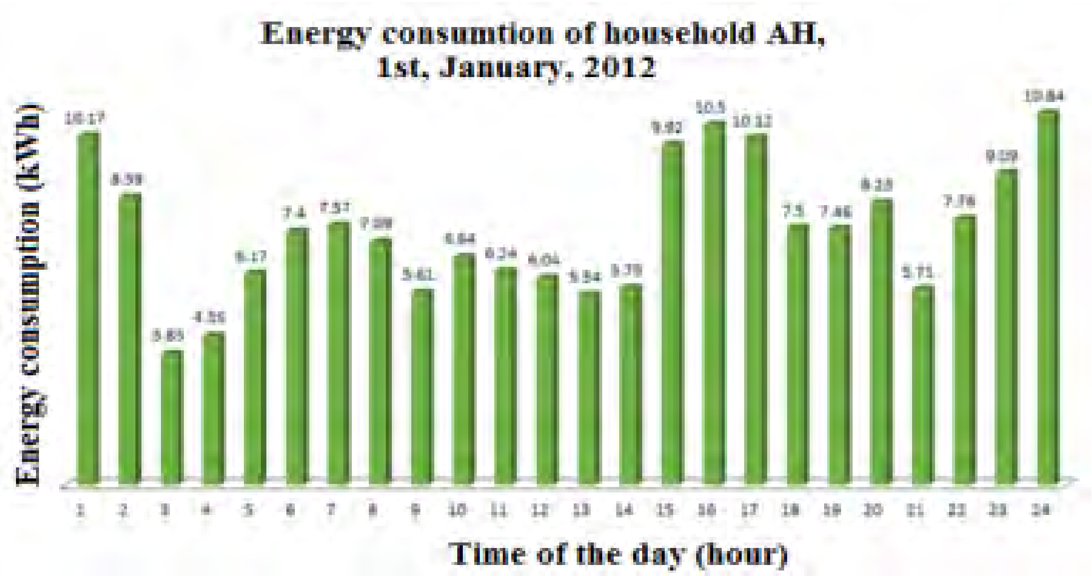


Figure 6.17: Household ‘AH’ Sunday Energy Consumption Profile (summer)

There are two ON peak periods are noticed in the household. The ON peak periods are 15 O’clock to 17 O’clock and 23 to 1 O’clock. The 15 O’clock to 17 O’clock peak hours are located in a high tariff hours and may probably affected from air-conditioning, entertainment appliances, office appliances, cooking appliances and swimming pool. The 23 O’clock to 1 O’clock peak hours are located in a low tariff hours on weekends, and may be affected from air-conditioning, electric fence, lighting appliance, office appliances and electric oven. The 6 O’clock to 8 O’clock energy consumption may be allotted to washing machine, electric iron, tumble dryer and water heater. The 10 O’clock to 12 O’clock energy consumption may be due to cooking appliances, cleaning appliances, entertainment appliances, office appliances and air-conditioning. Energy consumption at 13 O’clock and 14 O’clock may be allotted to the use of air-conditioning, swimming pool, entertainment appliances, office appliances and probably cooking appliances. The 18 O’clock to 20 O’clock energy consumption may probably due cooking appliances, entertainment appliances, air-conditioning, lighting appliance, and swimming pool. The 3 O’clock to 4 O’clock energy consumption may probably cause by air-conditioning, lighting appliance, electric fence, refrigerator and office appliances. Figure 6.18 presents household QA energy consumption profile on Sunday in summer.

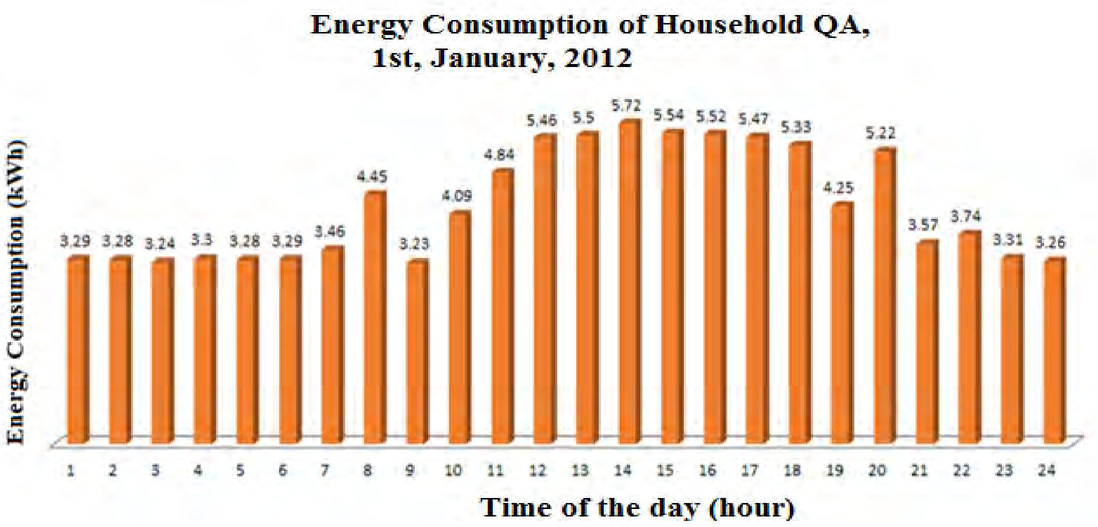


Figure 6.18: household 'QA' Sunday Energy Consumption Profile (summer)

The household has linear energy consumption within the hour of 12 O'clock to 18 O'clock and at these periods, the household energy consumption is at peak. These periods are located at higher tariff hours on weekends. The energy consumption at these hours may probably due to air-conditioning, cooking appliances, electric kettle, water heater, office appliances and entertainment appliances. Also, the energy consumption, at 21 O'clock to 7 O'clock is almost linear and the consumption may be due to lighting, electric fence, air conditioning, office appliances and entertainment appliances. The consumption at 8 O'clock may due to cooking appliances, washing machine and tumble dryer. The 10 O'clock and 11 O'clock consumption may be due to cooking appliances, cleaning appliances, entertainment appliances and water heater.

6.3.3.3 Comparison of Energy Consumption of the Six Selected High-Income Households in Johannesburg on Weekend in summer

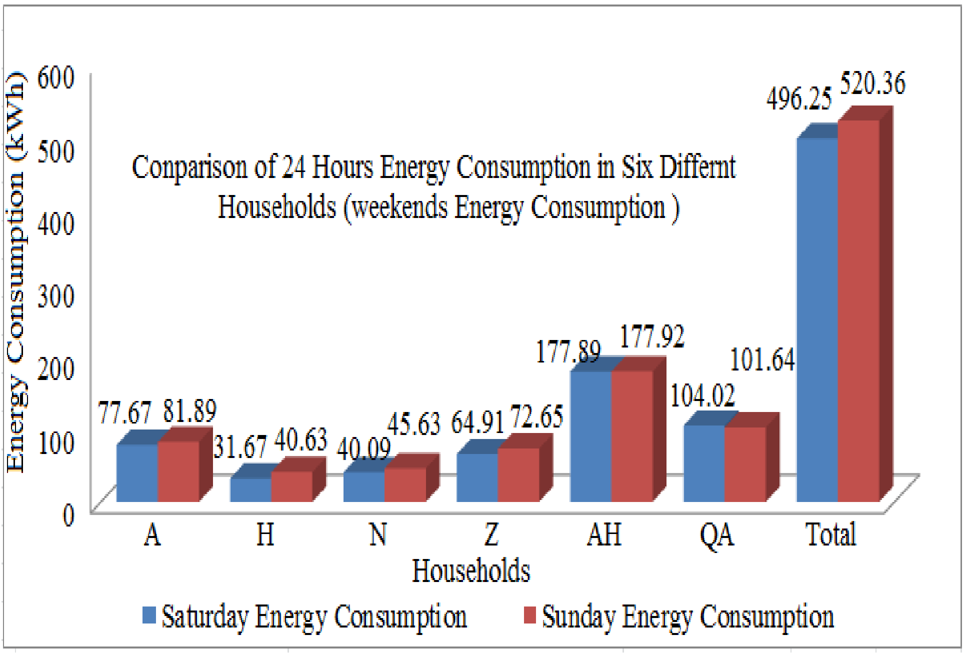


Figure 6.19: Comparison of the Total Energy Consumed on Weekends in the Six Different Selected High-Income Households

The total energy consumption for one day (24 hours) in six different households (A, H, N, Z, AH and QA) weekends respectively is shown in figure 6.19. The total energy consumed in one day in each household is greater on Sunday than on Saturday except in household QA where Saturday consumption is more than Sunday consumption. Generally, energy consumption is larger on Sunday than Saturday, due to the fact that the occupants of the houses are usually at home on Sundays to use electrical appliances for different purposes. Figure 6.20 depicts the comparison of the total energy consumed on weekdays and on weekends in the six selected households. It is obvious from the figure that the total energy consumption in the six households analyzed is greater on weekends than weekdays. This shows that more energy is consumed on weekend than weekdays.

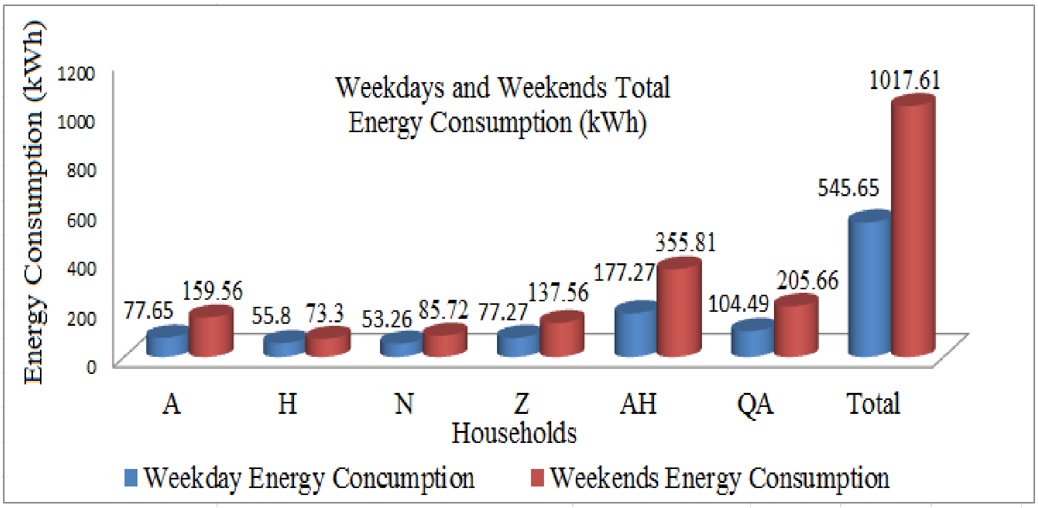


Figure 6.20 Comparison of the Total Energy Consumed on Weekdays and Weekends in Six Different High-Income Households in Johannesburg

6.4 Winter Energy Consumption Analysis

The appliances use in the winter period is slightly different from summer appliances hence, energy consumption also differs. Also, an increase in the use of hot water during winter contributes significantly to the increase in energy consumption. Usually, the high tariff hours in winter period are within 7 O'clock to 11 O'clock and 19 O'clock to 23 O'clock. Figure 6.21–6.38 show the energy consumption profiles of the six selected households in winter.

6.4.1 Weekdays Energy Consumption Analysis in Winter

The energy consumption profiles of the six selected households on weekdays are depicted in Figure 6.21 -6.26 respectively. Figure 6.21 shows the energy consumption profile of household A on weekday in the winter.

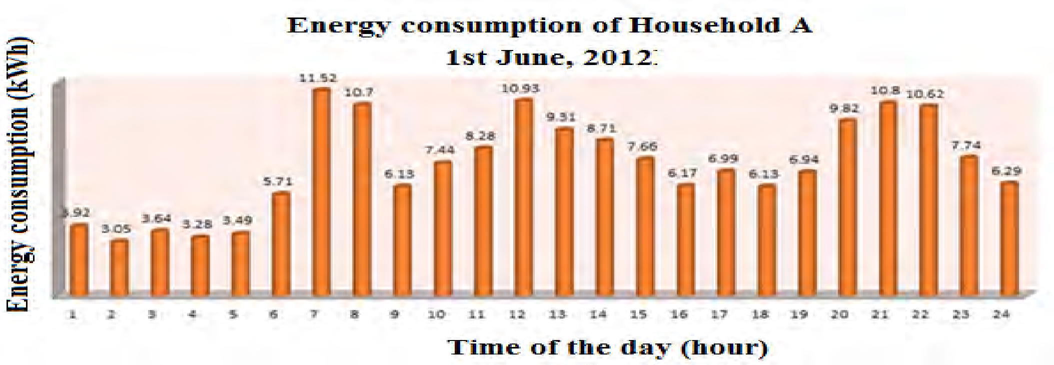


Figure 6.21: Household 'A' Weekday Energy Consumption Profile (winter)

There are three ON peak periods in the household 7 O'clock to 8 O'clock, 12 O'clock to 14 O'clock and 20 O'clock to 22 O'clock. The 7 O'clock to 8 O'clock peak hours are located at high tariff hours and may be affected by electric water heater, cooking appliances, electric heating appliance and electric kettle. The 12 O'clock to 14 O'clock peak hours are located at low tariff hours of the day and the energy consumption during this hour may probably due to an electric heating appliances, washing machine and tumble dryer. Also, the 20 O'clock to 22 O'clock peak periods are located at the high tariff hours and may be affected by heat circulation pump, electric heating appliances and cooking appliances. In addition, the energy consumption in 15 O'clock to 19 O'clock may be due to office appliances, electric heating appliances, air-conditioning or coffee machine. The 23 to 24 O'clock consumption may be affected from electric fence, electric heating appliances and heat circulation pump. The energy consumption of 1 to 6 O'clock may be allotted to cooking appliances, electric blanket, water heater, oven, lighting appliance or electric fence. Cleaning appliances and entertainment, office appliances (personal computer, modem, printer and hi-fi equipment) and electric heating appliances may be assigned to the 9 O'clock to 11 O'clock energy consumption of the household. Figure 6.22 depicts the energy consumption profile of household H.

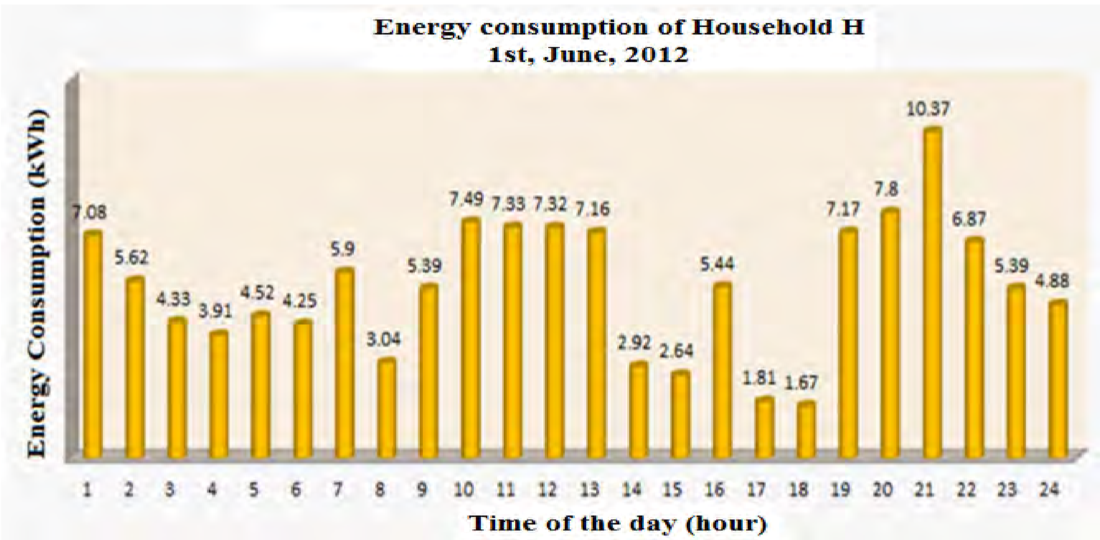


Figure 6.22: Household 'H' Weekday Energy Consumption Profile (winter)

The household has three peak periods 10 O'clock to 13 O'clock, 19 O'clock to 21 O'clock and 1 O'clock. The 10 O'clock to 13 O'clock on peak hours are located at high tariff periods and the energy consumption within these hours may probably affect from an electric heating appliances, washing machine, cleaning appliances, tumble dryer or office appliances (personal computer, modem, printer and hi-fi equipment). The 19 O'clock to 21 O'clock on peak period are located at high tariff hours and electric water heater, electric heating appliances, cooking appliances or heat circulation pump may contribute to the high energy consumption at these hours. The 1 O'clock the peak hour is located at the lower tariff house. The energy consumption may be due to lighting appliance, electric blanket, heating appliances and electric fence. The 22 O'clock to 24 O'clock may be due to electric heating appliances, electric blanket, electric fence, lighting appliance, water heater and probably office appliances. The 2 O'clock to 6 O'clock energy consumption may be allotted to electric fence, electric heating appliances, water heater, lighting appliance and electric blanket. Figure 6.23 depicts the energy consumption profile of household N.

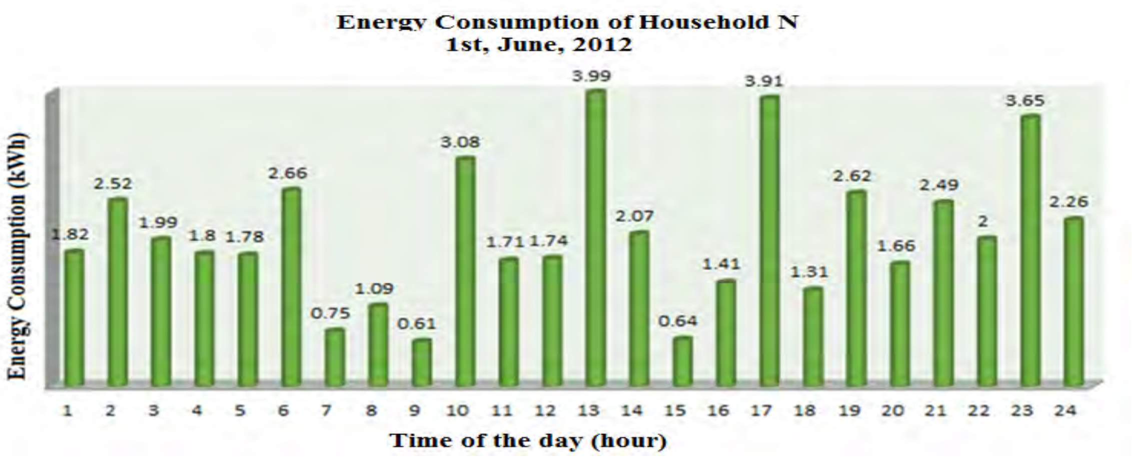


Figure 6.23: Household 'N' Weekday Energy Consumption Profile (winter)

There are three peak hours detected in Figure 6.23, 13 O'clock, 17 O'clock and 23 O'clock respectively. The 13 O'clock peak hour is located at low tariff hour and the consumption at the hour may be due to electric heating appliances, entertainment appliances and office appliances. The on peak hour at 17 O'clock is located at high tariff and the consumption may be allotted to cooking appliances, heating appliances and entertainment appliances. The 23 O'clock peak hour is located at a low tariff hour and the consumption may be probably affected from lighting, electric heating appliances, heat circulation pump, electric blanket or electric fence. In addition, the 10 O'clock energy consumption may be affected from swimming pool pump and probably cleaning appliances. The 6 O'clock energy consumption may be allotted to cooking appliances, electric water heater or electric kettle. The 2 O'clock energy consumption may probably cause by electric fence, electric blanket, lighting and probably heating appliances. The consumption at 3 O'clock to 5 O'clock may be due to electric blanket, electric fence, electric heating appliances and lighting appliance. The energy consumption at 7 O'clock to 9 O'clock may be due to refrigerator, electric fence and entertainment appliances. The 11 O'clock and 12 O'clock consumption may be due to cleaning appliances, electric heating appliances and entertainment appliances. The 18 O'clock to 22 O'clock consumption may be allotted to cooking appliances, electric heating appliances and lighting appliances. Figure 6.24 depicts energy consumption of household Z.

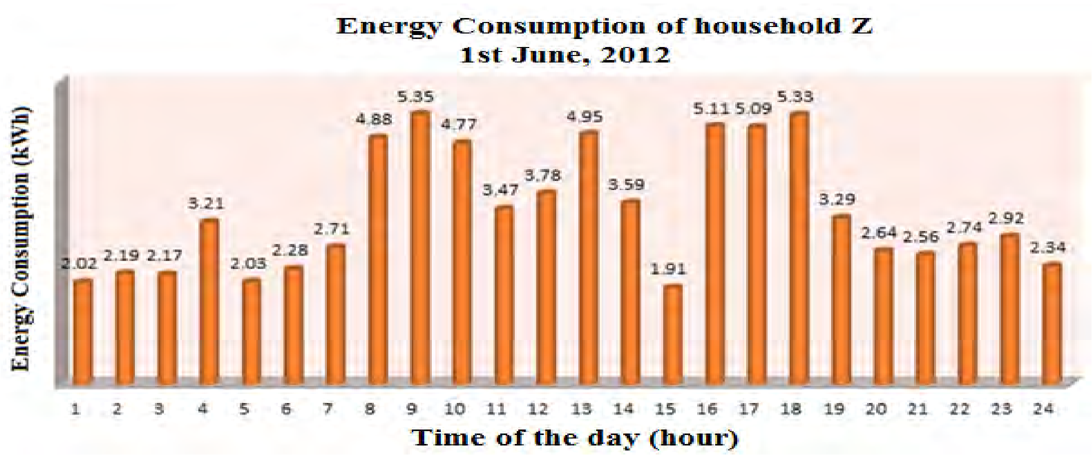


Figure 6.24: Household 'Z' Weekday Energy Consumption Profile (winter)

Three peak periods are detected in the household. The peak periods are: 8 O'clock to 10 O'clock, 13 O'clock and 16 O'clock to 18 O'clock. The 8 O'clock to 10 O'clock peak hours are located in low tariff hours and the energy consumption these hours may probably due to washing machine, water heater, tumble dryer, electric iron, cooking appliances and electric heating appliances. The 13 O'clock on peak hour is located at low tariff hours and the energy consumption at the hour may be allotted to electric heating appliances, office appliances (personal computer, modem, printer and hi-fi equipment) and entertainment appliance. The 16 O'clock to 18 O'clock peak periods are located at high tariff hours. The energy consumption at these hours may due to heating circulating pump, electric heating appliances, entertainment appliances and cooking appliances. In addition, 11 to 12 O'clock energy consumption may likely due to cleaning appliances, electric heating appliances, swimming pool, washing machine and tumble dryer. Furthermore, the consumption at 4 O'clock may probably due to water heater, electric blanket and lighting appliance. The 19 O'clock energy consumption may be due to cooking appliances, water heater, electric heating appliances, and entertainment appliances. The 5 O'clock to 7 O'clock energy consumption may be due to water heater, electric heating appliances, refrigerator and cooking appliances. The energy consumption at 20 O'clock to 3 O'clock may be allocated to cooking appliances, electric heating appliances, office appliances, lighting appliance, electric blanket and electric fence. Figure 6.25 depicts the energy consumption of household AH.

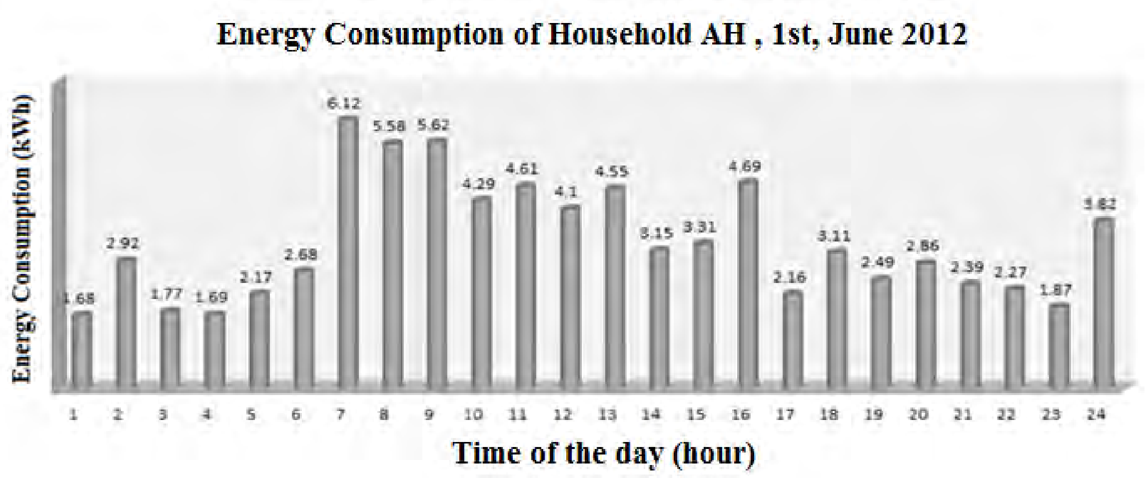


Figure 6.25: Household 'AH' Weekday Energy Consumption Profile (winter)

From the energy consumption profile shown in Figure 6.25, can be seen that the household energy consumption is at ON peak at 7 O'clock to 9 O'clock. The ON peak periods are located at high tariff hours and may likely due to electric water heater, cooking appliances, electric kettle or electric heating appliances. The consumption at 10 O'clock to 13 O'clock and may be likely affected from cleaning appliances, washing machine, electric heating appliances, entertainment appliances and office appliances. At 16 O'clock, the energy consumption may be due to cooking appliances, electric heating appliances, entertainment appliances and probably appliances. In addition, the 14 O'clock and 15 O'clock consumption may likely due electric heating appliances, entertainment appliances, office appliances, washing machine and tumble dryer. The energy consumption at 3 O'clock to 4 O'clock may be allotted to lighting appliance, electric fence, refrigerator and electric blanket. The consumption at 24 O'clock may likely due to an electric blanket, lighting appliance, electric fence and heat circulation pump. Figure 6.26 depicts the energy consumption profile of household QA.

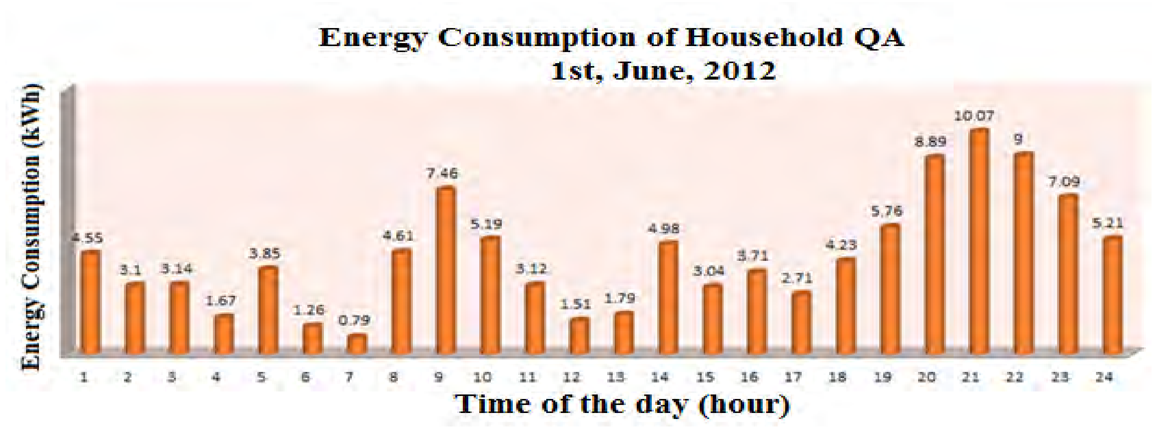


Figure 6.26: Household 'QA' Weekday Energy Consumption Profile (winter)

The household has its peak hours within the hour of 20 O'clock to 23 O'clock and 9 O'clock. The 20 O'clock to 23 O'clock peak periods are located in high tariff hours. The consumption at these hours may probably from cooking appliances, water heater, electric heating appliances, entertainment appliance and office appliances. The 9 O'clock ON peak hour is located at a high tariff hour and the consumption may be due to cleaning appliances, electric heating appliances, cooking appliances, washing machine and tumble dryer. In the same way, 10 O'clock energy consumption may likely due to cleaning appliances, cooking, electric heating appliances and entertainment appliances. The consumption at 11 O'clock and 13 O'clock may be allotted to swimming pool, entertainment appliances, office appliances and electric heating appliances. Furthermore, energy consumption at 14 O'clock to 16 O'clock may probably due to electric heating appliances, entertainment appliances and office appliances (personal computer, modem, printer and hi-fi equipment). 18 to 19 O'clock consumption may likely be from cooking appliances, electric heating appliances, or entertainment appliances. The consumption at 24 to 1 O'clock may likely due to lighting appliance, electric blanket, electric fence and electric heating appliances.

6.4.2 Weekends Energy Consumption Analysis

Then energy consumption profiles figures 6.27 to 6.38 depict the energy consumption of six different high-income households on weekends (Saturday and Sunday) during the winter period.

6.4.2.1 Saturday Energy Consumption Analysis

The energy consumption profile in figure 6.27 depicts the twenty-four hours energy consumption of household A on Saturday.

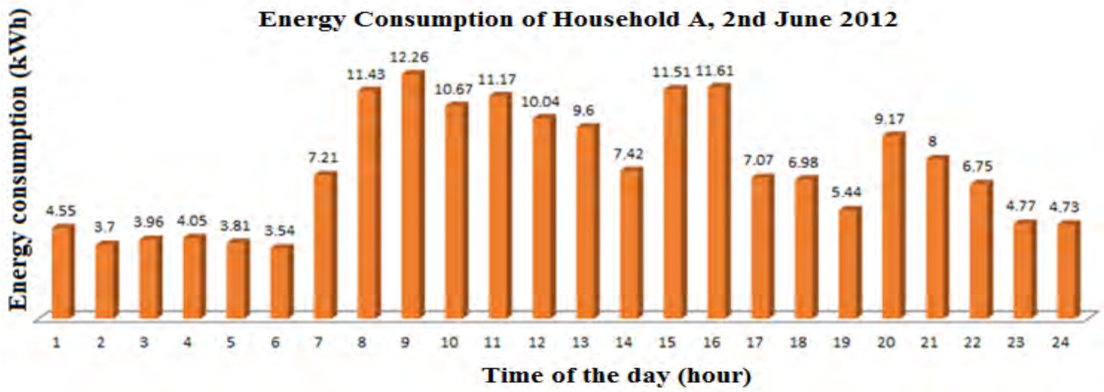


Figure 6.27: Household 'A' Saturday Energy Consumption Profiles (Winter)

In the household, two on peak periods are noticed. The peak periods are; 8 O'clock to 12 O'clock, 15 O'clock to 16 O'clock. The 8 O'clock to 12 O'clock on peak hours are located in high tariff hours on weekends. And the consumption may be due water heater, electric heating appliances, cooking appliances, cleaning appliances, electric iron, washing machine, tumble dryer and entertainment appliances. In addition, 15 O'clock to 16 O'clock peak periods is located at high tariff hours, on weekends and the consumption may probably due to office appliances (personal computer, modem, printer and hi-fi equipment), heat circulation pump, swimming pool pump and cooking appliances. The 20 to 21 O'clock consumption may likely be from cooking appliance, electric kettle, water heater or entertainment appliances. Furthermore, the 14 O'clock energy consumption may due mainly to an electric heating appliances, office appliances (personal computer, modem, printer and hi-fi equipment), tumble dryer or washing machine. The 17 O'clock to 18 O'clock consumption may be mostly from cooking appliance and entertainment appliances. The consumption at 23 O'clock to 1 O'clock may likely be from electric blanket, lighting, electric fence, heat circulation pump or oven. The 2 O'clock to 6 O'clock may be from electric blanket, lighting, electric fence and electric heating appliances. The energy consumption at 7 O'clock may be from water heater, and electric heating appliances. Figure 6.28 depicts the energy consumption profile of household H on Saturday in winter

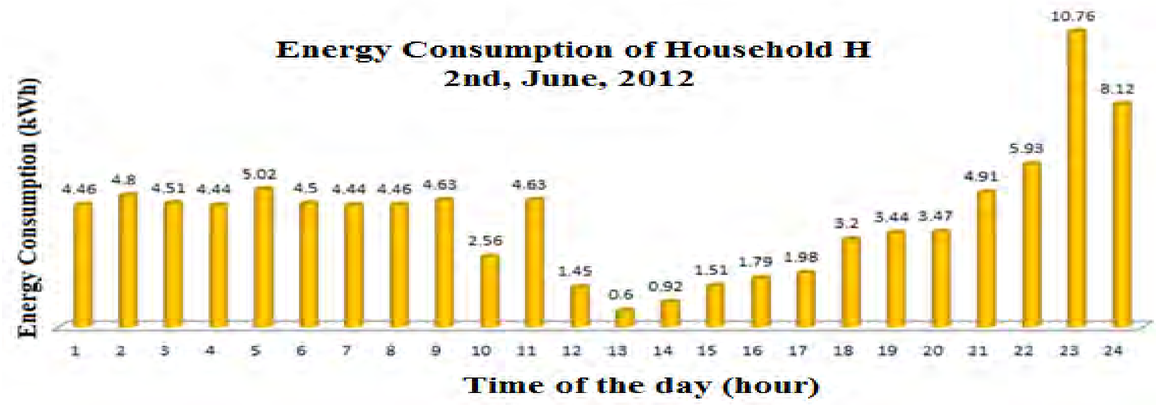


Figure 6.28: Household ‘H’ Saturday Energy Consumption Profiles (winter)

From the household energy consumption analysis, only one peak period is noticed. The peak period is within the hours of 23 O’clock and 24 O’clock. The consumption at this period may be from electric blanket, electric fence, lighting, appliances and electric heating appliances. In addition, 21 O’clock and 22 O’clock energy consumption may probably due water heater, electric heating appliances and electric fence. The 5 O’clock consumption may probably from water heater, electric blanket or electric heating appliances. The linear energy consumption of 6 O’clock to 9 O’clock may be due to cleaning appliance, cooking appliances, electric kettle or and heating appliances. The 11 O’clock energy consumption may be allotted to cleaning appliances, office appliances, entertainment appliances, electric heating appliances and swimming pool pump. 1 O’clock to 4 O’clock energy consumption may likely due to electric blanket, electric heating appliances, lighting appliances, and oven. Energy consumption at 5 O’clock may be due to water heater, electric heating appliances and washing machine. Figure 6.29 presents energy consumption of household N on Saturday in winter.

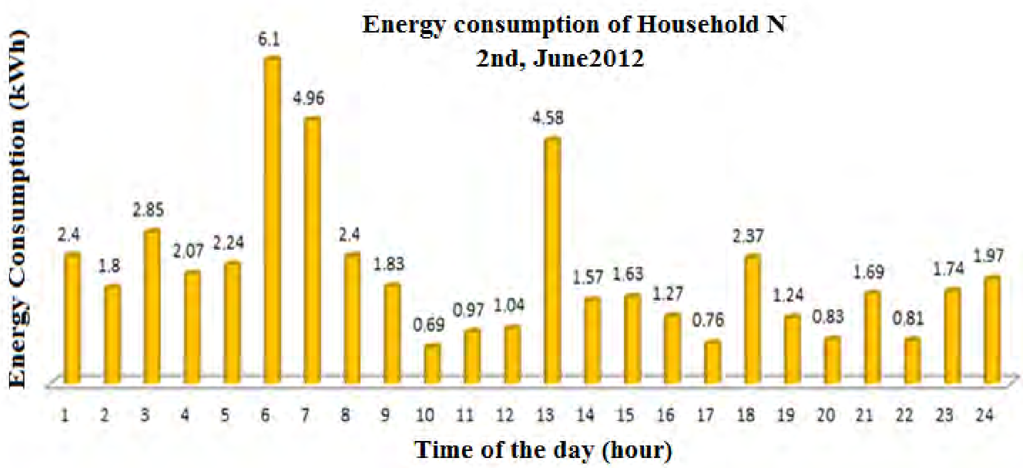


Figure 6.29: Household ‘N’ Saturday Energy Consumption Profiles (winter)

The household recorded two on peak periods. They are 6 O'clock to 7 O'clock and 13 O'clock respectively. The two ON peak periods are located in low tariff and high tariff hours respectively. The 6 to 7 O'clock ON peak hours may probably be from electric water heater, electric heating appliances and cooking appliances. At 13 O'clock, the energy consumption may be from washing machine, tumble dryer and entertainment appliances. The consumption at 3 O'clock to 5 O'clock may probably be from electric fence, electric heating appliances, refrigerator and lighting appliance. The 8 o'clock and 9 O'clock energy consumption may due to cleaning appliances, cooking appliances and electric heating appliances. The consumption within the hour of 10 O'clock and 12 O'clock may due to refrigerator or entertainment appliances. The 14 O'clock to 16 O'clock consumption may be allotted to entertainment appliances, office appliances and refrigerator. The consumption at 18 O'clock may likely be from cooking appliances, electric heating appliances, entertainment appliances and office appliances. The 23 O'clock to 1 O'clock energy consumption may be allotted to electric blanket, electric fence lighting appliances and electric heating appliances. Figure 6.30 depicts the energy consumption profile of household Z on Saturday in winter.

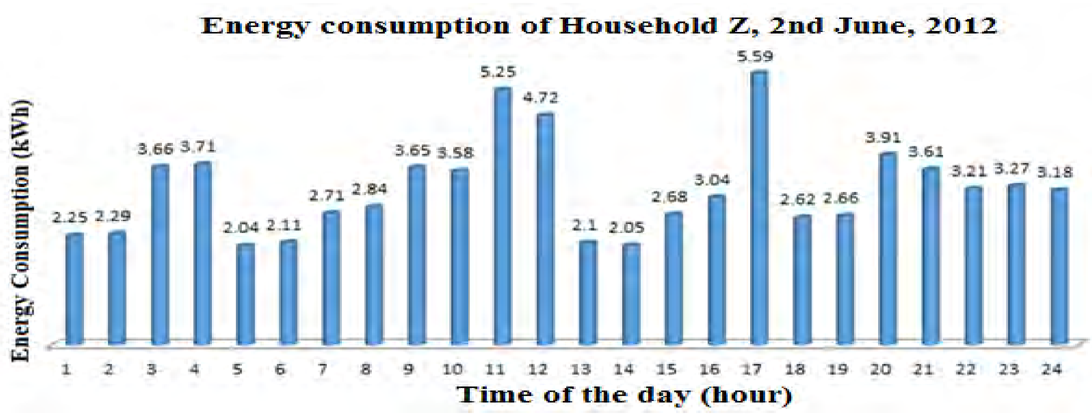


Figure 6.30: Household 'Z' Saturday Energy Consumption Profiles (winter)

From the hourly energy consumption profile in figure 6.30, two on peak periods are detected, 11 o'clock to 12 O'clock and 17 O'clock. The two peak periods are located in high tariff hours on weekends. The 11 o'clock and 12 O'clock energy consumption may probably be from washing machine, tumble dryer, electric heating appliances and cleaning appliances. Also, 17 O'clock energy consumption may be probably due to cooking appliances, electric heating appliances and water heater. In addition, 3 to 4 O'clock energy consumption may likely due to lighting appliance, electric fence, electric blanket or heat circulation pump. Furthermore, 9 O'clock and 10 O'clock energy consumption may be from cooking appliances, cleaning appliances and electric heating appliances. The 20 O'clock to 24 O'clock energy consumption are likely due to cooking appliances, entertainment appliances, office appliances, electric heating appliances, electric fence and lighting appliance. 1 O'clock and 2 O'clock energy consumption may be due to electric blanket lighting appliance and heat circulation pump. The 13 O'clock to 16 O'clock consumption may be due to electric heating appliances, cooking appliances, entertainment appliances and probably office appliances. The 18 O'clock and 19 O'clock energy consumption may due to cooking appliances, electric heating appliances and entertainment appliances. Figure 6.31 shows the energy consumption profile of household AH on Saturday in winter.

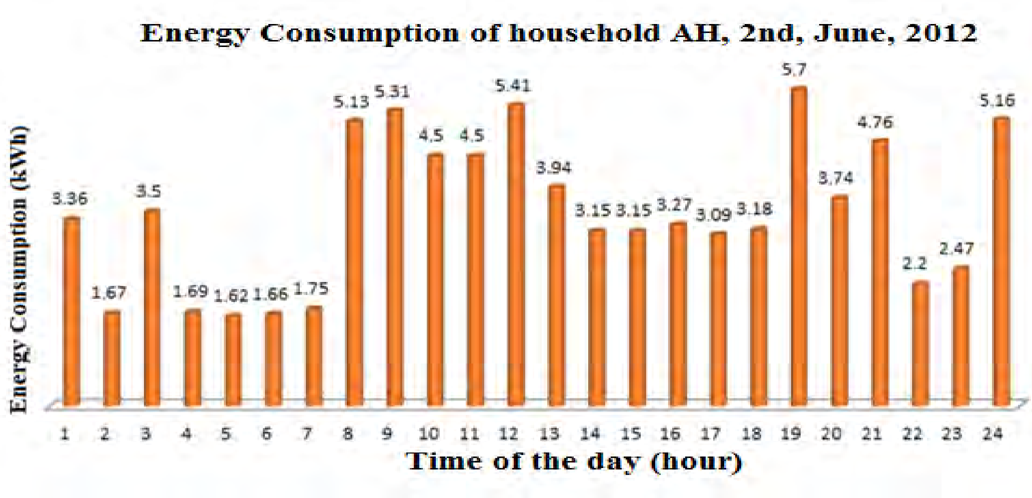


Figure 6.31: Household 'AH' Saturday Energy Consumption Profiles (winter)

The household recorded four on peak periods. The periods are 8 o'clock and 9 O'clock, 12 O'clock, 19 O'clock, and 24 O'clock respectively. The ON peak periods except the peak period at 24 O'clock are located in a high tariff period. The 24 O'clock ON peak hour is located in a low tariff hour. The 8 O'clock and 9 O'clock ON peak hours may likely be from electric water heater, electric heating appliances, washing machine and tumble dryer. The energy consumption at 12 O'clock may probably be from entertainment appliances, electric heating appliances, electric kettle and office appliance (personal computer, modem, printer and hi-fi equipment). Also, the consumption at 19 O'clock may be from cooking appliance, electric kettle or water heater. In addition, the 24 O'clock energy consumption may probably from, heat circulation pump, lighting appliance, refrigerator, electric fence, electric blanket and electric heating appliances. The linear consumption within the hour of 4 O'clock to 7 O'clock may be due to refrigerator, electric fence and electric blanket. In the same way the linear consumption within the hours of 14 O'clock and 18 O'clock may be allotted to cooking appliances, electric heating appliances, entertainment appliance and office appliance. The 21 O'clock energy consumption may be due cooking appliances, electric heating appliances and entertainment appliances. The 22 O'clock and 23 O'clock may be due to entertainment appliances, electric heating appliances, lighting appliances and office appliances. The energy consumption profile of household QA is represented in figure 6.32.

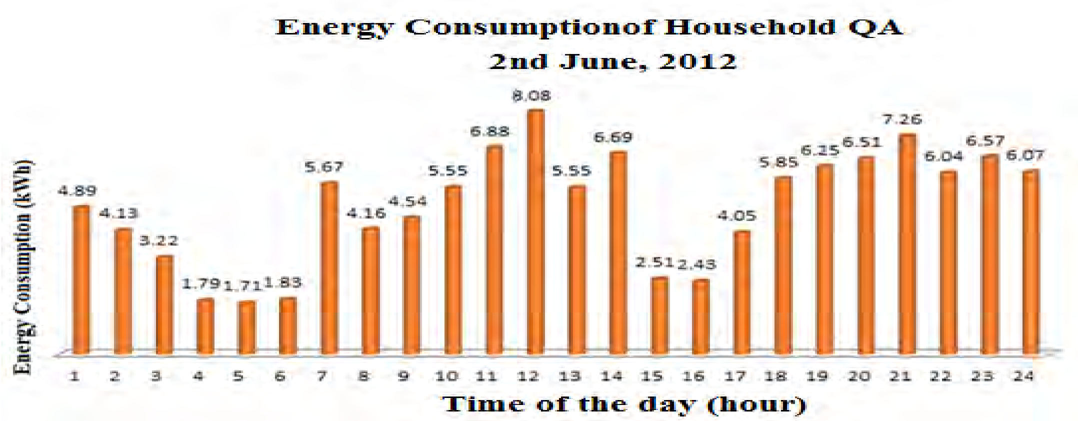


Figure 6.32: Household 'QA' Saturday Energy Consumption Profiles (winter)

The household peak hour is at 12 O'clock and 21 O'clock respectively, the peak hours are located at high tariff and low tariff hours respectively. The consumption at 12 O'clock may probably cause by electric heating appliances, office appliances (personal computer, modem, printer and hi-fi equipment) and entertainment appliances. In addition, the consumption at 21 O'clock may be due to cooking appliances, electric heating appliances, entertainment appliances and office appliances. The 10 O'clock and 11 O'clock energy consumption may be from washing machine, electric heating appliances and tumble dryer. The energy consumption at 7 o'clock may likely be from cooking appliances, electric heating, water heater and electric kettles. The 8 O'clock and 9 O'clock energy consumption may be from cooking appliances, electric heating appliances, cleaning appliances, and office appliances. The consumption at 13 O'clock and 14 O'clock may be due to entertainment appliances, office appliances (personal computer, modem, printer and hi-fi equipment) and electric heating appliances. Furthermore, the 18 O'clock to 20 O'clock, energy consumption may probably affect from cooking appliances, water heater, electric kettle and electric heating appliances. The 22 O'clock to 24 O'clock consumption may likely cause by lighting, electric heating appliances, electric blanket and electric fence. The energy consumption within the hours of 4 O'clock to 6 O'clock may be allotted to water heater, electric blanket, electric fence, refrigerator or electric heating appliances. Finally, 1 O'clock and 2 O'clock may probably be from lighting, electric blanket, electric fence and heat circulation pump.

6.4.2.2 Sunday Energy Consumption Analysis

Then energy consumption profiles in Figure 6.33 to 6.38 illustrate hourly energy consumption of the six selected households on Sunday during winter period. Figure 6.33 depicts the energy consumption profile of household A.

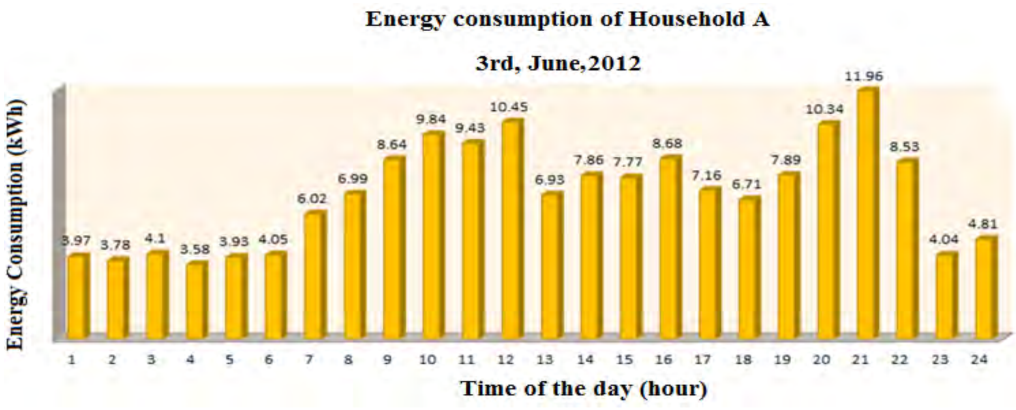


Figure 6.33: Household 'A' Sunday Energy Consumption Profiles (winter)

The energy consumption of the household has two peak periods; they are 10 O'clock to 12 O'clock and 20 to 21 O'clock respectively. The peak periods are located at high tariff hours. 10 O'clock to 12 O'clock energy consumption is probably due to cooking appliances, electric heating appliances, entertainment appliances, cleaning appliances and office appliances (personal computer, modem, printer and hi-fi equipment). The 20 O'clock to 21 o'clock energy consumption may likely due to cooking appliances, water heater, electric heating, entertainment appliances and office appliances. In addition, 23 O'clock and 24 O'clock energy consumption might probably cause by electric blanket, electric heating appliances, lighting and electric fence. The 16 O'clock energy consumption may be due to cooking appliances, electric heating appliances, entertainment appliances, and probably office appliances. Furthermore, the energy consumption within the hours of 17 O'clock and 19 O'clock might probably cause by cooking appliances, electric heating appliances, water heater, entertainment appliances and office appliances. The 13 O'clock to 15 O'clock energy consumption may probably cause by entertainment appliances, electric heating appliances, office appliances, water heater and swimming pool. Washing machine, tumble dryer, electric iron, water heater or electric heating appliances and cooking appliances may be responsible for 7 O'clock to 9 O'clock energy consumption of the household. The 1 O'clock to 6 O'clock energy consumption in the household may be due to electric fence, electric blanket, electric heating appliances, refrigerator and probably heat circulation pump. Figure 6.34 depicts Sunday energy consumption of household H in winter.

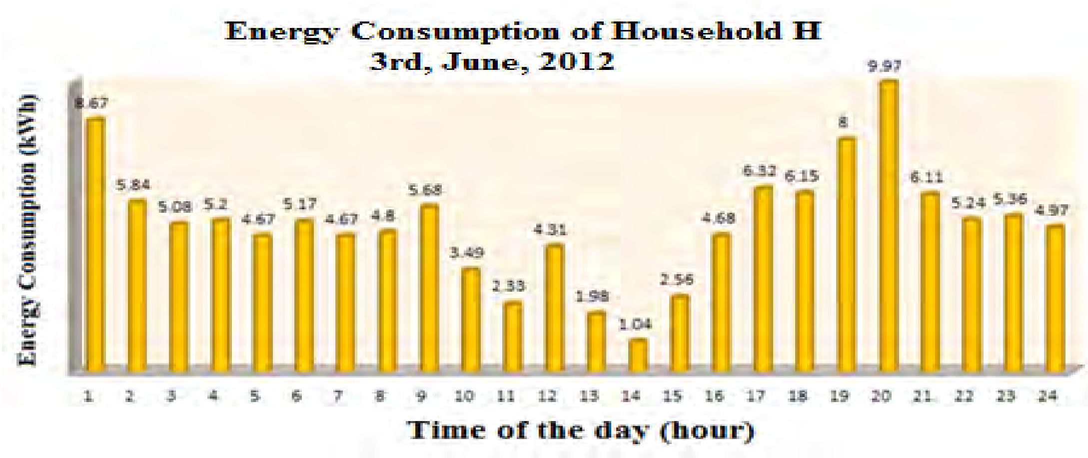


Figure 6.34: Household 'H' Sunday Energy Consumption Profiles (winter)

The energy consumption of a typical household H recorded two ON peak periods; 19 O'clock to 20 O'clock and 1 O'clock. The 19 o'clock to 20 O'clock ON peak period is located at high tariff hours on weekends. The energy consumption at these hours may be due to cooking appliances, electric heating appliances, lighting appliance, entertainment appliance, and office appliances. The 1 O'clock ON peak period is located at low a tariff hour and the energy consumption on this hour may be due to electric fence, electric blanket, electric heating appliances and lighting. In addition, 16 O'clock to 18 O'clock energy consumption might likely cause by cooking appliances, electric heating appliances, water heater, entertainment appliances and office appliances. The 12 O'clock consumption might be affected from office appliances (personal computer, modem, printer and hi-fi equipment), refrigerator, electric heating appliances, entertainment appliances and swimming pool. The energy consumption at 9 O'clock to 11 O'clock might due to washing machine, tumble dryer, cleaning appliances, and electric heating appliances. Furthermore, 5 O'clock to 8 O'clock energy consumption might probably cause by water heater, electric blanket, heat circulation pump, coffee machine, refrigerator and electric heating appliances. The 21 O'clock to 23 O'clock energy consumption may be allotted to cooking appliance, entertainment appliances, office appliances, refrigerator and electric heating appliances. Energy consumption within the hours of 2 O'clock to 4 O'clock might likely be from electric blanket, electric fence, electric heating appliances, lighting appliance, refrigerator and probably water heater. The Figure 6.35 presents the Sunday energy consumption profile of household N in winter.

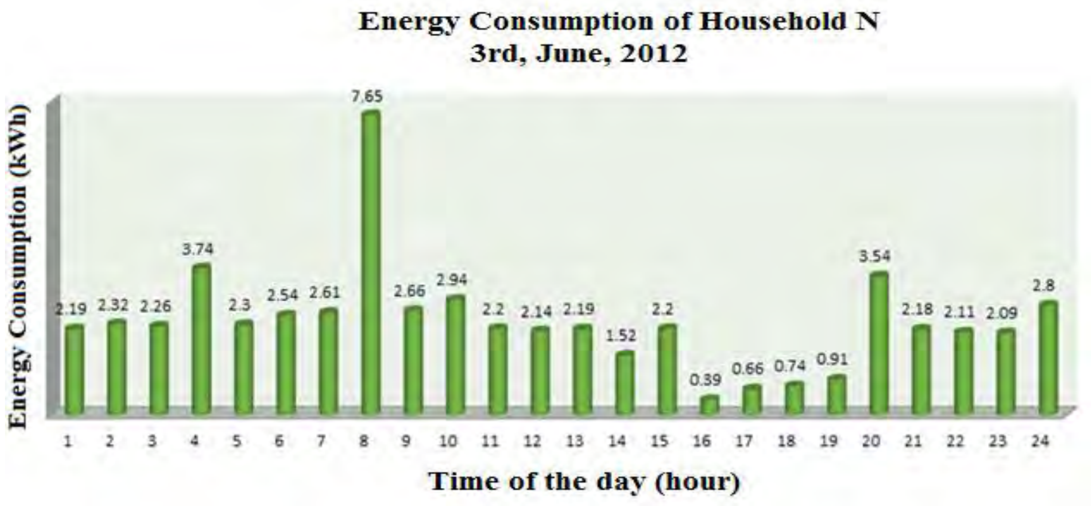


Figure 6.35: Household 'N' Sunday Energy Consumption Profiles (winter)

The household recorded its ON peak energy consumption at 8 O'clock; the hour is located at high tariff hour on weekends. Electric water heater, cooking appliances and electric heating appliances might likely responsible for the ON peak hour energy consumption. The 9 O'clock to 15 O'clock household energy consumption may be due to cleaning appliances, entertainment appliances, office appliances, refrigerator and electric heating appliances. The energy consumption at 16 O'clock to 19 O'clock may mainly due to refrigerator and lighting appliances probably at this period the occupant are not at home to on electrical appliances. The 20 O'clock energy consumption may probably due to cooking appliances, refrigerator, entertainment appliances and electric heating appliances. The energy consumption within the hours of 21 O'clock and 23 O'clock may be due to lighting appliance, refrigerator and electric heating appliances. The 24 O'clock to 3 O'clock energy consumption may be from electric heating appliances, electric blanket, electric fence and probably lighting appliance. The energy consumption at 4 O'clock might likely due to electric water heater and washing machine or tumble dryer. The 5 O'clock to 7 O'clock energy consumption may be from electric heating appliances, electric kettle and cooking appliances. The energy consumption of household Z on Sunday is depicted in Figure 6.36.

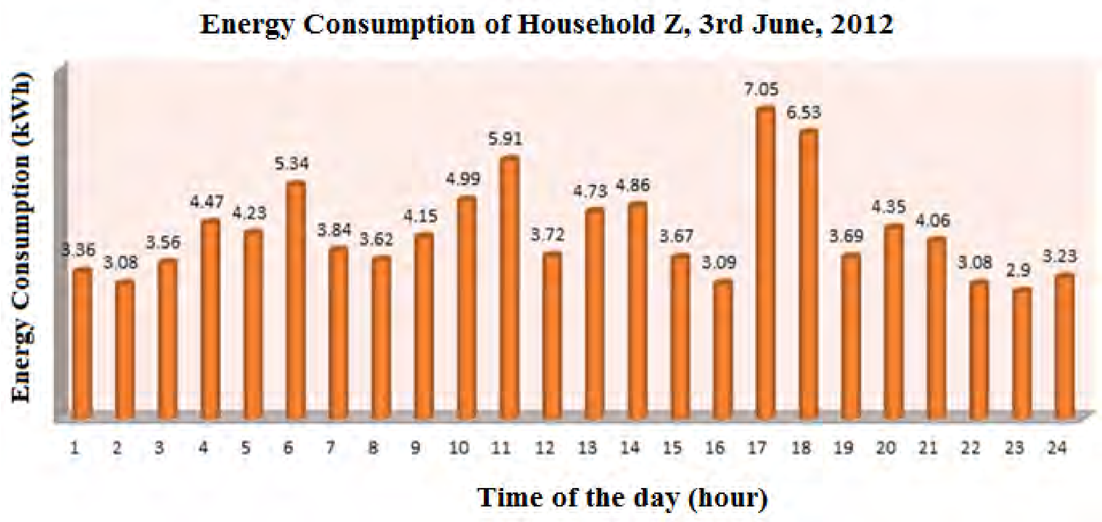


Figure 6.36: Household ‘Z’ Sunday Energy Consumption Profiles (winter)

The household recorded three on peak periods. The ON peak periods are 6 O’clock, 11 O’clock and 17 O’clock to 18 O’clock. The 6 O’clock on peak period is located at low tariff hour while 11 O’clock, 17 O’clock and 18 O’clock are located at high tariff hours respectively. The 6 O’clock peak consumption might likely cause by water heater, electric heating appliances or cooking appliances. 11 O’clock energy consumption might probably be from cleaning appliances, electric heating appliances, entertainment appliances or electric kettle, while the 17 O’clock and 18 O’clock energy consumption may likely affect from cooking appliances, electric heating appliances, entertainment appliances and office appliances. In addition, 12 O’clock and 14 O’clock energy consumption might be due to office appliances (personal computer, modem, printer and hi-fi equipment), entertainment appliances, electric heating appliances, coffee machine or swimming pool pump. The 15 O’clock and 16 O’clock energy consumption may be allotted to electric heating appliances, refrigerator, cooking appliances and swimming pool. Entertainment appliances, office appliances, cooking appliances, electric heating appliances and coffee machine might be responsible for the 19 O’clock to 21 O’clock energy consumption. The 9 O’clock and 10 O’clock consumption might likely be from washing machine, cleaning appliances, water heater, electric heating appliances or tumble dryer. Energy consumption at 7 O’clock and 8 O’clock may be due to electric heating appliances, cooking appliances and electric kettle. The 4 O’clock to 5 O’clock energy consumption in the household may probably due to electric heating appliances, refrigerator and water heater. The 22 O’clock to 24 O’clock energy consumption may be due to an electric blanket, lighting appliance, electric fence and electric heating appliances. The 1 O’clock to 3 O’clock energy consumption may be due to electric fence, electric heating appliances, electric blanket and lighting appliance. Figure 6.37 depicts the Sunday energy consumption profile of household AH in winter.

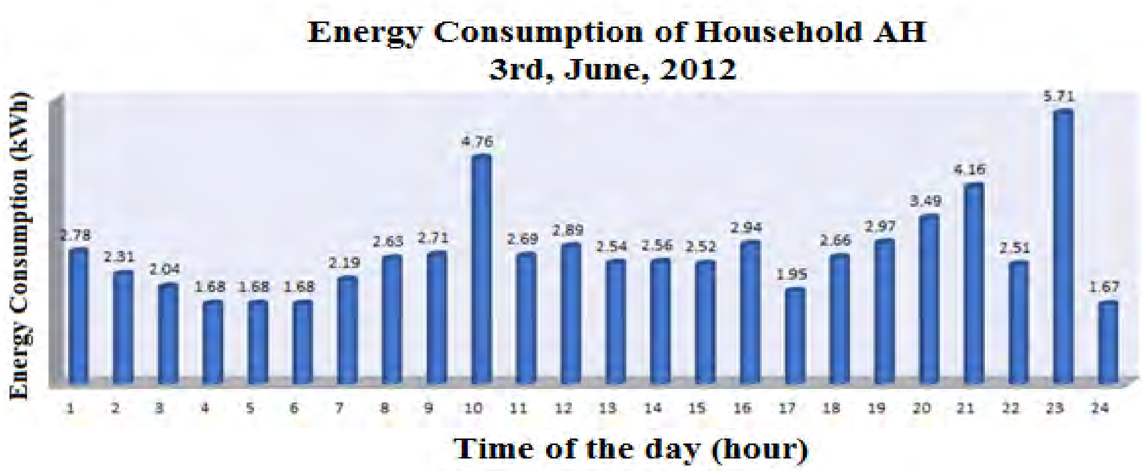


Figure 6.37: Household 'AH' Sunday Energy Consumption Profiles (winter)

10 O'clock and 23 O'clock are the two ON peak hours noticed in the household. The two peak hours are located in high tariff hours on weekends. Water heater, cooking appliances or electric heating appliances may likely cause the 10 O'clock energy consumption, while 23 O'clock energy consumption may be due to cooking appliances, electric water heater, electric kettle, entertainment appliances or office appliances (personal computer, modem, printer and hi-fi equipment). The energy consumption at 11 O'clock to 16 O'clock might probably due to entertainment appliances, refrigerator, swimming pool, office appliances and electric heating appliances. The 17 O'clock and 19 O'clock energy consumption may be due to cooking appliances, electric heating appliances, refrigerator, entertainment appliances, office appliances or swimming pool. The 20 O'clock to 22 O'clock energy consumption may be allotted to refrigerator, entertainment appliances, office appliances electric iron and electric heating appliances. The 24 O'clock to 2 O'clock energy consumption may be allotted to refrigerator, electric fence, electric blanket, lighting appliances and electric heating appliances. The 7 O'clock to 9 O'clock energy consumption may be due to washing machine, electric heating, tumble dryer or cleaning appliances. The Sunday energy consumption of household QA in winter is depicted in Figure 6.38.

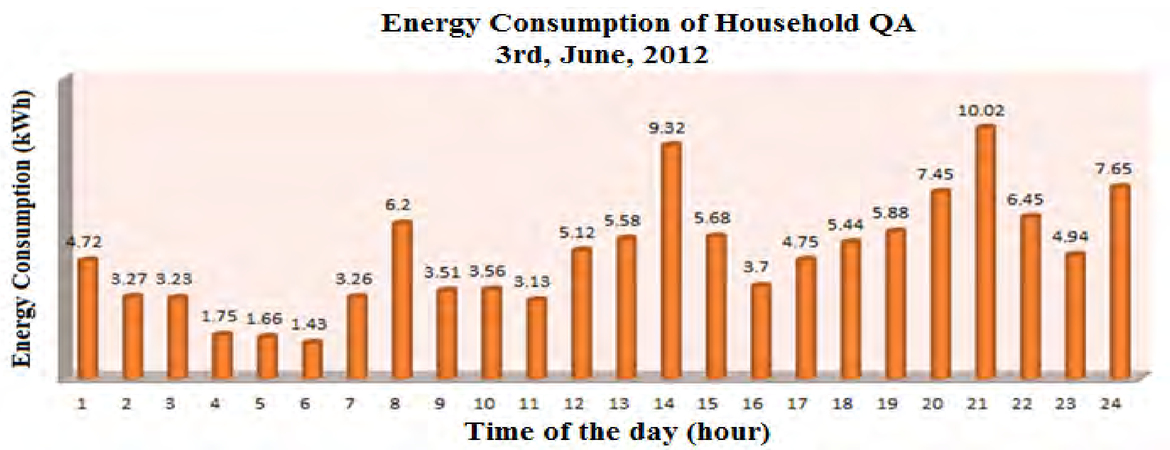


Figure 6.38: Household 'QA' Sunday Energy Consumption Profiles (winter)

The household has three ON peak periods. The ON peak periods are 14 O'clock and 20 O'clock to 21 O'clock and 24 O'clock. The periods are located in high and low tariff hours. The energy consumption at 14 O'clock may be due to entertainment appliances, office appliances, electric heating appliances and swimming pool. The 20 O'clock and 21 O'clock energy consumption may probably due to cooking appliances, electric heating appliances, entertainment appliances and office appliance. The energy consumption at 24 O'clock may probably due to refrigerator, electric oven, electric fence, electric blanket, lighting appliance and electric heating appliances. Also, 1 O'clock to 3 O'clock energy consumption may be due to an electric blanket, electric heating, lighting appliances, electric oven or heat circulation pump. The energy consumption within the hour of 4 O'clock and 6 O'clock may be due to refrigerator, electric blanket, electric fence, lighting appliance and heat circulation pump. The energy consumption at 7 O'clock and 8 O'clock may due to refrigerator, water heater, cooking appliances and electric heating appliances. The 9 O'clock to 11 O'clock household energy consumption may be due to refrigerator, washing machine and tumble dryer. In addition, 12 O'clock and 13 O'clock consumption may be affected from washing machine, electric heating appliances, entertainment appliances and tumble dryer. The 15 O'clock energy consumption may be allotted to entertainment appliances, swimming pool, office appliances and electric heating appliances. The energy consumption at 18 O'clock to 19 O'clock may likely due to cooking appliances, electric kettle, office appliances, entertainment appliances, swimming or electric heating appliances. The energy consumption at 22 O'clock and 23 O'clock may be due to refrigerator, electric heating appliances, electric fence, electric blanket entertainment appliances, office appliances or heat circulation pump.

6.4.2.3 Comparison of Energy Consumption in Six Different Households on Weekdays and Weekend in winter

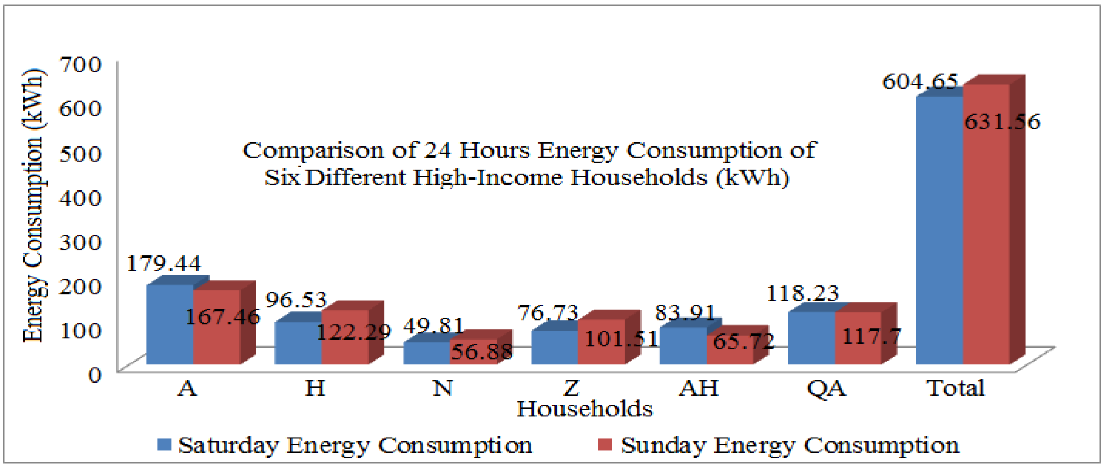


Figure 6.39: Total Energy Consumed on Weekdays and Weekends (Saturday and Sunday) in Six Different High-Income Households (winter)

The total energy consumption for one day (24 hours) for six different households (A, H, N, Z, AH and QA) is shown in figure 6.39. The total electricity consumed per day on weekend in each household is greater on Sunday than Saturday except in household QA where Saturday consumption is more than Sunday, this may due to the size of the household, appliance types, time of usage and their duration of usage.

Generally, energy consumption is larger on Sunday than Saturday. This is due to the fact that the occupants of the houses are usually at home on Sundays to use electrical appliances for a longer period of time than Saturday. The comparison of 24 hours energy consumption in six different households during weekday and weekends is shown in Figure 6.40. From the figure it is obvious that the total energy consumed on weekends in the six households is greater than the total energy consumed on weekdays in the households. This shows that more energy is consumed during weekends than weekdays, because the occupants are usually present during weekends to use more electrical appliances than weekdays. The Figure 6.40 summarizes the total energy consumption on weekdays and weekends.

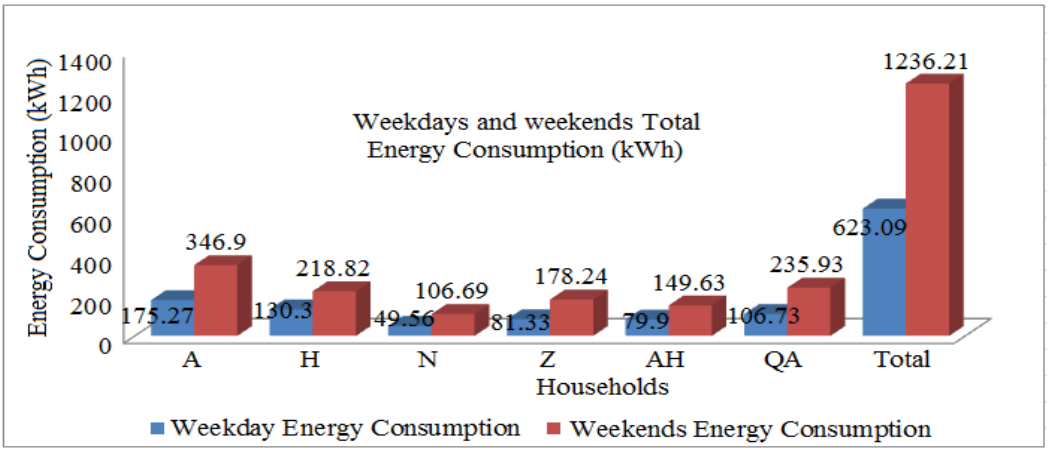


Figure 6.40: Comparison of Total Energy Consumption on Weekday and on Weekends (winter)

The Figure 6.41 summarizes the total energy consumption in the six different selected households in summer and in winter. Generally, from the analysis, energy consumption is larger during winter than summer. This is due to the use of more heating appliances in winter than in summer.

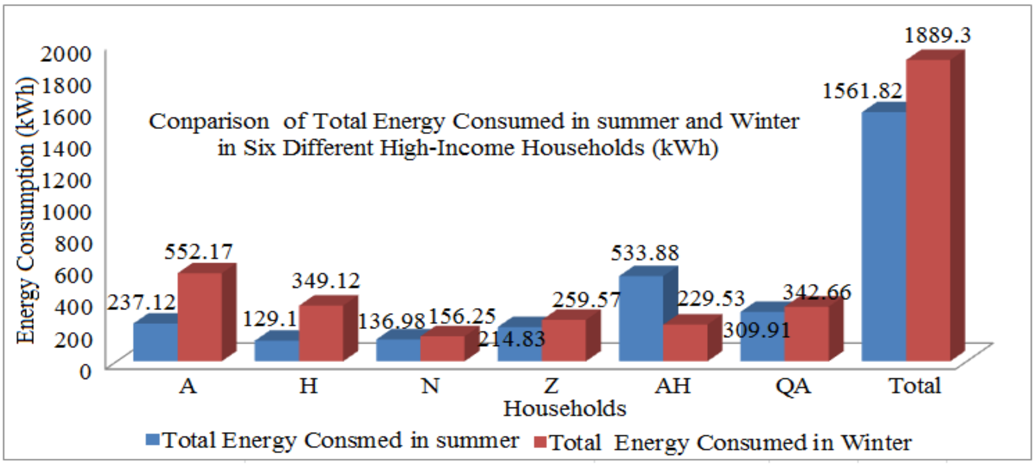


Figure 6.41: Comparison of Total Energy Consumption on winter and summer

6.5. Summary

This chapter has described the energy consumption profiles of six different households based on the high-income household consumption data. The different smart appliance is assumed for different hours of energy consumption. Comparison is made between weekday energy consumption of the six households and weekend's consumption. It was drawn out that electricity consumption is usually higher on weekend than weekdays. Finally, it was deduced that energy consumption is usually larger in winter than summer due to the use of more heating appliances in the winter. The following chapter describes the load profile analysis of some selected domestic appliances based on their energy consumption computed from their different power rating and time of usage.

CHAPTER 7

Energy Consumption and Cost Analysis of Some Selected Domestic Appliances

Introduction

Chapter six analyses hourly energy consumption profiles of six different high-income households in different time of the day (weekdays and weekends) and different season of the year (winter and summer) and comparison was made. For the purpose of proper monitoring and identification of the individual appliance based on their energy consumption, also provide a convenient means of reducing residential buildings energy consumption, it is essential to investigate individual appliance energy consumption patterns. Also, for customers to know how much is spent on running individual appliance in the household and which appliance contributes mostly to the household monthly energy bills, cost analysis on each appliance is also discussed in this chapter.

7.1 Classification of Domestic Appliances

Electrical appliances are an electricity-consuming item in a typical household. The load of a particular electrical appliance is the amount of electricity it requires to operate at any given moment. The more the number of appliances, the accurate the load profile will be. In analyzing household appliances, a multiple identical appliances that operate for a long period of time, can be listed once and indicate the quantity in the next column to it then multiply by the ratings. The result can be used for monitoring and identification purposes. Summing up the load values (in Watts) of all the appliances in the household will yield the total household connected loads, which is the maximum amount of power require by the household to operate all connected appliances at once. The energy consumption profile analysis of some selected domestic appliances on weekdays is shown in the table 7.1. Every appliance in the household should be logged into the profile. The average daily electricity consumption of the household will be known when properly completed. Beside the appliance identification, combining these data, the impact of these appliances on the electricity consumption as a whole and in comparison with other appliances will also be known. Apart from the fact that the use of certain appliances is common to a particular weather condition, weather condition also has significant impact on the energy consumption of domestic appliances; therefore, the analysis is going to be considered based on summer and winter. Generally, domestic appliances can be classified based on their functionality and usage patterns. The Functional classifications include the following categories:

- Entertainment and
- Lighting appliances;
- Kitchen appliances;
- Heating and cooling appliances;
- Cleaning appliances;
- Office appliances.

Entertainment appliances include television, dstv decoder, and swimming pool pump. Lighting appliances are bulbs (fluorescent and incandescent). Kitchen appliances are refrigerator, electric stove, electric frying pan, oven, microwave, cordless kettle and slow cooker. Heating and cooling appliances are electric water heater (Geyser), electric blanket, heating circulation pump, electric heating, electric heater and air-conditioning. Cleaning appliances are vacuum cleaner, dishwasher, washing machine, tumble dryer, electric iron and sewing machine. Office appliances are personal computer, modem, printer and Hi-Fi equipment. Classification based on the consumption or usage pattern depends on the customers' behaviour and it includes the following categories:

- Adjustable appliances;
- Non-adjustable appliances;

Adjustable appliances are appliances that can shift or adjust their usage or consumption from one period to another. Consumers can shift the usage of such appliances from on peak periods to off peak periods for the purpose of energy consumption cost reduction and consumption balancing. Appliances with adjustable consumption include water heaters, washing machines, dishwashers, tumble dryers etc.

Non-adjustable appliances are those appliances that cannot shift their usage or consumption. Non-adjustable appliances are entertainment appliances, kitchen appliances, cleaning appliances, heating and cooling appliances.

7.2 Analysis of Appliance Energy Consumption Patterns

The fundamental part of energy management and the first step in improving energy efficiency is an electrical load analysis. An electrical load analysis is itemizing electricity- consuming appliance in a household and estimate how much electricity each appliance use. The analysis may be per day or per month, but for the purpose of this paper it is considered in per day. Load Profile Analysis is the monitoring of electric consumption and appliance characteristics on a real-time basis. Electrical load analysis is advantageous to both consumers and utilities. Electrical loads analysis, manages energy consumption and costs. Also, is useful in load forecast, enhancing load factor (ratio of electricity consumption to peak demand for each billing period). In addition, power producers use the information to plan how much electricity they will need to make available at any given time. Furthermore, when properly executed, a load analysis can yield valuable insights into appliances, energy usage that can be used to save energy costs and increase productivity. Apart from the aforementioned benefits, load analysis can also be used to identify the particular appliances in use in a typical customer's household. The appliance that contributes the largest impact on the utility bill can be identified through load profile analysis and cost analysis. From this analysis, the utility can offer recommendations for load management to reduce peak demand and energy consumption. Basic electrical load assessment involves creating a table showing power ratings (in Watts) of all electrical appliances in a household alongside with estimation of the number of hours each device will operate on a daily basis in this dissertation it is assumed that each appliance will operate for an hour. The result can be used to know the total energy consumed in the household. It can also be used to track increases or reductions in energy usage, which is the major key in energy management activity. It is unlikely, however, that all electrical appliances in the house turned on at the same time - different appliances operate at different times of the day. For this reason, a load profile is created. A load profile sums appliance loads based on the time of day that the appliance operates. An hourly load profile, for instance, presents the total of all the loads operating during each hour of the day; it excludes any loads that are not operating. The load profile approximates actual demand for electricity throughout the day. During household normal operating hours, the load profile should show higher total loads, because almost all appliance devices are being used. In the evening, or during off-hours, loads are reduced because the house is supporting less activity. The load profile is an essential tool in analyzing energy usage in that it indicates the actual demand placed on the energy supply and reveals the minimum and peak loads through which appliances can be monitored and identified. The power rating of some selected domestic appliances to be considered in the dissertation is shown in appendix A table A1.

7.2.1 Summer Analysis

7.2.1.1 Weekday Appliance Energy Consumption Analysis

The energy consumption profile analysis of some selected domestic appliances on weekdays is shown in the table 7.1. In this dissertation, it is assumed that the situation on one working day applied to all other days (Monday -Friday).

Table 7.1: Weekday Load Profile Analysis of Some Selected Appliances (summer)

Appliances	Quantity	Power Rating (kWh)	Hourly Energy Consumption (kW)	Time of usage/ day (Hour)	Average Energy consumption/ day (kWh)	% of Energy Consumption (kWh)
Washing machine	1	1.50	1.50	1	1.50	5.4452
Electric stove	1	2.40	2.40	1	2.40	8.7124
Refrigerator	1	0.15	0.15	1	0.15	0.5445
Dishwasher	1	2.60	2.16	0.83	1.79	6.5021
Oven	1	2.50	2.50	1	2.50	9.0754
Television	1	0.30	0.30	1	0.30	1.0891
Incandescent bulb	5	0.07	0.35	1	0.35	1.2706
Air-conditioning	1	3.40	3.40	1	3.40	12.3426
Swimming pool	1	1.20	1.20	1	1.20	4.3562
Vacuum cleaner	1	1.60	1.07	0.67	0.72	2.6073
Electric iron	1	2.20	2.20	1	2.20	7.9864
Electric frying pan	1	2.00	2.00	1	2.00	7.2603

Coffee machine	1	1.40	0.14	0.1	0.02	0.0508
Cordless kettle	1	2.50	0.20	0.08	0.02	0.0581
Microwave	1	1.30	0.22	0.17	0.04	0.1364
Tumble dryer	1	3.00	3.00	1	3.00	10.8905
Dstv decoder	1	0.025	0.025	1	0.03	0.0908
Water heater	1	3.50	3.50	1	3.50	12.7056
Electric fence	1	0.35	0.35	1	0.35	1.2706
Slow cooker	1	0.25	0.25	1	0.25	0.9075
Personal computer	1	0.45	0.45	1	0.45	1.6336
Modem	1	0.015	0.015	1	0.02	0.0545
Printer	1	1.00	1.00	1	1.00	3.6302
Hi-fi equipment	1	0.20	0.20	1	0.20	0.7260
Sewing machine	1	0.10	0.10	1	0.10	0.3601
Electric fan	1	0.08	0.08	1	0.08	0.2904
Total	30				27.71	100

Varieties of parameters are evaluated for each appliance in the load profile analysis. The parameter details are quantity of the appliances, appliance voltage, power rating of the appliances, hourly consumption of the appliances, time of usage per day, total consumption per day and percentage of total consumption of each individual appliance. The detail allows for deep understanding of where and when electricity is being consumed. Also, the percentage of the total consumption will help in identifying specific high consumption appliances when taken efficiency measure.

❖ **Quantity*:*** This represents the total number of the same appliances in the household. Lighting appliances are examples of multiple identical appliances in any household. In this scenario, the total number of lights in the household must be included in the load profile analysis. For the purpose of this dissertation, incandescent bulbs are used as lighting appliance because they are not energy efficient and the quantity is assumed to be five.

- **Appliances Voltage and Power Rating*:*** Appliances voltage and power rating are one of the most important parameters to be considered in load profile analysis. Voltage and power rating are usually written on the appliances by the manufacturers. The load voltage at which the appliance operates varies from one country to another. For instance, in North America the standard voltage is 120 volts (AC) and 240 volts for large appliances like electric stove, clothes dryers and electric water heater. In South Africa, standard voltage is 230 volts (AC). The power rating is the continuous watts needed to keep appliances in operation. It is the maximum wattage an appliance will use during operation. If the power rating is not written on the appliance by the manufacturers, the equation below can be used to calculate power rating.
- **Time of Usage*:*** Another important parameter in the load profile analysis is how many hours per day each appliance is ON. Appliances that turn off and off automatically based on need have what is known as duty cycles. Examples are refrigerators, water pumps, and thermostatically controlled electrical appliances. The percentage of time they are in use is determined by how often they turn ON and how long they stay ON. Another set of appliance is called phantom appliances. Phantom appliances are those appliances that use energy even when they switched off except if they are unplugged or interrupted. Examples are television, personal computer, tumble dryer, oven etc.
- **Total Energy Consumed Per Day*:*** This parameter determines average amount of electrical energy that each appliance consumed in a day. It is simply estimated by multiplying the hourly consumption by the total number of hours each appliance operates per day. The total energy consumed per day by an individual appliance is computed by multiplying the appliance power rating by the total number of hours used per day and then multiply by the quantity of the appliance in the household. By multiplying the hourly energy consumption of the appliance by the number of days the appliance is used during the year will give the annual consumption of the appliance. Figure 7 shows the percent of total electricity used by each appliance in the household.

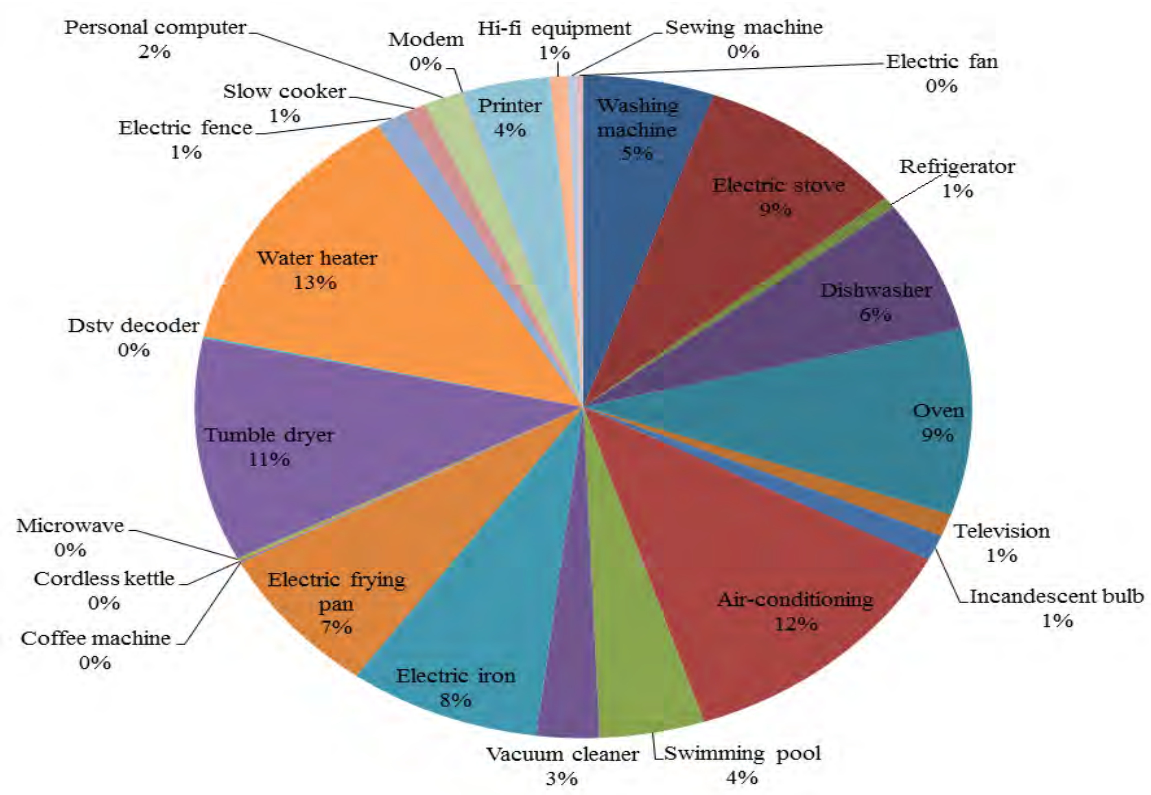


Figure 7.1: Weekday Average Energy Consumption of Some Selected Appliances

Figure 7.1 represents the percentage of energy consumed by each appliance in a typical high-income household over 24 hours for which the penetration rate for all appliances was assumed at 100 % meaning that each appliance is used in the household. The examination of the load profile analysis in table 7.1 shows that operating hours (time of usage per day) and power rating of each appliance determined the total energy consumed by each of the appliance. From the figure 7.1, the largest user of energy in the household is an electric water heater, which accounts for about 13 % of the total household energy consumption, followed by air-conditioning that account for 12 % of the total energy consumption of the household. Tumble dryer and cooking appliances (electric stove and oven) are similarly important as the third and fourth largest energy user in the house with total consumption of 11 %, and 9 % respectively. Appliances like television sets, incandescent bulb, and electric fence and Hi-Fi equipment consumed about 1 % each of the total energy consumption in the household. This consumption is due to the time of usage of the appliances and customer behaviour. Also the energy consumption of microwave, cordless kettle, coffee machine, Dstv decoder and electric fan is due to the total time of usage. Electric iron, vacuum cleaner, swimming pool pump, electric frying pan, and washing machine are due to the period of usage (either on-peak hours or off-peak hours). In load analysis in table 7.1, it is assumed that the use of tumble dryer, washing machine, vacuum cleaner and oven is in off- peak hours (24-6 o'clock), because their usage can be shifted. The use of cooking appliances such as electric stove and frying pan normally falls within the on-peak hours (5-10 o'clock) because they are non-adjustable appliances.

7.2.1 Weekends Appliance Energy Consumption Analysis in summer

7.2.1.1 Saturday Appliance Energy Consumption Analysis

The table below represents the Saturday load profile analysis in summer period of the same household as shown in table 7.1 above. Every assumption in weekday above also holds here except the increase in the time of usage. The increase in time of usage is due to the fact that the occupants of the household are usually present at home during the weekend. The increase in time of usage will increase the total energy consumption during this period.

Table 7.2: Saturday Load Profile Analysis of Some Selected Appliances for High-Income Households

Appliances	**Quantity**	**Power Rating (kWh)**	**Hourly Energy Consumption (kW)**	**Time of Usage/ Day (Hour)**	**Average Energy Consumption /day (kWh)**	**% of Energy Consumption (kWh)**
Washing machine	1	1.50	1.50	1	1.50	5.2319
Electric stove	1	2.20	2.40	1	2.40	8.3711
Refrigerator	1	0.15	0.15	1	0.15	0.5231
Dishwasher	1	2.50	2.60	1	2.60	9.0687
Oven	1	2.50	2.50	1	2.50	8.7199
Television	1	0.30	0.30	1	0.30	1.0464
Incandescent bulb	5	0.07	0.35	1	0.35	1.2208
Air-conditioning	1	3.50	3.40	1	3.40	11.8591
Swimming pool	1	1.20	1.20	1	1.20	4.1856
Electric iron	1	2.20	2.20	1	2.20	7.6735

Electric frying pan	1	2.00	2.00	1	2.00	6.9759
Coffee machine	1	1.40	0.70	0.5	0.35	1.2208
Cordless kettle	1	2.50	1.25	0.5	0.625	2.1710
Microwave	1	1.30	0.65	0.5	0.325	1.1336
Tumble dryer	1	3.00	3.00	1	3.00	10.4639
Dstv decoder	1	0.03	0.03	1	0.025	0.0872
Water heater	1	3.50	3.50	1	3.5	12.2079
Electric fence	1	0.30	0.35	1	0.35	1.2208
Slow cooker	1	0.25	0.25	1	0.25	0.8711
Personal computer	1	0.45	0.45	1	0.45	1.5696
Modem	1	0.015	0.02	1	0.015	0.0523
Printer	1	1.00	1.00	1	1.00	3.4880
Sewing machine	1	0.1	0.10	1	0.10	0.3488
Electric fan	1	0.08	0.08	1	0.08	0.2790
Total	28				28.67	100

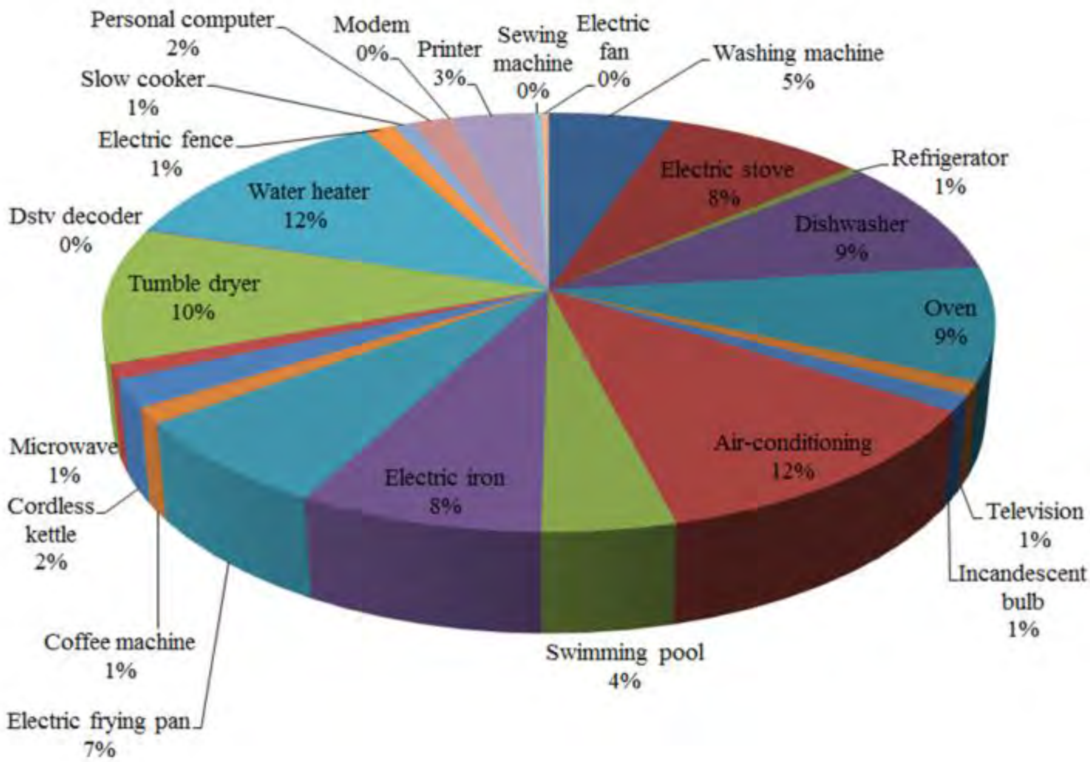


Figure 7.2: Saturday Average Energy Consumption of Some Selected Appliances

Figure 7.2 shows the percentage of energy consumed by each appliance in a household on Saturday. During this period water heater and air-conditioner is the largest user of energy in the household. The second largest is tumble dryer followed by electric stove and oven. The increase in the consumption of microwave, cordless kettle, and coffee machine is due to the increase in the time of usage.

7.2.1.2 Sunday Appliance Energy Consumption Analysis in summer

The table in Table 7.3 represents the load profile analysis of a typical household on Sunday. The analysis follows the same pattern as described on Saturday above, but with different time of usage per day.

Table 7.3: Sunday Load Profile Analysis of Some Selected Appliances for High-Income Households

Appliances	**Quantity**	**Power Rating (kW)**	**Hourly Energy Consumption (kWh)**	**Time of Usage/ Day (Hour)**	**Average Energy Consumption /day (kWh)**	**% of Energy Consumption (kWh)**
Electric stove	1	2.40	2.40	1	2.4	8.8618
Refrigerator	1	0.15	0.15	1	0.15	0.5539
Dishwasher	1	2.60	2.60	1	2.6	9.6003
Oven	1	2.50	2.50	1	2.5	9.2311
Television	1	0.30	0.30	1	0.3	1.1077
Incandescent bulb	5	0.07	0.35	1	0.35	1.2923
Air-conditioning	1	3.40	3.40	1	3.4	12.5542
Vacuum cleaner	1	1.60	1.6	1	1.6	5.9079
Electric iron	1	2.20	2.20	1	2.2	8.1233
Electric frying pan	1	2.00	2.00	1	2	7.3848
Coffee machine	1	1.40	1.05	0.75	0.79	2.9078
Cordless kettle	1	2.50	2.50	1	2.50	9.2311
Microwave	1	1.30	0.65	0.5	0.33	1.2000
Dstv decoder	1	0.025	0.03	1	0.025	0.0923
Water heater	1	3.50	3.50	1	3.50	12.9235
Electric fence	1	0.35	0.35	1	0.35	1.2924
Slow cooker	1	0.25	0.25	1	0.25	0.9231
Personal computer	1	0.45	0.45	1	0.45	1.6616

Modem	1	0.015	0.02	1	0.015	0.0554
Printer	1	1.00	1.00	1	1.00	3.6924
Hi-fi equipment	1	0.20	0.20	1	0.20	0.7385
Sewing machine	1	0.10	0.10	1	0.10	0.36921
Electric fan	1	0.08	0.08	1	0.08	0.2954
Total			27.67		27.08	100

The percentage of energy consumed by each appliance on Sunday in summer period is represented in Figure 7.3. Electric water heater and air-conditioning consumed the highest percentage from the total consumption, followed by a dishwasher and electric stove with average energy consumption of 10 % and 9 % respectively. Appliances like modem, electronic sewing machine and an electric fan consumed very little energy out of the total household energy consumption.

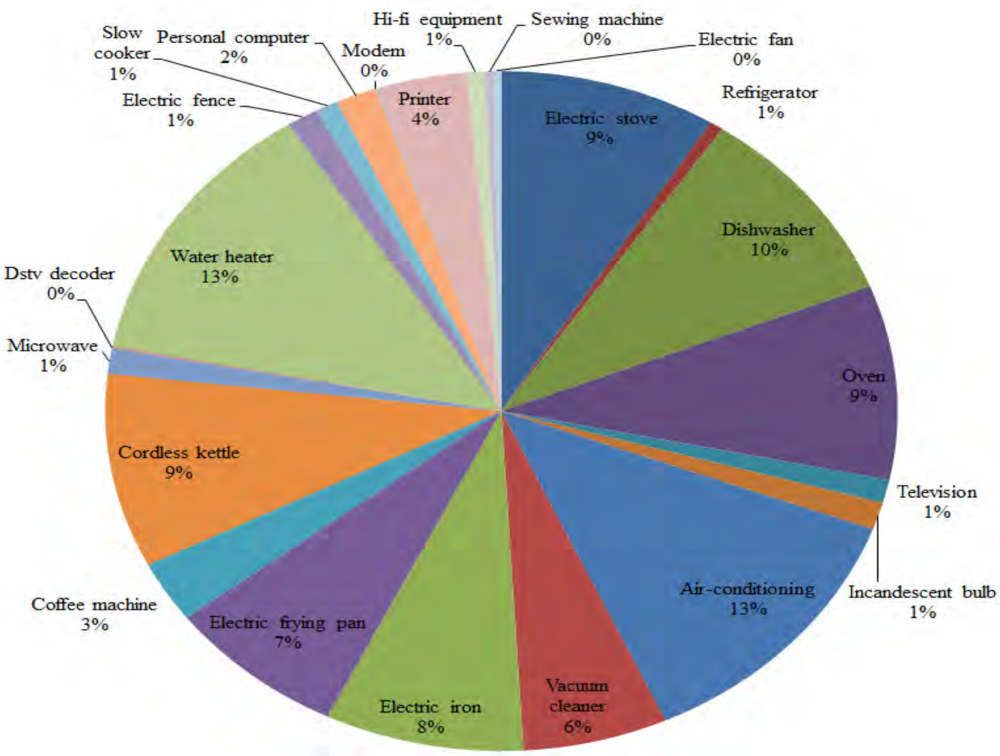


Figure 7.3: Sunday Average Energy Consumption of Some Selected Appliances

7.3 Comparison of Weekdays and Weekends Energy Consumption of Some Selected Domestic Appliances in summer

The energy consumption of appliances varies from weekdays to weekends, depending on the time of usage and the total number of occupants in the household. This section compares the energy consumption of some selected domestic appliances on weekdays and on weekends. Figures 7.3.1 and 7.3.1 compare the energy consumption of some frequently used household appliances on weekends (Saturday and Sunday) and weekdays and weekends respectively.

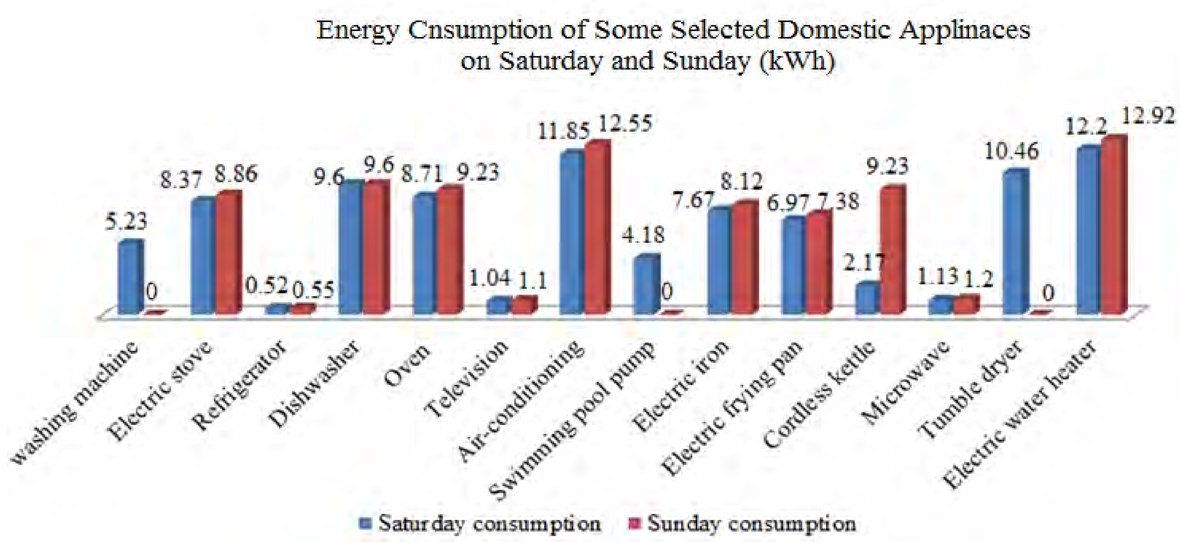


Figure 7.4: Comparison of Weekend's Energy Consumption of Some Selected Appliances

From the Figure 7.4, it is obvious that appliances consumed more energy on Sunday than Saturday. The largest user of energy from the figure above is an electric water heater with average consumption of about 12.92 % of the total consumption of the household. The second largest energy users are air-conditioning, cooking appliances, cordless kettle and oven. Generally, domestic appliances consume more energy on Sunday than weekday and Saturday. This is because occupants are usually at home to use electrical appliances for a longer period of time on Sunday than any other days. Figure 7.5 compares the energy consumption of some selected domestic appliances on weekdays and weekends.

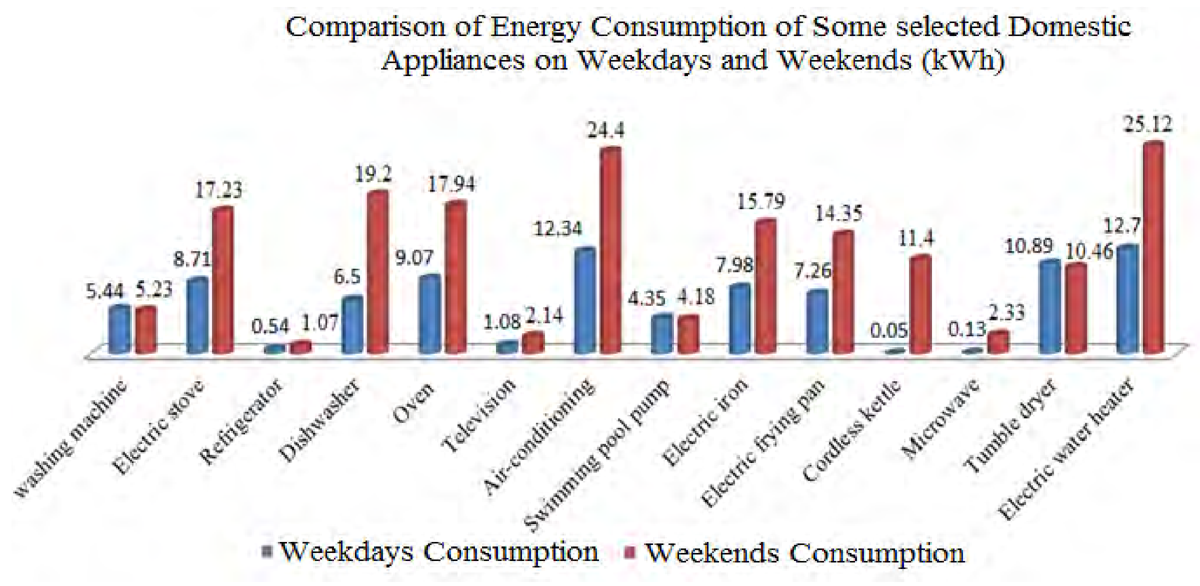


Figure 7.5: Comparison of Weekday and Weekends Energy Consumption of Some Selected Appliances

It is obvious from the figure 7.5 that the energy consumption of these appliances is significantly varies from weekday to weekends. On weekends, electric water heater consumed more energy than weekday the average consumption is about 25.12 % of the total consumption of the household on both Saturday and Sunday. The second largest energy consumption is air-conditioned; the average energy consumption on weekends is 24.4 % of the total household consumption.

Generally, domestic appliances consume more energy on weekend than weekdays, primarily due to the hours of usage, period of usage as well as the power rating of the appliances. In addition, the total number of occupants and their daily activities in the household also determines the hours of usage and hence total energy consumption of the appliances. The loads that mostly affect daily total energy consumption in summer period are electric water heater, air-conditioning and cooking appliances.

7.4 Analysis of Energy Consumption Patterns of Some Selected Domestic Appliances in Winter

Winter is the coldest season of the year. Being the coldest, certain appliances are commonly in use during this period, heating appliances such as an electric water heater, electric heater, electric blanket, heat circulation pump and air conditioning are the major appliances in use. The load analysis of these appliances in addition to the generally used appliances is shown the sections below.

7.4.1 Weekday Appliance Energy Consumption Analysis in Winter

It assumed that the condition that holds for one day in the weekday applies to the rest of the day of the week in the dissertation.

Table 7.4: Weekday Load Profile Analysis of Some Selected Appliances (winter)

Appliances	**Quantity**	**Power Rating (kW)**	**Time of Usage/ Day (Hour)**	**Hourly Energy Consumption (kWh)**	**Average Energy Consumption/ Day (kWh)**	**% Of Energy Consumption (kWh)**
Washing machine	1	1.50	0.75	1.13	0.84	2.9722
Electric stove	1	2.40	1	2.4o	2.40	8.4543
Refrigerator	1	0.15	1	0.15	0.15	0.5284
Dishwasher	1	2.60	0.5	1.30	0.65	2.2897
Oven	1	2.50	1	2.50	2.50	8.8066
Television	1	0.30	1	1.50	1.50	5.2840
Incandescent bulb	5	0.07	1	0.07	0.07	0.2466
Air-conditioning	1	3.40	1	3.40	3.40	11.9770
Swimming pool	1	1.20	1	1.20	1.20	4.2272
Vacuum cleaner	1	1.60	0.5	0.80	0.40	1.4091
Electric iron	1	2.20	0.5	1.10	0.55	1.9375
Electric frying pan	1	2.00	0.75	1.50	1.12	3.9630
Coffee machine	1	1.40	0.5	0.70	0.35	1.2329

Cordless kettle	1	2.50	0.75	1.88	1.41	4.9537
Microwave	1	1.30	0.75	0.98	0.73	2.5759
Tumble dryer	1	3.00	0.75	2.25	1.69	5.9445
Dstv decoder	1	0.025	1	0.03	0.03	0.0881
Water heater	1	3.50	1	3.50	3.50	12.3292
Electric fence	1	0.35	1	0.35	0.35	1.2329
Slow cooker	1	0.25	1	0.25	0.25	0.8807
Personal computer	1	0.45	0.75	0.34	0.25	0.8917
Modem	1	0.015	0.75	0.01	0.00	0.0297
Printer	1	1.00	0.5	0.50	0.25	0.8807
Hi-fi equipment	1	0.20	0.75	0.15	0.11	0.3963
Sewing machine	1	0.1	1	0.10	0.10	0.3523
Electric heater	1	3.60	1	3.60	3.60	12.6815
Electric blanket	1	0.075	1	0.08	0.08	0.2642
Heat circulation pump	1	0.9	1	0.90	0.90	3.1704
Total				32.64	28.39	100

Figure 7.6 summarizes the load analysis in table 7. 4 and reveals some insight about the energy consumption of the appliances. To begin the load analysis, the energy consumption of different appliances was broken down into their respective percentage of the total energy consumption of the household. Electric heater, electric water heater and air-conditioning are the highest user of energy in households with average consumption of 13%, and 12% respectively. Cooking appliances (oven and electric stove) are the second largest energy user in the household with average consumption of 8 % and 9 % of the total energy consumption of the household respectively. During the period, tumble dryer, washing machine, electric frying pan and swimming pool has moderate energy consumption. The consumption of electric fence, coffee

machine, personal computer, slow cooker, printer and vacuum cleaner and electric fan is relatively minimal. This may due to their period of usage, time of usage and their power rating. The energy consumption of modem, electric blanket and dstv decoder are very small.

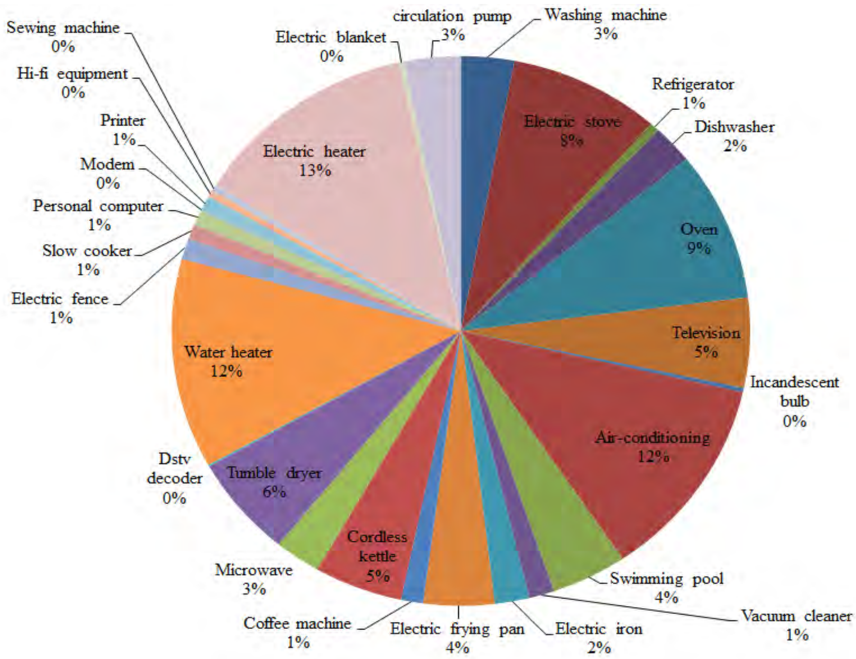


Figure 7.6: Weekday Average Energy Consumption of Some Selected Appliances

7.4.2 Weekends Appliance Energy Consumption Analysis in Winter

7.4.2.1 Saturday Analysis in Winter

Table 7.5: Saturday Load Profile Analysis of Some Selected Appliances for High-Income Households.

Appliances	Quantity	Power Rating (kW)	Hourly Energy Consumption (kWh)	Time of Usage/ Day (Hour)	Average Energy Consumption/ Day (kWh)	% of Energy Consumption (kWh)
Washing machine	1	1.50	1.50	1	1.50	3.8945
Electric stove	1	2.40	2.40	1	2.40	6.2312
Refrigerator	1	0.15	0.15	1	0.15	0.3895

Dishwasher	1	2.60	2.60	1	2.60	6.7504
Oven	1	2.50	2.50	1	2.50	6.4908
Television	1	0.30	0.30	1	1.50	3.8945
Incandescent bulb	5	0.07	0.35	1	0.07	0.1817
Air-conditioning	1	3.40	3.40	1	3.40	8.8274
Swimming pool	1	1.20	1.20	1	1.20	3.1156
Vacuum cleaner	1	1.60	1.20	0.75	0.90	2.3367
Electric iron	1	2.20	2.20	1	2.20	5.7118
Electric frying pan	1	2.00	2.00	1	2.00	5.1926
Coffee machine	1	1.40	0.938	1	1.40	3.6348
Cordless kettle	1	2.50	0.20	1	2.50	6.4908
Microwave	1	1.30	0.975	0.75	0.73	1.8986
Tumble dryer	1	3.00	3.00	1	3.00	7.7889
Dstv decoder	1	0.025	0.03	1	0.025	0.0649
Water heater	1	3.50	3.50	1	3.50	9.0871
Electric fence	1	0.35	0.35	1	0.35	0.9087
Slow cooker	1	0.25	0.25	1	0.25	0.6491
Personal computer	1	0.45	0.45	1	0.45	1.1683
Modem	1	0.015	0.02	1	0.02	0.0389
Printer	1	1.00	1.00	1	1.00	2.5963
Hi-fi equipment	1	0.20	0.20	1	0.20	0.5193
Sewing machine	1	0.1	0.10	1	0.10	0.2596
Electric heater	1	3.60	3.6	1	3.60	9.3467

Electric blanket	1	0.075	0.08	1	0.08	0.1947
Heat circulation pump	1	0.9	0.90	1	0.90	2.3367
Total					38.52	100

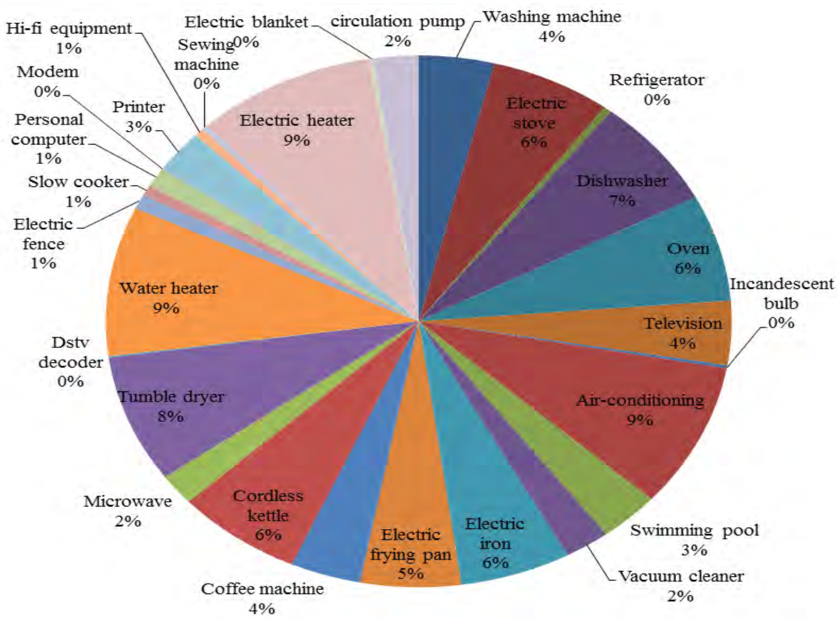


Figure 7.7: Saturday Average Energy Consumption of Some Selected Appliances

Table 7.5 and Figure 7.7 show the load analysis and the percentage of consumption of each appliance from the total household energy consumption. The analysis reveals that heating appliances (electric heater, electric water heater and air-conditioning) are the most significant energy user in the household and it accounts for approximately 9 % each of the total household energy consumption. The second largest energy users in the household are tumble dryer and dishwasher with energy consumption of 8 % of the total household consumption. Cooking appliances (oven and electric stove, cordless kettle) and the electric iron with energy consumption of 6 % each are the third largest energy users in the household. The least energy users are electronic sewing machines, modem, electric blanket and dstv decoder.

7.4.2.2 Sunday Appliance Energy Consumption Analysis in Winter

Table 7.6: Sunday Load Profile Analysis of Some Selected Appliances for High-Income Households

Appliances	Quantity	Power Rating (kW)	Time of Usage/ Day (Hour)	Hourly Energy Consumption (kWh)	Average Energy Consumption/ Day (kWh)	% of Energy Consumption (kWh)
Electric stove	1	2.40	1	2.40	2.4	9.1937
Refrigerator	1	0.15	1	0.15	0.15	0.5746
Dishwasher	1	2.60	0.67	1.74	1.16714	4.4710
Oven	1	2.50	1	2.50	2.5	9.5767
Television	1	0.30	1	1.5	1.5	5.7460
Incandescent bulb	5	0.07	1	0.07	0.07	0.2681
Air-conditioning	1	3.40	1	3.40	3.4	13.0243
Vacuum cleaner	1	1.60	0.5	0.80	0.4	1.5323
Electric iron	1	2.20	0.5	1.10	0.55	2.1069
Electric frying pan	1	2.00	0.75	1.50	1.125	4.3095
Coffee machine	1	1.40	0.5	0.70	0.35	1.3407
Cordless kettle	1	2.50	1	2.50	2.5	9.5767
Microwave	1	1.30	0.75	0.98	0.73125	2.8012
Dstv decoder	1	0.025	1	0.03	0.025	0.0958
Water heater	1	3.50	1	3.50	3.5	13.4074
Electric fence	1	0.35	1	0.35	0.35	1.3407
Slow cooker	1	0.25	1	0.25	0.25	0.9577
Personal computer	1	0.45	0.75	0.34	0.253125	0.9696
Modem	1	0.015	0.75	0.01	0.0084375	0.0323
Printer	1	1.00	0.5	0.50	0.25	0.9577

Hi-fi equipment	1	0.20	0.5	0.10	0.05	0.1915
Electric heater	1	3.60	1	3.60	3.6	13.7905
Electric blanket	1	0.075	1	0.08	0.075	0.2873
Heat circulation pump	1	0.9	1	0.90	0.9	3.4476
Total			20.17	28.99	26.1049525	100

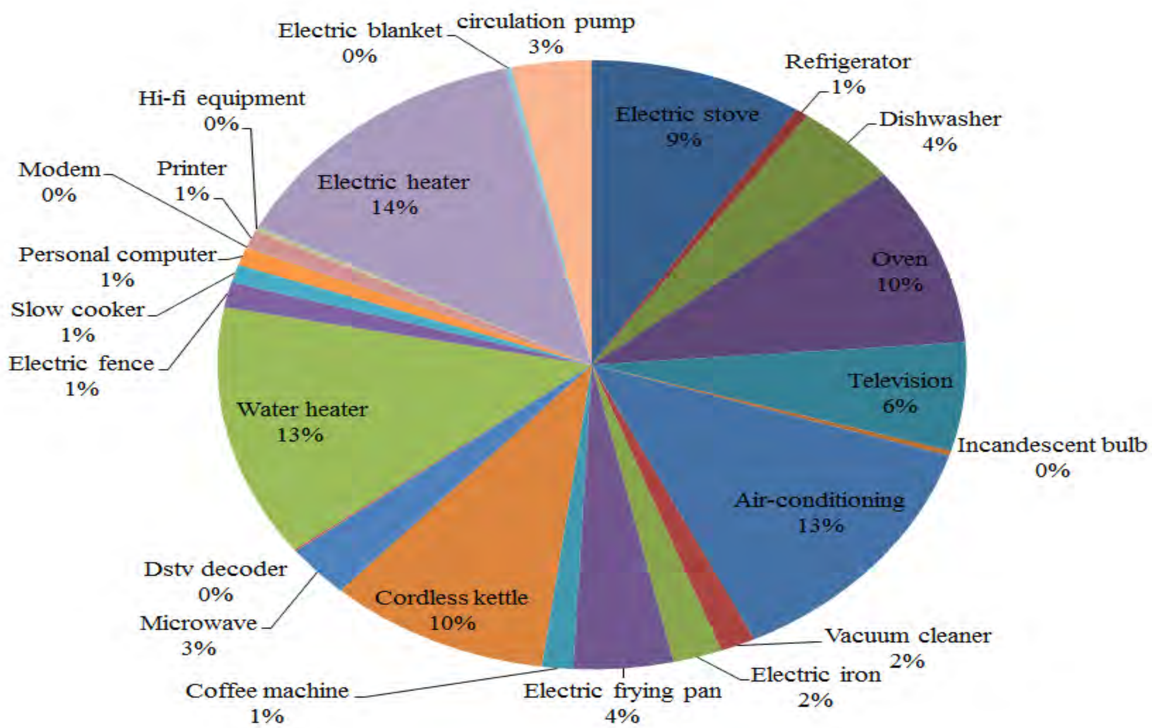


Figure 7.8: Sunday Average Energy Consumption of Some Selected Appliances

The Figure 7.8 summarizes the load analysis in figure 7.4.3 above and shed more light on the energy consumption of the appliances. Electric heater, electric water heater and air-conditioning are the highest users of energy on Sunday in the household with average energy consumption of 14 %, and 13 % respectively. Cordless kettle and oven are the second largest energy users with average consumption of 10 % respectively of the household total energy consumption. An electric stove is the third largest energy user in the household with average consumption of 9 % of the total energy consumption of the household. Dishwasher, electric frying pan and electric circulation pump has moderate energy consumption of 4 %, and 3 % of the total energy consumption in the household. Vacuum cleaner, electric iron, electric fence, coffee machine, personal computer, slow cooker, and printer have minimal energy consumption by 2 % and 1 % respectively.

7.5 Comparison of Weekdays and Weekends Energy Consumption of Some Selected Domestic Appliances in Winter

The comparison of energy consumption of some selected domestic appliances on weekends (Saturday and Sunday) and weekdays is depicted in figures 7.9 and 7.10.

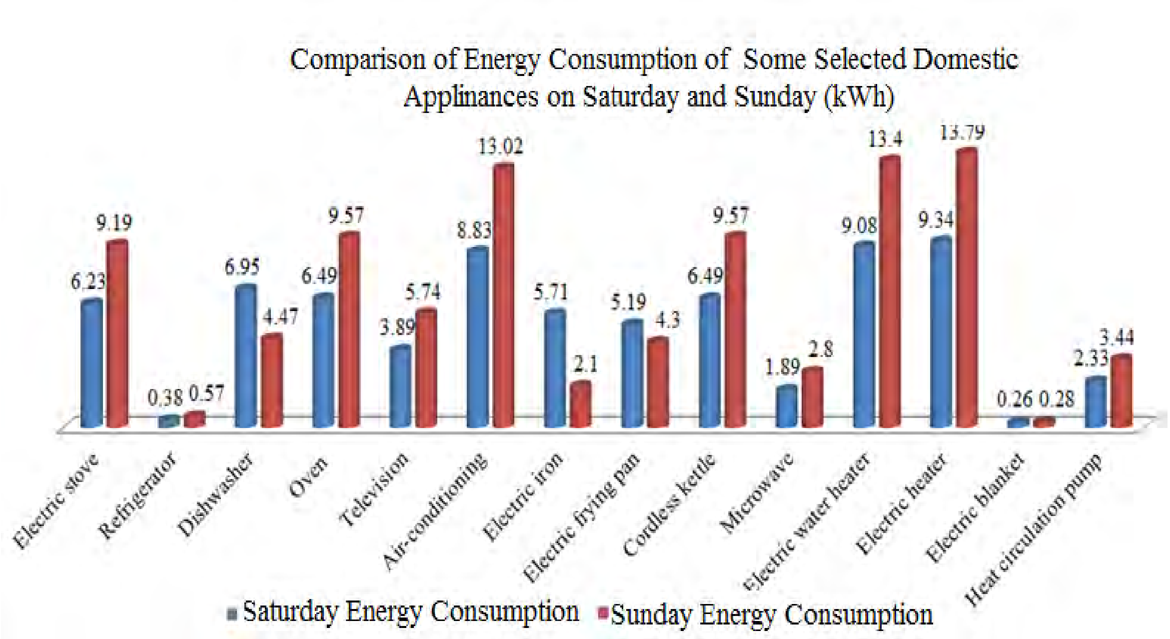


Figure 7.9: Comparison of Weekend's Energy Consumption of Some Selected Appliances

From the Figure 7.9, it is obvious that appliances consumed more energy on Sunday than Saturday. The largest user of energy is electric heating with average consumption of about 13.72 % of the total consumption of the household. The second largest energy users are electric water heater and air-conditioning with about 13.4 % and 13.02 % of the total household energy consumption respectively. The third largest consumption of energy in the household is an oven and electric stove with total consumption of 9.57 % and 9.19 % respectively. Generally, domestic appliances consume more energy on Sunday than Saturday. This is because occupants are usually at home to use electrical appliances for a long period of time on Sunday. Figure 7.10 depicts the energy consumption on weekdays and weekends.

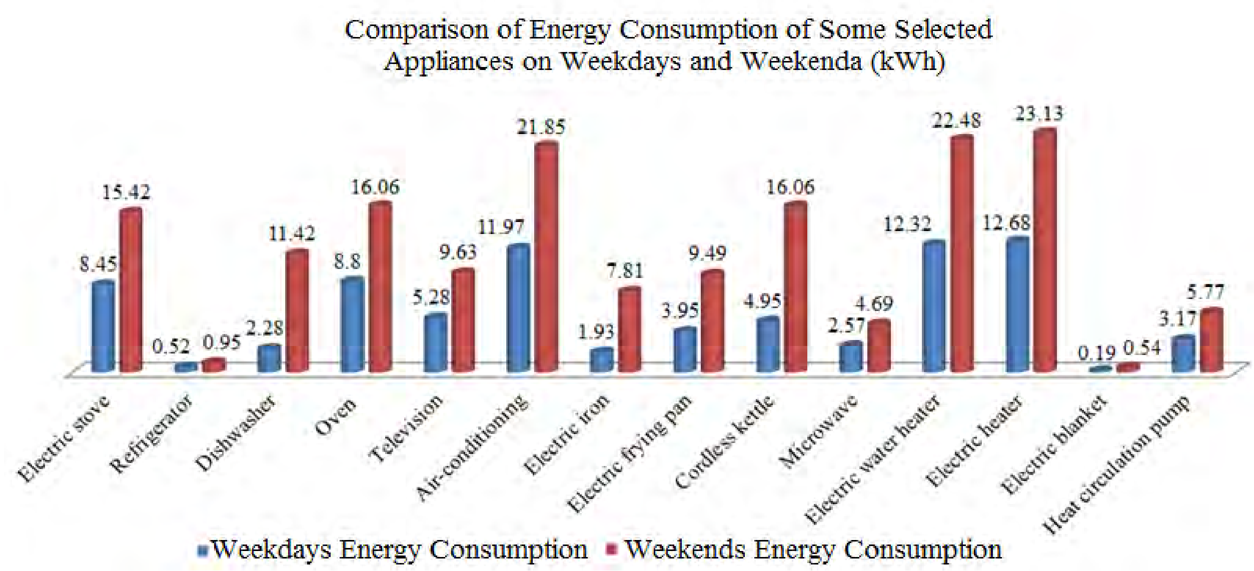


Figure 7.10: Comparison of Weekday and Weekend's Energy Consumption of Some Selected Appliances

The largest users of energy in the household in winter period are electric heater and electric water heater with consumption of 23.13 % and 22.48 % respectively. Air-conditioning, oven and electric stove are the second energy user in the household with average consumption of 21.85 %, 16.06 % and 15.45 % respectively. In general, domestic appliances consumed more energy on weekends in winter period than weekdays and the principal users are electric heater, water heater and air-conditioning.

7.5.1 Comparison of Energy Consumption of Some Frequently Used Appliances in Summer and Winter Periods

The energy consumption of some selected and frequently used appliances in both winter and summer based on the analysis in the previous section is depicted in the chart below. Due to the electric water heater having an element of relatively high rating and this element being energized for long periods each day, the water heater is the largest user of energy of all the appliances in a typical household both in winter and summer. The second largest users of energy are air-conditioned and electric heaters. Air- conditioning is used as heating appliances in winter period.

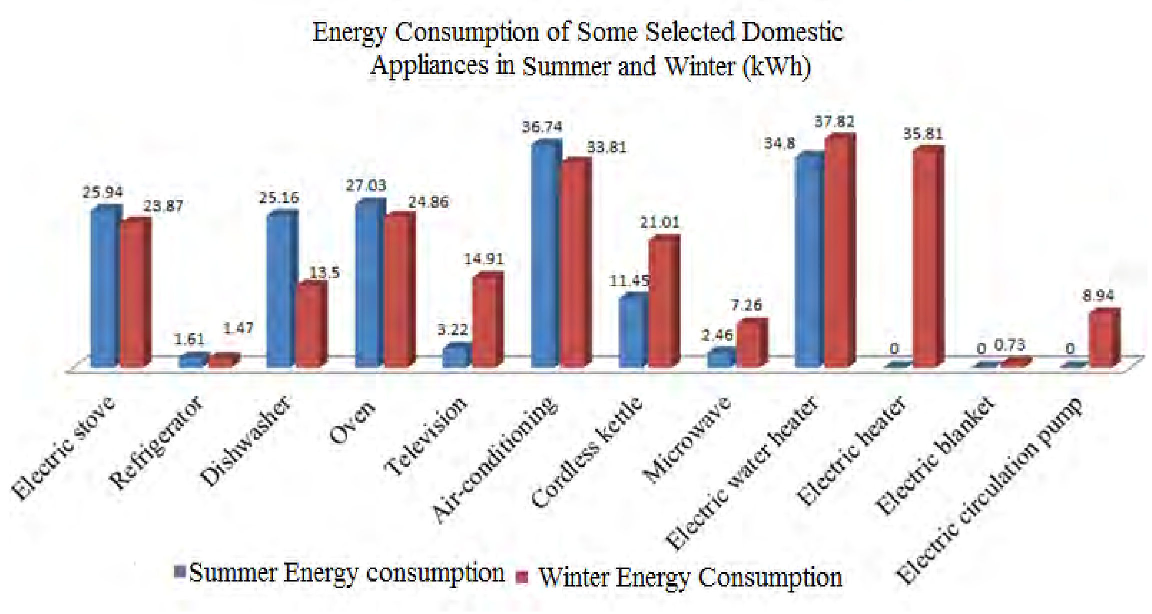


Figure 7.11: Comparison of summer and winter Energy Consumption of Some Selected Appliances

7.6 Cost Analysis

The previous section analyzed hourly energy consumption of some domestic appliance, in this section the cost of operating each of these appliances are analyzed. Electricity pricing varies widely from country to country, from locality to locality, and from sector to sector within a particular country. The city of Cape Town electricity tariffs have been formulated in accordance with the local government, municipality system Act, municipality finance managements Act as well as guidelines established by the national energy regulator of South Africa. In South Africa, there are two types of tariffs available for residential energy consumers:

- Domestic tariff
- Lifeline tariff

The Domestic Tariff: This type of tariff is only applies to consumers who their average consumption is more than 450 kWh per month including any free basic electricity that may be applicable. Domestic tariff includes domestic high and domestic low. Domestic high tariff charge 91.17 cents per kWh, while domestic low charges 106.37 cents per kWh

Lifeline Tariff: This type of tariff is only available to consumers who their consumption is less than or equal to 400 kWh per month. The charge per hour of the tariff is 80.34 cents per kWh. The table below shows the average cost of energy consumed by different domestic appliances. All tariffs and costs indicated in the table are inclusive of VAT [94].

Table 7.7: Cost Analysis of Some Selected Domestic Appliances in South Africa

Appliances	**Quantity**	**Power Rating (kW)**	**Time of Usage /Day (Hour)**	**Hourly Energy Consumption (kWh)**	**Domestic High 91.17 cents/ kWh**	**Domestic low 106.37 cents/ kWh**	**Lifeline 80.34 cents /kWh**
Washing machine	1	1.00	1	1.00	91.17	106.37	80.34
Electric stove	1	2.00	1	2.00	182.34	212.74	160.68
Refrigerator	1	0.10	1	0.01	9.12	10.64	8.03
Dishwasher	1	2.30	1	2.30	209.69	244.65	184.78
Oven	1	2.00	1	2.00	182.34	212.74	160.68
Television	1	0.25	1	0.25	22.79	26.59	20.09
Incandescent bulb	1	0.06	1	0.06	5.47	6.38	4.82
Air-conditioner	1	3.00	1	3.00	273.51	319.11	241.02
Swimming pool	1	1.00	1	1.00	91.17	106.37	80.34
Vacuum cleaner	1	1.00	1	1.00	91.17	106.37	80.34
Electric iron	1	2.00	1	2.00	182.34	212.74	160.68
Electric frying pan	1	1.50	1	1.50	136.76	159.56	120.51
Coffer machine	1	1.20	1	1.20	109.40	127.64	96.41
Cordless kettle	1	1.80	1	1.80	164.12	191.47	144.61
Microwave	1	0.8	1	0.60	54.70	63.82	48.20

Tumble dryer	1	2.80	1	2.80	255.28	297.83	224.95
Dstv decoder	1	0.02	1	0.02	1.82	2.13	1.61
Water heater	1	3.00	1	3.00	273.51	319.11	241.02
Electric fence	1	0.30	1	0.30	27.35	31.91	24.10
Slow cooker	1	0.15	1	0.15	13.68	15.96	12.05
Personal computer	1	0.30	1	0.30	2735	31.91	24.10
Modem	1	0.012	1	0.012	1.09	1.28	0.96
Printer	1	0.60	1	0.60	54.70	63.82	48.20
Hi-fi equipment	1	0.15	1	0.15	13.68	6.38	12.05
Sewing machine	1	0.07	1	0.07	6.38	7.45	5.62
Electric fan	1	0.06	1	0.06	5.47	6.38	4.82
Electric heater	1	3.00	1	3.00	273.51	319.11	241.02
Electric blanket	1	0.05	1	0.05	4.56	5.32	4.02
Heat circulation pump	1	0.60	1	0.60	54.70	63.82	48.20

From the table 7.7, electric water heater, electric heater, air-conditioning and dishwasher incur the highest energy consumption cost in a typical household. Of the three types of tariff considered, consumer on domestic high tariff (91.17 cents/kWh), domestic low tariff (106.37 cents/kWh) and lifeline consumer (80.34 cents/kWh) will spend 273.51cents, 319.11cent and 241.02 cents respectively for operating an electric water heater for an hour. However, by reducing the use of the hot water cylinder and electric heaters, a noticeable reduction in overall energy consumption cost can be achieved. High consumption of electric water heater can be reduced:

- Avoiding the use of the water heater during peak hours;
- Avoiding switching off the hot water cylinder for a long period of time since more electricity is needed to heat up the cylinder back to the set temperature when it is switched on again;

- Use recommended temperature;
- Use insulated cylinder and pipes.

Electric heater and air-condition can be reduced by switching them off whenever leaving the room for a longer period of time. In addition, electric blanket can be used in the bedroom instead of electric heater. Phantom appliances (appliances that continue to consume a small amount of power when they are switched off) will increase the appliance energy consumption a few watt-hours, these load can be avoided by unplugging the appliances anytime they are not in used. Generally, the cost of running each appliance can be reduced by using energy efficient appliances and avoiding the use of high consuming appliances such as electric heaters, air conditioners and electric water heater during on peak hours of the day.

7.7 Summary

This chapter began by classifying domestic appliances into five different categories: Entertainment appliances, lighting appliance, kitchen appliances, heating and cooling appliances, cleaning appliances and office appliance. Load profile analysis was prepared for these appliances. The load profile was based on hourly energy consumption of the appliances. The charts in the chapter depict the percentage of daily energy consumption of the appliances. Furthermore, comparison was made between the energy consumption of the appliances on weekday and weekends as well as summer and winter this comparison showed that water heater and air- conditioning consumed the highest percentage of energy in winter and summer. Finally, for the purpose of knowing the high consuming appliances and thus reducing energy consumption cost, cost analysis was carried out on each appliance.

Having carried out the load and cost analysis of some selected domestic appliances and knowing the appliances that consumed high energy, the following chapter proposes a method of identifying these appliances using aggregate data from household energy meter and hourly energy consumption of the appliances from the load profile analysis above.

CHAPTER 8

Load Modelling and Simulations Based on Artificial Neural Networks

Introduction

Residential homes are equipped with electrical meter, which record the energy consumption of the household at regular interval. The raw data from the electrical meter are aggregate data; this data has to be decomposed into appliances active power consumption for effective load identification. However, the effective energy saving method for residential homes always needs the real-time energy consumption data of each of the appliance in the household. The major setback to the real-time energy consumption of individual appliances is the cost of monitoring the appliances separately. Thus the most economical means of load monitoring in residential home is to disaggregate the total energy consumption of the house from the main meter into individual appliances using the total energy consumed by each appliance(s) (active power). The consumption may be hourly or daily. Different algorithms used to analyze the load data are very complex, but can be summarized as follows: edge detection, cluster analysis, cluster matching, and anomaly resolution [95]. This dissertation makes use of only the active power in monitoring and identification of domestic appliances. It is intelligently efficient, inherently reliable, economical and easy to compute. The major setback to the use of active power is that many appliances may have overlapping energy consumption (active power). However, in this dissertation, the set back is overcome by developing an algorithm for identifying the actual appliances that are ON at a given time using the outputs of neural networks. In addition, the method employed in the dissertation overcomes the problem of phantom appliance energy consumption since the hourly appliance energy consumption is used for the modelling. For the purpose of modelling, appliances can generally be categorized into three different categories:

- Two-state appliances.
- Multi-state appliances.
- Continuously-varying appliances

Two-state appliances are those appliances that can only be ON or OFF at a given point in time, but allows for only a single type of ON. It is a good model for most household appliances, such as light bulb or water pump. Multi-state appliances are the appliances that have more than one operating state. It is also known as a Finite State Machine (FSM). Continuously-varying appliances are the appliances that do not consume a constant power. The Different appliances types based on their energy consumption pattern are shown in Figure 8.1.

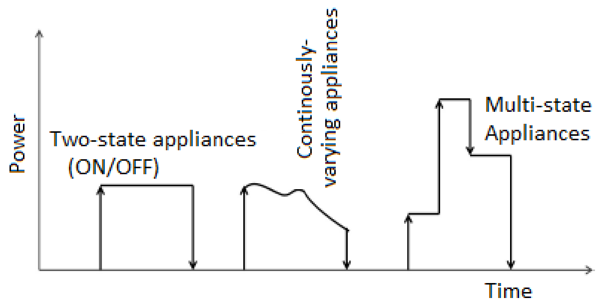


Figure 8.1: Different Appliances Types Based on their Energy Consumption Pattern [60]

In addition to the above appliance classification is the permanent consumer appliances. They are the appliances that remain permanently ON with nearly constant active and reactive power consumption. An example of this type of appliances is smoke detectors [5]. The following appliance characteristics are needed for proper identification of a particular appliance: power rating of the appliances, duty Cycle (on time) and cyclic parameters such as OFF time characteristics of the appliances [96].

8.1 Theory of Modelling Appliance Power Demand

Data log from electricity utility about domestic energy consumption usually come in the aggregate of multiple households without knowledge about the event in the individual households. In order to decompose the total load into its components, models of individual appliances and their load combinations will be needed. Appliances can be modelled based on the amount of energy they consumed. The total load depends on the number of appliances that are switched ON at any given time, based on the switch process S_i(t). Assuming that there are n number of appliances and S_i(t) is the Boolean vector describing the state of the appliances at time t. $S_i(t) = 0$ if the appliances i is OFF at time t, and $S_i(t) = 1$ if the appliances i is ON at time t. Note that $i = 1 \ldots n$. The switch process modulates the power consumption of the individual appliances. A multiphase load with p phases can be modelled as a p-vector in which each component is the load on one phase. The total load p-vector is the sum of the individual appliance load that is ON at any given time. For $i = 1 \ldots n$, let p_i be the p-vector of the power ith appliances consumption when switch ON. For a two-phase system each p_i is a two-component complex vector. The real and imaginary parts of the vector in jth component of the vector corresponding to the active and reactive power consumed on the jth phase. The total appliances can be modelled as [66], [96].

$$\mathrm{P}(t) = \sum_{i=1}^{n} S_i(t)p_i + e(t) \tag{8.1}$$

$$S_i(t) = [s_1(t), \dots, s_n(t)] \tag{8.2}$$

where $P(t)$ is the measured power as seen in the utility at the time *t,* and $e(t)$ is the error. Equation 8.1 is a straightforward method of estimating the state of the individual appliances. If all *n* of p_i are known and measured *P (t),* at a given time, the error term can be undetectable for continuously on appliances or untraceable for continuously-varying and multi-state appliances. The general aim is to reduce the error term, thus the *n*-vector which minimizes error can be chosen [66], [96].

The change (rise and drop) in power consumption levels is as a result of switching on and off of the appliance; by estimating the differences in the power consumption level the switching characteristics of appliances could be detected.

$$\Delta p\ (t) = p(t) - P(t-1) \tag{8.3}$$

The ideal situation for transition of appliance from one state to another (on or off) is that it would take place quickly over a small period of time, this is mostly not the case, as some appliances such as microwaves take up to five seconds to completely turn on. The small step changes over the five second period needs to be summed up, or else it will not match up correctly. Also, certain appliances require a big switch on transient currents for a short time, and then go to steady state [96]. The algorithm developed in this paper, will overcome these challenges since an hourly energy consumption readings is used in the appliances modelling.

8.1.1 Neural Networks for Appliances Modelling

In this section, an application of ANN in energy consumption pattern recognition is developed from hourly energy consumption data and hourly energy consumption of appliances from load profile analysis in chapter seven. The use of ANN in modelling residential energy consumption pattern for load monitoring and identification has historically been limited due to the computationally and data requirements. Lack of physical means of relating energy consumption with dwelling characteristics has also been a setback to the use of ANN in load monitoring and identification. However, due to their ability to capture non-linear characteristic and accuracy, the neural network has been used to predict or recognize domestic appliances in the real-time [96].

In this dissertation, multi-layer feed backward neural network also known as multi-layer perception (MLP) with a Levenberg -Marquardt back propagation algorithm is found to be suitable for the proposed task.

The Neural networks consist of one or more hidden layer whose computational nodes are correspondingly called hidden neurons. The hidden neurons add-up more computation between the input and output layers of the neurons in the second layer. The output signal of the hidden layer is used as input to the output layer of the network. Multilayer neural network operates in two ways training, testing and validation. The training function is used to reduce the difference between the output and target values of the network, while the testing function is used to verify the final solution in order to confirm the actual predictive power of the network.

8.1.2 Flowchart for the Development of ANN Models

The algorithm described in the flowchart diagram in the Figure 8.2 depicts the step by step arrangement of the neural network used for the modelling. The Flow chart shows the step by step modelling of domestic appliances using artificial neural networks (ANN). The first step is to determine the neural network architectures which include the inputs, outputs, the hidden layers, the transfer function and delay. The second step is to determine the number of hidden neurons. The number of hidden neurons is determined by trial by error. The training of neural network is the next step to determine the hidden neuron. The training is carried out with the input data and the target. After the training, the targets from neural networks are obtained. Before the next training is carried out, the accuracy of the training is determined using means square error with regularization (MSEREG). A good training will give a MSEREG value that is close to zero. The closer the MSEREG value to zero, the better is the training. Validation is performed after the training. A code is developed in MatLab software™ to predict the actual appliance(s) that are ON at a given period of time using the outputs of the neural network training. The algorithm described in the flowchart diagram in the Figure 8.2 depicts the step by step arrangement of the neural network used for the modelling.

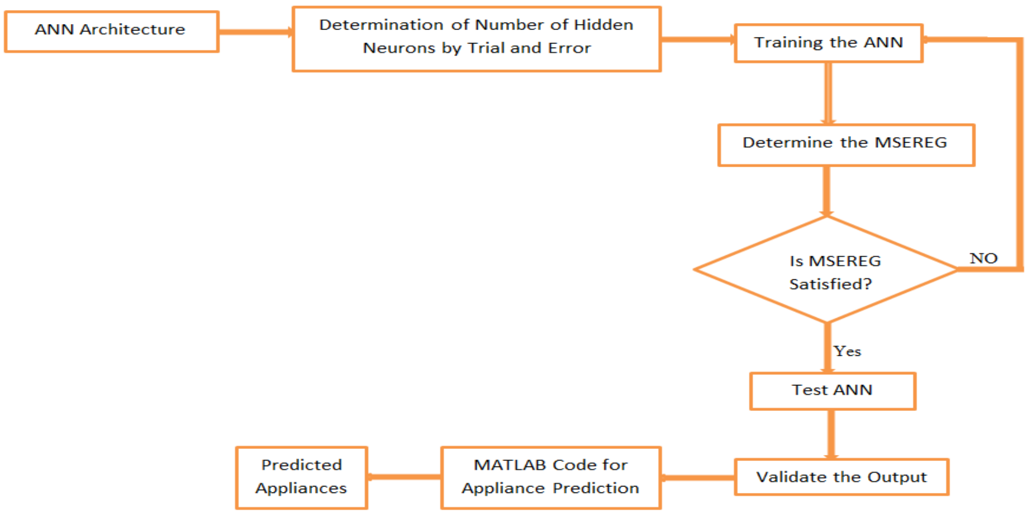


Fig 8.2: Flowchart for ANN and Appliance Prediction

8.1.3 Selection of Parameters for the Artificial Neural Network Training

The selection of appropriate network parameters such as the number of neurons in each layer, the number of network layers, and the activation functions are some of the important parameters to be considered in the network design. The layered recurrent neural network (LRN) toolbox in MATLAB was used to develop, train, test and validate the performance of the neural networks for energy consumption pattern recognition the appliances. The parameters used in the network for the development of the appliance energy consumption pattern recognition are shown in table 8.1

Table 8.1: Artificial Neural Network Parameters

S/N	**Parameters**	
1	Neural network (NN)	Feed backward neural network
2	Number of inputs	Hourly energy consumption and time of the day
3	Number of outputs	1
4	Training algorithm	Levenberg Marquardt
5	Training epoch	30
6	Transfer function	Tan-sigmoid and purlin
7	Error tolerance	0.05
8	Testing data	25%
9	Number of layers	2
10	Number of hidden neurons	10

8.1.3.1 Data Preparation and Training

The first step in training the neural network is to obtain accurate historical data about the case (phenomena) of interest. The training data involved a large number of input and target data. The input data for the proposed task is the household hourly energy consumption from the utility, while the target data is the calculated hourly energy consumption of the appliances using both the power rating of the appliances and the assumed hour of usage. For the purpose of accuracy in the modelling of the appliances, forty-eight hours usages are considered. After data selection, the next step is to normalize the data so that each value will falls within a specified range. This is just to prevent the simulated neuron from being driven far into saturation. Once the saturation is reached, change in the input value results in little or no change in the output.

8.1.3.2 Validation of the Neural Network

Having completed training, the error rate of the predictions is estimated. The aim of neural network validation is to proceed to a visual comparison between the actual energy consumption and predicted energy pattern. There are several error measurement techniques that can be used as metrics for evaluating the accuracy of the trained neural model. They include: mean absolute percentage error (MAPE), symmetric mean absolute percentage error (SMAPE), root means square error (RMSE) and standard deviation of the absolute error (STD) [97].

Mean Absolute Percentage Error (MAPE): MAPE is the most common measure of predicting error. MAPE functions perform best when there are no extremes in the data (including zero). With zero or near zero, MAPE can give a distorted error. The error on a near-zero item can be infinitely high, causing a distortion to the overall error rate when it is averaged in. MAPE is the average absolute percent error for each time period or predicted value minus actual values divided by actual values. It is defined as:

$$\text{MAPE}= \frac{1}{N}\sum_{i=1}^{N}\left|\frac{F_i-A_i}{A_i}\right| \times 100\% \tag{8.4}$$

where N represents the number of predicted time, F_i is the predicted value at period i, A_i and is the actual value at period i.

Symmetric Mean Absolute Percentage Error (SMAPE): It was proposed by Makridakis [97] to deal with some of the limitations of the MAPE. Using the SMAPE, the problem of large error when the actual values are close to zero are avoided. It is defined as:

$$\text{SMAPE} = \frac{1}{2}\sum_{i=1}^{N}\frac{[F_i-A_i]}{F_i-A_i} \tag{8.5}$$

Root Mean Square Error (RMSE) is defined as:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(F_i - A_i)} \tag{8.6}$$

Standard Deviation (STD) is defined as:

$$\text{STD}=\sqrt{\frac{\sum_{i=1}^{N}|AE-MAE|}{N-1}} \tag{8.7}$$

AE is the absolute error which is the absolute difference between the predicted values and the actual values.

MAE is used to measure the closeness between the predicted and the actual values at period i and N is the number of predicted time.

$$\text{MAE} = \sum_{i=1}^{N}\frac{|x_i-\hat{x}_i|}{N} \tag{8.8}$$

where N is the total values, x_i is the actual values, and $\hat{x}_i$ is the predicted values.

Mean Absolute Scaled Error (MASE): Is a measure of the accuracy of prediction. It was proposed in 2006 by Australian statistician *Rob J. Hyndman* [98]. The scale is less than one if the prediction is better than the average computed data. Conversely, it is greater than one if the prediction is worse than the average computed data. The mean absolute scaled error is given by [98].

$$\text{MASE} = \text{mean}\ (|q_t|) \tag{8.9}$$

where

$$q_t = \frac{e_t}{\frac{1}{n-1}\sum_{i=2}^{n}|Y_i-Y_{i-1}|} \tag{8.10}$$

where the numerator e_t is the predicted error for a given period, and the denominator is the average predicted error. Y_i is the actual value and Y_{i-1} is the predicted value. The mean absolute error is a statistical measure of how far predicted or estimated values are from the actual values.

8.2 Concept of the Algorithm

The algorithm is developed using the output of the trained neural network and the range (y) of the appliance energy consumption. The estimated hourly energy consumption of the appliances is computed based on their power rating on the manufacturer label. In this dissertation, the standard South African appliances ratings are used [99]. The detail of the computation is explained in chapter seven under load analysis. The table below shows the appliances actual hourly consumption of high income household in Johannesburg, predicted energy consumption (output of the trained neural network) and the computed energy consumption range of the appliances. In this dissertation, the average and maximum power ratings are used to compute the hourly energy consumption of the appliances. The consumption ranges may be overlapped for some appliances groups, the overlapped may be in form of intersections or subsets. In this scenario, the challenge of selecting which range the energy consumption falls is a difficult task. To resolve this challenge, "probability of belonging" is worked out for each of the appliance group that are overlapped. Figures 8.3 and 8.4 explain the two scenarios of overlapping. The type of overlapping in Figure 8.3 is an intersection while figure 8.4 is a subset overlapping. Identifying the appliances that are ON in each overlapping scenario, the algorithm will work out the probability of belonging and predicts the range of appliances with the highest probability as the appliance group that are switched ON for that period of time. In this regards, the algorithm will predict the appliances range at'd' in Figure 8.3 for the appliances that are ON for the intersection scenario and appliances range at 'b' in Figure 8.4 for the appliances that are ON for the subset scenario.

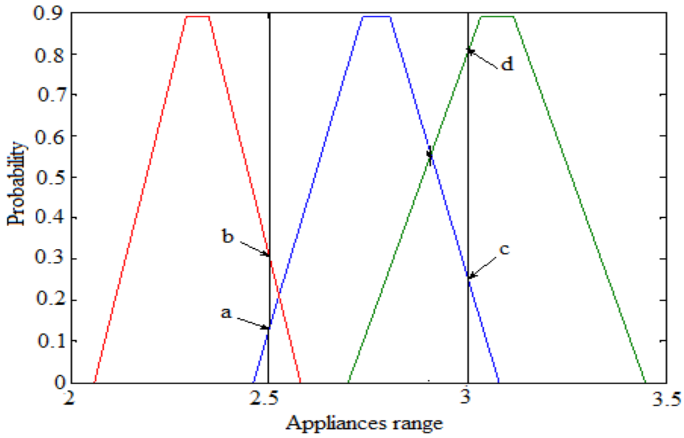


Figure 8.3: Intersection Overlapping

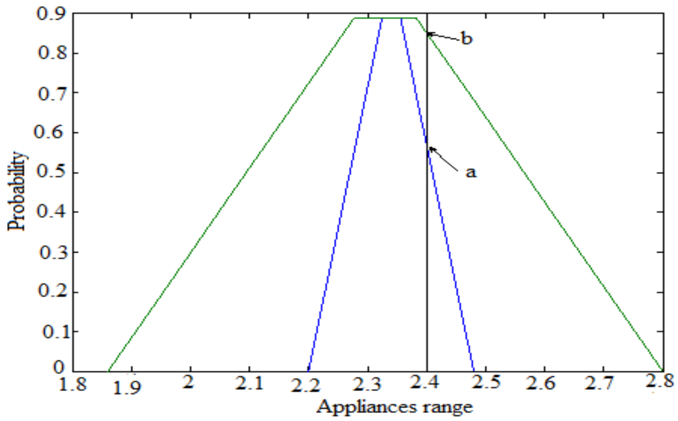


Figure 8.4: Subsets Overlapping

For this task, an individual appliance has been grouped within the group of x_{27}, x_{28}… x_n based on the household hourly energy consumption and the computed hourly individual appliance energy consumption ranged as shown in table 8.2. The hourly individual appliance energy consumption is computed using the average and maximum power rating of the appliance and the corresponding individual appliance energy consumption ranges are denoted by "y" as shown in table 8.2. The energy consumption of the appliance is computed straightforward by multiplying the power rating of the appliances in Watt by the time in hour that the appliance is ON. Each appliance energy consumption has a range of R_{imin} and R_{imax}. Firstly, for each energy consumption range, the algorithm check for the range in which data *(i)* (NN outputs) fall under and compute the mean as indicated in equation 8.11. The Probability distribution is generated for each appliance energy consumption range by determining where the consumption value data *(i)* fall in the range and then work out the proportion to the mean of the range as indicated in equation 8.12 and 8.13.

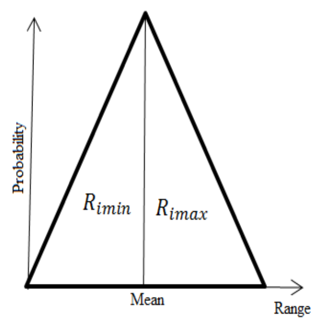


Figure 8.5: Probability Distribution Function

$$\bar{x} = \frac{R_{imin} + R_{imax}}{2} \tag{8.11}$$

where R_{imin} and R_{imax} are the lower and upper limits, respectively and $\bar{x}$ is the mean.

If the data *(i)* is *less* than the mean (i.e., data *(i)* < mean), the algorithm computes xprob *(j)* using equation 8.12.

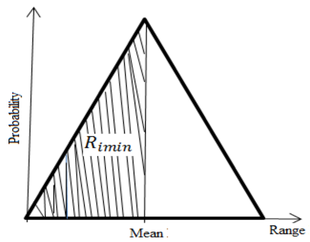


Figure 8.6: Probability Distribution Function for Data *(i)* < Mean

$$xprob\ (j) = \frac{data(i) - R_{imin}}{\bar{x} - R_{imin}} \tag{8.12}$$

Otherwise, the algorithm computes xprob *(j)* using equation 8.13

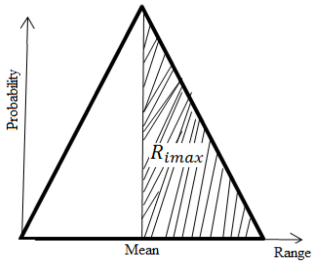


Figure 8.7: Probability Distribution Function for Data *(i)* > Mean

$$exprob\ (j) = \frac{R_{imax - data(i)}}{\bar{x} - R_{imin}} \tag{8.13}$$

where exprob (*j)* is the index for the range of the appliances energy consumption.

The algorithm processes the data (NN output) and compares the result with every switched ON appliance and with the corresponding appliances range within a given period of time. Thereafter, display the range with the highest probability. For each hour chosen, the appliance range with the highest probability value is corresponding to the appliance group that are switched ON at that hour. The appliance group X1 to X26 are not considered in the dissertation because it is assumed that a single appliance is unlikely to be ON in a typical household. Also, considering the actual household hourly energy consumption in table 8.2 is it assumed that a single appliance cannot consume such high amounts of kWh energy in only one hour. Hence appliances group X27 to X74 are considered. Table 8.2 depicts the appliance data for the algorithm.

Table 8.2: Appliances Data for the Algorithm

Appliances Group (x)	**Household hourly Energy Consumption (kWh)**	**ANN Output (kWh)**	**Appliances Energy Consumption Range/hour (kWh) (y)**
X27	3.04	3.080992	2.46-3.08
X28	3.41	3.447869	2.70-3.45
X29	2.57	2.578602	2.06-2.58
X30	3.02	3.041749	2.54-3.04
X31	2.61	2.658599	2.39-2.66
X32	2.58	2.598565	2.24-2.60

X33	2.98	2.991894	2.15-2.99
X34	2.59	2.618482	1.31-2.62
X35	3.83	3.84367	3.35-3.85
X36	3.91	3.943024	3.35-3.95
X37	2.74	2.769911	1.81-2.77
X38	3.24	3.251758	2.97-3.25
X39	3.59	3.649982	3.17-3.65
X40	2.67	2.678964	2.13-2.68
X41	2.67	2.678862	2.13-2.68
X42	4.1	4.194872	3.54-4.20
X43	3.63	3.649336	3.17-3.65
X44	3.46	3.480368	2.87-3.48
X45	3.28	3.280399	2.65-3.28
X46	3.31	3.330413	2.68-3.33
X47	3.05	3.049756	2.55-3.05
X48	4.53	4.528943	3.81-4.53
X49	3.31	3.329637	2.68-3.33
X50	3.44	3.449356	2.77-3.45
X51	2.96	3.079433	2.31-2.97
X52	2.91	3.452867	2.31-2.97
X53	2.68	2.580639	2.21-2.70
X54	2.95	3.038681	2.3-2.95
X55	2.56	2.659026	2.21-2.61
X56	2.85	2.601602	2.35-2.85
X57	2.45	2.986501	2.20-2.48
X68	2.69	2.621768	2.21-2.70
X59	2.82	3.851853	1.84-2.82
X60	2.79	3.950908	1.86-2.80
X61	3.01	2.76963	2.62-3.05
X62	2.81	3.249579	2.08-2.83
X63	2.63	3.65054	2.31-2.65
X64	3.06	2.681566	2.45-3.08
X65	2.85	2.683973	2.35-2.85
X66	3.73	4.202024	3.24-3.75
X67	2.85	3.651032	2.35-2.85
X68	2.89	3.480861	2.36-2.89
X69	2.59	3.282982	1.90-2.60
X70	3.2	3.328344	2.82-3.30
X71	3.08	3.050148	2.67-3.09

X72	3.51	4.528751	3.07-3.60
X73	3.26	3.328593	3.01-3.30
X74	2.80	3.454022	2.40-2.80

Figure 8.8 depicts the main steps in the non-intrusive appliance monitoring and identification algorithm.

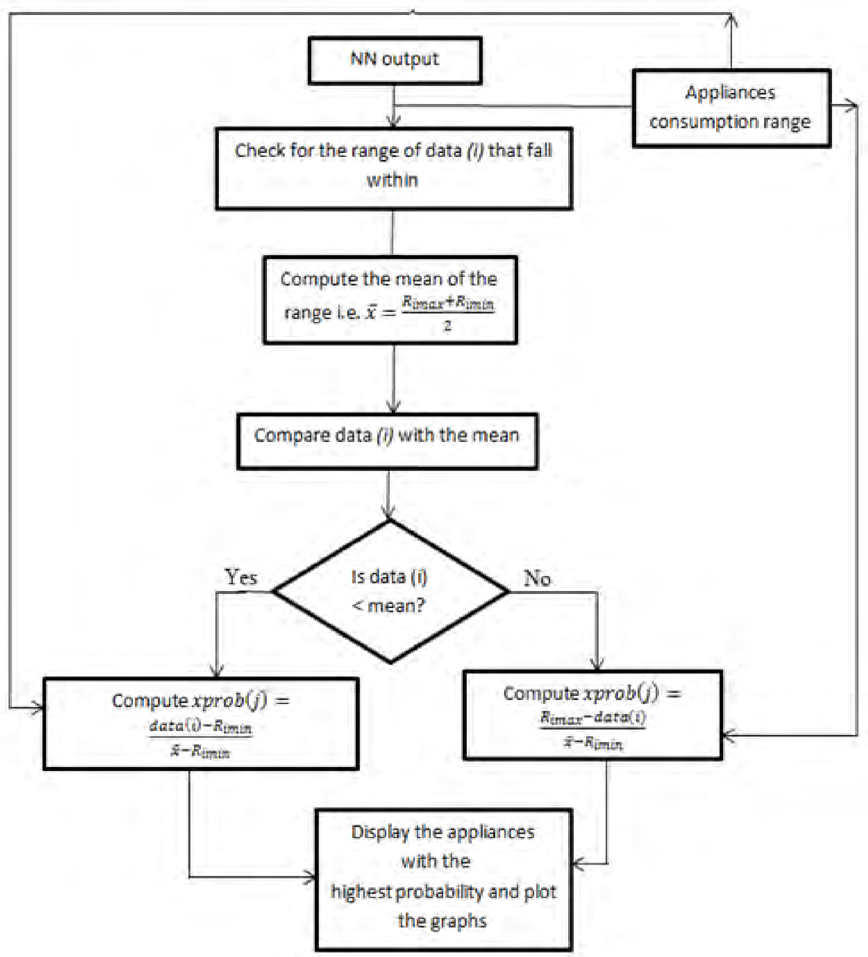


Figure 8.8: Overview of the Algorithm for Appliance Prediction

8.3 Appliance Modelling for Identification

For proper monitoring and identification of domestic appliances, modelling can be considered in different days of the week and different seasons of the year. The two scenarios be considered are:

- Case 1: Summer load modelling
- Case 2: Winter load modelling.

8.3.1 Summer Load Modelling

Summer is the warmest season of the year. Therefore, certain appliances which are commonly used during this season differ from those appliances used in winter, though some appliances are common to both seasons. Moreover, overall energy consumption of a typical household in the summer has been always different from that of winter probably due to the difference in the appliance usage and their energy consumption. In addition, energy consumption during the weekdays is different from the energy consumption during the weekends (Saturday and Sunday). Hence, weekdays and weekends energy consumption are modelled separately in this dissertation, nevertheless, the same procedures are followed. For this task, it is assumed that the condition that holds for one day during the weekday applies to the rest of the day in the week. Hence two days (Monday and Tuesday) are considered in the modelling.

8.3.1.1 Weekday modelling in summer

- **Training of Neural Network**

Neural network with multilayer perceptron (MLP) architecture, which is usually used in pattern recognition and identification, is employed for the task. The neural network used in this work consists of two layers. The number of input is two, to which the household hourly consumption for 48 hours and the time of the day have been assigned. The historical hourly consumption is obtained from the energy recording at the electric meter in a high-income household in Johannesburg. The time of the day is the time at which the energy consumption is taken and the readings were taken at five minute interval. An algorithm was developed to convert the five minute data to hourly energy consumption. The neural network target is the hourly consumption of the individual appliances, which is computed according to equation 8.1, for all appliances monitored in the household. The training process uses trial and error technique to achieve the optimal performance of the network. The 48 hours energy consumption record of the high-income household was fed as input for the training of the neural network. The computed energy consumption from the power rating and assumed hour of usage is used as the target into the network. Sixty percent (60 %) of the data was used for the network training, twenty-five (25 %) for validation and fifteen 15 % of the data were used for testing. The neural network was trained using Leverburg Marquardt back propagation algorithm. The simulation took 5minute and the training stopped at 30 epochs, when the training conditions were satisfied. Figure 8.9 depicts the actual and the predicted energy consumptions for weekdays from the neural network training, while table 8.3 depicts the parameters (input and target) for the neural network training.

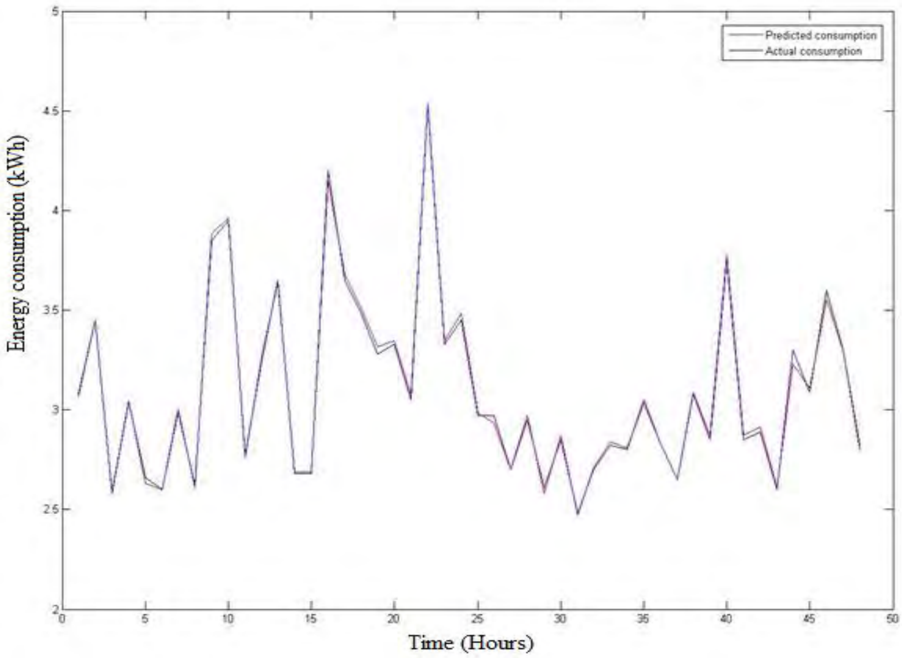


Fig 8.9: Plot of the Actual and the Predicted Energy Consumption

In Figure 8.9, the red line is the predicted household energy consumption from the output of the artificial neural network training, while the blue line depicts the actual household hourly energy consumption as recorded from the household energy meter. The parameters for the neural network training are depicted in table 8.3. The input parameters consist of the time of the day (Hour) and the actual household hourly energy consumption (kWh), the target is the estimated hourly appliance energy consumption (kWh). Table 8.3 (a) to 8.3 (f) summary the inputs and target for the neural network training.

Table 8.3 (a): Hour 1.00-8.00

Input	**Time (Hour)**	01.00	02.00	03.00	04.00	05.00	06.00	07.00	08.00
	Household Hourly Consumption (kWh)	3.04	3.41	2.57	3.02	2.61	2.58	2.98	2.59
Target	**Appliances Hourly Energy Consumption (kWh)**	3.08	3.45	2.58	3.04	2.66	2.60	2.99	2.62

Table 8.3 (b): Hour 9.00-16.00

Input	**Time (Hour)**	09.00	10.00	11.00	12.00	13.00	14.00	15.00	16.00
	Household Hourly Consumption (kWh)	3.38	3.91	2.74	3.24	3.59	2.67	2.67	4.10
Target	**Appliances Hourly Energy Consumption (kWh)**	3.85	3.95	2.77	3.25	3.65	2.68	2.68	4.02

Table 8.3 (c): Hour 17.00-24.00

Input	**Time (Hour)**	17.00	18.00	19.00	20.00	21.00	22.00	23.00	24.00
	Household Hourly Consumption (kWh)	3.63	3.46	3.28	3.31	3.05	4.53	3.31	3.44
Target	**Appliances Hourly Energy Consumption (kWh)**	3.65	3.48	3.23	3.33	3.05	4.53	3.33	3.45

Table 8.3 (d): Hour 25.00-32.00

Input	**Time (Hour)**	25.00	26.00	27.00	28.00	29.00	30.00	31.00	32.00
	Household Hourly Consumption (kWh)	2.29	2.91	2.68	2.95	2.56	2.85	2.45	2.69
Target	**Appliances Hourly Energy Consumption (kWh)**	2.97	2.97	2.70	2.95	2.61	2.85	2.48	2.70

Table 8.3 (e): Hour 33.00-40.00

Input	**Time (Hour)**	33.00	34.00	35.00	36.00	37.00	38.00	39.00	40.00
	Household Hourly Energy Consumption (kWh)	2.82	2.79	3.01	2.81	2.63	3.06	2.85	3.73
Target	**Appliances Hourly Energy Consumption (kWh)**	2.82	2.80	3.05	2.83	2.65	3.08	2.85	3.75

Table 8.3 (f): Hour 41.00-48.00

Input	**Time (Hour)**	41.00	42.00	43.00	44.00	45.00	46.00	47.00	48.00
	Household Hourly Energy Consumption (kWh)	2.85	2.89	2.59	3.20	3.08	3.51	3.26	2.80
Target	**Appliances Hourly Energy Consumption (kWh)**	2.85	2.89	2.60	3.30	3.09	3.60	3.30	2.80

8.3.1.2 Validation of the Neural Network Training in summer

Artificial neural networks are increasingly used as non-linear, non-parametric prediction and models for pattern recognition tasks. Neural network models are constructed by training using a data set, i.e. the model alters from a random state to a trained state and must be validated. Once a neural network has been trained it must be evaluated to see if it is ready for the propose task. Data validation is intended to provide certain well-defined guarantees for fitness, accuracy, and consistency in any of various kinds of user input into an application or automated system. The evaluation and validation of an artificial neural network prediction model are based upon one or more selected error metrics. Generally, neural network models which perform a function of approximation task will use a continuous, error metrics such as absolute error (AE), mean absolute error (MAE), root mean squared error (RMSE), standard deviation (STD), mean absolute percentage error (MAPE), symmetric mean absolute percentage error (SMAPE) or mean absolute scaled error (MASE). The definitions for these error metrics are defined in the equations in section 8.1.3.2. Table 8.4 depicts the validation using error metrics described previously for weekdays and weekends in summer.

Table 8.4: Validation error metrics for weekdays and weekends in summer

Validation Techniques	**Weekdays Validation (%)**	**Weekends Validation (%)**
Absolute Error (AE)	4. 4104	9.0113
Mean Absolute Error (MAE)	0.0284	0.0593
Standard Deviation (SD)	2.5466	3.6216
Root Mean Squared Error (RMSE)	0.1664	0.3552
Mean Absolute Percentage Error (MAPE)	1.1672	1.6872
Symmetric Mean Absolute Percentage Error (SMAPE)	0.0273	0.0593
Mean Absolute Scaled Error (MAE)	0.2085	0.4280

Typically, artificial neural networks are trained to decreasingly lower training tolerances in an attempt to achieve the “best” performing network. It is assumed that lower training tolerances equate with improved performance, hence, the criterion for selecting the best trained neural network is to choose the neural network training with the minimum error, hence, the neural network training for weekdays is the best performance networks, because all the errors have the minimum values.

8.3.1.3 Appliances Prediction

Upon the completion of the neural network training, the next step is to predict the appliance(s) that contribute to the household energy consumption at a given period of time. The output of the neural network training is used for the appliance identification of the household. Undisputedly, using only energy consumption (active power) for monitoring and identifying appliances has some limitations. The most outstanding challenge is that many appliances have overlapped energy consumptions. Nevertheless, the algorithm is developed to overcome this challenge by calculating the probability of belonging as explained in section 8.2 (concept of the algorithm developed) and predict the appliances with the highest probability the appliance range that are ON at a given period of time.

8.4 Simulation Results

Since the main focus of this research is the identification of domestic appliances that are switched on at a given period of time, an algorithm was developed and utilized to display the real-time activity of the appliances in response to the output of the neural network. The algorithm determines the probability of belonging, classified the appliances into ranges, displays the information and plots the graph as shown figures, 8.10 to 8.13 respectively. In the graphs, the y-axis represents the probabilities of the appliances switched ON, while x-axis represents the appliance group (X27 –X74). The group of the appliances with highest probability is predicted to be the appliance(s) that was switched ON for the hour considered. Figure D1 in appendix D shows the cross-section of the information displayed by the algorithm. Some of the graphical representations of the predicted appliances are shown in the Figures 8.10 to 8.13. Figure 8.10 depicts the graphical representation of the predicted appliances for 1o’clock. The appliance group with the highest probability falls at X28; the appliances predicted are refrigerator, oven, electric fence and personal computer.

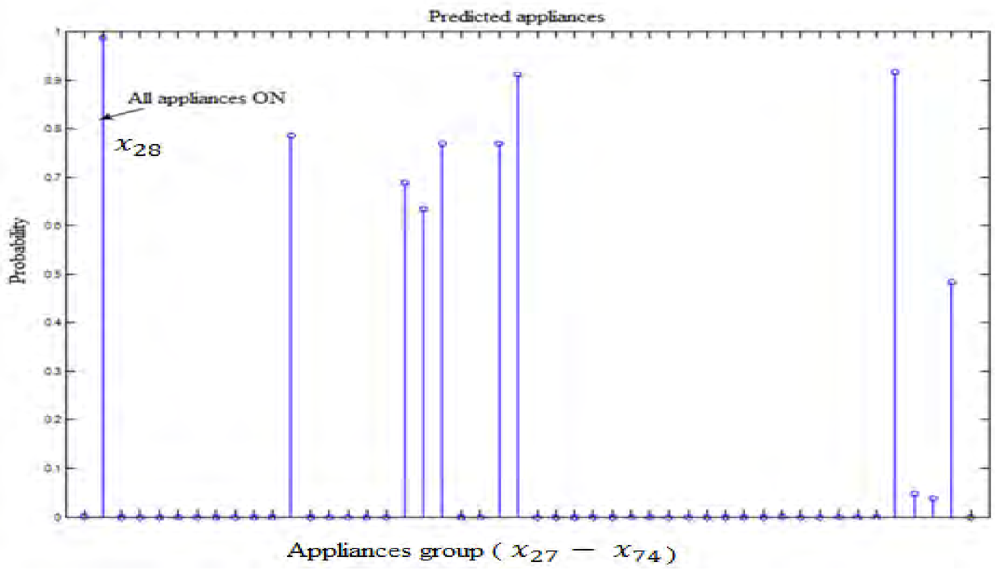


Figure 8.10: Predicted Appliances at1 O'clock

Figure 8.11 shows the graphical representation of the predicted appliances at 2 o'clock. The highest probabilities fall at X39 and X43.The predicted appliances are refrigerator, air-conditioning, and sewing machine.

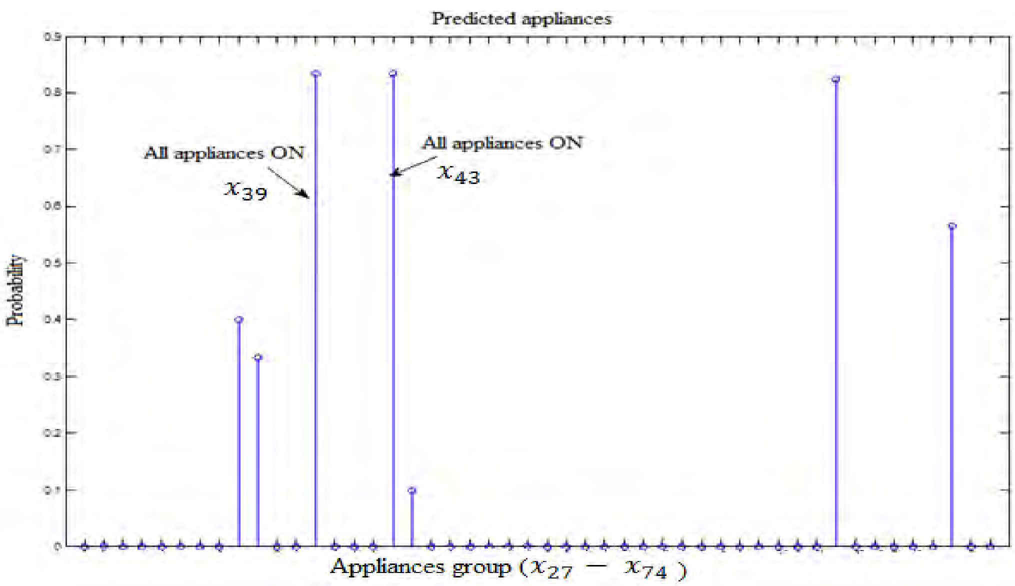


Figure 8.11: Predicted Appliances at 2 O'clock

Figure 8.12 depicts the graphical representation of the predicted appliances at 9 o'clock; the highest probability fall at X42. The predicted appliances are refrigerator, air-conditioning, cordless kettle and personal computer**.**

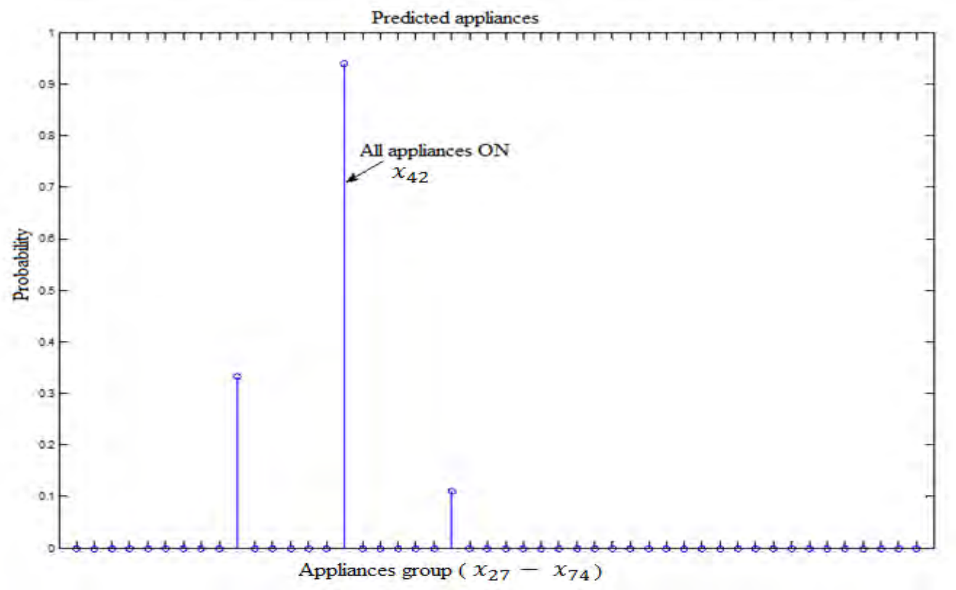
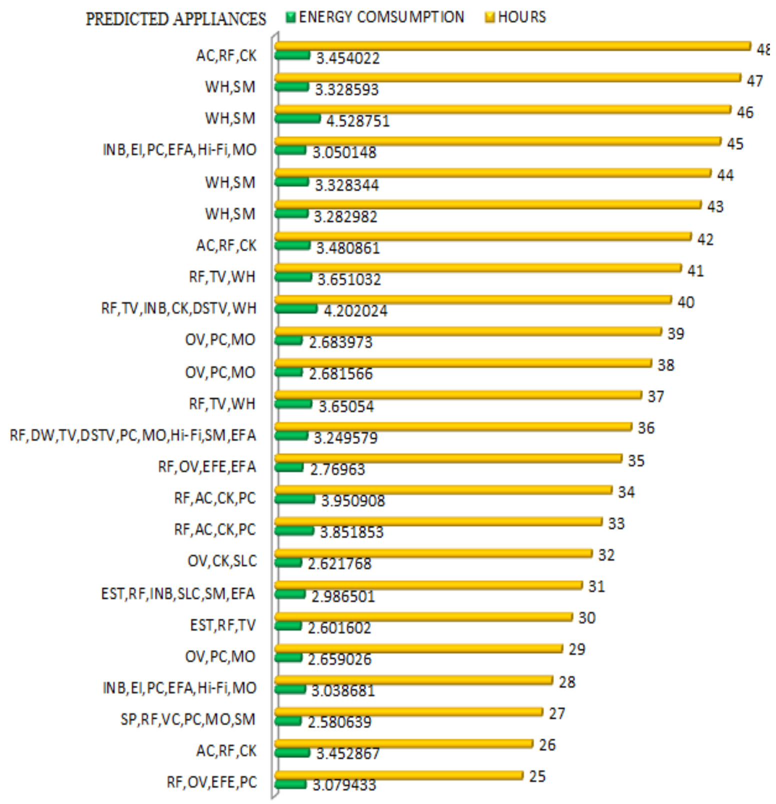


Figure 8.12: Predicted Appliances at 9 O'clock

For easy identification and analysis, the Figure 8.13 summarizes the switched ON appliances predicted for the first 48 hours in the household.



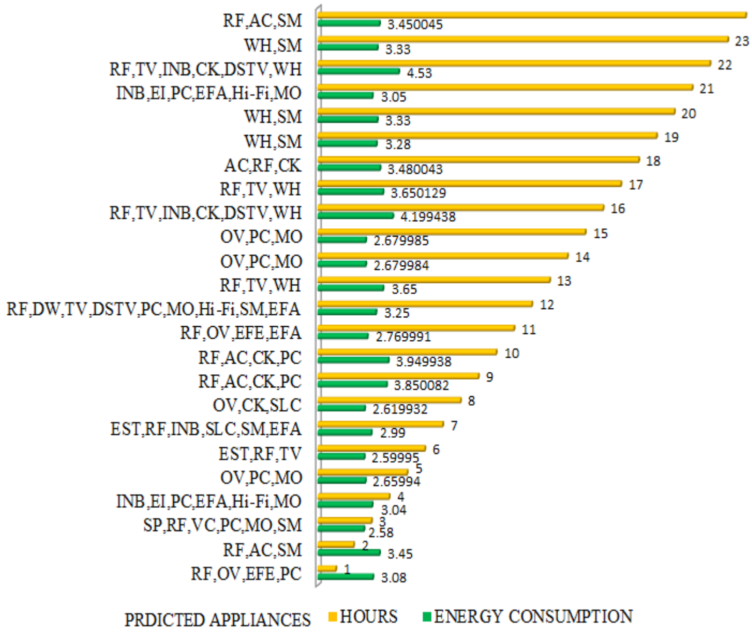


Figure 8.13: Predicted Appliances for 48 hours

8.5 Weekends Modelling in Summer

The energy consumption during the weekends is normally different from the energy consumption during the weekdays. Therefore, it is essential to model weekends separately for adequate recognition of the appliances responsible for the energy consumption. The training procedure utilized in weekday was adopted for weekends. Sixty percent (60 %) of the data was used for training, fifteen percent (15 %) for validation and twenty-five percent (25 %) for testing. The Mean Squared Error (MSE) achieved is 4.3831e-0.3 and the gradient of performance is 5.80e-10. Fig 8.14 and table 8.5 depict the actual and the predicted energy consumptions for weekend's neural network training and the input and output data for the training respectively.

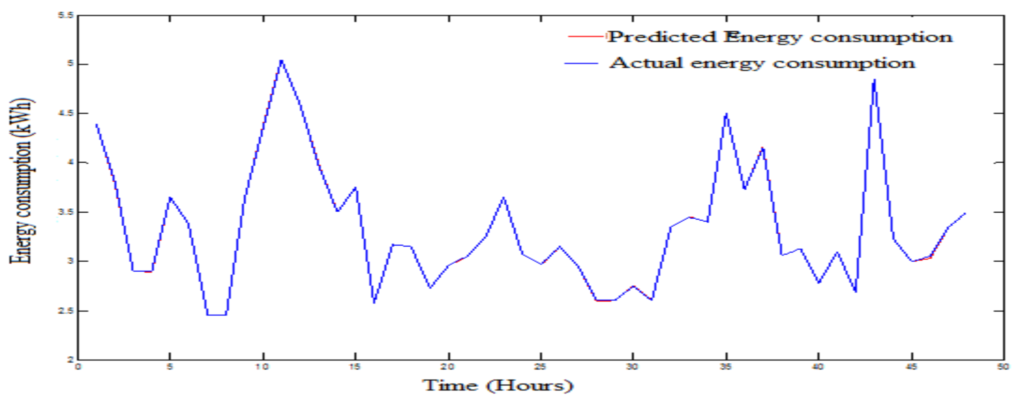


Fig 8.14: Plot of the Actual and the Predicted Energy Consumption

Table 8.5 (a) to 8.5(f) summary of the input and target for the neural network training

Table 8.5 (a): Hour 1.00-8.00

Input	**Time (Hour)**	01.00	02.00	03.00	04.00	05.00	06.00	07.00	08.00
	Household Hourly Consumption (kWh)	4.37	3.75	2.88	2.90	3.61	3.33	2.44	2.43
Target	**Appliances Hourly Energy Consumption (kWh)**	4.39	3.80	2.90	2.90	3.65	3.38	2.45	2.45

Table 8.5 (b): Hour 9.00-16.00

Input	**Time (Hour)**	09.00	10.00	11.00	12.00	13.00	14.00	15.00	16.00
	Household Hourly Consumption (kWh)	3.63	4.34	5.04	4.57	3.96	3.47	3.75	2.55
Target	**Appliances Hourly Energy Consumption (kWh)**	3.63	4.35	5.05	4.60	3.97	3.50	3.75	2.58

Table 8.5 (c): Hour 17.00-24.00

Input	**Time (Hour)**	17.00	18.00	19.00	20.00	21.00	22.00	23.00	24.00
	Household Hourly Consumption (kWh)	3.15	3.13	2.71	2.96	3.02	3.23	3.62	3.05
Target	**Appliances Hourly Energy Consumption (kWh)**	3.17	3.15	2.73	2.96	3.05	3.24	3.65	3.08

Table 8.5 (d): Hour 25.00-32.00

Input	**Time (Hour)**	25.00	26.00	27.00	28.00	29.00	30.00	31.00	32.00
	Household Hourly Consumption (kWh)	2.96	3.15	2.95	2.59	2.60	2.75	2.60	3.32
Target	**Appliances Hourly Energy Consumption (kWh)**	2.97	3.15	2.95	2.60	2.60	2.75	2.60	3.35

Table 8.5 (e): Hour 25.00-32.00

Input	**Time (Hour)**	33.00	34.00	35.00	36.00	37.00	38.00	39.00	40.00
	Household Hourly Consumption (kWh)	3.43	3.39	4.50	3.69	4.12	3.06	3.12	2.77
Target	**Appliances Hourly Energy Consumption (kWh)**	3.45	3.40	4.50	3.73	4.15	3.06	3.13	2.78

Table 8.5 (f): Hour 25.00-32.00

Input	**Time (Hour)**	41.00	42.00	43.00	44.00	45.00	46.00	47.00	48.00
	Household Hourly Consumption (kWh)	3.09	2.67	4.83	3.23	2.99	3.01	3.35	3.50
Target	**Appliances Hourly Energy Consumption (kWh)**	3.10	2.68	4.85	3.23	3.00	3.05	3.35	3.50

The table 8.6 depicts the data used in the algorithm for the appliance identification. The appliance group is denoted X, the household energy consumption is the actual hourly energy consumption of the household in kWh, the predicted energy consumption is the output of the neural network training and appliance energy consumption range is the energy consumed per hour by each appliance computed from the power rating of the appliances. The algorithm works on the same principle as in weekday modelling.

Table 8.6: Appliances Data for the Algorithm

Appliances Groups (x)	**Household Hourly Energy Consumption (kWh)**	**ANN Output**	**Appliances Energy Consumption Range/Hour (kWh) (y)**
X27	4.37	4.389709	3.27-4.39
X28	3.75	3.798578	3.00-3.80
X29	2.88	2.897826	2.25-2.90
X30	2.90	2.896349	2.25-2.90
X31	3.61	3.650052	3.10-3.65
X32	3.33	3.379913	2.36-3.38
X33	2.44	2.451227	1.85-2.45
X34	2.43	2.451519	1.85-2.45
X35	3.63	3.629428	2.78-3.63

X36	4.34	4.353638	3.47-4.35
X37	5.04	5.049171	3.90-5.05
X38	4.57	4.599102	3.50-4.60
X39	3.96	3.972694	3.82-3.97
X40	3.47	3.499572	3.47-3.50
x41	3.75	3.751981	3.22-3.75
x42	2.55	2.579504	1.92-2.58
X43	3.15	3.168259	2.72-3.17
X44	3.13	3.148193	2.28-3.15
X45	2.71	2.728245	2.27-2.73
X46	2.96	2.960213	2.43-2.96
X47	3.02	3.047081	2.50-3.05
X48	3.23	3.239366	2.77-3.24
X49	3.62	3.64995	3.10-3.65
X50	3.05	3.076739	2.46-3.08
X51	2.96	2.968672	1.912-2.97
X52	3.15	3.150569	2.90-3.15
X53	2.95	2.951494	2.60-2.95
X54	2.59	2.599413	2.30-2.60
X55	2.60	2.604909	2.30-2.60
X56	2.75	2.753158	2.40-2.75
X57	2.60	2.604953	2.30-2.60
X68	3.32	3.346683	2.75-3.35
X59	3.43	3.451109	2.65-3.45
X60	3.39	3.400342	2.50-3.40
X61	4.50	4.499873	3.85-4.50
X62	3.69	3.730045	3.27-3.73
X63	4.12	4.158663	3.55-4.15
X64	3.06	3.060882	2.50-3.06
X65	3.12	3.130212	2.44-3.13
X66	2.77	2.780234	2.44-2.78
X67	3.09	3.100408	2.25-3.10
X68	2.67	2.680699	2.36-2.68
X69	4.83	4.849193	3.85-4.85
X70	3.23	3.230154	2.61-3.23
X71	2.99	3.000854	2.25-3.00
X72	3.01	3.030744	2.30-3.05
X73	3.35	3.349757	3.10-3.35
X74	3.50	3.499374	3.00-3.50

Results and Discussion for Weekends Modelling in summer

The cross-section of the result displayed by the algorithm for weekend modelling is shown in Figure D2 of Appendix D. Also, Figures 8.15, to 8.18 show some of the graphical representations of the predicted appliances for 1 o'clock, 2 O'clock, and 11 O'clock and 20 O'clock respectively. For the 1 O'clock, the group of appliances with the highest probability falls at X69 as shown in Figure 8.15, the predicted appliances are electric stove, refrigerator, television, electric frying pan.

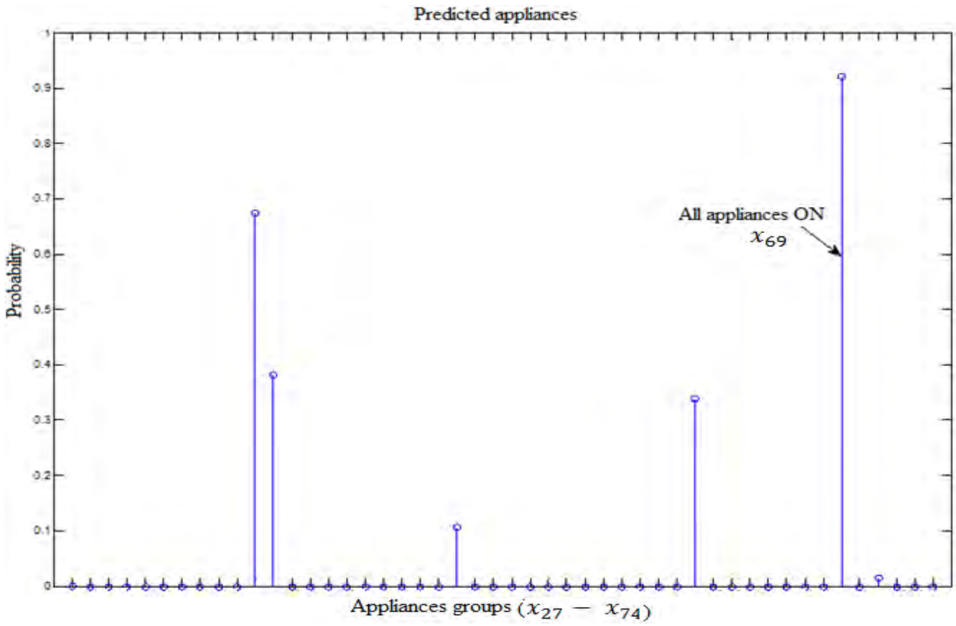


Figure 8.15: Predicted Appliances at 1 O'clock

The graphical representation of the predicted appliances for 2 O'clock is depicted in Figure 8.16. The highest probability falls at X27 and the predicted appliances are oven, incandescent bulb, personal computer, modem, electric fence and printer.

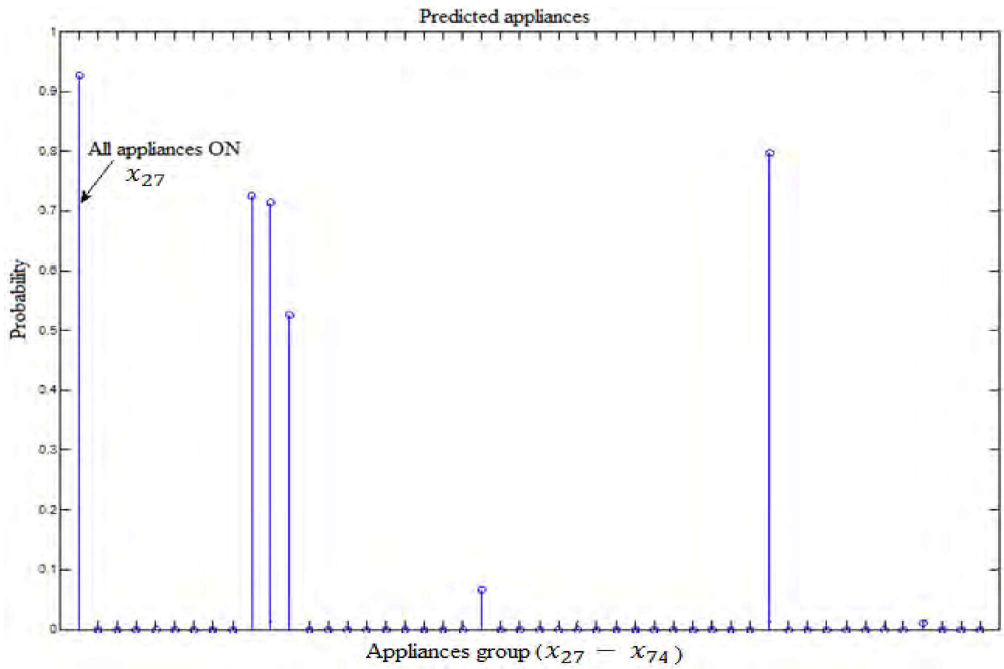


Figure 8.16: Predicted Appliances at 2 O'clock

Figure 8.17 depicts the graphical representation of the predicted appliances at 11 O'clock, the highest probability falls at X48 and the predicted appliances are refrigerator, electric iron, incandescent bulb, personal computer, modem, and electric fan.

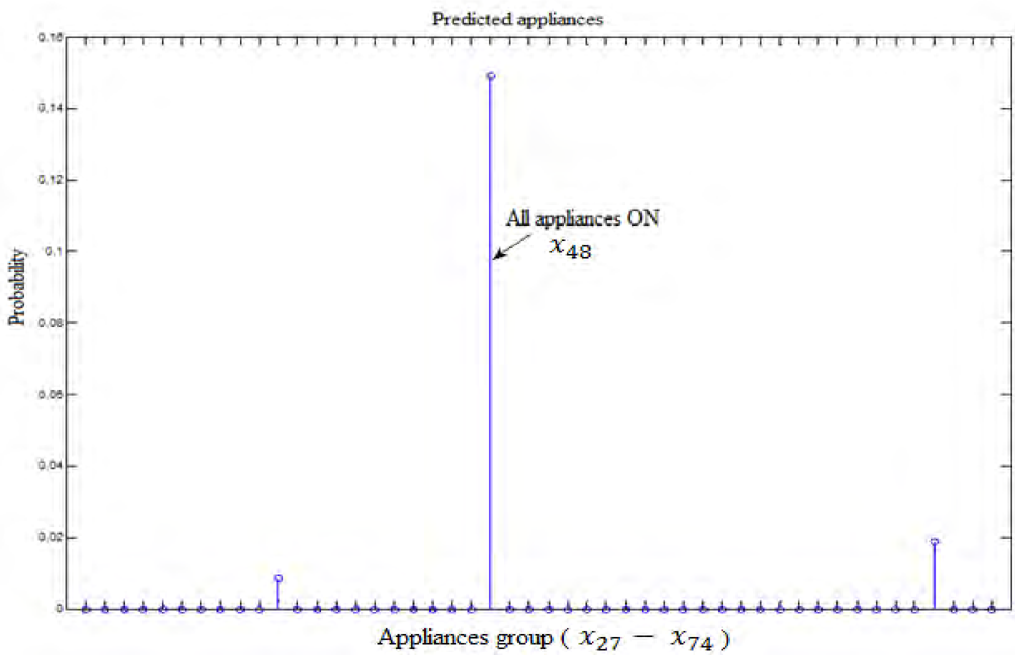


Figure 8.17: Predicted Appliances at 11 O'clock

Figure 8.18 depicts the graphical representation of the predicted appliances at 20 O'clock. The highest probability falls at X60 and the predicted appliances at this hour are electric frying pan, cordless kettle and refrigerator.

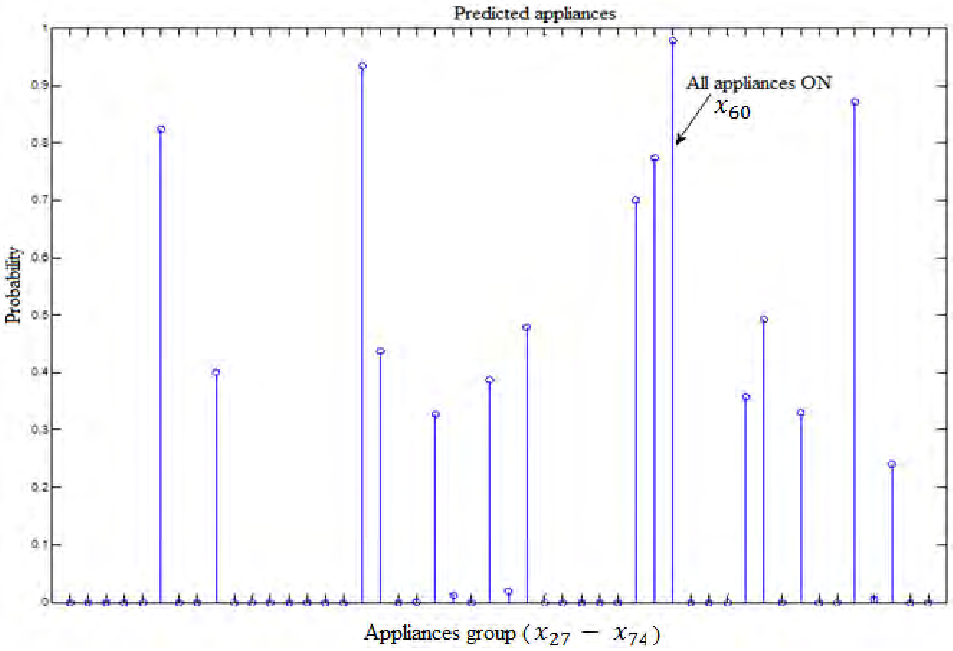
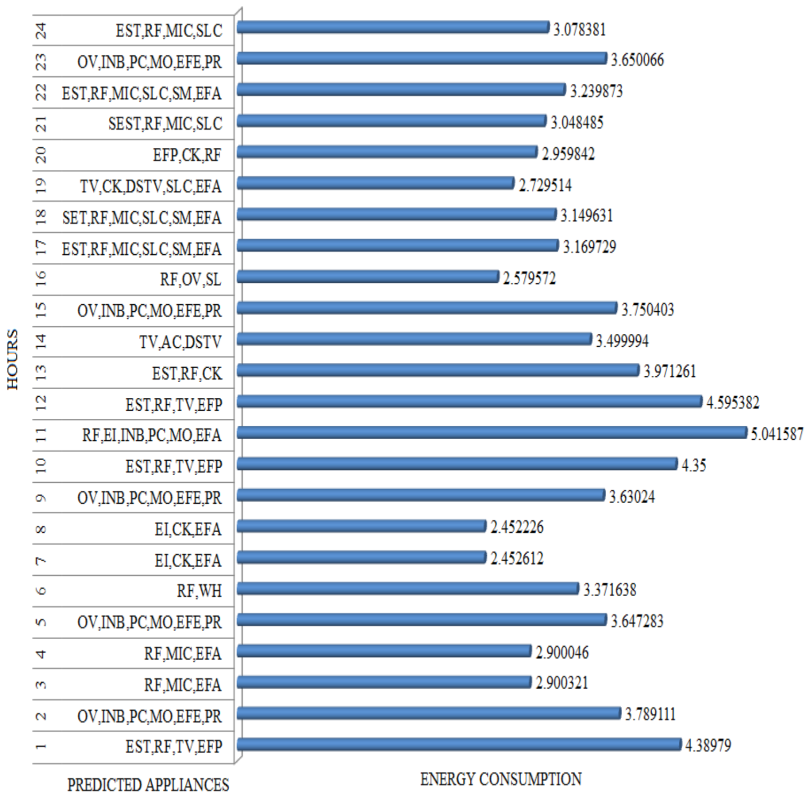


Figure 8.18: Predicted Appliances at 20 O'clock

Figure 8.19 summarizes the appliances predicted for the 48 hours (2days) in the household.



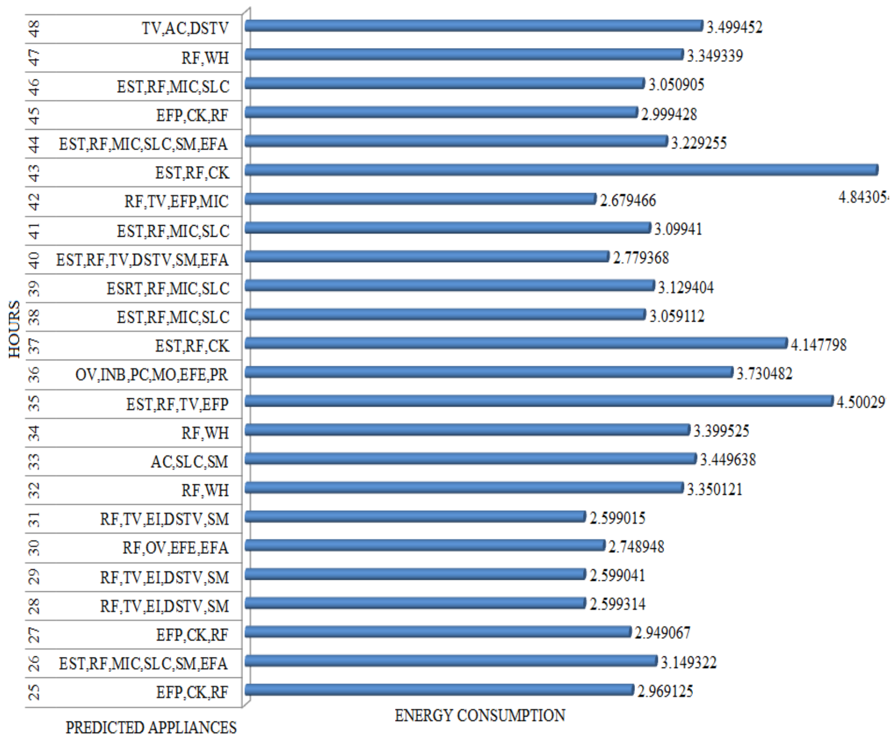


Figure 8.19: Predicted Appliances for 48 hours

8.4 Winter Appliances Modelling

Winter is the coldest season of the year in temperate climate between autumn and spring. It is caused by the axis of the Earth in the respective hemisphere being oriented away from the Sun. Different country defines different month as the start of winter, for instance, in southern Africa, winter falls between May to July. In many regions, winter is associated with snow and freezing temperatures. Because winter is the coldest season, certain appliances are often used than in summer. Nevertheless, winter load modelling techniques is the same as summer load modelling. As in summer, winter load modelling is also grouped into weekdays and weekends load modelling. Table 8.7 depicts the parameters (inputs and target) for the training of the neural network in the winter. Table 8.7 (a) to 8.7(f) summary the input and target for the neural network training.

Table 8.7 (a) Hour 1.00-8.00

Inputs	**Time (Hour)**	01.00	02.00	03.00	04.00	05.00	06.00	07.00	08.00
	Household Hourly Consumption (kWh)	3.92	3.05	3.64	3.28	3.49	5.71	11.52	10.70
Target	**Appliances Hourly Energy Consumption (kWh)**	3.95	3.08	3.65	3.28	3.50	3.60	11.53	10.80

Table 8.7 (b) Hour 9.00-16.00

Inputs	**Time (Hour)**	09.00	10.00	11.00	12.00	13.00	14.00	15.00	16.00
	Household Hourly Consumption (kWh)	6.13	7.44	8.28	10.98	9.31	8.71	7.66	6.17
Target	**Appliances Hourly Energy Consumption (kWh)**	6.15	7.50	8.28	10.98	9.35	8.85	7.67	6.18

Table 8.7 (c) Hour 17.00-24.00

Inputs	**Time (Hour)**	17.00	18.00	19.00	20.00	21.00	22.00	23.00	24.00
	Household Hourly Consumption (kWh)	6.99	6.13	6.99	9.82	10.80	10.62	7.74	6.29
Target	**Appliances Hourly Energy Consumption (kWh)**	6.99	6.15	6.99	9.83	10.80	10.63	7.74	6.30

Table 8.7 (d) Hour 25.00-32.00

Inputs	**Time (Hour)**	25.00	26.00	27.00	28.00	29.00	30.00	31.00	32.00
	Household Hourly Consumption (kWh)	6.97	4.38	4.26	3.39	4.00	4.84	9.95	6.09
Target	**Appliances Hourly Energy Consumption (kWh)**	6.97	4.40	4.30	3.39	4.00	4.85	9.95	6.09

Table 8.7 (e) Hour 33.00-40.00

Inputs	**Time (Hour)**	33.00	34.00	35.00	36.00	37.00	38.00	39.00	40.00
	Household Hourly Consumption (kWh)	7.42	8.67	8.62	7.76	10.37	5.90	4.98	5.55
Target	**Appliances Hourly Energy Consumption (kWh)**	7.43	8.70	8.65	7.80	10.45	5.90	4.98	5.60

Table 8.7 (f) Hour 41.00-48.00

Inputs	**Time (Hour)**	41.00	42.00	43.00	44.00	45.00	46.00	47.00	48.00
	Household Hourly Consumption (kWh)	8.77	10.47	7.11	7.32	9.14	6.41	6.05	6.90
Target	**Appliances Hourly Energy Consumption (kWh)**	8.78	10.48	7.15	7.35	9.14	6.43	6.05	6.95

The training procedure is the same as in summer. Sixty percent (60 %) of the data was used for training, twenty-five percent (25 %) for testing and fifteen percent (15 %) for validation. The Mean Squared Error (MSE) achieved is 5.387-06 and the gradient of performance is 1.00e-10. The training stopped at 30 epochs, when the training conditions were satisfied. Figure 8.20 depicts the comparison between actual and the predicted energy consumption from the neural network training.

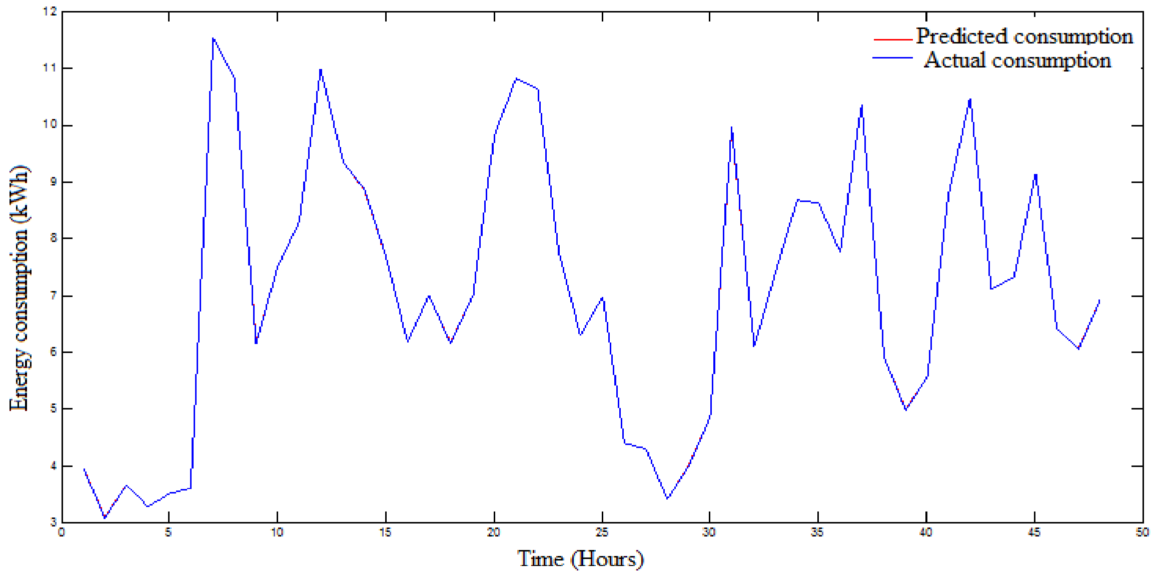


Figure 8.20: Plot of the Actual and the Predicted Energy Consumption

8.4.1 Validation of the Neural Network Training in Winter

The validation results of the winter training of the household hourly energy consumption are shown in table 8.8. In the same way as explained in summer neural network training, the criterion for selecting the best trained neural network is to choose the neural network training with the minimum error, hence, the neural network training for weekends is the best performance networks in winter, because all the errors have the minimum values.

Table 8.8: Validation result of winter neural network training

Validation Techniques	Weekdays Validation (%)	Weekends Validation (%)
Absolute Error (AE)	12.4656	3.8491
Mean Absolute Error (MAE)	0.0517	0.0118
Standard Deviation (STD)	4.6089	2.6437
Root Mean Squared Error (RMSE)	0.3218	0.1088
Mean Absolute Percentage Error (MAPE)	1.57534	0.7512
Symmetric Mean Absolute Percentage Error (SMAPE)	0.0517	0.0118
Mean Absolute Scaled Error (MASE)	0.01568	0.0593

The Validation of the neural network training for both summer and winter modelling is shown in Figure 8.21.

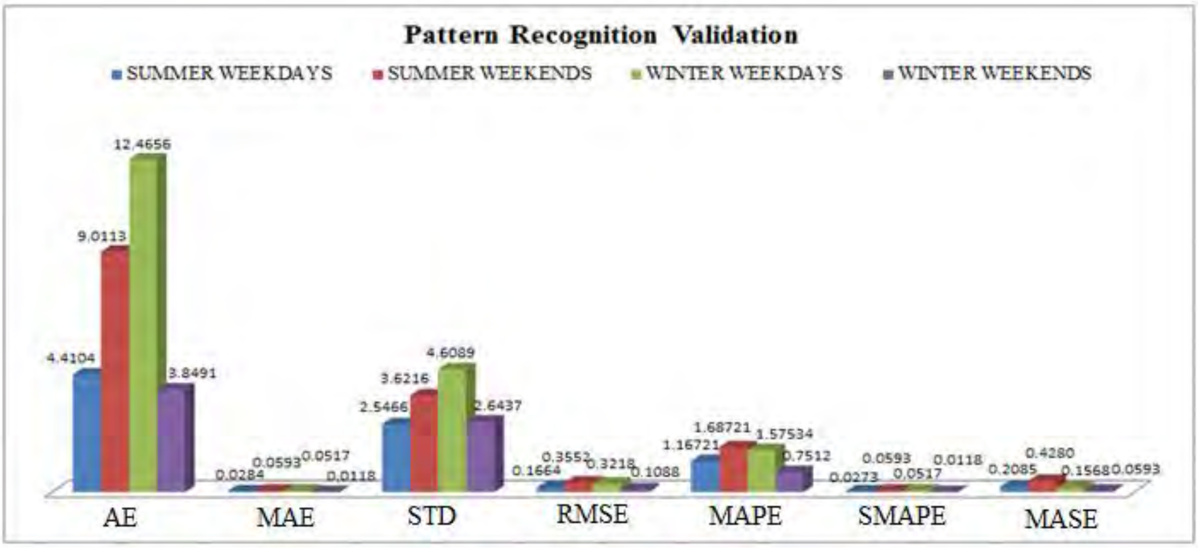


Figure 8.21: Validation and Error Metric for Both Summer and winter Training

Obviously, from the Figure 8.21, that weekend training in winter gives the best performance because they have the smallest error in all validation techniques.

8.4.2 Weekday Modelling in Winter

The table 8.9 depicts the data used in the developed algorithm for appliance identification. The appliances X is the appliances group, the actual consumption is the household energy consumption per hour, the predicted consumption is the output of the neural network training and appliance energy consumption is energy consumed per hour by each appliance computed from the power rating of the appliances. The algorithm works on the same principle as in summer. Table 8.9(a) to 8.9(g) summary the Algorithm parameters for the appliance identification.

Table 8.9 (a) Appliances Group X29-X35

Appliances Group (X)	X29	X30	X31	X32	X33	X34	X35
Household Hourly Energy Consumption (kWh)	3.92	3.05	3.64	3.28	3.49	5.71	11.52
Predicted Consumption (kWh)	3.950	3.080	3.65	3.280	3.500	3.600	11.50
Appliances Energy Consumption Range	3.30-3.95	2.45-3.08	2.66-3.65	2.41-3.28	2.61-3.50	5.00-3.60	9.07-11.53

Table 8.9 (b) Appliances Group X 36-X42

Appliances Group (X)	X36	X37	X38	X39	X40	X41	X42
Household Hourly Energy Consumption (kWh)	10.70	6.13	7.44	8.28	10.98	9.31	8.71
Predicted Consumption (kWh)	10.80	6.15	7.500	8.279	10.97	9.350	8.849
Appliances Energy Consumption Range	8.50-10.80	5.10-6.15	6.60-7.50	6.27-8.28	8.77-10.98	7.77-9.35	7.15-8.85

Table 8.9 (c) Appliances Group X43-X49

Appliances Group (X)	X43	X44	X45	X46	X47	X48	X49
Household Hourly Energy Consumption (kWh)	7.66	6.17	6.99	6.13	6.99	9.82	10.8
Predicted Consumption (kWh)	7.670	6.180	6.989	6.150	6.989	9.830	10.79
Appliances Energy Consumption Range	5.78-7.67	5.42-6.18	5.56-6.99	5.10-6.15	5.56-6.99	7.80-9.83	8.50-10.8

Table 8.9 (d) Appliances Group X50-X56

Appliances Group (X)	X50	X51	X52	X53	X54	X55	X56
Household Hourly Energy Consumption (kWh)	10.62	7.74	6.29	6.97	4.38	4.26	3.39
Predicted Consumption (kWh)	10.63	7.739	6.300	6.969	4.400	4.299	3.389
Appliances Energy Consumption Range	8.38-10.63	6.23-7.74	5.07-6.30	4.46-6.97	3.36-4.40	3.55-4.30	2.29-3.39

Table 8.9 (e) Appliances Group X 57-X63

Appliances Group (X)	X57	X58	X59	X60	X61	X62	X63
Household Hourly Energy Consumption (kWh)	4.00	4.84	9.95	6.09	7.42	8.67	8.62
Predicted Consumption (kWh)	3.999	4.849	9.949	6.089	7.419	8.669	8.619
Appliances Energy Consumption Range	2.16-4.00	3.85-4.85	8.30-9.95	4.58-6.09	6.12-7.43	6.70-8.70	6.67-8.65

Table 8.9 (f) Appliances Group X 64-X70

Appliances Group (X)	X64	X65	X66	X67	X68	X69	X70
Household Hourly Energy Consumption (kWh)	7.76	10.37	5.90	4.98	5.55	8.77	10.47
Predicted Consumption (kWh)	7.759	10.369	5.890	4.979	5.54	8.769	10.469
Appliances Energy Consumption Range	6.20-7.80	8.0-10.45	4.92-5.90	3.85-4.98	4.42-5.60	6.31-8.78	8.60-10.48

Table 8.9 (g) Appliances Group X 71-X76

Appliances Group (X)	X71	X72	X73	X74	X75	X76
Household Hourly Energy Consumption (kWh)	7.11	7.32	9.14	6.41	6.05	6.90
Predicted Consumption (kWh)	7.1099	7.31	9.13	6.409	6.049	6.89
Appliances Energy Consumption Range	5.70-7.15	6.1-7.35	7.24-9.14	4.87-6.43	5.10-6.05	5.33-6.95

Results and Discussion for Weekdays Modelling in Winter

Figure D3 of Appendix D shows the cross-section of the information displayed by the algorithm. The graphical representations of some of the predicted appliances are shown in Figures 8.22 to 8.25. The concept of identifying the appliances is still the same as in summer. The appliances ranges with the highest probability represent the predicted appliances. Figure 8.23 represents the predicted appliances at 1 O'clock. The appliance range that falls at the highest probability is X58. The predicted appliances at this hour are electric stove, refrigerator and television.

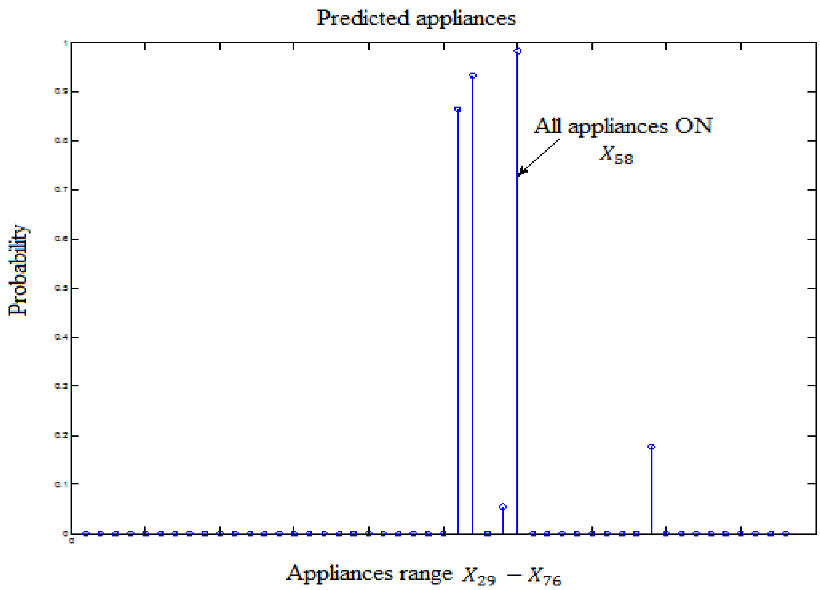


Figure 8.22: Predicted Appliances at 1 O'clock.

Figure 8.23 shows the predicted appliances at 2 O'clock, the appliances range with the highest probability is at X57 and the predicted appliances are water heater, incandescent bulbs and refrigerator.

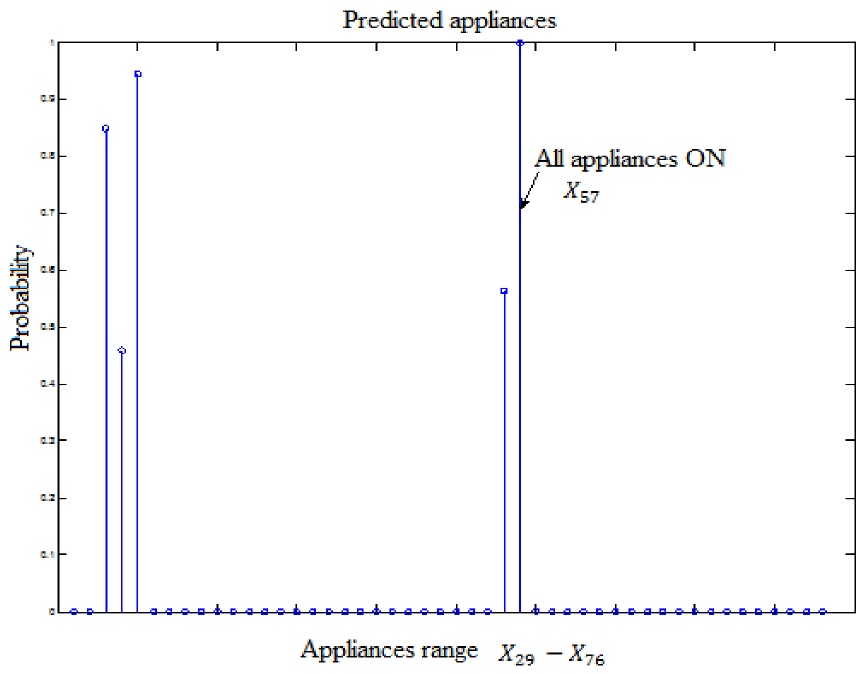


Figure 8.23: Predicted Appliances at 2 O'clock

Figure 8.24 depicts the predicted appliances at 3 O'clock, the highest probability falls at X29. The predicted appliances at this hour are electric heater and electric fence.

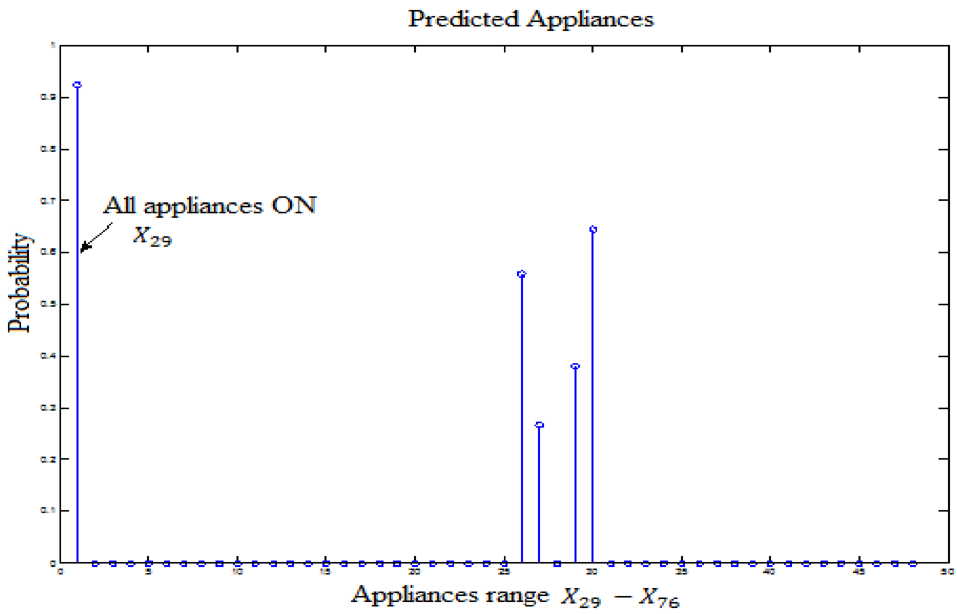


Figure 8.24: Predicted Appliances at 3 O'clock

Figure 8.25 shows the predicted appliances at 8 O'clock, the highest probability falls at X35. The appliances predicted are; electric heater, cordless kettle, electric frying pan, electric iron, microwave, printer and sewing machine.

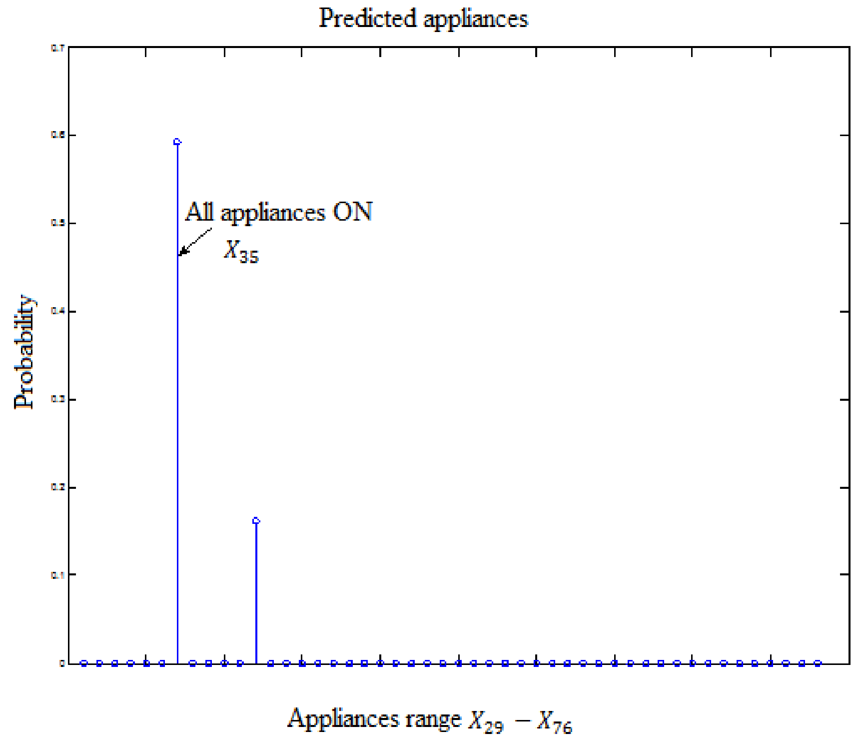
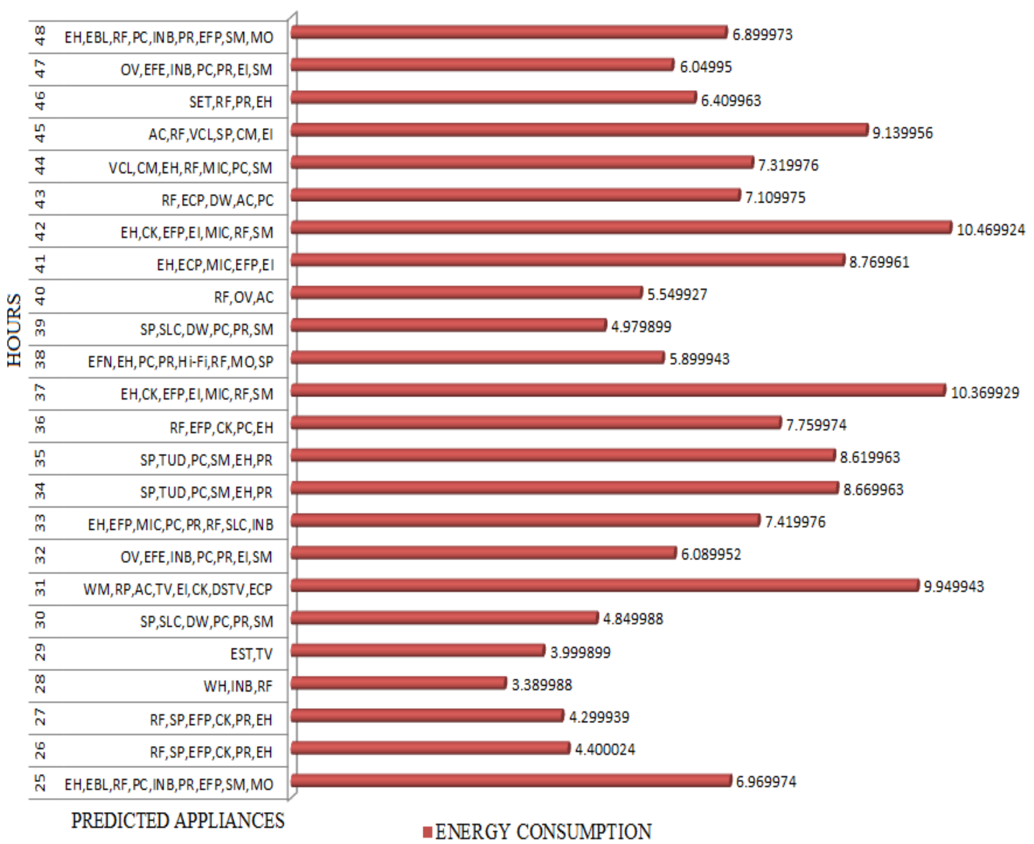


Figure 8.25: predicted Appliances at 8 O'clock

For easy identification, Figure 8.26 summarizes the appliances predicted for 48 hours (2days).



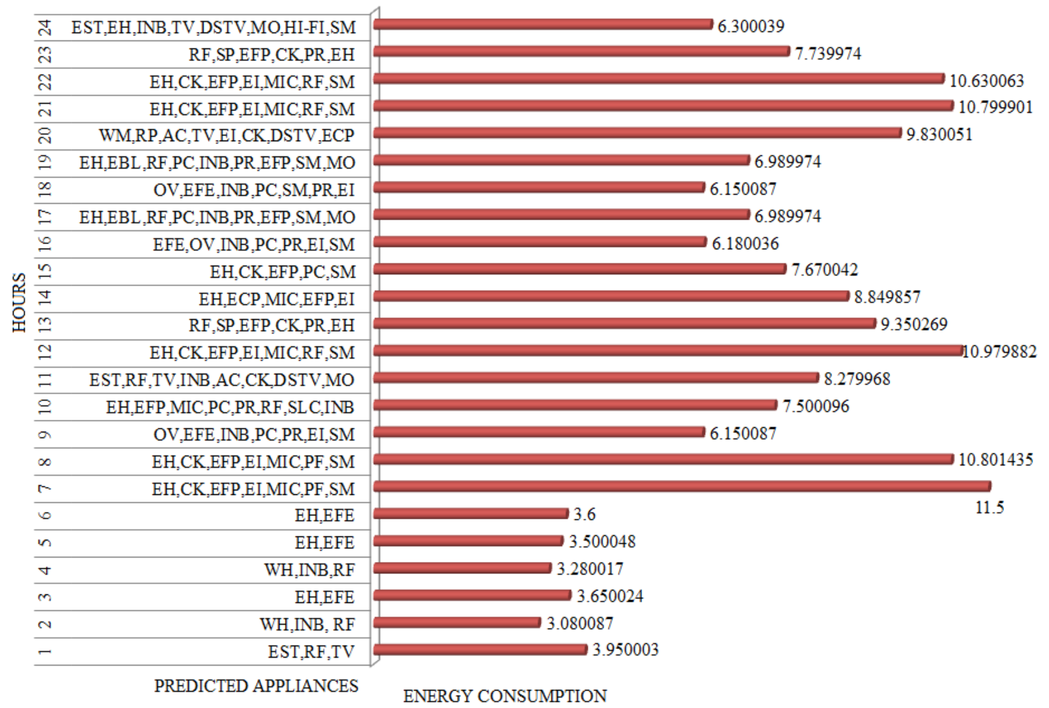


Figure 8.26: Predicted Appliances for 48 hours

8.4.3 Weekends Modelling in Winter

Table 8.10 depicts the weekend's parameters for the neural network training. The household hourly consumption and the time of usage are the inputs while the target is the estimated hourly appliances energy consumptions. Table 8.10(a) to 8.10 (f) summary the input and target for the neural network training.

Table 8.10 (a) Hour 01.00-08.00

Inputs	**Time (Hour)**	01.00	02.00	03.00	04.00	05.00	06.00	07.00	08.00
	Household Hourly Consumption (kWh)	3.97	3.78	4.10	3.58	3.93	4.05	6.02	6.99
Target	**Appliances Hourly Energy Consumption (kWh)**	3.98	3.83	4.10	3.58	3.93	4.08	6.05	6.99

Table 8.10 (b) Hour 09.00-16.00

Inputs	**Time (Hour)**	09.00	10.00	11.00	12.00	13.00	14.00	15.00	16.00
	Household Hourly Consumption (kWh)	8.64	9.84	9.43	10.43	6.93	7.86	7.77	8.68
Target	**Appliances Hourly Energy Consumption (kWh)**	8.65	9.85	9.43	10.45	6.95	7.86	7.78	8.70

Table 8.10 (c) Hour 17.00-24.00

Inputs	**Time (Hour)**	17.00	18.00	19.00	20.00	21.00	22.00	23.00	24.00
	Household Hourly Consumption (kWh)	7.16	6.71	7.89	10.34	11.96	8.53	4.04	4.81
Target	**Appliances Hourly Energy Consumption (kWh)**	7.17	6.72	7.90	10.36	11.98	8.58	4.08	4.85

Table 8.10 (d) Hour 25.00-32.00

Inputs	**Time (Hour)**	25.00	26.00	27.00	28.00	29.00	30.00	31.00	32.00
	Household Hourly Consumption (kWh)	4.55	3.70	3.96	4.05	3.81	3.54	7.21	11.43
Target	**Appliances Hourly Energy Consumption (kWh)**	4.63	3.73	3.98	4.08	3.82	3.60	7.30	11.44

Table 8.10 (e) Hour 33.00-40.00

Inputs	**Time (Hour)**	33.00	34.00	35.00	36.00	37.00	38.00	39.00	40.00
	Household Hourly Consumption (kWh)	12.26	10.67	11.17	10.04	9.60	7.42	11.51	11.61
Target	**Appliances Hourly Energy Consumption (kWh)**	12.26	10.68	11.23	10.04	9.60	7.43	11.53	11.63

Table 8.10 (f) Hour 41.00-48.00

Inputs	**Time (Hour)**	41.00	42.00	43.00	44.00	45.00	46.00	47.00	48.00
	Household Hourly Consumption (kWh)	7.07	6.98	5.44	9.17	8.00	6.75	4.77	4.73
Target	**Appliances Hourly Energy Consumption (kWh)**	7.07	6.99	5.53	9.18	8.00	6.75	4.77	4.74

The training procedure is the same as on weekdays. Seventy percent (70 %) of the data was used for training, fifteen percent (25 %) for testing and fifteen percent (15 %) for validation. The Mean Squared Error (MSE) achieved is 4.5929e-3 and the gradient of performance is 8.03e-06. Figure 8.27 depicts the actual and the predicted energy consumption from the neural network training.

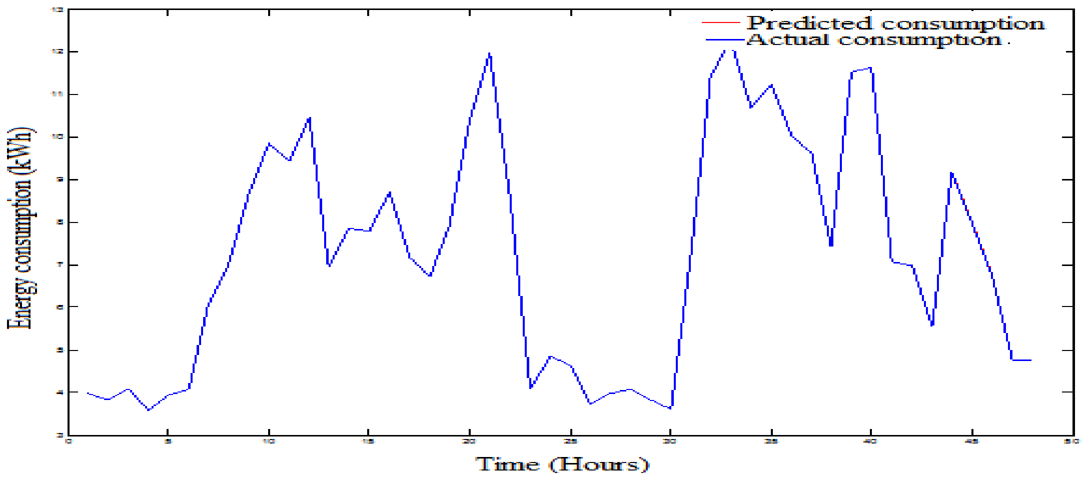


Figure 8.27: Plot of the Actual and the Predicted Energy Consumption

Table 8.11(a) to 8.11(f) summary the parameters used in the algorithm for the appliance identification.

Table 8.11(a): Appliances Group X29-X37

Appliances Group (X)	X29	X30	X31	X32	X33	X34	X35	X35	X37
Household Hourly Energy Consumption (kWh)	3.97	3.78	4.10	3.58	3.93	4.05	6.02	6.99	8.64
Predicted Energy Consumption (kWh)	3.979	3.830	4.099	3.5801	3.9298	4.0799	6.049	6.989	8.650
Appliances Energy Consumption Range (kWh)	3.45-3.98	3.15-3.83	3.40-4.10	3.05-3.58	3.11-3.93	3.30-4.08	5.10-6.05	5.56-6.99	6.67-8.65

Table 8.11(b): Appliances Group X38-X46

Appliances Group (X)	X38	X39	X40	X41	X42	X43	X44	X45	X46
Household Hourly Energy Consumption (kWh)	9.48	9.43	10.43	6.93	7.86	7.77	8.68	7.16	6.71
Predicted Energy Consumption (kWh)	9.850	9.430	10.45	6.949	7.860	7.780	8.700	7.1698	6.7196
Appliances Energy Consumption Range (kWh)	7.65-9.85	8.02-9.43	8.0-10.45	5.33-6.95	5.92-7.86	6.20-7.78	5.50-8.70	5.71-7.17	5.66-6.72

Table 8.11(c): Appliances Group X47-X55

Appliances Group (X)	X47	X48	X49	X50	X51	X52	X53	X54	X55
Household Hourly Energy Consumption (kWh)	7.89	10.34	11.96	8.53	4.04	4.81	4.55	3.70	3.96
Predicted Energy Consumption (kWh)	7.900	10.36	11.97	8.5802	4.080	4.849	4.630	3.730	3.979
Appliances Energy Consumption Range (kWh)	6.25-7.90	8.32-10.36	9.20-11.98	7.20-8.58	3.21-4.08	3.90-4.85	3.51-4.63	3.15-3.73	3.30-3.98

Table 8.11(d): Appliances Group X56-X64

Appliances Group (X)	X56	X57	X58	X59	X60	X61	X62	X63	X64
Household Hourly Energy Consumption (kWh)	4.05	3.81	3.45	7.21	11.43	12.26	10.67	11.17	10.04
Predicted Energy Consumption (kWh)	4.0799	3.8200	3.600	7.299	11.43	12.25	10.68	11.22	10.04
Appliances Energy Consumption Range (kWh)	3.30-4.08	3.26-3.82	2.70-3.60	6.30-7.30	9.48-11.44	9.97-12.26	8.62-10.68	8.89-11.23	8.28-10.04

Table 8.11(e): Appliances Group X65-X73

Appliances Group (X)	X65	X66	X67	X68	X69	X70	X71	X72	X73
Household Hourly Energy Consumption (kWh)	9.60	7.42	11.51	11.61	7.07	6.98	5.44	9.17	8.00
Predicted Energy Consumption (kWh)	9.600	7.429	11.52	11.62	7.069	6.989	5.529	9.180	8.000
Appliances Energy Consumption Range (kWh)	7.57-9.60	5.87-7.43	9.07-11.53	9.27-11.63	5.71-7.07	5.50-6.99	3.66-5.53	7.63-9.18	6.50-8.00

Table 8.11(f): Appliances Group X74-X76

Appliances Group (X)	X74	X75	X76
Household Hourly Energy Consumption (kWh)	6.75	4.77	4.73
Predicted Energy Consumption (kWh)	6.7496	4.739	4.769
Appliances Energy Consumption Range (kWh)	5.66-6.75	3.74-4.77	3.72-4.74

- **Results and Discussion for Weekends Modelling in winter**

Figure D4 of Appendix D shows the cross-section of the information displayed by the algorithm. As explained in the previous section, the appliances range with the highest probability represents the predicted appliances for the considered hour. Figure 8.28 depicts the graphical representation of the predicted appliances for 1 O'clock. The appliances range with the highest probability falls at X53. The predicted appliances at this hour are oven, incandescent bulbs, swimming pool, electric fence and electric blanket.

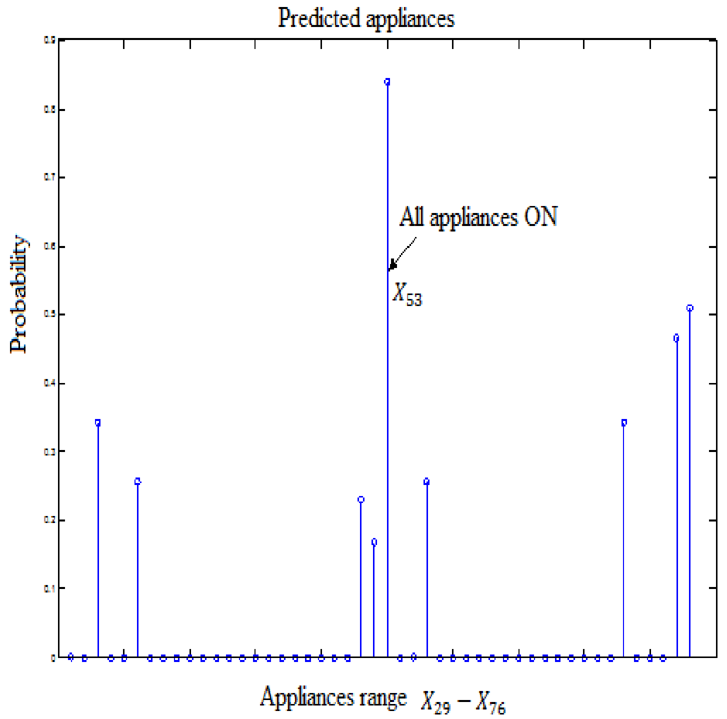


Figure 8.28: Predicted Appliances at 1O'clock

Figure 8.29 shown the graphical representation of the predicted appliances at 2 O'clock, the appliances range with the highest probability falls at X31 and the predicted appliances are refrigerator, electric heater and electric fence.

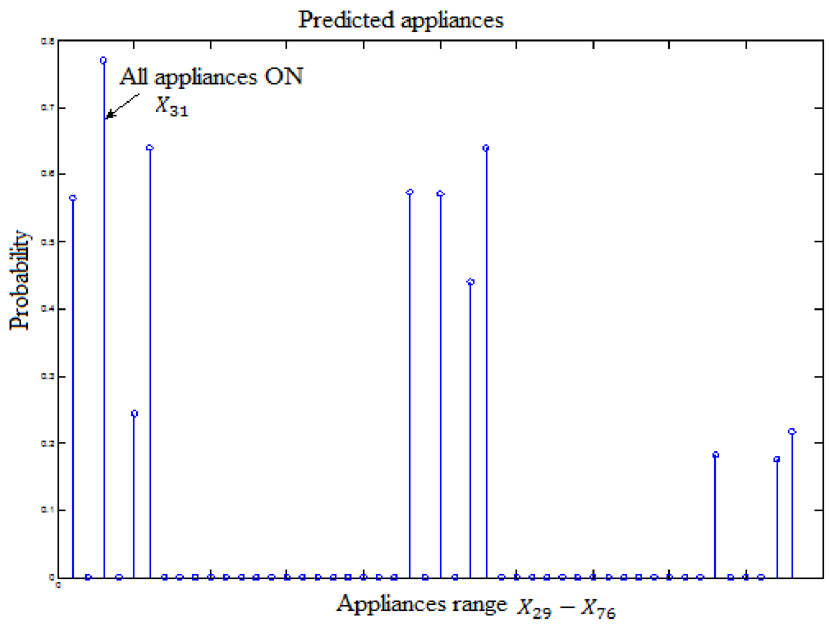


Figure 8.29: Predicted Appliances at 2 O'clock

The graphical presentation of the predicted appliances at 7 O'clock is shown in Figure 8.30, the appliances range with the highest probability falls at X41. The appliances predicted are oven, electric fence, incandescent builds, personal computer, printer, electric iron sewing machine.

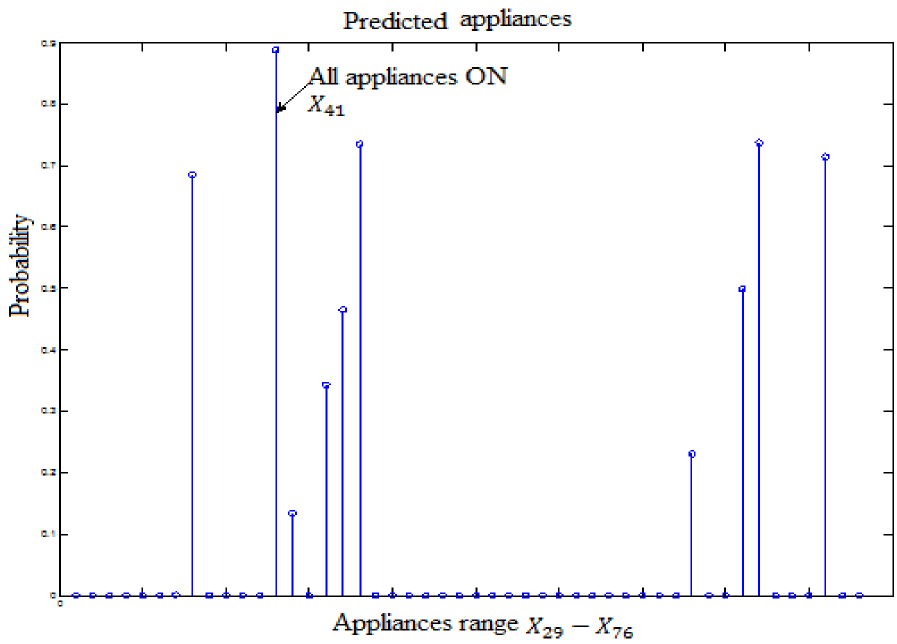


Figure 8.30: Predicted Appliances at 7 O'clock

Figure 8.31 depicts the graphical presentation of predicted appliances at 23 O'clock, the appliances range with the highest probability fall at X53. The appliances predicted are oven, incandescent bulb, swimming pool, refrigerator, electric fence and electric blanket.

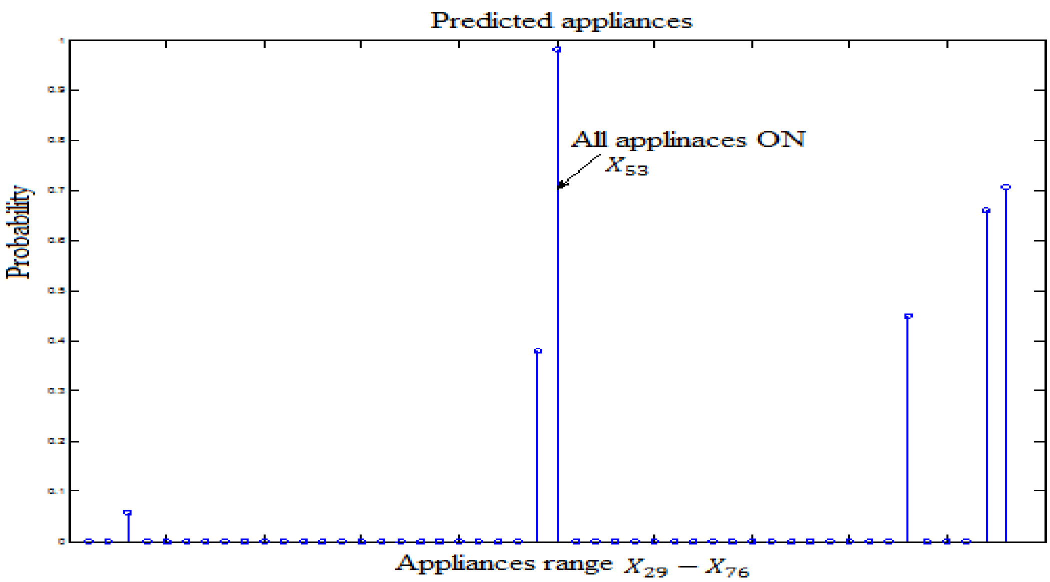


Figure 8.31: Predicted Appliances at 23 O'clock

Figure 8.32 shows the graphical representation of predicted appliances at 33 O'clock, the appliances range with the highest probability falls at X61. The appliances predicted are air-conditioning, electric iron, electric stove, cordless kettle, personal computer, television, DSTV decoder, and microwave.

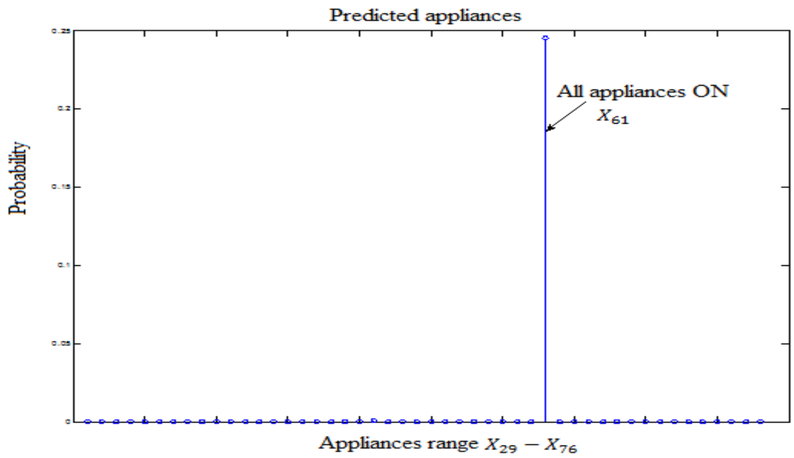
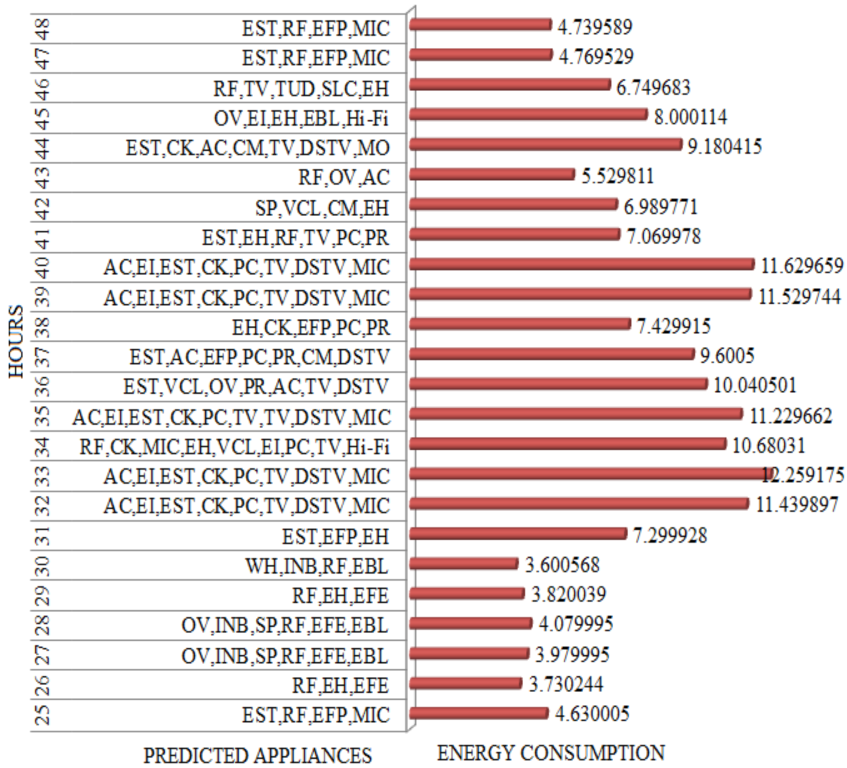


Figure 8.32: Predicted Appliances at 33 O'clock

The predicted appliances for the 48 hours are summarized in Figure 8.33



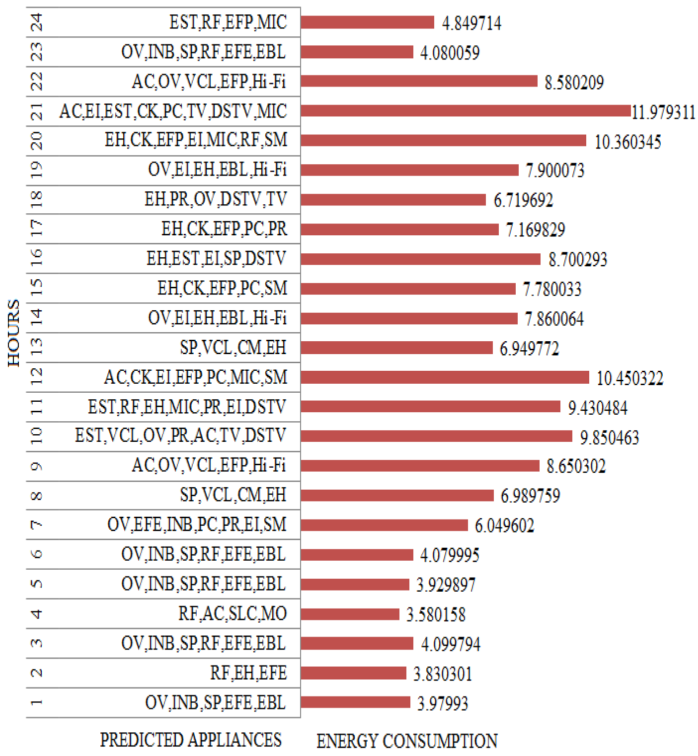


Figure 8.33: Predicted Appliances for 48 hours.

8.6 Summary

In this chapter, we have presented the appliances modelling using artificial neural network. The chapter began by classifying appliance into three different categories (Two-state appliances, multi-state appliances and continuously- varying appliances) for the purpose of modelling. Theory of modelling appliance power demand, concept of neural network for appliances modelling, data validation of the prediction was also examined. The neural network uses 60 % of the total consumption data for training, 25 % for testing and the rest 15 % were used for validation. Modelling of appliance for identification was examined in two different scenarios- summer and winter; an algorithm was developed for the purpose of identifying appliances based on the power consumption of the appliance range. The developed algorithm uses the output of the neural network training and the appliance energy consumption range to predict the actual appliances that are used for a given hour. In this dissertation, and for the purpose of appliances identification, it is agreed that appliances ranges with the highest probability bin were considered to be the predicted appliances for a given hour. The appliances predicted for different hours were displayed after executing the algorithm and these were depicted graphically. The following chapter summaries the dissertation and gives recommendation for future work.

CHAPTER 9

9.1 Conclusions and Recommendations

Due to the high cost and intrusive nature of intrusive load monitoring (ILM) techniques, the research in the field of appliance load monitoring and identification has been focused towards non-intrusive load techniques in the last few years. Non-intrusive load monitoring techniques are a unique approach to monitoring the energy consumption of major domestic appliances. NILM technique show promising result in measuring domestic appliance energy consumption at a single point without intruding into the customer's premises, while keeping installation cost and complexity low. The technique employed in this dissertation, will allow electricity consumers to monitor the energy consumption of their individual appliance by observing the operation and time of use of the appliances, it will allow consumers to improve their electricity consumption habits to save energy and reduce cost. In addition, the energy consumption analysis will allow for load shifting, to alter the pattern of energy usage so that the use of any adjustable appliances can be shifted from on-peak period to off-peak period. Furthermore, the load profile analysis in chapter seven will create awareness for both homeowners and utilities to pinpoint the actual appliances that consumed high energy at a given period of time. The utility can also give auxiliary services such as advice on how to implement electricity usage shifting techniques for certain appliances for effective energy management.

In this dissertation, non-intrusive load monitoring techniques for identifying appliances by exploiting energy consumption of some selected appliances and energy consumption from high-income household in Johannesburg using computational intelligence (CI) approach based on ANN is developed. The CI approach is combined with an algorithm developed to predict appliance at a given period of time. In addition, in order to identify different appliances that contribute to energy consumption at a given period of time, the algorithm uses the outputs of the neural network and appliance energy consumption range computed from the average and maximum power ratings of the appliances. The algorithm is able to identify appliances with overlapping consumptions by calculating the mean of the consumption range using "probability of belonging" and display the appliance range with the highest probability as the predicted appliances for the hour. The proposed algorithm is simple and requires only the active power (energy consumed by the appliances) and the turn ON times of the devices to be identified.

In the simulations, the proposed algorithm was able to identify the entire appliances that are ON within the given period of time usually every one hour. Also, the algorithm was able to display the time of use, names of the appliances as well as the total energy consumed within the given period. Furthermore, appliances with a very small range of energy consumption or appliances with overlapping consumption and the energy consumed by the phantom appliances such as television and Dstv-decoder and modem are also identified by the algorithm, since the detection is based on hourly energy consumption. The accuracy of the proposed method depends on the correctness in which the appliance signatures are defined by the user. The accuracy can be increased, by including all the appliance parameters in the database. The method can detect and identify every device in the household, irrespective of their energy consumption level. Nevertheless, the algorithm cannot detect and identify newly bought appliance in the household, since it has not been included in the household database. In addition, the algorithm requires a large database.

9.2 Recommendations for Future Works

The focus in the near future will be based on deploying the system in various households to gather real-time appliance energy consumption data for the purpose of monitoring and identification. Also, the focus will be on how to automatically update individual household appliance database immediately when a new appliance is plugged in. In addition, further research is necessary for deploying a system that will provide automatic feedback in regards to the appliances profiling and user interface for the purpose of energy consumption monitoring and appliance identification.

Appendices

Appendix A

Table A1: South African Standard Appliances Rating

S/N	Electrical Appliances	Minimum (Watts)	Average (Watts)	Maximum (Watt)
1	Washing Machine (cold wash)	800	1000	1500
2	Electric Stove	1600	2000	2400
3	Refrigerator	80	100	150
4	Dishwasher	2000	2300	2600
5	Oven	1500	2000	2500
6	Television	200	250	300
7	Incandescent Bulb	40	60	70
8	Air-condition	2600	3000	3400
9	Swimming Pool Pump	800	1000	1200
10	Vacuum Cleaner	80	1000	1600
11	Electric Iron	1600	2000	2200
12	Electric Frying Pan	1200	1500	2000
13	Coffee Machine	1000	1200	1400
14	Cordless Kettle	1500	1800	2500
15	Microwave	60	800	1300
16	Tumble Dryer	2400	2800	3000
17	Dstv decoder	15	20	25
18	Water Heater	2000	3000	3500
19	Electric Fence	250	300	350
20	Slow Cooker	120	150	250
21	Personal Computer	200	300	450
22	Modem	8	12	15
23	Printer	300	600	1000
24	Hi-fi Equipment	100	150	200
25	Sewing Machine	50	70	100
26	Electric Fan	50	60	80
27	Electric Heater	2400	3000	3600
28	Electric Blanket	40	50	75
29	Electric circulation Pump	350	600	900

Appendix B

Table B1: Appliances Event Table for Weekday (summer)

Time (h)	Household Hourly Energy Consumption (kWh)	Minimum Appliances Hourly Consumption (kWh)	Average Appliances Hourly Consumption (kWh)	Maximum Appliances Hourly Consumption (kWh)	Likely Appliances
1	3.04	1.88	2.46	3.08	RF, OV, EFE and EFA,
2	3.41	1.98	2.70	3.45	RF, OV, EFE, EFA and PC
3	2.57	1.55	2.06	2.58	OV and EFA
4	3.02	1.98	2.54	3.04	EST, RF, INB and CM
5	2.61	1.94	2.39	2.66	DW, RF and INB
6	2.58	1.78	2.24	2.60	RF, EI and CK
7	2.98	1.68	2.15	2.99	SP, RF, VCL, PC, MO and SM
8	2.59	1.52	1.31	2.62	SP, RF, VCL and CK
9	3.83	2.68	3.35	3.85	RF, TV, SP and EI
10	3.91	2.28	3.35	3.95	RF, TV and WH
11	2.74	1.46	1.81	2.77	WM, VCL and CK
12	3.24	2.53	2.97	3.25	RF, TUD and SM
13	3.59	2.73	3.17	3.65	RF, AC and SM
14	2.67	1.60	2.13	2.68	OV, SM and EFA
15	2.67	1.60	2.13	2.68	OV, SM and EFA
16	4.10	3.00	2.54	4.20	RF, AC, CK and PC
17	3.63	2.73	3.17	3.65	RF, AC and SM
18	3.46	2.36	2.87	3.48	RF, DW,TV,DSTV,PC,MO,SM EFA
19	3.28	2.09	2.65	3.28	EST, INB, CK,S LC and EFA
20	3.31	2.10	2.68	3.33	EST, RF, INB, SLC, SM and EFA
21	3.05	2.00	2.55	3.05	EST, TV and INB
22	4.53	2.62	3.81	4.53	EST,TV, INB, CK,DSTV and WH
23	3.31	2.1	2.68	3.33	EST, RF, INB, SLC, SM, and EFA
24	3.44	2.08	2.77	3.45	EST, OV, INB, EFE and EFA
25	2.96	1.71	2.31	2.97	OV, PC and MO
26	2.91	1.71	2.31	2.97	OV, PC and MO
27	2.68	1.77	2.21	2.7	EST, CK and SM
28	2.95	1.70	2.30	2.95	OV, and PC
29	2.56	1.90	2.21	2.61	DW, CK and SLC
30	2.85	1.88	2.35	2.85	EST, RF and TV
31	2.45	1.77	2.20	2.48	EI, CK and EFA
32	2.69	1.77	2.21	2.70	EST,CK and SM
33	2.82	1.50	1.84	2.82	MW, RF,VCL and SM
34	2.79	1.49	1.86	2.80	MW,VCL,CM and SM
35	3.01	2.05	2.62	3.05	TV, EI, PC, and SM
36	2.81	1.60	2.08	2.83	EFP, SM, PC, HI-Fi, and EFA
37	2.63	1.85	2.31	2.65	RF, EI, CK, and SM
38	3.06	1.97	2.45	3.08	EST, RF, CK, SLC and EFA
39	2.85	1.88	2.35	2.85	EST, RF, and TV
40	3.73	2.80	3.24	3.75	AC, RF and CK
41	2.85	1.88	2.35	2.85	EST,RF, and TV
42	2.89	1.90	2.36	2.89	EST,RF,CM and CK

43	2.59	1.48	1.90	2.60	RF, EFP, and PC
44	3.20	2.16	2.82	3.30	INB, EI, PC, EFA, HI-FI and MO
45	3.08	2.13	2.67	3.09	INB, EI, PC, MO and EFA
46	3.51	2.05	3.07	3.60	WH, and SM
47	3.26	2.57	3.01	3.30	CK,TUD and M
48	2.80	1.88	2.40	2.80	EI, PC and RF

Table B2: Appliances Event Table for Weekend (summer)

Time (h)	Household Hourly Energy Consumption (kWh)	Minimum Appliances Hourly consumption (kWh)	Average Appliances Hourly consumption (kWh)	Maximum Appliances Hourly Consumption (kWh)	Likely Appliances
1	4.37	2.37	3.27	4.39	OV, INB, PC, MO, EFE and PR
2	3.75	2.23	3.00	3.80	RF, OV, INB, PC and MO
3	2.88	1.70	2.25	2.90	RF, OV, and SLC
4	2.90	1.70	2.25	2.90	RF, OV and SLC
5	3.61	2.08	3.10	3.65	RF, and WH
6	3.33	1.93	2.36	3.38	RF, CK, MIC, and EFA
7	2.44	1.48	1.85	2.45	RF, TV and EFP
8	2.43	1.48	1.85	2.45	RF, TV and EFP
9	3.63	2.02	2.78	3.63	EST, RF, MIC, SLC, SM and EFA
10	4.34	2.78	3.47	4.35	EST, RF, CM, MIC and SM
11	5.04	3.18	3.90	5.05	EST, RF, and CK
12	4.57	2.78	3.50	4.60	RF, CK, VCL, and EI
13	3.96	2.86	3.82	3.97	AC, PC, MO, and SM
14	3.47	3.45	3.47	3.50	AC and SM
15	3.75	2.77	3.22	3.75	AC, SLC and SM
16	2.55	1.54	1.92	2.58	EFP, TV, SLC and DSTV
17	3.15	2.34	2.72	3.17	DW, SLC,TV and DSTV
18	3.13	1.89	2.28	3.15	TV, CK, DSTV, SLC, EFA
19	2.71	1.82	2.27	2.73	EST, TV and DSTV
20	2.96	1.95	2.43	2.96	EST, RF, TV, DSTV and EFA
21	3.02	2.00	2.50	3.05	EST, RF, TV, DSTV, EFA and SM
22	3.23	2.14	2.77	3.24	RF, EI, INB, PC, MO and EFA
23	3.62	2.08	3.10	3.65	WH, and RF
24	3.05	1.88	2.46	3.08	RF, OV, EFE and EFA
25	2.96	1.31	1.91	2.97	EFA, PC, MO and PR
26	3.15	2.48	2.90	3.15	RF, and TUD
27	2.95	2.20	2.60	2.95	OV and INB
28	2.59	2.00	2.30	2.60	RF,TV,EI,DSTV and SM
29	2.60	2.00	2.30	2.60	RF,TV, EI, DSTV and SM
30	2.75	2.08	2.40	2.75	RF and OV
31	2.60	2.00	2.30	2.60	RF, TV, EI, DSTV and SM
32	3.32	2.22	2.75	3.35	EST, SLC and CM
33	3.43	2.10	2.65	3.45	EST, RF, MIC and SLC
34	3.39	2.03	2.5	3.40	EFP, CK and RF
35	4.50	3.30	3.85	4.50	RF, AC, CM and SLC
36	3.69	3.00	3.27	3.73	TV, AC, and DSTV,
37	4.12	4.15	3.55	4.15	TV, AC and PC

38	3.06	2.00	2.50	3.06	EST, RF, TV, DSTV, SM and EFA
39	3.12	1.97	2.44	3.13	TV, EFA, CM, DSTV,CM, EFA
40	2.77	1.95	2.44	2.78	RF,TV, EID, STV and SM
41	3.09	1.73	2.25	3.10	RF,TV, EFP and MIC
42	2.67	2.05	2.36	2.68	DW and EFA
43	4.83	3.08	3.85	4.85	EST, RF, TV and EFP
44	3.23	2.05	2.61	3.23	EST, RF, INB, SLC and EFA
45	2.99	1.80	2.25	3.00	WM, SP and TV
46	3.01	1.80	2.30	3.05	WM, INB and SP
47	3.35	2.60	3.10	3.35	INB and TUD
48	3.50	2.00	3.00	3.50	TV, AC, DSTV

Table B3: Appliances Event Table for Weekday (winter)

Time (h)	Household Hourly Energy Consumption (kWh)	Minimum Appliances Hourly Consumption (kWh)	Average Appliances Hourly Consumption (kWh)	Maximum Appliances Hourly Consumption (kWh)	Likely Appliances
1	3.92	2.65	3.30	3.95	EH and EFE
2	3.05	1.87	2.45	3.08	OV,RF, EFE and EBL
3	3.64	2.15	2.66	3.65	OV, INB, EFE and PC
4	3.28	1.99	2.41	3.28	OV, EFE, INB, and EBL
5	3.49	2.25	2.61	3.50	EST, EFE, INB, RF and SLC
6	5.71	5.90	5.00	3.60	WH and EST
7	11.53	7.28	9.07	11.53	EH, CK, EFE, EI, MIC, RF and SM
8	10.70	6.93	8.50	10.80	RF, CK, ECP, AC,VCL and EI
9	6.13	4.08	5.10	6.15	EST, RF and EH
10	7.44	5.23	6.60	7.50	RF, ECP, DW, AC and PC
11	8.28	4.98	6.27	8.28	VCL, CM, EH, RF, MIC, PC and SM
12	10	7.16	8.77	10.98	WM, RF, AC, TV, EI, CK, DSTV
13	9.31	6.15	7.77	9.35	SP, TUD, PC, SM, EH and PR
14	8.71	5.70	7.15	8.85	RF, AC, SLC, PR, PC and TV
15	7.66	4.46	5.78	7.67	EH, PC, PR, CK, MO and SM
16	6.17	4.70	5.42	6.18	AC, DW, RF and DSTV
17	6.99	4.57	5.56	6.99	EST, EH, INB,TV, DSTV ,MO, SM
18	6.13	4.08	5.10	6.15	EST, RF and EH
19	6.99	4.58	5.56	6.99	EST, EH, INB, TV, DSTV, MO,SM
20	9.82	6.08	7.80	9.83	EH, ECP, MIC, EFP and EI
21	10.80	6.93	8.50	10.80	RF, CK, ECP, AC,VCL and EI
22	1.62	6.27	8.38	10.63	EH,WH, RF, INB, PC, PR, EBL,
23	7.74	4.48	6.23	7.74	EH, EBL, RF, PC, INB, PR, PC, SM
24	6.29	3.93	5.07	6.30	EFE, EH, RF, ECP, SP and SM
25	6.97	3.34	4.46	6.97	EFE, EH, PC, PR, HI-FI, RF, MO and
26	4.38	2.80	3.36	4.40	EH, PC and INB
27	4.26	2.83	3.55	4.30	RF, EFE, HI-FI and EH
28	3.39	2.05	2.29	3.39	RF, INB, CK, DSTV, EFE and MO
29	4.00	2.28	2.16	4.00	WH, INB and RF
30	4.84	3.08	3.85	4.90	EST, RF, and TV
31	9.95	6.88	8.30	9.95	AC, RF, VCL, SP, CM and EI
32	6.09	3.70	4.58	6.09	RF, DSTV, SLC, PC, VCL, EH and
33	7.42	4.90	6.12	7.43	VCL, EI, DSTV and EH
34	8.67	5.38	6.70	8.70	RF, EFP, CK, PC and EH
35	8.62	5.35	6.67	8.65	EH, CK, EFP, PC and SM
36	7.76	5.00	6.20	7.80	SP, VCL, CM and EH

37	10.37	6.08	8.00	10.45	RF, SP, EFP, CK, PR and EH
38	5.9	3.95	4.92	5.90	EI, EFP, CM, HI-FI and SM
39	4.98	3.05	3.85	4.98	RF, MIC, SLC and EH
40	5.55	3.47	4.42	5.60	SP, SLC, DW, PC, PR and SM
41	8.77	4.95	6.31	8.78	EH, EFP, MIC, PC, PR, RF, SLC
42	10.47	6.45	8.60	10.48	EH, WH, EST and MIC
43	7.11	4.38	5.70	7.15	EST, RF, PR and EH
44	7.32	4.88	6.10	7.35	EST, RF, SP and EH
45	9.14	6.20	7.24	9.14	RF, EST, TV, INB ,AC, DSTV and
46	6.41	3.55	4.87	6.43	RF, TV, DSTV, PC,PR, EH and ECP
47	6.05	4.18	5.10	6.05	RF, OV and AC
48	6.90	4.10	5.33	6.95	OV, EFE, INB, PC, PR, EI and SM

Table B4: Appliances Event Table for Weekends (winter)

Time (h)	Household Hourly Energy Consumption (kWh)	Minimum Appliances Hourly Consumption (kWh)	Average Appliances Hourly Consumption (kWh)	Maximum Appliances Hourly Consumption (kWh)	Likely Appliances
1	3.97	3.97	3.45	3.98	RF, AC, EBL and EFE
2	3.78	2.52	3.15	3.83	RF, EH and EBL
3	4.10	2.73	3.40	4.10	RF, EH and EFE
4	3.58	2.04	3.05	3.58	WH and EBL
5	3.93	2.24	3.11	3.93	WH, INB and EBL
6	4.05	2.64	3.30	4.08	RF, SLC, EH and EBL
7	6.02	4.18	5.10	6.05	RF, OV and AC
8	6.99	4.58	5.56	6.99	EST, EBL and INB
9	8.64	5.35	6.67	8.65	EH, CK, EFP, PC and SM
10	9.84	5.70	7.65	9.85	EH, EST, EFP, RF, PC, PR
11	9.43	6.42	8.02	9.43	EH, EST, EI, SP and DSTV
12	10.43	6.08	8.00	10.45	DW, SP, EFP, CK, PR and EH
13	6.93	4.10	5.33	6.95	OV, EFE, INB, PC, PR, EI and
14	7.86	4.67	5.92	7.86	SP, VCL, CM, EBL, EH, PC
15	7.77	5.00	6.20	7.78	SP, VCL, CM and EH
16	8.68	4.33	5.50	8.70	EH, CK, EFP, PC and RF
17	7.16	4.39	5.71	7.17	EST, RF, PR, EBL and MO
18	6.71	4.69	5.66	6.72	PC, EST,A C, RF, TV and MO
19	7.89	4.78	6.25	7.90	EST, EBL, RF, TV, PC and PR
20	10.34	6.45	8.32	10.36	EST, RF, EH, MIC, PR, EI,
21	11.96	7.33	9.20	11.98	RF, CK, MIC, EH,VCL, EI,
22	8.53	5.64	7.20	8.58	OV, EI, EH, EBL and Hi-Fi
23	4.04	2.32	3.21	4.08	WH, INB, RF and EBL
24	4.81	2.55	3.90	4.85	EFE, WH and PR
25	4.55	2.87	3.51	4.63	OV, INB, SP, PR, EFE ,EBL
26	3.70	2.12	3.15	3.73	RF, WH and EBL
27	3.96	2.24	3.30	3.98	RF, EBL,WH and SLC
28	4.05	2.64	3.30	4.08	EF, SLC, EH and EBL
29	3.81	2.81	3.26	3.82	RF, AC, SLC and MO
30	3.54	2.20	2.70	3.60	WM, SLC, RF, CM and TV
31	7.21	5.20	6.30	7.30	RF,TV,TUD,SLC and EH
32	11.43	7.80	9.48	11.44	RF,AC,EI,EST,CK,PC,MO,TV
33	12.26	8.17	9.97	12.26	AC, EI, EST, CK, PC, TV, DSTV,TV, MIC
34	10.67	6.92	8.62	10.68	EST, AC, EFP, PC, PR, CM,
35	11.17	7.03	8.89	11.23	EST, VCL, OV, PR, AC, TV,

36	10.04	6.92	8.28	10.04	EST,C K, AC, CM,TV, DSTV
37	9.60	6.15	7.57	9.60	AC, OV, VCL, EFP and SM
38	7.42	4.42	5.87	7.43	EH, PR, OV and DSTV
39	11.51	7.28	9.07	11.53	EH, CK,E FP, EI, MIC, RF
40	11.61	7.60	9.27	11.63	AC, CK, EI, EFP, PC, MIC
41	7.07	4.49	5.71	7.07	AC, OV, RF, PR and MO
42	6.98	4.37	5.50	6.99	AC, PC, PR, EFP, MO , DET,
43	5.44	3.33	3.66	5.53	EST, RF, EFP and MIC
44	9.17	6.62	7.63	9.18	AC, DW, EST, RF, SLC, INB
45	8.00	5.20	6.50	8.00	EST, EFP and EH
46	6.75	4.85	5.66	6.75	AC, INB, PC, EI and EFE
47	4.77	2.71	3.74	4.77	WH, EBL, INB, EFE, PC, MO
48	4.73	2.70	3.72	4.74	WH, EBL, INB, EFE, PC, MO

Appendix C

Appliances Identification Algorithm

```
function y = ola(acc)
clc

% Matlab code or script for load identification
x1 = 'washing_machine';
x2 = 'electric_stove';
x3 = 'refrigerator';
x4 = 'dish_washer';
x5 = 'oven';
x6 = 'television';
x7 = 'incadescent_bulb';
x8 = 'air_conditioning';
x9 = 'swimming_pool';
x10 = 'vacuum_cleaner';
x11 = 'electric_iron';
x12 = 'electric_frying pan';
x13 = 'coffee_machine';
x14 = 'cordless_kettle';
x15 = 'microwave';
x16 = 'tumble_dryer';
x17 = 'dstv decoder';
x18 = 'water heater';
x19 = 'electric fence';
x20 = 'slow cooker';
x21 = 'personal computer';
x22 = 'modem';
x23 = 'printer';
x24 = 'Hi-Fi equipment';
x25 = 'sewing machine';
x26 = 'electric fan';
x27 = 'refrigerator,oven,electric fence n electric fan'; y27= [2.46, 3.08];
x28 = 'refrigerator,oven,electric fence n personal computer'; y28 = [2.70,
3.45];
x29 = 'oven n sewing machine'; y29 = [2.06, 2.58];
x30 = 'electric_stove, refrigerator, incadescent_bulb n coffee machine'; y30
= [2.54, 3.04];
x31 = 'dish_washer,refrigerator n incadescent_bulb'; y31 = [2.39, 2.66];
x32 = 'refrigerator,electric_iron n cordless_kettle'; y32= [2.24, 2.60];
x33 = 'swimming_pool,refrigerator, vacuum_cleaner, personal computer,modem n
sewing machine'; y33 = [2.15, 2.99];
x34 = 'swimming_pool,refrigerator,vacuum_cleaner n cordless_kettle';y34 =
[1.31, 2.62];
x35 = 'refrigerator,television,swimming_pool n electric_iron'; y35 = [3.35,
3.85];
x36 = 'refrigerator,television n water heater'; y36 = [3.35, 3.95];
x37 = 'washing_machine,vacuum_cleaner n cordless_kettle'; y37 = [1.81, 2.77];
x38 = 'refrigerator,tumble_dryer n sewing machine'; y38 = [2.97, 3.25];
x39 = 'refrigerator,air_conditioning n sewing machine'; y39 = [3.17, 3.65];
x40 = 'oven,sewing machine n electric fan'; y40 = [2.13, 2.68];
x41 = 'oven,sewing machine n electric fan'; y41 = [2.13, 2.68];
x42 = 'refrigerator,air_conditioning,cordless_kettle n personal computer';
y42 = [3.54, 4.20];
x43 = 'refrigerator, air_conditioning,n sewing machine'; y43 = [3.17, 3.65];
x44 = 'refrigerator, dish_washer, television, dstv decoder,personal
computer,modem,Hi-Fi equipment,sewing machine, electric fan'; y44 = [2.87,
3.48];
```

```
x45 = 'electric_stove,incadescent_bulb,cordless_kettle,slow cooker n electric
fan'; y45 = [2.65, 3.28];
x46 = 'electric_stove, refrigerator,incadescent_bulb,slow cooker, sewing
machine n electric fan'; y46 = [2.68, 3.33];
x47 = 'electric_stove, television n incadescent_bulb'; y47 = [2.55, 3.05];
x48 = 'refrigerator, television,incadescent_bulb,cordless_kettle,dstv decoder
n water heater'; y48 = [3.81, 4.53];
x49 = 'electric_stove, refrigerator,incadescent_bulb,slow cooker, sewing
machine n electric fan'; y49 = [2.68, 3.33];
x50 = 'refrigerator,oven,incadescent_bulb,electric fence n sewing machine';
y50 = [2.77, 3.45];
x51 = 'oven, personal computer n modem'; y51 = [2.31, 2.97];
x52 = 'oven, personal computer n modem'; y52 = [2.31, 2.97];
x53 = 'oven n personal computer'; y53 = [2.21, 2.70];
x54 = 'oven, cordless_kettle n slow cooker'; y54 = [2.30, 2.95];
x55 = 'dish_washer, cordless_kettle, slow cooker'; y55 = [2.21, 2.61];
x56 = 'electric_stove, refrigerator n television'; y56 = [2.35, 2.85];
x57 = 'electric_iron,cordless_kettle n electric fan'; y57 = [2.20, 2.48];
x58 = 'electric_stove, cordless_kettle n sewing machine'; y58 = [2.21, 2.70];
x59 = 'washing_machine,refrigerator, vacuum_cleaner n sewing machine'; y59 =
[1.84, 2.84];
x60 = 'washing_machine,vacuum_cleaner,coffee_machine n sewing machine'; y60 =
[1.86, 2.80];
x61 = 'television,electric_iron,personalcomputer n sewing machine'; y61 =
[2.62, 3.05];
x62 = 'electric_frying pan,sewing machine,personal computer, Hi-Fi equipment
n electric fan'; y62 = [2.08, 2.83];
X63 = 'refrigerator, electric_iron,cordless_kettle n sewing machine'; y63 =
[2.31, 2.65];
X64 = 'electric_stove, refrigerator, cordless_kettle, slow cooker n electric
fan'; y64 = [2.45, 3.08];
X65 = 'electric_stove, refrigerator n television'; y65 = [2.35, 2.85];
x66 = 'air_conditioning, refrigerator n cordless_kettle'; y66 = [3.24, 3.75];
x67 = 'electric_stove, refrigerator n television'; y67 = [2.35, 2.85];
x68 = 'electric_stove, refrigerator,coffee_machine n cordless_kettle'; y68 =
[2.36, 2.89];
x69 = 'refrigerator, electric_frying pan n personal computer'; y69 = [1.90,
2.60];
x70 = 'incadescent_bulb,electric_iron,personal computer, electric fan, Hi-Fi
equipment n modem'; y70 = [2.82, 3.30];
x71 = 'incadescent_bulb,electric_iron, personal computer, modem n electric
fan'; y71 = [2.67, 3.09];
x72 = 'water heater n sewing machine'; y72 = [3.07, 3.60];
x73 = 'cordless_kettle,tumble_dryer n sewing machine'; y73 = [3.01, 3.30];
x74 = 'electric_iron, personal computer n refrigerator'; y74 = [2.40, 2.80];

xx = {x27 x28 x29 x30 x31 x32 x33 x34 x35 x36 x37 x38 x39 x40 x41 x42 x43 x44
x45 x46 x47 x48 x49 x50 x51 x52 x53 x54 x55 x56 x57 x58 x59 x60 x61 x62 x63
x64 x65 x66 x67 x68 x69 x70 x71 x72 x73 x74}; %appliances group
yx = [y27; y28; y29; y30; y31; y32; y33; y34; y35; y36; y37; y38; y39; y40;
y41; y42; y43; y44; y45; y46; y47; y48; y49; y50; y51; y52; y53; y54; y55;
y56; y57; y58; y59; y60; y61; y62; y63; y64; y65; y66; y67; y68; y69; y70;
y71; y72; y73; y74]; %appliances consumption ranges

xprob = zeros(1,length(yx)); %probability bins for each appliances range
xprobr = xprob; %probability bin reset vector
xprob_acc = xprob;

filename = 'y.xlsx';
A = xlsread(filename);
% Read a specific range of data:
```

```
data = xlsread('y.xlsx', 'sheet1');
%data = xlsread('y.xlsx', 'sheet1', 'A1:A24');
% columnA = xlsread(filename
% Declare appliances
ave_hourly_data = A; %(y = neural network output_consumption)
appliance=[];

probplot = zeros(length(A),length(yx));
count =1; count2 =length(A) + 1;

for i = 1:length(A)
    xprob = xprobr; % reset probability bins to 0
    for j = 1:length(yx)
        if(data(i)>= yx(j,1) && data(i)<= yx(j,2))
            m = (yx(j,1)+ yx(j,2))/2;
            mr = m - yx(j,1);

            if(data(i) < m)
                xprob(j) = (data(i) - yx(j,1))/mr;
            else
                 xprob(j) = (yx(j,2) - data(i))/mr;
            end
        end
    end



    %plot data
    fprintf(1,'hour:%i ',i)
    fprintf(1,'data:%f ',data(i))

    [prob, ind] = max(xprob); %select probability bin with the highest value.

    fprintf(1,'output:%s',xx{ind}) % index from previous step corresponds to
appliance group that is most likely on

    % look for other appliance groups with a matching probability to the
    % max
    for k = (ind+1):length(yx)
        if k < length(yx)
            if (xprob(k)== prob)
                fprintf(1,'; %s ',xx{k})
            end
        end
    end
    display(' ')

  figure(i)
    stem(xprob)

   %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    if(count < acc)
        xprob_acc = xprob_acc + xprob;
        count = count + 1;
    else

        figure(count2)

        stem (xprob_acc)
```

```
    xprob_acc = xprobr;
    count =1;
    count2 = count2 + 1;
end
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

Appendix D
Cross-Section of the Information Displayed From the Algorithm

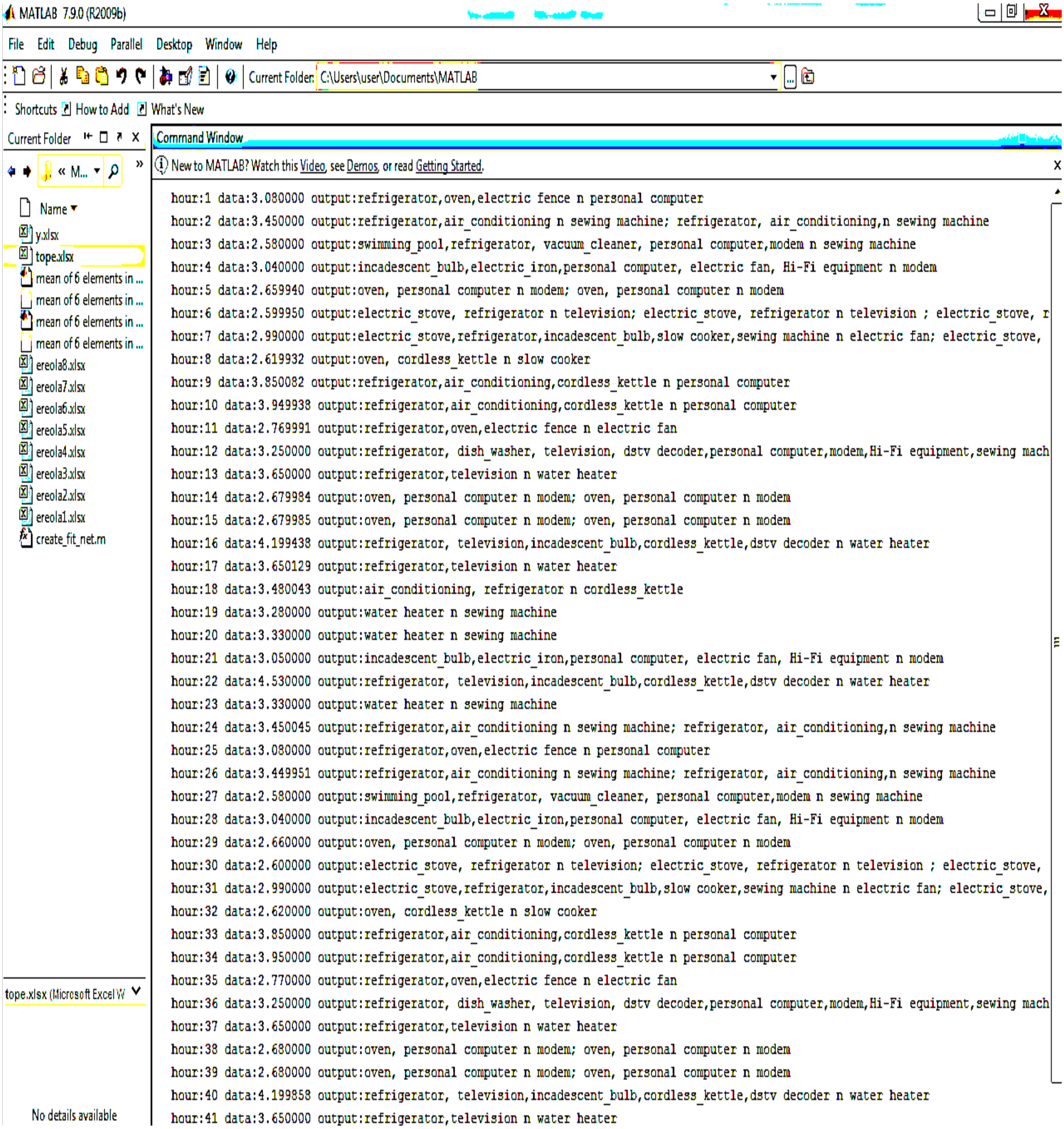


Figure D1: Cross-Section of the output of the algorithm in weekdays (summer).

```
hour:1 data:4.389790 output:electric_stove, refrigerator, television n electric_frying pan
hour:2 data:3.789111 output:oven,incadescent_bulb,personal computer,modem,electric fence n printer
hour:3 data:2.900321 output:refrigerator,microwave n electric fan
hour:4 data:2.900046 output:refrigerator,microwave n electric fan
hour:5 data:3.647283 output:oven,incadescent_bulb,personal computer,modem,electric fence n printer
hour:6 data:3.371638 output:refrigerator n water heater ; water heater n refrigerator,
hour:7 data:2.452612 output:electric_iron,cordless_kettle n electric fan; lectric_iron,cordless_kettle n electric fan ; electric_iro
hour:8 data:2.452226 output:electric_iron,cordless_kettle n electric fan; lectric_iron,cordless_kettle n electric fan ; electric_iro
hour:9 data:3.630240 output:oven,incadescent_bulb,personal computer,modem,electric fence n printer
hour:10 data:4.350000 output:electric_stove, refrigerator, television n electric_frying pan
hour:11 data:5.041587 output:refrigerator, electric_iron,incadescent_bulb, personal computer, modem n electric fan
hour:12 data:4.595382 output:electric_stove, refrigerator, television n electric_frying pan
hour:13 data:3.971261 output:electric_stov,refrigerator n cordless_kettle
hour:14 data:3.499994 output:television, air_conditioning n dstv decoder
hour:15 data:3.750403 output:oven,incadescent_bulb,personal computer,modem,electric fence n printer
hour:16 data:2.579572 output:refrigerator,oven n slow cooker; refrigerator,oven n slow cooker
hour:17 data:3.169729 output:electric_stove,refrigerator,microwave,slow cooker,sewing machine n electric fan
hour:18 data:3.149631 output:electric_stove,refrigerator,microwave,slow cooker,sewing machine n electric fan
hour:19 data:2.729514 output:television, cordless_kettle, dstv decoder, slow cooker n electric fan
hour:20 data:2.959842 output:electric_frying pan,cordless_kettle n refrigerator
hour:21 data:3.048485 output:electric_stove,refrigerator, microwave n slow cooker
hour:22 data:3.239873 output:electric_stove,refrigerator,microwave,slow cooker,sewing machine n electric fan
hour:23 data:3.650066 output:oven,incadescent_bulb,personal computer,modem,electric fence n printer
hour:24 data:3.078381 output:electric_stove,refrigerator, microwave n slow cooker
hour:25 data:2.969125 output:electric_frying pan,cordless_kettle n refrigerator
hour:26 data:3.149322 output:electric_stove,refrigerator,microwave,slow cooker,sewing machine n electric fan
hour:27 data:2.949067 output:electric_frying pan,cordless_kettle n refrigerator
hour:28 data:2.599314 output:refrigerator, television, electric_iron, dstv decodern sewing machine
hour:29 data:2.599041 output:refrigerator, television, electric_iron, dstv decodern sewing machine
hour:30 data:2.748948 output:refrigerator,oven, electric fence n electric fan
hour:31 data:2.599015 output:refrigerator, television, electric_iron, dstv decodern sewing machine
hour:32 data:3.350121 output:refrigerator n water heater ; water heater n refrigerator,
hour:33 data:3.449638 output:air_conditioning,slow cooker n sewing machine
hour:34 data:3.399525 output:refrigerator n water heater ; water heater n refrigerator,
hour:35 data:4.500297 output:electric_stove, refrigerator, television n electric_frying pan
hour:36 data:3.730482 output:oven,incadescent_bulb,personal computer,modem,electric fence n printer
hour:37 data:4.147798 output:electric_stov,refrigerator n cordless_kettle
hour:38 data:3.059112 output:electric_stove,refrigerator, microwave n slow cooker
hour:39 data:3.129404 output:electric_stove,refrigerator, microwave n slow cooker
hour:40 data:2.779368 output:electric_stove, refrigerator, television, dstv decoder,sewing machine n electric fan
hour:41 data:3.099410 output:electric_stove,refrigerator, microwave n slow cooker
hour:42 data:2.679466 output:refrigerator n television, electric_frying pan n microwave
hour:43 data:4.843054 output:electric_stov,refrigerator n cordless_kettle
```

Figure D2: Cross-Section of the output of the algorithm in Weekend (summer).

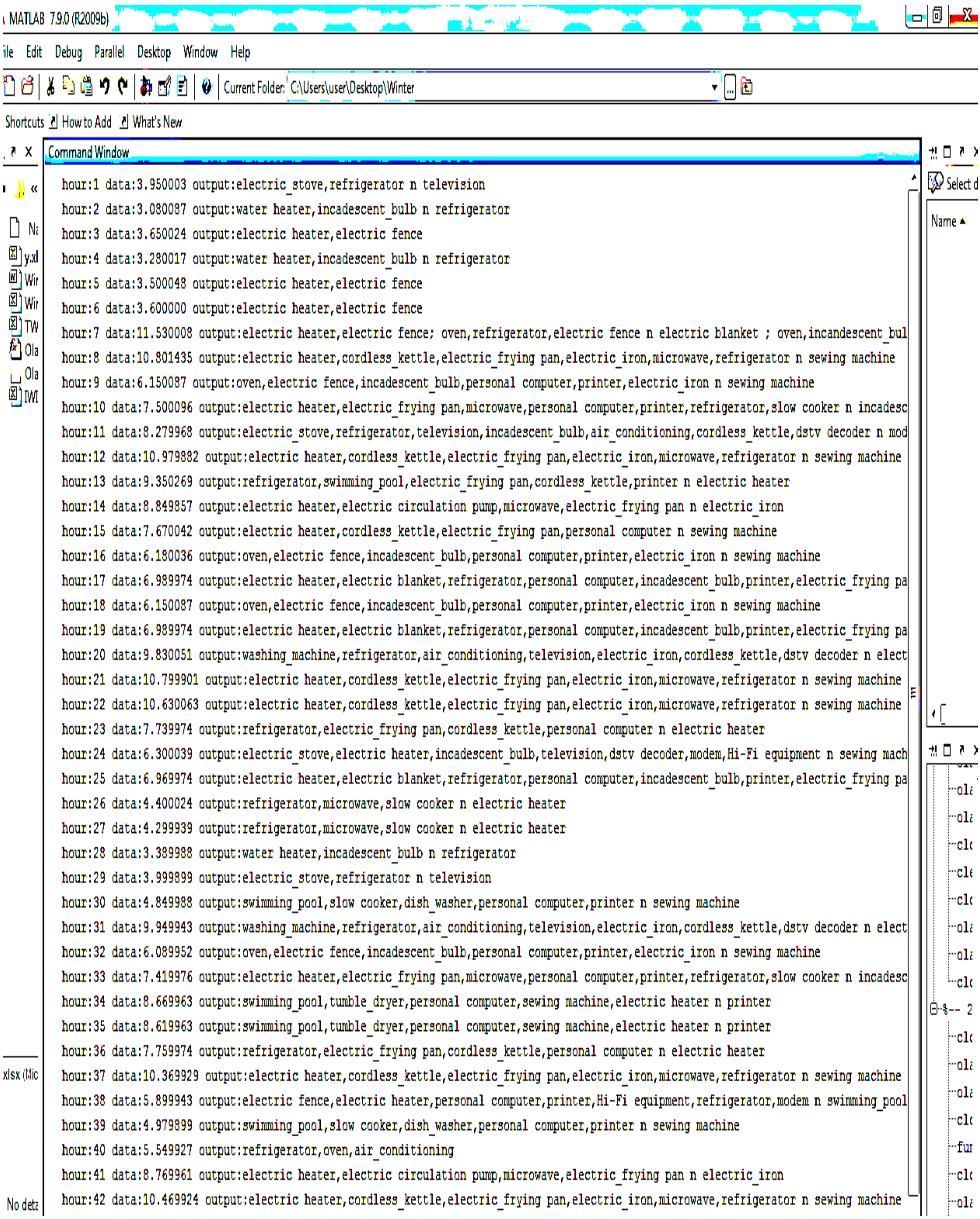


Figure D3: Cross-Section of the output of the algorithm in Weekdays (winter).

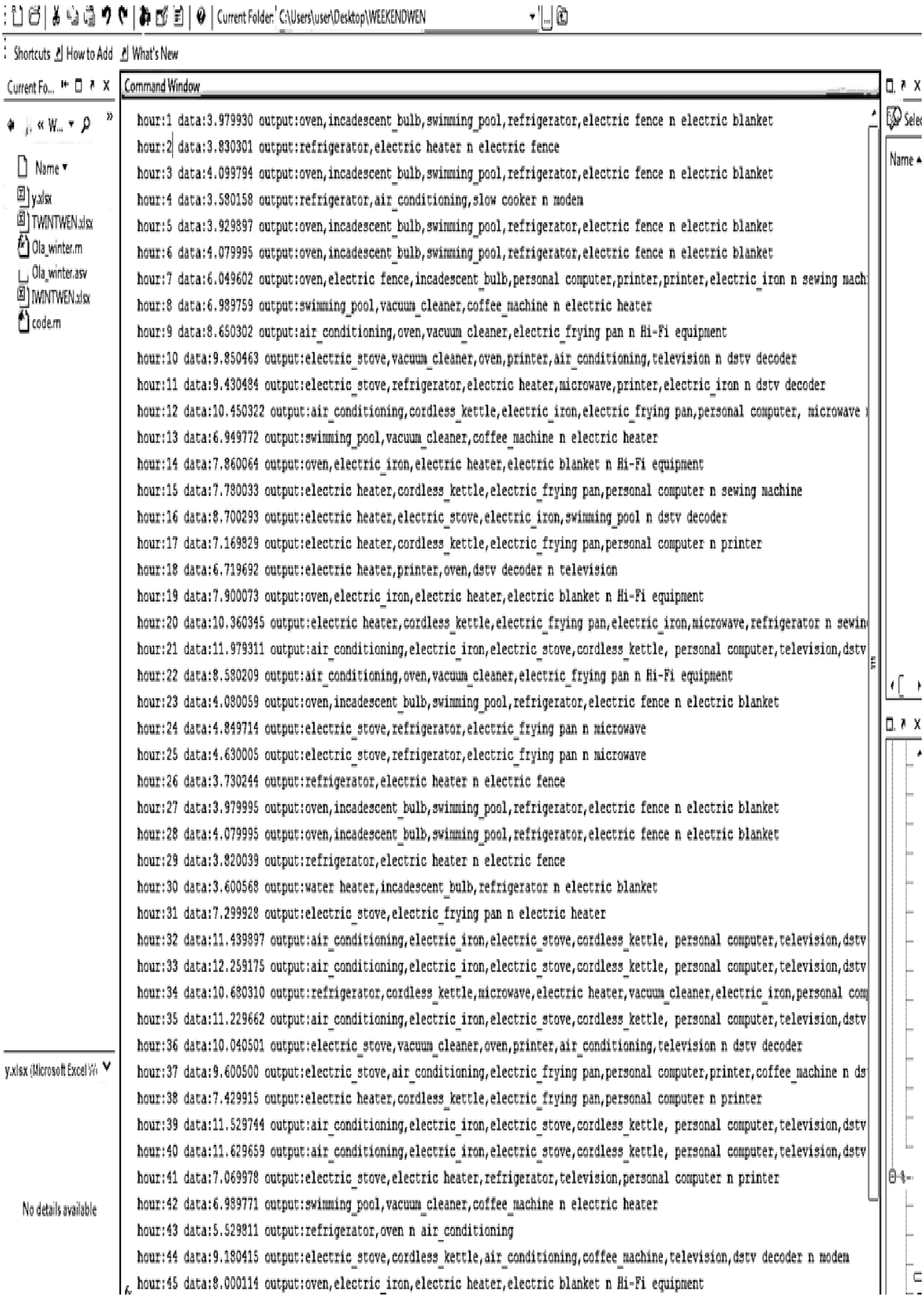


Figure D4: Cross-Section of the output of the algorithm in Weekends (winter).

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