Adaptive Health Monitoring Using Aggregated Energy Readings from Smart Meters

By

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ABSTRACT

Worldwide, the number of people living with self-limiting conditions, such as Dementia, Parkinson's disease and depression, is increasing. The resulting strain on healthcare resources means that providing 24-hour monitoring for patients is a challenge. As this problem escalates, caring for an ageing population will become more demanding over the next decade, and the need for new, innovative and cost effective home monitoring technologies are now urgently required. The research presented in this thesis directly proposes an alternative and cost effective method for supporting independent living that offers enhancements for Early Intervention Practices (EIP). In the UK, a national roll out of smart meters is underway. Energy suppliers will install and configure over 50 million smart meters by 2020. The UK is not alone in this effort. In other countries such as Italy and the USA, large scale deployment of smart meters is in progress. These devices enable detailed around-the-clock monitoring of energy usage. Specifically, each smart meter records accurately the electrical load for a given property at 10 second intervals, 24 hours a day. This granular data captures detailed habits and routines through user interactions with electrical devices.

The research presented in this thesis exploits this infrastructure by using a novel approach that addresses the limitations associated with current Ambient Assistive Living technologies. By applying a novel load disaggregation technique and leveraging both machine learning and cloud computing infrastructure, a comprehensive, nonintrusive and personalised solution is achieved. This is accomplished by correlating the detection of individual electrical appliances and correlating them with an individual's Activities of Daily Living. By utilising a random decision forest, the system is able to detect the use of 5 appliance types from an aggregated load environment with an accuracy of 96%. By presenting the results as vectors to a second classifier both normal and abnormal patient behaviour is detected with an accuracy of 92.64% and a mean squared error rate of 0.0736 using a random decision forest. The approach presented in this thesis is validated through a comprehensive patient trial, which demonstrates that the detection of both normal and abnormal patient behaviour is possible.

INDEX OF TERMS

Smart Meters, Advanced Metering Infrastructure, Health Monitoring, Independent Living, Automated Meter Readings, Home Area Network, Consumer Access Device, ZigBee, Smart Energy Profile, ZigBee Cluster Library, Web Services, Cloud Computing, In-Home Display Unit, Appliance Load Monitoring, Non-Intrusive Load Monitoring, Intrusive Load Monitoring, Profiling, Assistive Technologies, Early Intervention Practice, Activities of Daily Living, Mini Mental State Examination, 6 Item Cognitive Impairment Test, Dementia, Alzheimer’s Disease, Parkinson’s Disease, Depression, Quality Adjusted Life Year, Data Analysis, Data Classification, Machine Learning, Support Vector Machine, Multiclass Decision Forest, Temporal Pattern.

GLOSSARY

- **6 Item Cognitive Impairment Test (6CIT):** The 6CIT is employed as a dementia screening tool in Primary Care. Various clinicians, which include GPs, consultants and nurses, use 6CIT as set of predefined questions to measure the response of the patient. By utilising a scoring system, the patient's answers ascertain their level of cognitive function.
- **Activities of Daily Living (ADLs):** ADL is a healthcare term that refers to a person's daily set of actions. These activities are used as a measurement of functional status and the overall wellbeing of a patient. ADLs are used by healthcare professionals to assess a patient's ability or inability to maintain their independence.
- **Advanced Metering Infrastructure (AMI)**: AMI is an advanced integrated system of smart meters, communication gateways and data storage systems. This infrastructure offers bidirectional communication between the consumer and utilities. It replaces the traditional requirement for energy and gas usage readings to be collected manually.
- **Alzheimer's Disease**: Alzheimer's is a neurological condition and a progressive disease, during which, proteins build up in the brain to form structures called 'plaques' and 'tangles'. This leads to the loss of connections between nerve cells, eventually resulting in the death of the cell and a reduction of brain tissue. As a consequence, this leads to severe cognitive impairment and memory loss.
- **Ambient Assistive Living:** Are concepts, products and services which utilise the deployment of information communication technology (ICT) to improve and extend the quality of life of the user.
- **Ambient Intelligence:** A collection of devices used to create a smart home, which is sensitive and responsive to the presence of the occupant. The main objective of these devices is to facilitate and support the occupant in carrying out their activities of daily living.
- **Appliance Load Monitoring (ALM):** ALM is the process of identifying the usage of individual electrical devices from their energy consumption characteristics.
- **Assistive Technologies:** Devices or systems that support a person to maintain or improve their independence, safety and wellbeing in their own home.
- **Automated Meter Readings (AMR):** AMR is the process, by which, the automatic collection of amenity consumption is obtained and reported to utilities. Other information, such as diagnostic and status data, is collected and transferred to a central database.

- **Consumer Access Device (CAD):** Consumers are able to pair other devices that operate the ZigBee Smart Energy Profile (SEP) to the network; such devices are typically known as Consumer Access Devices. A CAD is able to access updated consumption and tariff information directly from a smart meter.
- **Dementia:** is a term which is used to define the set of symptoms that occur when the brain is affected by specific diseases. These include Alzheimer's, Parkinson's, Huntington's disease and Lewy body.
- **Depression:** This is a mood disorder which, results in a variety of different emotions. Depression affects people in diverse that is unique to the sufferer. However, common trends range from lasting feelings of unhappiness and hopelessness, to losing interest in previously enjoyable activates. It often presents as nervous ailments that affects the person both mentally and physically.
- **Disaggregation:** energy disaggregation, is the process for identifying electrical devices from the aggregated data acquired from a single point of measurement. Typically the use of machine learning is used to classify the appliance used within the premise.
- **Early Intervention Practice (EIP):** EIP is used by many services to intervene and take action as soon as possible to limit the effects of an event. These events could be in the form of a fall or the identification of a deterioration in an existing health condition.
- **Home Area Network (HAN):** A HAN is a secure network, which enables the smart meter to communicate with other smart devices around the home. Specifically, the HAN utilises ZigBee to connect with trusted devices up to a maximum range of 15 meters.
- **Intrusive Load Monitoring (ILM):** ILM is regarded as a distributed sensing method, as it uses multiple individual sensors. One sensor is installed for each electrical device being monitored.
- **Mini Mental State Examination (MMSE):** MMSE is used to test patients with complications accosted with memory or other mental abilities. Specifically, it is used by clinicians to assist in the diagnoses of dementia, while helping to assess its progression and severity.
- **Non-Intrusive Load Monitoring (NILM):** NILM is a single point sensing method for the identification of electrical devices from aggregated load readings. Typically, the sensor analyses the energy consumption for a given property, deducing the appliances used in the premise, as well as, their individual energy utilisation.

- **Parkinson’s Disease:** This is a progressive neurological condition, which is caused by a reduction of nerve cells in the part of the brain called the substantia-nigra. This results in a decreased amount of a chemical called Dopamine. Without the presence of dopamine patients can find that their movements become slower so it takes longer to undertake certain daily activities. In addition to affecting movement, people with Parkinson's exhibit symptoms of tiredness, pain and depression, which can have a severe impact on their daily life.
- **Profiling:** The recording and analysis of an individual’s psychological and behavioural characteristics is known as profiling. Profiles are used to detect any changes or alterations in a person’s behaviour.
- **Quality Adjusted Life Year (QALY): QALY** is a generic measurement of disease burden, which ascertains and quantifies both the quality and quantity of life. It is utilised to establish the overall effectiveness of an intervention metric.
- **Smart Meters:** Smart meters are in premise gas, electricity and water monitors, which provide consumers with reliable and accurate readings. They offer real time analysis, at granular intervals, for both the consumer and all of the smart grid stakeholders.
- **Web Services:** Are a collection of open protocols and standards, which can be used for exchanging data between applications or systems. Applications, which can be written in programming languages (such as Java, C# and Python), are hosted on different platforms (such as Windows, IOS and Linux) to exchange data over networks such as the internet.
- **ZigBee Cluster Library (ZCL):** ZCL is a repository for cluster functionality, which is developed and maintained by the ZigBee Alliance. A developer can utilise the ZCL when developing a new application profile by leveraging certain features and functionality of the various clusters. The ZCL consists general purpose clusters and specialised clusters, which are designed to perform specific functions within the ZigBee framework.
- **ZigBee Smart Energy Profile (SEP):** SEP is an agreed wireless standard that all UK smart meters adhere to. This enables interoperable devices to communicate directly with a smart meter, ensuring compatibility with certified ZigBee smart energy products.

PUBLICATIONS RESULTING FROM THIS THESIS

JOURNAL PAPERS

1. **Chalmers, C.,** Hurst, W., Mackay, M., & Fergus, P., *Behavioural Changes for Health Monitoring Applications using the Advanced Metering Infrastructure*, Behaviour & Information Technology (TBIT), Taylor & Francis, 2017 – (Under Review).
2. **Chalmers, C.,** Hurst, W., Mackay, M., & Fergus, P., *Health Monitoring Applications using Aggregated Energy Readings from Smart Meters*, Submitted to the Special Issue on Internet of Things for Personalised Healthcare System, Pervasive and Mobile Computing Journal, 2016 – (Under Review).

3. **Chalmers**, **C**., Mackay, M., & Mac Dermott, A., *Securing the smart grid: threats and remediation*, International Journal of Smart Grid and Green Communications (IJSGGC), 2015, ISSN print: 2052-2002.

CONFERENCE PAPERS

4. **Chalmers, C**., Hurst, W., Mackay, M., & Fergus, P., *Smart Monitoring: An Intelligent System to Facilitate Health Care across an Ageing Population*, In Proceedings of the Eighth International Conference on Emerging Networks and Systems Intelligence (EMERGING), Venice, Italy, 9th – 13th October 2016.
5. **Chalmers, C**., Hurst, W., Mackay, M., & Fergus, P., *A Smart Health Monitoring Technology*, International Conference on Intelligent Computation, Lanzhou, China, 2-5Th August 2016.
6. **Chalmers, C**., Hurst, W., Mackay, M., & Fergus, P., *Smart Health Monitoring Using the Advanced Metering Infrastructure*, The Workshop on the Internet of Things and Big Data for Healthcare (IoTBDH-2015) in conjunction with CIT 2015, Liverpool, UK, October 2015.
7. **Chalmers, C**., Hurst, W., Mackay, M., & Fergus, P., *Profiling Users in the Smart Grid*, The Seventh International Conference on Emerging Networks and Systems Intelligence, (EMERGING), Nice, France, 19th-24th July 2015.

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BOOK CHAPTERS

9. Hurst, W., Shone, N., **Chalmers, C.,** Cyber Security Education and Training for Critical Infrastructure Protection, Modern Cyber Security Policies and Nuclear Plant Protection, Publishers: Technische Hochshule Brandenburg, University of Applied Sciences, Institute for Security and Safety, 2017.

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POSTERS

11. **Chalmers, C**., Hurst, W., Mackay, M., & Fergus, P., *Smart Profiling for Health Applications*, Inaugural conference on Policy-making in the Big Data Era: Opportunities and Challenges, University of Cambridge, 16th June 2015.

AWARDS

1. Second place in the Research Spotlight Awards, for a project titled Facilitating Health Monitoring using Smart Devices - Awarding body: Liverpool John Moores University, 2016.
2. Third Place winner at the London Innovation Awards on Big Data Analysis, for a project titled *Smart profiling for healthcare applications* - Awarding body: London Innovation Society, 2015.

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CHAPTER 1 INTRODUCTION

1.1 PREAMBLE

In the UK around one in five adults are registered disabled. More than one million of these are currently living alone [1]. Additionally, the number of people in the UK living with dementia is currently estimated to be 850,000 and forecasted to exceed two million by 2051 [2]. Providing a safe and secure living environment places a considerable strain on social and healthcare resources. Effective around the clock monitoring of these conditions is a significant challenge and adversely affects the level of care provided. However, a safe and independent living environment is hard to achieve, yet vital for early intervention. Community mental health groups, crisis and home resolution teams all play a key role in preventing costly inpatient admissions. Current public policy enables sufferers to live independently in their homes for as long as possible. Yet present monitoring services are expensive and are often met with patient resistance due to their complexity and intrusiveness.

As demonstrated through this research, substantial research gaps in non-invasive and cost effective monitoring technology exist [3] specifically, for safe and effective monitoring solutions that are beneficial to the patient and healthcare providers alike.

As such, the challenge addressed through this research is how to develop a system which analyses the data collected by smart meters for health monitoring applications. The system depends entirely on a single discrete sensor which interfaces with the patient’s smart meter to facilitate a highly accurate and personalised monitoring service for a variety of different conditions. Electricity readings are taken at 10 second intervals [4] and relate to interactions with electrical devices; specifically, operation time and duration of use. ADLs are imperative in determining a patient’s overall health and enabling an accurate evaluation of any changes in their condition [5]. By focusing on the patient’s ability to undertake normal ADLs, both normal and abnormal behaviours can be identified while detecting deviations in routine.

In this chapter the research within this thesis is introduced, along with the motivation and the aims and objectives of the work. This is followed by a discussion on our contributions to knowledge, the methodology used, and the overall structure of the thesis is outlined.

1.2 ADVANCED METERING INFRASTRUCTURE

The Advanced Metering Infrastructure brings many benefits over the traditional energy grid. In order to maximise its true potential, different applications need to be considered beyond the traditional uses of electricity and gas generation, distribution and consumption. The bidirectional communication capabilities provided are a core part of the Advanced Metering Infrastructure (AMI) and forms part of the smart grid. This provides an attractive opportunity for service providers and other vendors, as it enables access to a fully maintained and highly accurate sensing network [6]. Providers are able to utilise this resource by integrating their own frameworks through an agreed communication standard, as discussed in detail in chapter 2. The AMI, in particular the smart meter, is an integral part of our system and approach.

1.3 MOTIVATION

The following provides a description of the motivation behind this research, which will be elaborated on throughout the remainder of this thesis.

- **Health and Social Challenges:** Each year the number of people living with self-limiting conditions such as Dementia, Parkinson's disease and mental health problems, is increasing [7]. Furthermore, there are an increasing number of people living alone with such medical conditions. This is placing significant demand on health care and social services and already stretched resources [8]. As this problem escalates, caring for an ageing population will become increasingly more challenging over the next decade. That said, duty of care is a legal obligation for governments, and arguably, an ethical and moral duty for any modern society.

  For many countries the emergence of an ageing population is fast becoming an increasing public health concern. Although an international issue, the UK in particular faces considerable challenges due to historical birth trends [9]. The origins of this ageing demographic can be partially attributed to the baby boom. During the mid-1950s up until the early 1970s the UK birth rate was above 850,000 per year [10]. In 2012, the number of people aged 65 and over surpassed 10 million for the first time. In addition to a maturing population, a vastly improved life expectancy is set to increase pressures further. Longer life expectancy is widely regarded to be one of the greatest challenges of the next century. Typically, a man born in 1981 has an estimated life expectancy of 84 years. However, for a baby born in the present day, this increases to 89 years with future increases predicted in upcoming years [11]. In contrast, when the NHS was founded in 1948, 48 percent of the population died before the age of 65 [12]. The success of modern medicine has completely transformed our health and care requirements. The impact on NHS resources also has a strong association with the following problem areas:

- An ageing population may suffer from multiple health issues and illness. This group of patients often relay on a wide variety of support including family, friends, social care and other third party organisations.
- An increasing prevalence of chronic and complex health conditions such as Dementia, Parkinson's, Alzheimer's, arthritis, kidney disease, and mental health problems. These ailments often result in frequent hospital admissions or the requirement of long term care.
- Higher numbers accessing outpatient or emergency care due to frailty, falls and secondary complications [13].
- Absence of effective early intervention practice. The lack of EIP is a major contributor to increased hospital admissions, higher treatment costs and escalating secondary complications [14].
- Bed blocking, where a patient is medically ready to be discharged but is delayed because of inadequate care, support and rehabilitation services outside hospitals [15].

Ultimately health and social care has failed to adequately adapt to this dramatic demographic shift. The challenge is to explore alternative, sustainable, ways of supporting independent living within ageing populations. However, the development of an effective and reliable monitoring solution presents challenges, which need to be addressed.

- **Current Limitations of Assistive Technologies:** The use of smart technologies in primary care delivery is increasing in an effort to meet the challenges described [16]. In recent years, there has been rapid development in monitoring technologies for independent living, early intervention services and in-patient condition management. However, research in non-invasive and cost effective monitoring technology lag far behind. Affordability and associated costs with existing technologies mean they cannot be implemented on a large scale. This leaves many solutions inaccessible to NHS trusts, councils and social services in the UK. Furthermore, most technologies are considered too intrusive [17]. For example, the use of sensors and cameras around the living environment raise many privacy and protection concerns and this leads to a general reluctance to use the technology.

Often technical solutions are tailored to a specific application and do not meet the ongoing changing requirements of a patient. Many current technologies and services are limited to the monitoring of physical ailments and are not feasible for monitoring the mental wellbeing of the patient. A detailed review of current assistive technologies and their feasibility is therefore discussed in chapter 3.

- **Absence of Condition Knowledge, Personalisation and Behavioural Pattern Recognition:** Existing telehealth solutions fail to include and exploit the use of clinical knowledge in their approach. As a result, one of the research motivations is to find an approach to include both clinical knowledge and personalisation into a solution. Being able to detect and predict changes in activities requires a detailed understanding of the symptoms and behaviours that are expected for each condition. The capacity of any patient monitoring system can be dramatically enhanced with the inclusion of medical insight [18]. An example scenario is as follows: A dementia patient has started to exhibit increased activity in the evening. For most systems this behaviour would be identified as normal as the patient is undertaking activities. However, if medical insight is applied to the observed behaviour, we recognise that for dementia patients this is a potentially concerning behavioural trait and could signify disease progression [19]. This however introduces significant challenges as any behavioural changes need to be assessed for medical importance and meaning.

1.4 DISCUSSION

The research in this thesis is motivated by the significant challenges that face health and social care, both in the UK and internationally. More importantly the motivation is drawn from the patients themselves and their family and friends who work tirelessly every day to manage these serious illnesses.

Having a dramatically ageing population means more people than ever before wish to live independently in their own home. Unfortunately, it is a choice that many of us will have to make in the future, either for ourselves or on behalf of a loved one. In many cases this could be one of their last major independent choices. Yet, there is currently no accurate, affordable and scalable monitoring system to support people in their own homes and alert relatives, friends or health professionals if there is a problem or a worsening of a condition.

The introduction of the smart meter provides an extraordinary opportunity to create an accurate, cost effective and personalised patient monitoring system. Although the intended use for these devices is to modernise the metering infrastructure, they also provide an accurate and cost effective gateway into consumers' homes for a variety of different applications. Arguably one of the most significant uses for these devices is to facilitate the monitoring of various illnesses, both physical and mental.

1.5 AIMS AND OBJECTIVES

In the following section both the overreaching aim and key objectives of the research are presented. The key aim of this thesis is as follows:

- To research a novel approach for the assessment of both the physical and mental wellbeing of a person, by analysing only the electricity readings obtained from their smart meter. The solution must 1) address the current limitations that are associated with existing technologies to facilitate a nonintrusive and personalised monitoring system; 2) Identify Activities of Daily Living (ADLs) to facilitate early intervention, while applying medical knowledge to the obtained results; 3) Employ specific behavioural indicators, such as prolonged and reoccurring instances of activity or inactivity to assess the patient's ability to undertake normal ADLs and monitor their state of health. 4) Commission a clinical trial to evaluate whether the approach can support vulnerable people living independently with ongoing healthcare needs.

Interoperating and analysing the vast amounts of data generated by smart meters is a significant challenge; this is especially true for the novel health-monitoring application proposed in this research. Additionally there are many challenges associated with machine learning, all of which have been studied by a variety of disciplines over many years [20].

In order to fulfil the aims of this project, the key objectives of this research are as follows:

- The development of novel algorithms that facilitates a personalised patient monitoring solution.
- The deployment of energy monitors for the collection of granular energy readings (10 second intervals). These are obtained from an assortment of patients provided by Mersey Care NHS Trust. This is undertaken to simulate the deployment of a consumer access device to ensure that the models are trained on accurate data.
- Identify a variety of behavioural patterns and trends by investigating patient behaviours while applying medical knowledge to the results. This establishes the individual conditions and applications that can be accurately monitored by using a patient's energy usage data.

- Deploy aggregated load monitoring techniques to classify individual device interactions to aid in the overall assessment of the patient. The identification of individual devices is imperative requirement for determining and identifying the patient's activities of daily living.
- Propose a novel method for the identification of concerning behaviour and routine alteration. The system must accommodate predefined thresholds to classify the importance of the observed behaviours while acting accordingly. The system must learn and adjust to misclassifications to reduce future false alarms and adequately adapt to disease progression.

1.6 NOVEL CONTRIBUTIONS

As previously discussed, current assistive technologies are not adequate for the monitoring of self-limiting conditions. They are largely incapable of monitoring both the physical and mental welfare of a patient and cannot aid in early intervention practice and the prediction of progression.

As such, a novel approach and solution for this problem is put forward, in the form of a system which analyses smart meter data for healthcare applications. The following outlines the specific novel contributions offered through this research:

- The analysis of energy usage data obtained from smart meters for remote patient monitoring and healthcare applications.

- A novel approach for smart meter load disaggregation by interfacing directly with the smart meter using a CAD.

- A novel method for the disaggregation and classification of type 1 (on / off), 2 (multi-state) and 3 (continuously variable) electrical devices using only smart meter data.

- A method for generating electrical device signatures using a reduced observation period for device classification.

- A method which supports remote in-home health monitoring that is both accurate and scalable. The approach removes the requirement for expensive distributed sensors and intrusive wearable monitoring equipment. Thus using a single non-intrusive sensor that can be modified for different monitoring applications [21].

- The creation of a novel behavioural algorithm that learns the distinct attributes and routines of the patient through the detection of device interactions. The system can correctly identify both normal and abnormal patient behaviour based on the frequency of events with a specified observation period [22].
- A novel approach for assessing the correlation of electrical device usage with the expected activities of daily living that is specific to the patient's condition [23].
- Integration with NHS services through a common API that uses energy usage to enhance patient care plans and intervention strategies.

1.7 THESIS STRUCTURE

The remaining sections in this thesis are organised as follows:

Chapter 2 – Background: In this chapter the advanced metering infrastructure and its various components are examined. The chapter discusses the role of smart grids and highlights their various benefits and the motivation behind their deployment. Additionally, the chapter discuss the numerous communication standards and infrastructures, which are used within the Advance Metering Infrastructure (AMI) and smart grid. The chapter also provides a detailed background on smart meters and their associated technologies. Particular focus is given to the UK smart meter implementation program. We define the specific technology standards and features that are used in our approach. In this chapter different the load monitoring techniques are discussed in detail while paying particular attention to their different advantages and disadvantages. In addition, the chapter also introduces the concept of cloud computing, highlighting its many benefits and its role within the wider smart grid. The chapter is concluded with a discussion regarding machine learning and its associated considerations and concepts. In addition the application of cloud computing for machine learning is discussed. The chapter also introduces the concept of edge computing and its applications and benefits. Here a comparison between edge and cloud computing is presented while highlighting the limitations of each technology.

Chapter 3 – Related Work: This chapter presents a critical review of the current assistive technologies and research areas. In particular, the chapter focuses on their various limitations and inadequacies, which provides the motivation for the approach presented in this research. The chapter introduces the concept Ambient Assistive Living (AAL) and the wide variety of disciplines that support its ongoing development. Finally, 6 specific areas have been identified, which directly impede both the deployment and adoption of any existing solution, which will also be discussed in this chapter. Furthermore, the chapter discusses the illness and behavioural characteristics of a person that are monitored by the system.

Chapter 4 – Personalised Intelligent Health Monitoring using Smart Meters (PIMS): This chapter presents the design of the proposed patient monitoring system. Here a breakdown of the various components and processes are presented, while highlighting their specific functions and interactions. The chapter provides a complete end-to-end framework, discussing the processes that are required to interface with a smart meter. Additionally, the data processing functions that are required to identify individual electrical devices are also described. Additionally, the chapter provides a detailed description of the alert process and how it integrates with the monitoring applications of the system. The chapter is concluded with a description of how the framework integrates with existing medical systems to exploit additional functionality.

Chapter 5 – NHS Case Study: This chapter presents a case study of an ongoing patient trial that is being conducted in partnership with Mersey Care NHS Trust. By using the PIMS framework, data is collected from three different dementia patients with the aspiration of validating the algorithms used in the approach. Both the collected data and obtained knowledge is used in the implementation of the PIMS framework and its evaluation. In addition the individual sensors which are installed in the patient's property are introduced.

Chapter 6 – Implementation: This section, introduces the data collection methods that were used to generate both the device and behavioural training data. The data is analysed using statistical methods to substantiate the techniques used in our approach. In addition the PIMS implementation is presented along with the associated technologies used to create the system. Here the both the on premise and cloud technologies are deployed to facilitate the real time detection of both normal and abnormal patient behaviour. Additionally the chapter presents the machine learning algorithms used and how they are configured to classify both the individual electrical appliances and patient behaviours.

Chapter 7 – Results and Discussion: In this chapter, the results from the PIMS implantation are presented. The evaluation involves a detailed analysis of the classification results to ascertain the optimal configuration for the PIMS framework. Both the device and behavioural models are assessed to determine their suitability using the data collected from the deployed energy monitor. Here the classification challenges are highlighted while discussing the relationships between the different device classes. An assessment between the use of the raw data and the generated statistical features is presented along with the number of observations used in the classification process.

Chapter 8 – Conclusion and Future Work: In the final chapter of the thesis, the findings of the research are summarised. The future work and direction of the research is discussed outlining potential tasks, which could be undertaken based on the proposed methodology and the results of this work. The thesis is concluded by summarising both the work presented and the various challenges it has overcome.

CHAPTER 2 SMART GRID METERING INFRASTRUCTURE

2.1 INTRODUCTION

This chapter discusses the areas of work examined to provide a fundamental insight into the components and considerations that are utilised in our approach. Here, the advanced metering infrastructure and the different components that reside within its framework are outlined. Particular focus is given to the smart meter and its associated technologies. The chapter also provides an overview of the main drivers behind the smart meter implementation program while highlighting its benefits and aspirations. The chapter discusses the particulars of the UK smart meter implementation highlighting the specific technological standards. Additionally, this chapter introduces the process for interfacing with the smart meter, which is achieved through the utilisation of the ZigBee Smart Energy Profile.

The chapter also provides a detailed insight into the various load monitoring methods that are available for the purpose of device identification. Two primary methods are discussed, which include intrusive and non-intrusive load monitoring. Additionally, the chapter discusses the concept of cloud computing highlighting its various, benefits, platforms and applications. We discuss how cloud computing has been utilised to mitigate some of the challenges that are associated with the smart gird implementation. In addition the concept of machine learning and its associated considerations are discussed. The chapter is concluded with a discussion surrounding cloud computing, and its utilisation in the machine learning paradigm.

2.2 SMART GRIDS AND THE ADVANCED METERING INFRASTRUCTURE

The motivation behind the smart grid concept is attributed to different factors. Arguably the main objective for the smart grid is to balance grid load effectively [24]. According to the latest projections from the International Energy Agency (IEA), smart grid technologies are an essential grid component in order to meet future energy requirements [25]. Additionally, the IEA expects worldwide energy demands to increase at an annual rate of 2.2 percent, eventually doubling the global energy demand by 2040 [26]. Energy companies and governments must also consider the ever increasing environmental impact caused by C02 emissions. These emissions are projected to accelerate faster than the increased demand for energy, forcing many countries to deploy smart grid technologies rapidly to help them achieve their C02 reduction obligations. The increasing social awareness of such issues has resulted in mounting pressure for governments and organisations to tackle these challenges [27].

2.2.1 SMART GRID

Smart grids fundamentally change the way in which we generate, distribute and monitor our electricity and gas. It dramatically improves the efficiency, flexibility and reliability of the existing utility infrastructure [28]. The smart grid is also essential for the integration of renewable and locally generated energy. Through this approach, it improves the efficiency and sustainability of the grid and its services [29]. However, the smart grid is regarded as more than just an infrastructure for the generation of smarter electricity and its distribution and consumption. There are social and consumer benefits associated with the smart grid. These include lower costs, improved customer service, decreased outage times and increased reliability. Additionally, the smart gird has been designed to accommodate and integrate new technologies over time. This is achieved by utilising diverse interoperable protocols and communication standards. This openness provides a gateway for additional social opportunities, which can be used to directly benefit the consumer and other organisations.

2.2.2 ADVANCED METERING INFRASTRUCTURE FRAMEWORK

A smart grid is a complex modern utility system [30]. It uses sensors, monitoring, communications, and automation, to improve grid infrastructure and services. A robust automatic reporting system with greater granularity of readings is offered [31].

One of the key differences over the existing grid is the introduction of the Advanced Metering Infrastructure (AMI) [32]. The AMI is not a single piece of technology, but a complex infrastructure which integrates with a variety of different technologies [33]. This framework contains many new components, such as the smart meter and the communication gateways that provide energy usage information to all of the grids stakeholders in real time. One of the most important components of AMI is the smart meter [34]. It fundamentally changes the way in which electricity and gas consumption is monitored and reported. These smart devices provide new possibilities for a variety of different applications that where impossible using a traditional grid topology.

As part of the larger smart grid, the AMI can be broken down into three specific areas, each with their own unique roles and functions; these include the Home Area Network (HAN), Wide Area Network (WAN) and the Data and Communication (DCC) Service users. The HAN is housed inside consumer premises and is made up of a collection of different devices. Firstly, the In-Home Display Unit (IHD) is the most visible and accessible part of the AMI. Essentially, it provides the consumer with information in real time on electricity and gas usage, as well as the units of energy that are being consumed. This information is obtained directly from the smart meter using a wireless communication technology called ZigBee [35]. The WAN handles the communication between the HAN and the utility companies. The WAN is responsible for sending all polled meter data to the utility companies and other grid stakeholders, using a robust backhaul network, such as Carrier Ethernet, GSM, CDMA or 3G [36].

The geographical location of the consumer's premise dictates the type of WAN technologies required, due to the constraints associated with certain communication protocols. The Data Aggregator Unit (DAU) is a communication device that is used to collect the energy usage data form the home gateway or the smart meter. The acquired data is transmitted, using one of the communication technologies mentioned above, to the control centre. Figure 1 highlights the UK AMI layout.

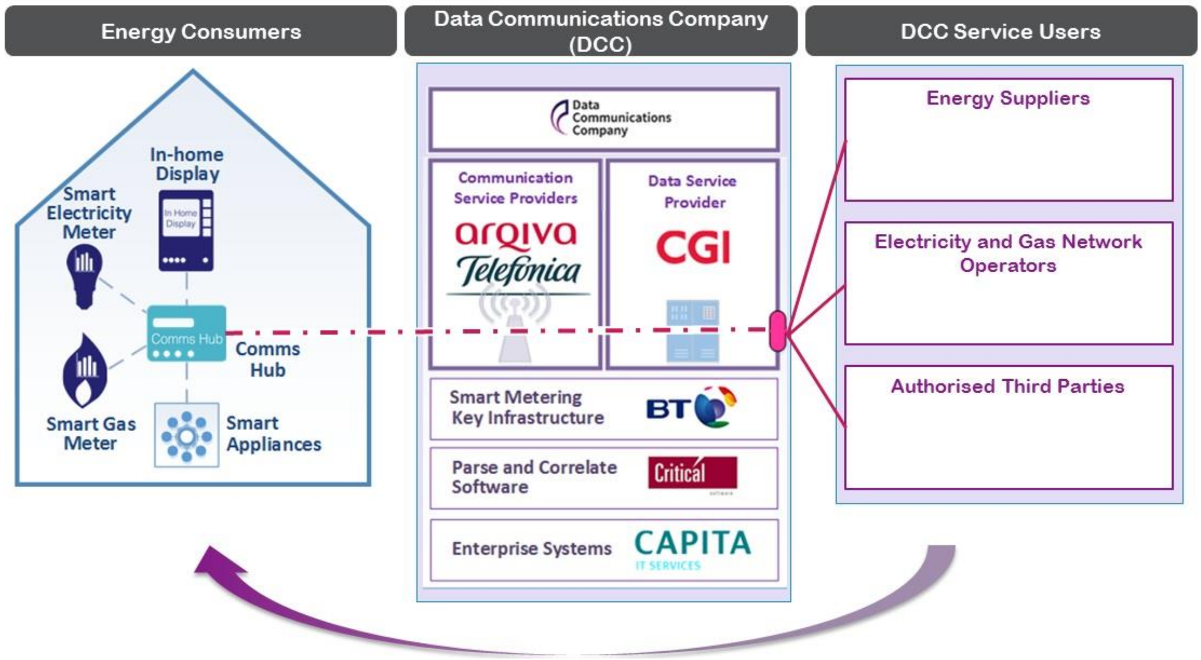


Figure 1: UK Advanced Metering Infrastructure[1]

However, the AMI is not limited to the distribution and monitoring of electricity. It facilitates the supply and billing of gas usage too. Other readings that are obtained from the various sensors, which are distributed throughout the entire grid, are also collected. All of the acquired data is sent to the Meter Data Management System (MDMS), which is responsible for storing, managing and analysing the data [37]. The MDMS sits within the data and communications layer of the AMI. This component is an advanced software platform, which deploys data analytics while facilitating the various AMI applications and objectives. These

[1] https://www.smartdcc.co.uk/about-dcc/

applications include: managing metered consumption data, outage management, demand and response, remote connect / disconnect, and smart meter events and billing [38]. This information can be shared with consumers, partners, market operators and regulators. Figure 2 provides an overview of the MDMS.

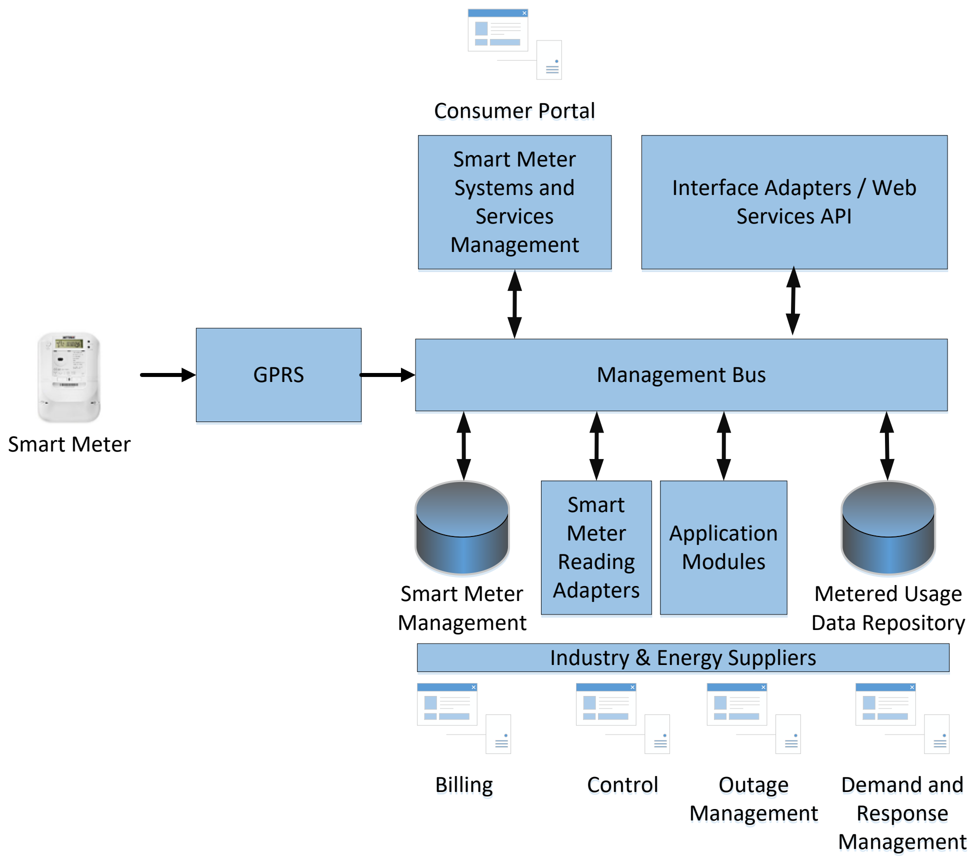


Figure 2: Overview of MDMS Framework

The MDMS is considered the central management system for the entire AMI. It has the capabilities to react to real time events and emergencies, while providing a reactive service to consumers through demand and response. In order to achieve this aim, open network protocols have been introduced in each layer of the framework [39]. The communication layer of the AMI is one of the most crucial elements in the system [40]. It facilitates the integration of components that reside within its framework by providing the communication link between each of the following layers:

- **The consumers home**: is the outer boundary of the AMI and is the most visible and accessible part of the entire smart grid. This section of the infrastructure is referred to as the Home Area Network (HAN). The HAN is a secure wireless network that utilises ZigBee Smart Energy to support real time data transfer between the smart meter and the

In-Home Display (HID) [41]. ZigBee is based on the wireless IEEE 802.15.4 standard and is technologically similar to Bluetooth [42]. Supplementary devices, which are known as Consumer Assess Devices (CAD), can join the HAN network and provide additional services to the consumer. Additionally, the smart meter utilises the HAN to collect energy usage readings and other parameters in real time. The energy usage readings are transmitted to the MDMS through a communications gateway, which can be a standalone entity or integrated into smart meter devices.

- **The Wide Area Network (WAN):** utilises GPRS communication technologies to send and receive data from the AMI. Essentially the WAN provides secure bidirectional connectivity to the public utility, customer premises, power generators, and transmission, and distribution subsystems. It enables the smart meter to securely communicate outside of the HAN using the mobile network.

Currently, there is no agreed standard for in-home communication in the market. Each country deploys different communication technologies depending on the technical requirements of their own regulations and supporting infrastructure. However, ZigBee, and ZWave, are the most commonly used solutions. In the UK, the Department of Energy and Climate Change (DECC) has opted for the exclusive use of ZigBee Smart Energy [43].The various roles and communication technologies utilised for the HAN and WAN are illustrated in figure 3.

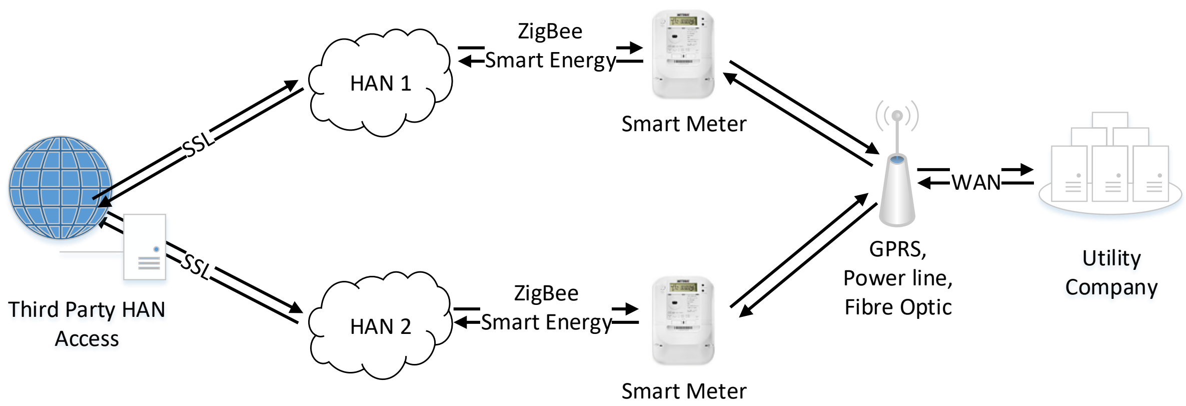


Figure 3: AMI HAN and WAN architecture and communication protocols

Each of the above components satisfies the specific requirements of the smart grid. The creation of a HAN provides third party access to the smart meter using agreed communication standards.

2.2.3 DATA CHALLENGES

With the deployment of the AMI and intelligent Supervisory Control and Data Acquisition (SCADA) systems, the collection and storage of data is becoming a significant challenge. In order to manage the data flow, smart meters in the UK collect and transmit energy usage information to the MDMS every 30 minutes [44]. Although, lower sampling rates are technically possible, processing such quantities is costly for the utility company. The sources of data that contribute to the overall data size are highlighted in Table 1 [45]:

Table 1: Sources of data within the smart gird

Data Type	**Technology**	**Description**
AMI	Smart Meters	Consumption data that is generated from smart meters at a predefined frequency.
Distribution and Automation	Grid Equipment	The distribution automation system, which collects data from the various sensors that are distributed throughout the entire grid. These sensors can generate up to 30 readings per second per sensor [46].
Third - Party	External Data Sets	The integration of 3rd party data, such as demand and response.
Asset Management	OS / Firmware	Communication between the MDMS and the various smart technologies. This involves the management of the various smart devices including their software and firmware.

Managing, processing and analysing vast quantities of data require the deployment of specialist hardware and software tools. As such, the MDMS relies on the following infrastructures to store, analyse, and process the acquired data [45]:

- **Data centre:** This is a dedicated facility to host the data collected from the systems and supporting infrastructure. These systems include: high speed fibre channels, redundant Uninterruptible Power Supply (UPS / generator) systems, ventilation and cooling systems, and security access. Typically, data centres are paired for replication to ensure high service availability. Historically, most data centres are hosted locally at the company's premises, however with the introduction of cloud platforms, an increasing numbers of services are being hosted off site.

- **Servers:** Typically, servers consist of specialist hardware, which are used for the purposes of data handling and processing. These systems can be run independently or within a cluster for increased performance. Typically, servers are categorised in terms of their individual roles. Common roles include web servers, application servers, proxy servers and file servers. Most servers run in a client server model whereby the server waits and handles incoming requests from the client.
- **Storage system:** These are block-based, file-based, or object storage systems, such as Enterprise Virtual Arrays (EVAs). They contain a variety of hardware for storing data and connecting with other hardware. This specialist platform can host hundreds of servers, while processing large volumes of data.
- **Database system:** The database system is a specialised software system, which is used for data management and analysis. Stored information is structured and organised so it can be accessed, managed and updated using a query language. The most common type of database is a relational database.
- **Virtualisation systems:** A standard virtualisation system facilitates more efficient use of discrete storage and computing resources. Multiple operating systems (guests) can be hosted on a single piece of hardware using a hypervisor. In addition, the use of virtualisation facilitates easy migration of guests from one host to another.

The acquired data ensures that the MDMS can facilitate the optimisation of the smart grid, utility management and the accommodation of customer engagement. The introduction of the AMI significantly increases the overall quality and availability of the acquired data [47]. However, the collection and accessibility of such information does not provide any significant value. Essentially it remains ineffective without the deployment of software tools and indeed the expertise to exploit it. As a result, the application of data analytics has become a major focus for smart gird research [48]. The main focus of such studies is to compile sources of data and extract meaningful information for decision making and service offerings for industry and society as a whole.

2.3 SMART METERS

Fundamentally, smart meters are a new generation of gas and electricity meter [49]. They deliver vast amounts of additional information that cannot be obtained from a conventional analogue energy meter [50]. The main aim of the smart meter is to facilitate real time energy usage readings at granular intervals, to both the consumer and smart grid stakeholders [51]. In order to achieve this aim, load information is obtained from consumer electrical devices while measuring the total aggregated energy consumption for the given property. Additional information, such as home generated electricity is provided to the utility company and/or system operator for enhanced monitoring and accurate billing. This is achieved by monitoring the performance and the energy usage characteristics of the load on the grid. Some of these roles and benefits include:

- Accurate recording, transmitting and storing of information for defined time periods (to a minimum of 10 seconds). All UK smart meters must store energy usage readings for a maximum of 13 months providing a unique insight into energy consumption.
- Offer two way communications to and from the meter so that, for example, suppliers can read meters remotely [52], facilitate demand and response and upgrade tariff information.
- Enable customers to collect and use energy usage data by creating a Home Area Network, to securely support data access devices [53]. Smart meters must accommodate third party access to energy usage data and other parameters through an agreed communication standard.
- Support time-of-use tariffs, under which the price varies depending on the time of day electricity is used [54]. Energy prices are more expensive during peak times. Consequently, billing consumers by time, as well as usage, encourages them to change their consumption habits. Additionally, this type of information enables the detection of both on and off peak usage for establishing consumer routines.
- Support future management of energy supply to help distribution companies manage supply and demand across their networks [55]. This is achieved automatically through previously agreed Demand Response (DR) actions.

The smart meter implementation has largely been driven as a result of the European Union Energy Efficiency (EE) Directive (2012/27/EU) which was adopted on the 25 October 2012 [ref]. The EE directive was introduced to provide legislation to facilitate the EU's target of a

20% reduction in C02 by 2020[2]. This is archived by ensuring that each smart meter can provide consumer tailored real time energy consumption information and advice.

The smart meter project represents more than just a simple replacement from the traditional analogue meter to a digital substitute. Instead a comprehensive understanding of current and future needs has been considered.

Between now and 2020 UK energy suppliers will be responsible for replacing over 53 million traditional gas and electricity meters [56]. This replacement programme requires visits to over 30 million homes and small businesses throughout the UK. The UK government estimates that the installation of smart meters will provide £6.2 billion net benefits to the United Kingdom [56] while monitoring 51% of the UK's electricity usage. Figure 4 highlights the current smart meter installation figures for the UK.

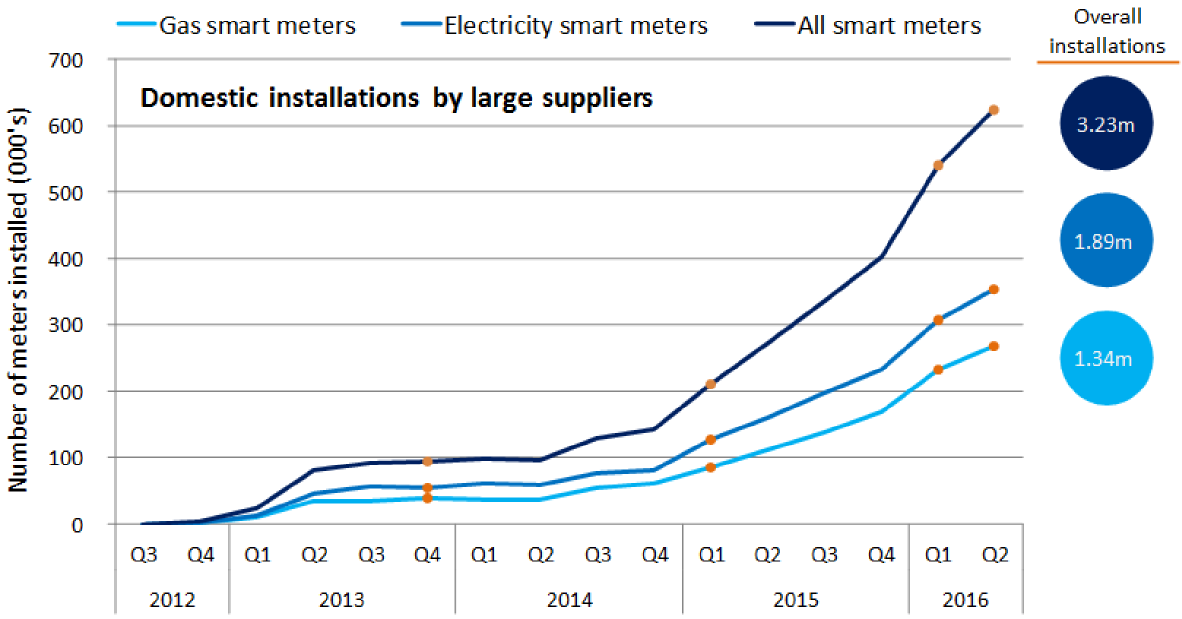


Figure 4: Quarterly domestic installation figures for the UK [56]

There are various data parameters and features that are available from the smart meter. Without considering adequately the different attributes and data values it would be challenging to obtain or extract meaning from the acquired data. This ensures that the correct data analytics approach is undertaken, while identifying any limitations in the technology or acquired data.

[2] https://ec.europa.eu/energy/en/topics/energy-efficiency/energy-efficiency-directive

In order for utilities to install smart meters in the UK, each device must adhere to a set of minimum requirements. Smart Metering Equipment Technical Specifications (SMETS) sets out these prerequisites and consist of two variants SMETS 1 and SMETS 2. SMETS 1 meters were primarily installed during the foundation stage and continue to be installed up until August 2017, when the main installation phase commences. During the main installation stage, SMETS 2 meters will be used until the roll out is complete. As some smart meter specifications are not yet fully defined, and while some feature are not yet fully available, researchers must make assumptions regarding data accusation and anticipated secondary functions. However, SMETS 2 meters are able to record energy usage, voltage and demand; and perform the following functions is shown in Table 2 [57].

Table 2: Smart meter SMETS 2 capability

Category	Description of Electricity Smart Metering Capability
Power and Energy Use	• Able to record energy import/export (kWh) on each of the 731 previous days. • Able to record half hourly data (kWh) for: 1. Three months of Consumption; 2. Three months of Active Energy Exported; 3. Three months of Reactive Energy Imported; and 4. Three months of Reactive Energy Exported. • Able to record maximum energy use measured over a half hour period (since last reset). • Able to compare active power to configurable thresholds (‘Low-Medium’, ‘Medium-High’ and ‘Load-limit’). • Able to record status of energy use as ‘Low’, ‘Medium’ or ‘High’ respectively.
Voltage Monitoring	• Able to compare measured voltage to 6 configurable thresholds (3 high, 3 low); Root Mean Square (RMS) over/under voltage detection, ‘Extreme’ over/under voltage detection and voltage sag/swell detection. Done across 4 configurable time frames RMS period, ‘Extreme’ period, sag and swell periods). • Able to record events and send alerts when the voltage rises above high thresholds or falls below low thresholds for the related timeframe.

	• Able to record supply interruptions. Sends supply restoration notification if interruption is over 3 minutes.
Demand response	• Time of use pricing; Able to store 48 half-hourly prices (beginning at 00 or 30 minutes past the hour). • Able to calculate an 'instantaneous cost' based on active power and tariff. • Able to read status of and send commands to 5 HAN connected auxiliary load control switches. • Able to store a set of 'time-of-use switching' rules (in a 'calendar') for load switching (with a randomised offset); for changes in state across half-hours, days and dates. • Able to request, ad-hoc, following receipt of a command, that one or more HAN connected auxiliary load control switches change state. • Able to, on receipt of a command, disable or enable the supply. • Capable of supply disablement if power rises above 'Load-limit' threshold.

In addition to a smart meter, all domestic consumers are offered an In-Home Display (IHD) as part of the smart meter roll-out that connects to the smart meter using the ZigBee Smart Energy profile. The IHD is a small electrical device, which has a number of unique functionalities that include displaying energy usage, and real time costing. Figure 5 highlights the different functions provided by a standard IHD unit.

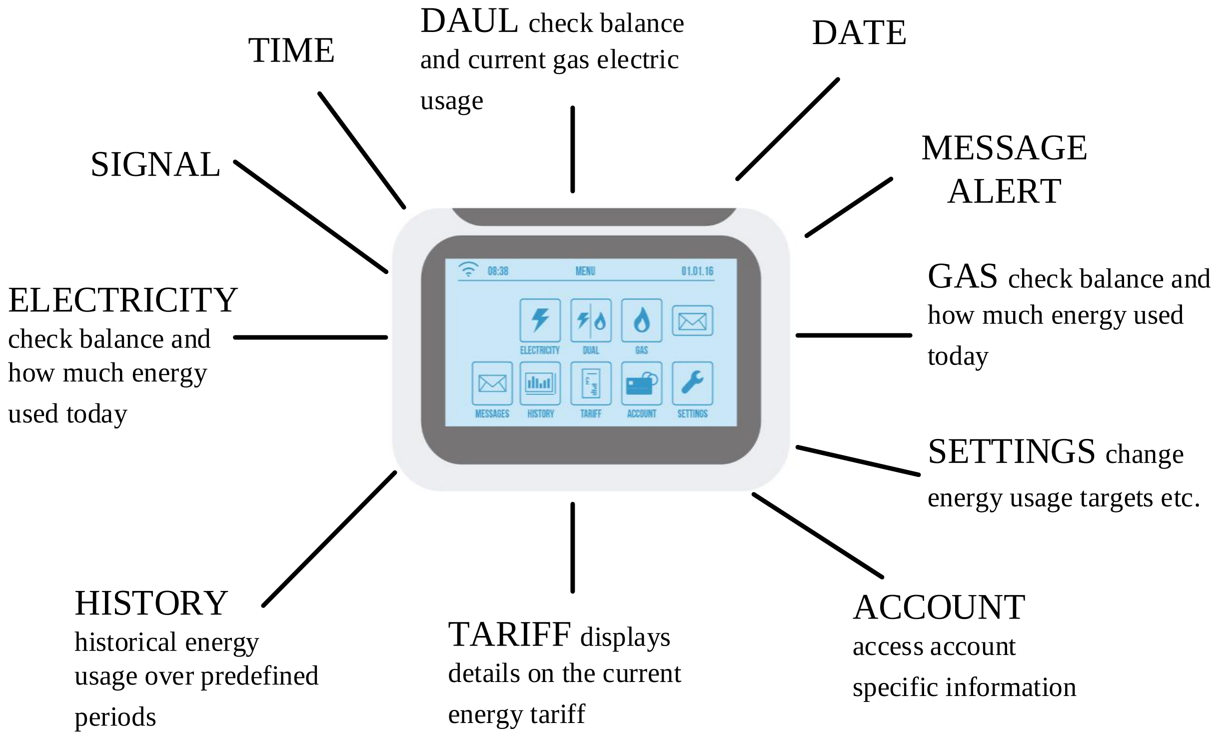


Figure 5: IHD functionalities and interface

2.3.1 AUTOMATIC METER READINGS

The specific function of the traditional meter, and indeed the smart meter, is to accurately measure and report energy consumption in Kilowatt Hours (KWh), as highlighted in table 3. These include the Coordinated Universal Time (UTC) date and time, at the end of the 30-minute period, to which the data relates in the Profile Data Log. Generally smart meter data is in the form of time series.

Table 3: Smart Meter System Data Set

Data Item	Description
Total generated kWh	Supports the high level list of functional requirements for domestic smart meters. It provides the capacity to communicate with a measurement device within a micro generator, and receive, store, communicate total generation for billing.
Generated interval data kW	Half hourly interval data held on meter for 13 months – average kW demand over half hour period.

Generated interval data KWh	Half hourly interval readings held on meter for 13 months.
Generated Kilovolt-Ampere-Reactance (kVAr)	Reactive power measurement, in half hourly intervals, held on meter for 13 months – Specifically, Average Kilo Volt-Ampere Reactive (kVAr) demand over half hour period.
Generation Technology Type	e.g. Solar Photovoltaic (PV), micro Combined Heat and Power (CHP), wind, hydro, Anaerobic Digestion
Total consumption (net demand) kW	Provides the total consumption by adding both the imported and generated Kw and subtracting the export.
Import demand kW	Load being drawn from grid
Export kW	kW being exported to grid.
Generated kW	kW being generated by micro-generation unit.
Total consumption today (kWh)	The total daily consumption by adding both the imported and generated Kw and subtracting the export.
Total Import today (kWh)	Load drawn from Grid today (kWh).
Exported energy today (kWh)	Exported energy today (kWh).
Generated	Generated energy today (kWh).

energy today (kWh)	
Total CO2 rate (kg/hr) and CO2 today (kg)	This is based on generated energy to give customers an indication of the amount saved through the implementation if a micro generation unit.
Cost of energy imported (£/hr) and £ today	Provides the net cost of imported energy less value of generated exported energy to the grid. These costs are calculated from meter consumption using cost rates entered on display, which is pushed to the IHD via ZigBee Smart Energy.

2.3.1 CONSUMER ACCESS DEVICE

In order to overcome the default reading limitation of every 30 minutes and obtain readings at higher sampling rates, the installation of a Consumer Access Device (CAD) is necessary. Smart meters utilise the ZigBee Smart Energy profile, which can be used to pair such devices using the ZigBee protocol. ZigBee has an operating range up to 70 meters with a data transmission speed of 250kbs. In addition, the UK DECC have declared SMETS2, which cites the use of ZigBee Smart Energy 1.x. Currently, there are two types of CAD, each with their own functions and limitations:

- **Type 1 CAD Devices:** Type 1 devices perform low level tasks. These include Interface Commands, which set specific variables, such as tariffs, thresholds, perform commands (e.g. auxiliary load switch control) and read data. Type 1 devices are restricted to energy suppliers and other authorised parties.
  Type 2 CAD Devices: The Type 2 CAD connects to the SM HAN in the same way as the IHD. Typically, the device collects the live energy data from the smart meter in the home. The obtained data is used for two main functions; the management of smart appliances in the home; transmission of data to the cloud through a broadband connection.

The ongoing development of the ZigBee Smart Energy profile has resulted in multiple CAD paring methods [58]. Currently, locally initiated CAD pairing is not possible. Instead consumers and service providers must initiate remote CAD pairing. The consumer provides connection information to authorised third parties in order for their devices to be paired remotely. Later versions of the SEP will introduce a means of allowing consumers to pair a CAD without needing the involvement of a DCC[3]. Therefore, a consumer will be able to initiate pairing of a CAD by using a function on their smart meter. Figure 6 highlights the CAD remote pairing procedure.

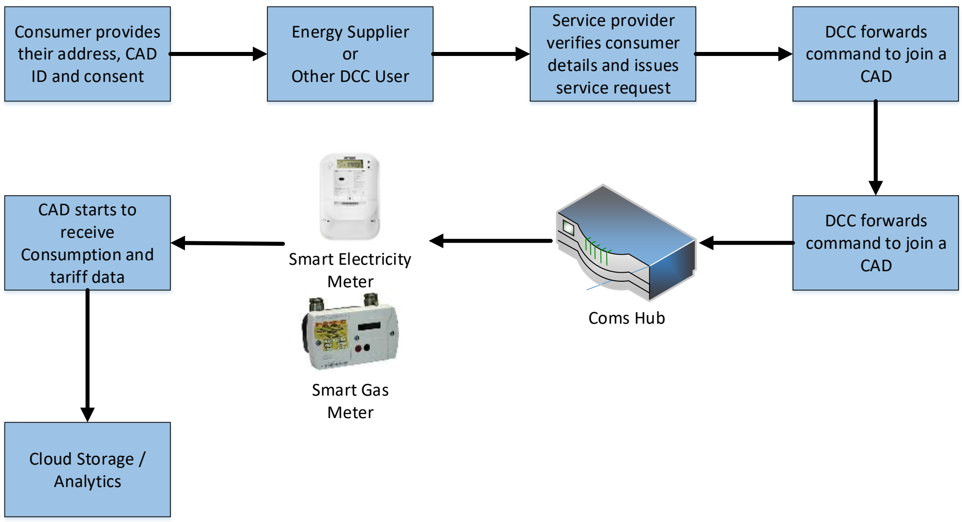


Figure 6: Remote CAD Pairing Procedure SMETS 1

The data collected from the CAD includes the date and time of the reading, the aggregated energy load in watts and the node ID. The process, by which the CAD operates, is shown in figure 7.

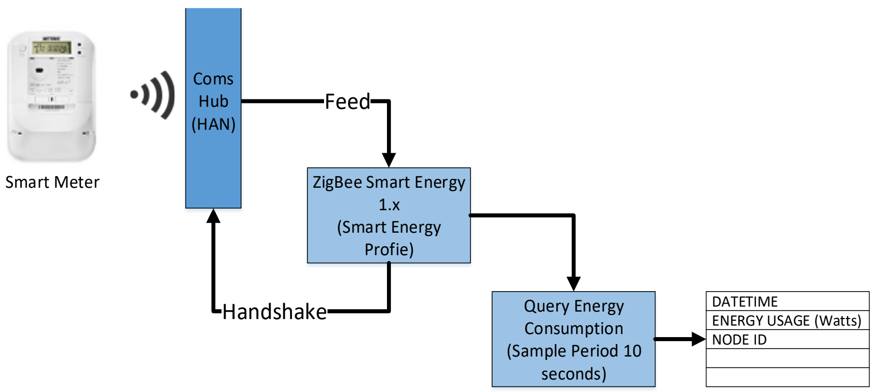


Figure 7: CAD Reading process when paired with a smart meter

This is archived through a ZigBee Smart Energy module, which contains dedicated hardware to support the lower layers of the ZigBee stack. Here a processor facilitates the functions of

[3] https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/591322/09022017_-_Smart_Meters__Data__Growth_DR_-_updated.pdf

the higher layers of the ZigBee SE application. The software stack within the CAD uses a high-level smart metering API, which contains a set of data items and functions that are available to the CAD when paired in the SMHAN.

The ZigBee Cluster Library (ZCL) specification provides functions to obtain and collect data from ZigBee devices using a command format. The ZigBee alliance uses application profiles, which contain a set of supported functions, datatypes and operations. An example of an application profile is the ZigBee SE profile, which contains a number of unique functions and features. Figure 8 highlights the layers of the ZigBee stack and how they are combined to support the application.

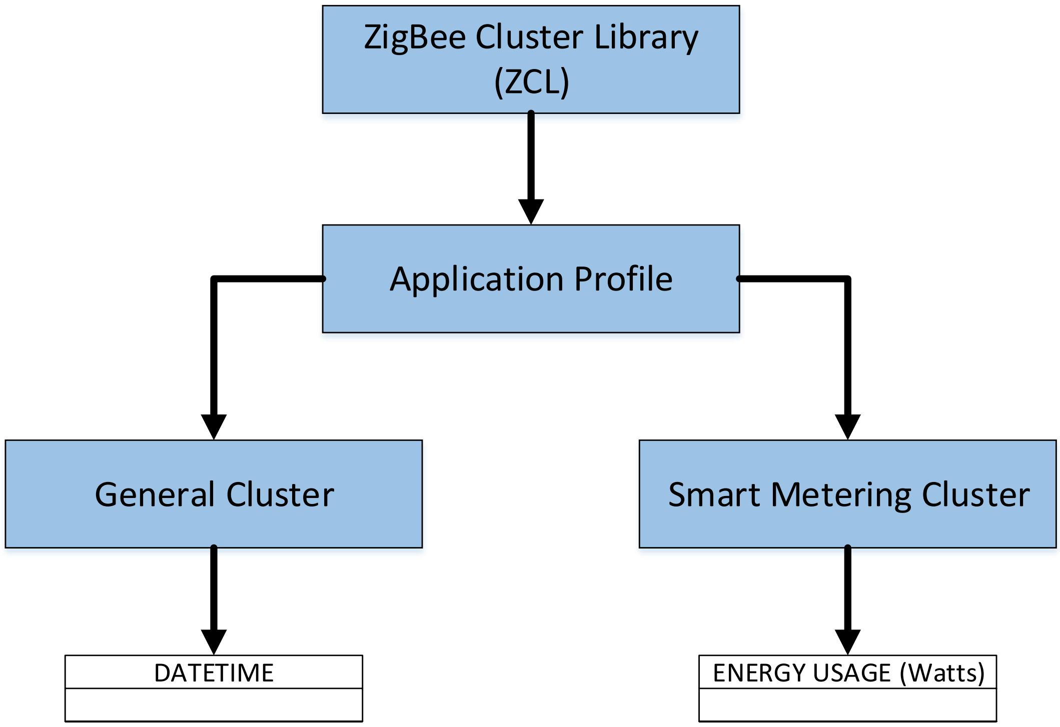


Figure 8: ZigBee stack cluster combination

The ZigBee SE profile uses a set of clusters from the library, which are specific to the SE cluster. However, the ZigBee Alliance has standardised a number of general clusters, which are available to any application profile[4]. For example, a CAD uses the time cluster from the ZCL, while combining it with the Simple Metering Cluster. The Simple Metering Cluster is specific to the ZigBee SE profile to provide functions which are unique to the Smart Metering Cluster. These two individual clusters are pooled to ascertain the time of the

[4] ZigBee Interoperability: http://www.zigbee.org/zigbeealliance/white-papers/

reading and the energy value. Table 4 highlights the general and specific clusters in the ZCL, which are accessed by the CAD.

Table 4: General and Smart Energy clusters

Category	Cluster	Function
General Clusters	Time	The time cluster provides a set of functions which facilitates access to a real time clock. The cluster includes local time zones and daylight time saving functionality.
	Alarms	Alarms can be used for sending alarm notifications to other clusters in the ZCL.
	Basic	The basic cluster provides a number of properties, which include software firmware versions.
	Over the Air Upgrade (OTA)	The OTA cluster provides the ability to upgrade the software on the ZigBee device remotely.
Smart Energy Clusters	Price	The Price cluster provides the communication functions that enable the updating of pricing and tariff information from the AMI.
	Demand-Response and Load Control	These clusters facilitate the integration of smart devices, which support load control. Specifically, the functions enable the CAD to receive instructions from the utility company, which enable grid load balancing operations.

	Simple Metering	The simple meter cluster provides the collection of consumption data.
	Messaging	The messaging cluster enables communication between devices.

2.3.2 SMART METER DATA COLLECTION AND FREQUENCY

Smart meters in the UK collect and transmit energy usage data at 30 minute intervals using their default setting. However, smart meters are able to report energy usage as low as 10 second intervals through the use of a CAD; even though this is not currently deployed due to the vast amount of data it would generate [59]. Table 5 highlights the data volume difference based on the sampling resolution[5].

Table 5: Smart meter data volume by resolution

Data Type	Resolution	Source	Approximate maximum data volumes (whole city, 1 year)
Smart meter data	30 minutes	DCC	400 Gigabytes
Smart meter data	10 seconds	CAD	80 Terabytes
Existing NILM	0.001 seconds	CT	400 Petabytes

Table 6 illustrates a data sample from obtained from a smart meter during a single period. This sample highlights the granularity of the data collected compared to traditional meters, where the readings are submitted collectively over a much larger period (for example monthly, quarterly or yearly). It displays the data parameters obtained at each 30-minute interval; totalling 48 individual readings in a 24 hour period (for illustrative purposes only 10 readings are presented). Customer Key identifies the individual smart meter device within the AMI; Time of Reading indicates the time and date of the reading; while General Supply highlights the amount of on peak electricity being used in KWH.

[5] Bristol Smart Energy Collaboration (2016), https://bristol-smart-energy.cse.org.uk/

Table 6: Single Smart Meter 30 Minute Data Sample

CUSTOMER_KEY	Time of Reading	General Supply (KWH)
8150103	05:59:59	0.042
8150103	06:29:59	0.088
8150103	06:59:59	0.107
8150103	07:29:59	0.040
8150103	07:59:59	0.042
8150103	08:29:59	0.041
8150103	08:59:59	0.049
8150103	09:29:59	0.189
8150103	09:59:59	0.051
8150103	10:29:59	0.050

Figure 9 highlights a data sample of a single smart meter. It represents half hourly readings over a 24 hour period totalling 48 individual readings. The data illustrates the total energy consumption in Kwh.

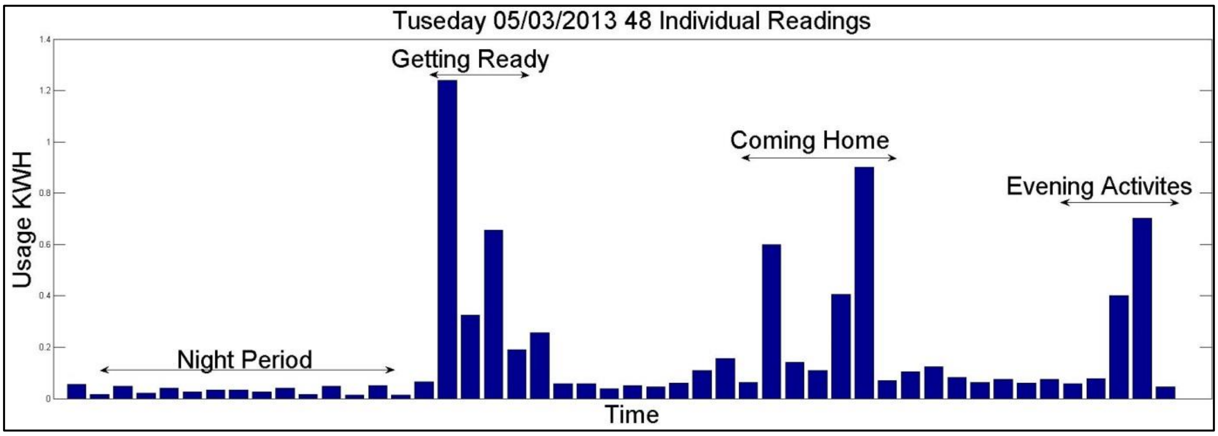


Figure 9: 48 individual readings highlighting a single 24-hour period

The default reading frequency of a smart meter impedes the level of information that can be obtained from the acquired data. Increasing the reading frequency is essential when trying to identify individual devices and their duration of use. Figure 10 highlights the additional information that can be obtained by increasing the reading frequency.

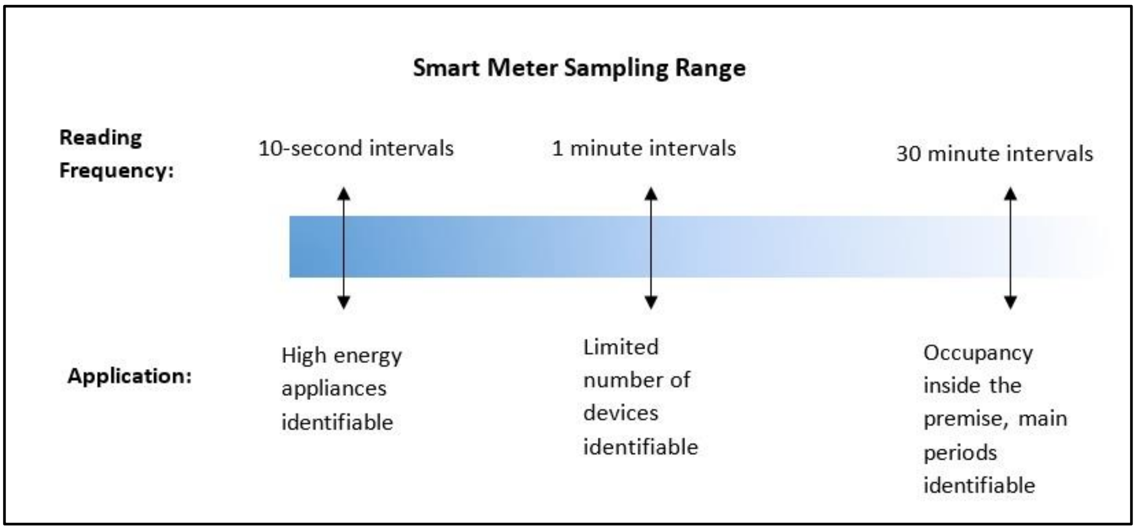


Figure 10: Information obtained by increasing the reading interval

At 30 minute intervals it is possible to detect occupancy within the premise and main periods of electricity usage. When the reading frequency is increased to 1 minute intervals the use of type 1 electrical devices is identified. Type 1 devices refer to appliances that only operate in two states either on or off. A reading frequency of 1 sample every 10 seconds, which is the reading frequency for a smart meter when paired with a CAD, is able to identify type 2 electrical devices. These types of devices operate in multiple states. Increasing the reading frequencies facilitates the identification of individual device utilisation. This approach is demonstrated in figure 11. The y-axis highlights the energy usage in Watts, while the x-axis shows the reading time.

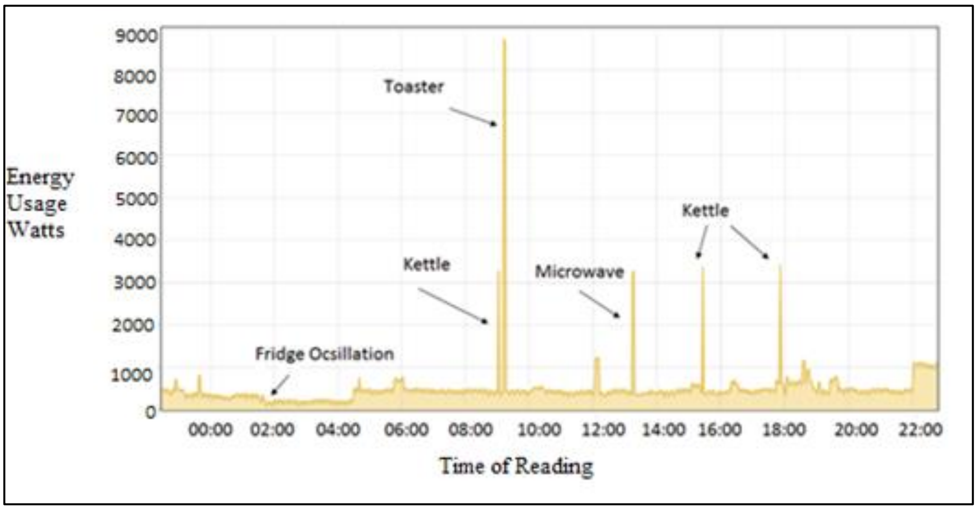


Figure 11: Real time energy readings obtained from an aggregated load

Obtaining energy readings at 1 to 10 second intervals provides energy signatures for each device. This is achieved by identifying the amount of energy being consumed, as demonstrated in figure 12; this enables background noise from certain devices, such as fridge oscillations, air conditioning and standby electricity usage, to be filtered out. This leaves clear usage signatures for devices that are being used.

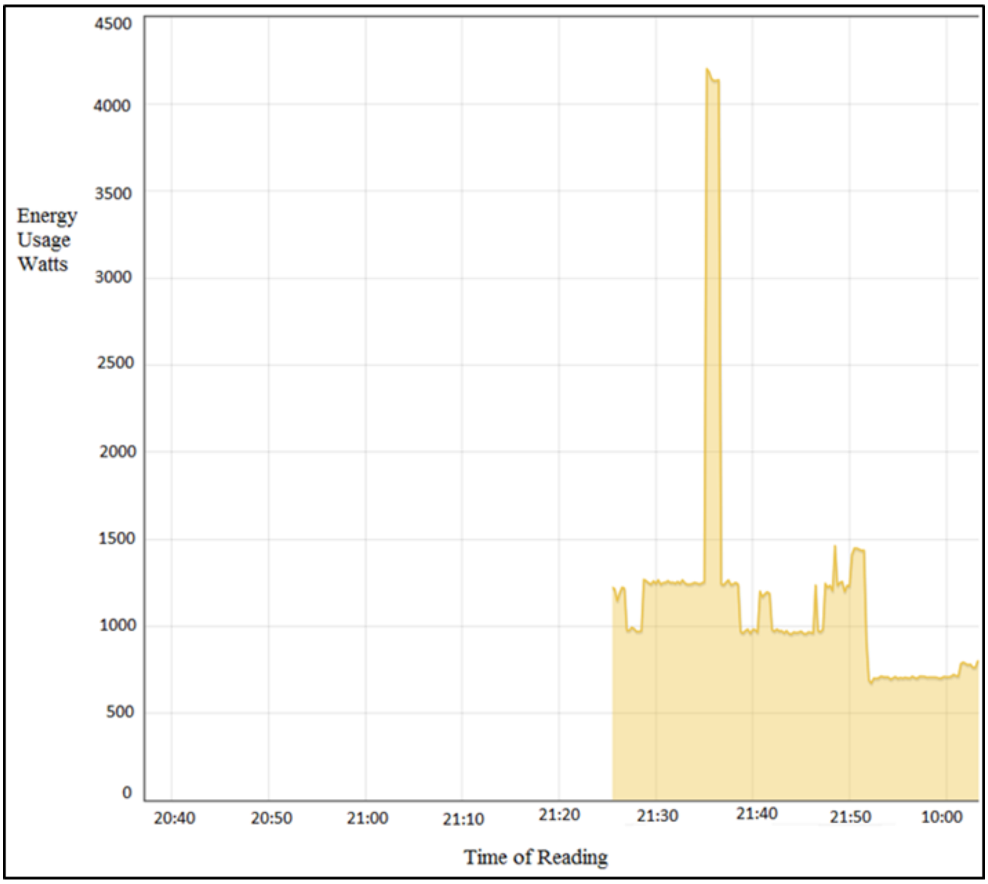


Figure 12: Energy signature for a kettle

2.4 LOAD MONITORING

Our proposed method utilises Appliance Load Monitoring (ALM) to provide detailed appliance identification. The concept of ALM is not new [60]. Typically, ALM methods are divided into two distinct categories: firstly, Non-Intrusive Load Monitoring (NILM) and secondly Intrusive Load Monitoring (ILM). NILM is typically described as a single point sensing method, as it requires the use of a single sensor such as a smart meter. In contrast ILM is regarded as a distributed sensing method and requires the use of multiple individual sensors [61]. Normally, one sensor is installed for each electrical device being monitored.

There are different advantages and disadvantages with each method. The ILM is regarded as a more accurate method as readings are obtained directly from the device [62]. However, this type of monitoring is both costly and complex. ILM also has the risk of sensors being removed or transferred onto different devices. While NILM is regarded as less accurate, it requires the use of a single nonintrusive sensor, which is cost effective.

NILM introduces challenging issues that are not present with ILM approaches. NILM signal analysis involves identifying multiple electrical devices that can be used simultaneously or in quick succession. Although the identification of individual devices is possible using disaggregation algorithms, their performance is largely dependent on the appliance type, sampling rates and device usage [63].

ILM has benefited from increased popularity due to decreased sensor costs. Additionally, technical improvements, such as improved sensor communications, ensure that ILM can be used in a variety of different applications. These applications include local energy consumption analysis, appliance recognition, device failure identification and human activity recognition [64]. Figure 13 provides a high level overview of a typical ILM environment. Here, each device of significance is fitted with a smart plug, to identify when a particular device is being operated. The smart plug wirelessly transmits consumption data to the home router using a predefined sampling rate. Energy readings are transmitted remotely to analysis services using ADSL.

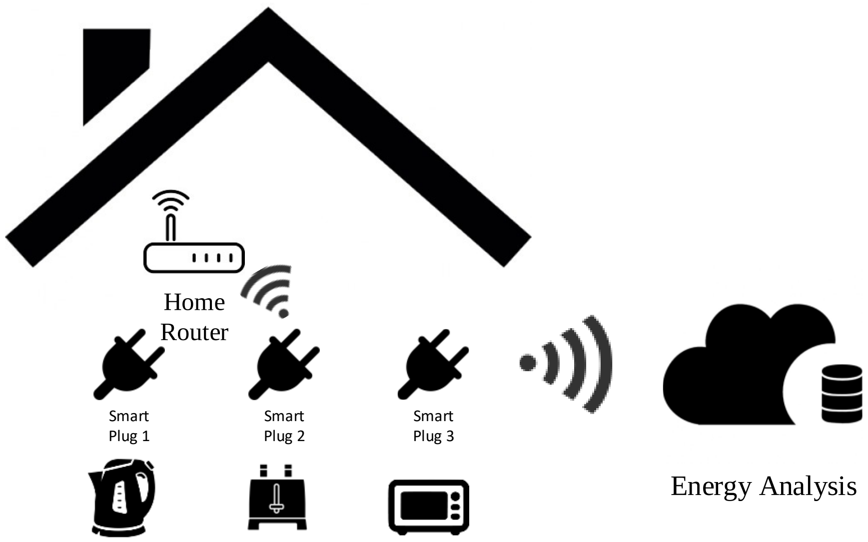


Figure 13: Distributed sensing method

The data obtained from aggregated loads is different to that of disaggregated monitoring. Table 7 provides a data sample, which was obtained from a typical ILM environment. The read time, plug name and the amount of energy being consumed in KWh is shown. In terms of monitoring, smart plugs have limitations and restrictions.

Table 7: Smart plug readings

Half Hour Period End	Plug Name	Reading Time	Total KWH
17/09/2013 07:29	Air conditioning	17/09/2013 07:08	5.141
17/09/2013 07:29	Dishwasher	17/09/2013 07:08	1.04
17/09/2013 07:29	Hot Water System	17/09/2013 07:08	8.156
17/09/2013 07:29	Kitchen	17/09/2013 07:08	2.154
17/09/2013 07:29	Microwave	17/09/2013 07:08	12.849
17/09/2013 07:29	Oven	17/09/2013 07:08	2.447
17/09/2013 07:29	Washing	17/09/2013 07:08	10.97
17/09/2013 07:59	Air conditioning	17/09/2013 07:38	5.141
17/09/2013 07:59	Dishwasher	17/09/2013 07:38	1.04
17/09/2013 07:59	Hot Water System	17/09/2013 07:38	8.156
17/09/2013 07:59	Kitchen	17/09/2013 07:38	2.154
17/09/2013 07:59	Microwave	17/09/2013 07:38	12.85
17/09/2013 07:59	Oven	17/09/2013 07:38	2.447
17/09/2013 07:59	Washing	17/09/2013 07:38	10.97

As a result, an ILM approach increases the overall financial costs for a system using this approach. Additionally, residents may move or remove sensors used for ILM which introduces misclassification.

NILM, which is sometimes referred to as load disaggregation, focuses on the development of algorithms to disaggregate specific devices that are utilised on a metered power line [65]. NILM was first proposed by Heart et al., as a method for identifying appliance power signatures from within aggregated load readings, by detecting the on / off states of the appliance [66]. Data is obtained from the smart meter directly, which is mathematically defined as:

$$P(t) = p_1(t) + p_2(t) + \cdots + p_n(t) \tag{1}$$

Where p is the power consumption of the individual device that is contributing to the total aggregated measurement, and n is the total number of devices within the time period t. Figure 14 highlights a typical NILM environment, where the smart meter is responsible for the identification of device usage.

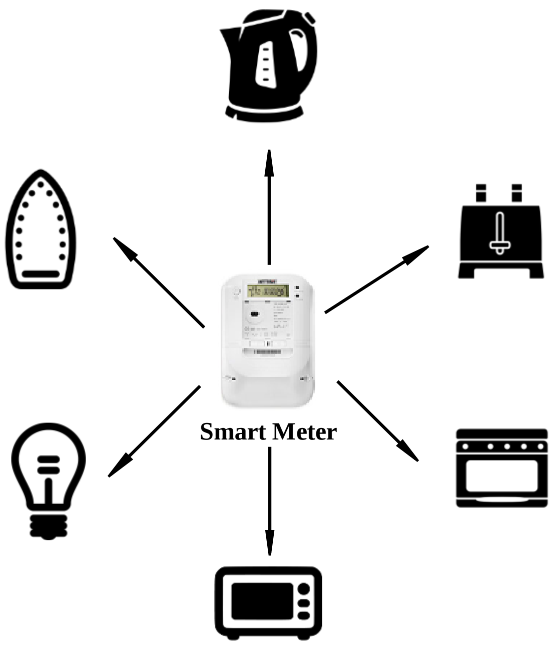


Figure 14: Appliance identification through a smart meter

Historical load monitoring techniques involve the deployment of financially expensive and complex hardware with simple data processing techniques. In NILM solutions hardware is deployed but more complex software tools are required for device identification. Typically, NILM consists of four stages; data acquisition (using a sensor transformer clip (CT) fastened around the main feed), event detection, appliance feature extraction and finally, device classification. Figure 15 highlights the NILM stages, along with the considerations for each stage.

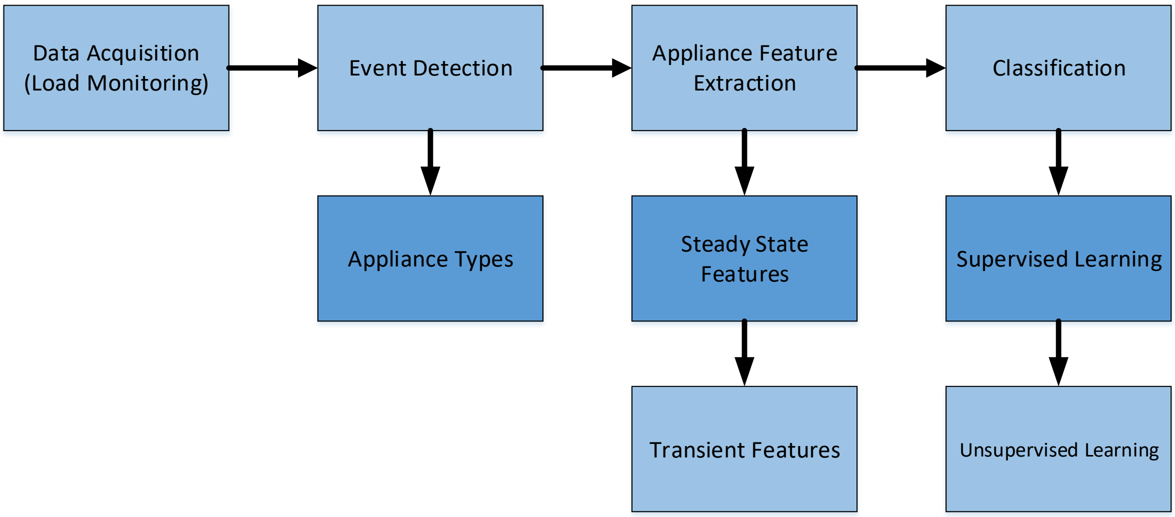


Figure 15: NILM process and considerations

There are considerations with an NILM approach, which include the following:

- **Electrical sampling rates:** is one of the most important considerations as it impacts directly the overall accuracy of the method [67]. Typically, lower sampling rates introduce more errors in device identification due to event triggers being overlooked. There are two groups of sampling used in NILM; high frequency (greater than 60Hz) and low frequency, (less than 60Hz) [68]. In order to obtain higher sampling rates, the deployment of specialist hardware is required. These devices measure electrical load a few thousand times a second, which greatly improves the overall accuracy of the approach. However, the installation and maintenance of such equipment has a cost and data storage requirement. With the introduction of smart meters, with low frequency sampling of 1 sample every 10 seconds, NILM has now to become the main focus of research [69].
- **Electrical features:** The most widely used feature selection methods for device identification include: event detection, whereby devices are detected by their state on/off; steady-state, which identifies devices based on variations in their steady state signatures; transient methods, which extract more complex features, such as frequency harmonics. However, transient methods require high sampling rates and additional reading parameters, which are beyond the specifications of a smart meter [70]. Typically, most load monitoring devices provide parameters that include voltage, current, real power (P), power factor, phase angle and reactive power (Q). These additional parameters enable the generation of more advance features using signal analysis and harmonics.

Recently more humble approaches have become the main research focus, such as real power measurements. The main reason for using only real power readings is because of the ever-increasing availability of smart meters. As smart meters only collect real power readings, severe feature extraction constraints exist. As a result, extracting more complex features is unmanageable, as neither the voltage nor phase angle is present. Many research approaches have been suggested to combat such limitations. Kim H *et.al.,* utilise real power measurements for disaggregation. Their approach found identifying individual appliances, which were of the steady state class difficult, but had more success with steady state changes. In conclusion, they stated that additional features would be required to improve accuracy [71]. Likewise, George C *et.al.,* propose a novel load disaggregation algorithm using only smart meter power readings. They use the obtained power readings to generate a set on discrete pulses, which were associated to a registered appliance. They claim that that the algorithm accounts for external factors, such as appliance signatures and human behaviour. Overall, accuracy of the algorithm is in 85% in total [69].

2.4.1 EVENT DETECTION AND APPLIANCE TYPES

Event detection is the method by which device identification can occur [72]. However, this approach is complicated by the various devices that are present in a home Modern electrical appliances run in multiple modes other than on and off. Many devices have low power requirements or standby modes, while appliances, such as ovens, operate in a number of different states. Such devices introduce additional complexity to the classification task. Understanding the different device categories is vital for NLIM as they provide information on electrical usage characteristics. Device categories are explained as follows:

- **Type 1:** devices refer to appliances that only operate in two states either on or off and are their detection from an aggregated load is rudimentary. Examples of such devices include kettles, toasters and lighting. Figure 16 shows a power reading for a type 1 device; a kettle.

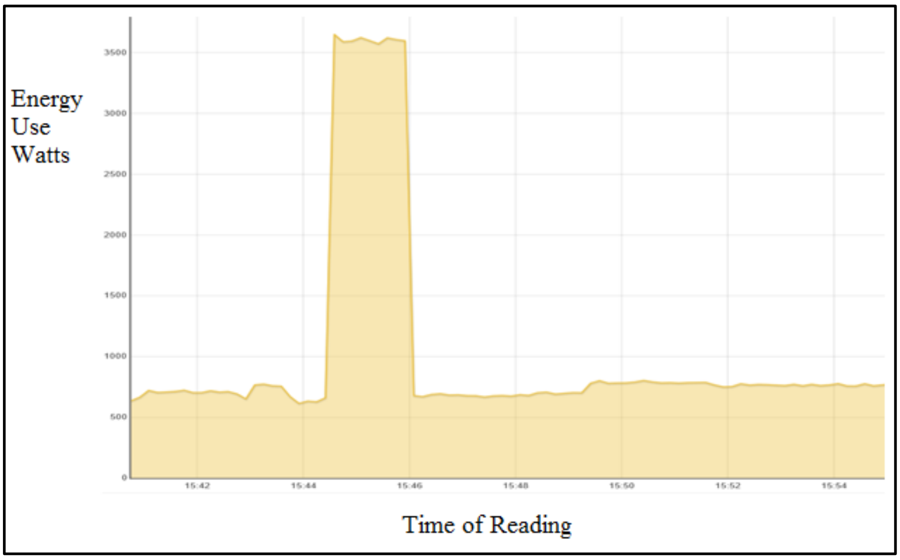


Figure 16: Type 1 electrical device (on / off)

- **Type 2:** devices are commonly known as Multi-State Devices (MSD) or finite state appliances. Such appliances can operate in multiple states and include washing machines, dryers and dishwashers. As these devices can exist in multiple states they add further complexity for device identification. Figure 17 shows a power sample for a type 2 electrical device; an electric oven.

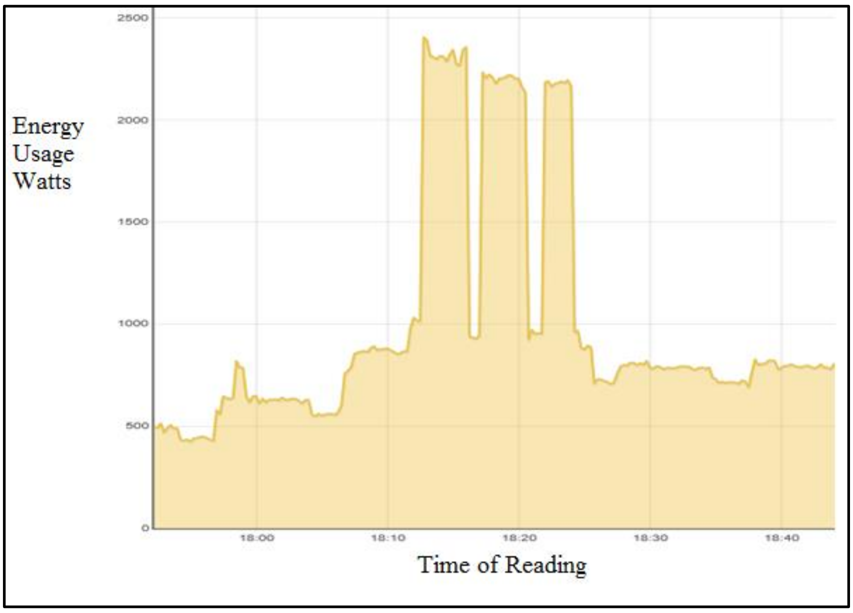


Figure 17: Type 2 electrical device (multi-state)

- **Type 3:** devices are known as Continuously Variable Devices (CVD). Typically, their power draw has no fixed state. As type 3 devices have no repeatability in their characteristics they are particularly problematic for NILM. Examples of such devices include power tools. Figure 18 shows multiple type 3 electrical devices.

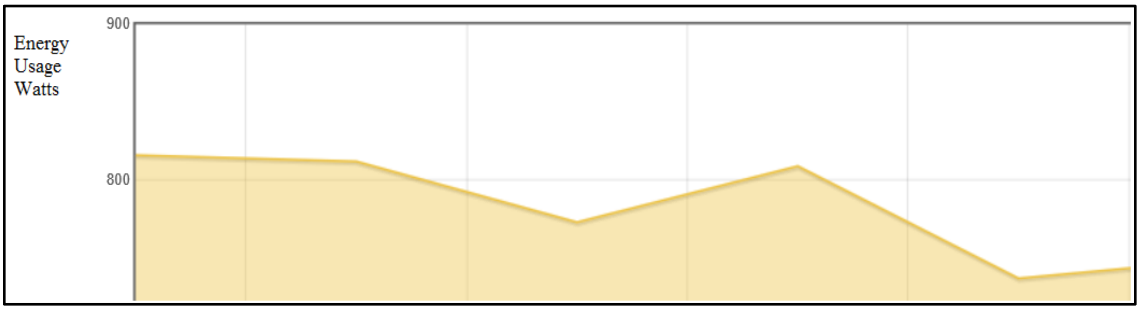


Figure 18: Type 3 electrical device (continuously variable)

- **Type 4:** are fairly new in terms of device category, at the time of writing this thesis. They remain active for long periods and consume electricity at a constant rate [72]. As these devices are always on there are no major events to detect other than small fluctuations, which are too small for event detection. Such devices include smoke detectors and intruder alarms. Figure 19 shows multiple type 4 electrical devices.

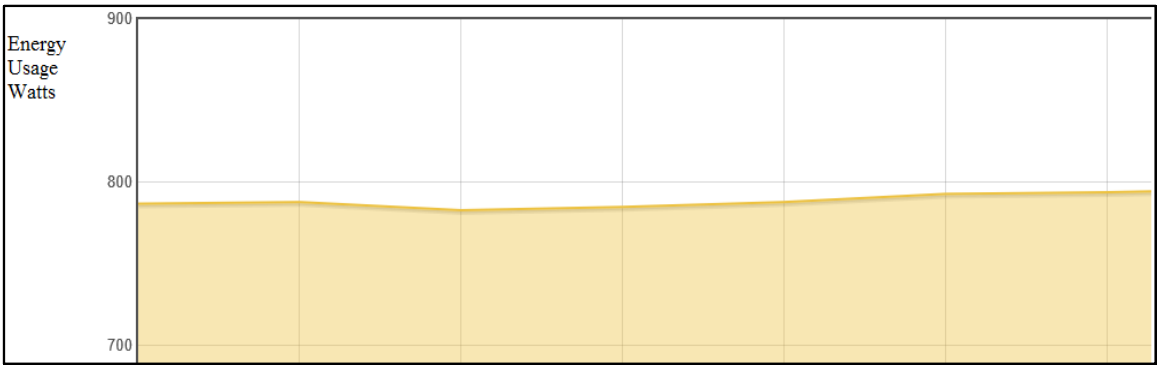


Figure 19: Type 4 electrical device (constant rate)

2.4.2 APPLIANCE CONSIDERATIONS

Electrical devices in the home are a key resource for the identification and modelling of the occupant's routine and habits. However, the range of domestic appliances within a modern dwelling is complex [73]. Careful consideration is required when selecting which set of appliances to detect. However, selecting too many appliances introduces additional complexity and results in supplementary training and model creation. This scenario ultimately introduces greater resource requirements.

The study presented by the Department of Energy and Climate Change interviewed a total of 2616 households to ascertain the types of appliances present [74]. Table 8 highlights the appliance type and ownership.

Table 8: Appliance type and ownership

Appliance	Percentage of households (%)
Washing Machine	97%
Tumble Dryer	62%
Refrigerators and Freezers	99% of households own a refrigerator (either as a separate unit or combined with a freezer)
Dishwasher	41%
Oven	95%

Hob	93%
Microwave	82%
Televisions	Just under 2% of households report that they do not have a television. Just over 83% of households have three or fewer televisions.
Portable Fans	43%
Air conditioning	Less than 3%

Although both televisions and refrigeration show a prevalence in excess of 98%, they cannot be disaggregated using a CAD. However washing machines (97%), Microwaves (82%) and ovens (95%) which exhibit a high presence can be disaggregated using a CAD device.

2.5 CLOUD COMPUTING AND INFRASTRUCTURE

The data generated from the smart grid means that cloud processing platforms are now required to process and extract meaning from the acquired data while ensuring a robust energy delivery network. As such, this section introduces the concept of cloud computing and its adoption for both smart grid data processing applications. There are numerous advantages that are associated with cloud computing platforms, which can be applied to the smart metering infrastructure to support its various objectives [75].

2.5.1 THE USE OF CLOUD COMPUTING WITHIN SMART GRIDS

Cloud computing is an ever developing computational platform, which combines hardware, storage and high bandwidth networking to provide scalable solutions to third party organisations. There are many benefits to cloud computing; which are increasingly exploited to overcome both the data processing and scalability challenges associated with the smart grid. The smart grid requires a fault tolerant, efficient data processing and communications infrastructure in order to deliver a reliable and affordable power distribution network [76]. The emergence of smart grids brings many benefits but also various challenges in terms of data management and integration. This infrastructure relies on information technology to run more efficiently while ensuring that grid load and demand is balanced. However, the smart grid by its very nature is a complex platform with vast storage, communication and computational requirements. In order to facilitate these requirements smart grids can leverage the following cloud computing benefits:

- Cloud computing is both flexible and scalable ensuring adequate resource allocation and provisioning [77]. As smart grid components are deployed on a large scale, cloud computing can be used to overcome scalability problems by provisioning additional resources as required.
- Cloud services maintain the underlying computational hardware and software. Smart grids are regarded as a critical infrastructure, which supplies essential utilities to the consumer. Any down time in services can have a detrimental impact on service users. As most cloud components are virtualised, guests can be migrated from one host to another while maintenance is undertaken. This removes the need for downtime and minimises service disruption [78].
- Many cloud providers are geographically distributed, which not only ensures low latency but also provides service replication. Essentially, services are mirrored in one or more additional data centres to prevent service disruption in the event of an outage.

There are three service levels offered to smart grid utilities which are Infrastructure as a Service (IaaS), Platform as a Service (PaaS) and Software as a Service (SaaS). Each category provides different levels of management which are highlighted in figure 20.

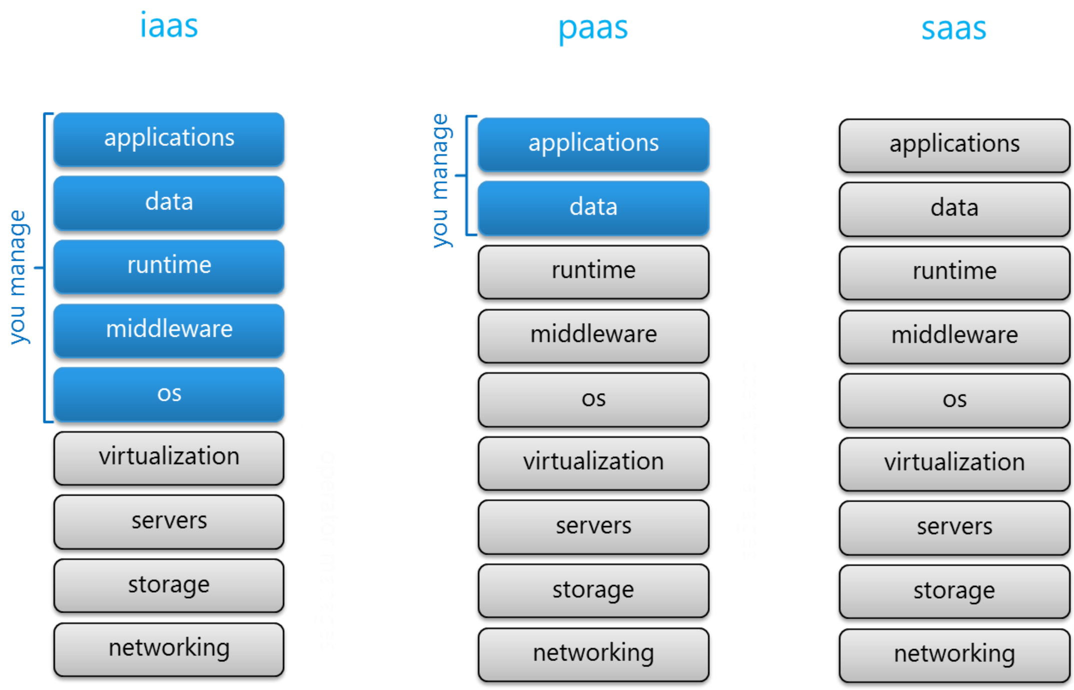


Figure 20: Cloud computing platforms and management

IaaS provides fundamental computing resources that are required to run any hosted service [79]. These resources consist of servers, storage, virtualisation and networking, and hardware, which are directly managed by the cloud provider. In this scenario, smart grid utilities manage the operating systems and any services that reside further up the stack. This model facilitates the smart grids demand and response requirements by provisioning additional resources as demand increases.

PaaS provides a managed platform to the customer enabling them to develop, manage and run their services. Typically, utilities have full control of their application and can access various programming models through the cloud to execute their programs. Using this model, smart grid utilities can develop in house applications without considering the development environment. Similarly, PaaS includes servers, storage and networking. In addition, PaaS also provides middleware, development tools and services.

In the case of SaaS the utility uses an application or service, but does not have any control or management of it or its underlying stack. SaaS provides a complete solution that is usually purchased as a pay as you go or licencing model. Each of the smart grids service users are licenced to use the platform through a common API. All of the underlying infrastructure which includes, middleware, software and data are hosted and managed exclusively by the service provider.

Additionally, smart grid utilities are able to run their services using a hybrid environment. Here a mix of both on premise services and cloud resources are managed in conjunction. Using this approach enables workloads and demands to move seamlessly between private and cloud services. Organisations have the ability to flex out resources during periods of high demand without the requirement to purchase new hardware while contracting services when utilisation subsides. For smart gird utilities this may be a favourable approach to alleviate concerns regarding the location of data. As cloud computing can be geographically distributed the replication of both sensitive data and data management is vital for the security of grid applications [80]. By running a grid infrastructure in a hybrid model, sensitive data can be confined to the utilities data warehouse.

As discussed, the various challenges and opportunities associated with the smart grid can be effectively managed through the use of cloud computing. Therefore, researchers have proposed the utilisation and adoption of the cloud infrastructure and services in an attempt to mitigate many of these issues. The various aspirations and benefits of the smart grid introduce the following key challenges [81]:

- Demand and response.
- Peak demand and dynamic pricing.
- Real time monitoring.
- Communication and information management.
- Smart meter data collection and analysis.

One of the biggest challenges associated with the smart grid is demand and response whereby consumers can actively participate in balancing grid load [82]. However, the introduction of real time energy management and dynamic pricing further increases the demand for resources especially during peak times; as the cloud computing model provides flexible dynamic bandwidth and resources, these issues can be effectively addressed. Research undertaken by Rusitschka *et al.,* proposed such a model for smart grid data management [83]. Here the cloud's distributed computing resources are leveraged to undertake real time data access and analysis.

As smart grids become more sophisticated the need for higher bandwidth and computational resources is an ever growing requirement. Within the smart grid smart meters are deployed to collect, process, and exchange data between utilities and consumers in real time. This vast infrastructure introduces big data which many traditional data management solutions fail to accommodate. As such, cloud computing models are equipped to process such vast amounts of data and have become the focus of many research studies.

2.6 MACHINE LEARNING

Many data-centre domains utilise machine learning to derive meaning from the acquired sensory data. The vast majority of technologies deploy a supervised machine learning approach which relies on labelled data for training [84]. As such, the following section provides an introduction to the various machine learning approaches, while highlighting their function.

- **Artificial Neural Networks:** An Artificial Neural Network (ANN) is a machine learning technique that simulates the way in which the human brain operates. It is able to solve complicated problems by simulating the complex interconnected processing elements (neurons) of the brain. ANNS learn by example, and previous training, which can be used to extract patterns and detect trends within the collected data.

  Typically, there are two main forms of ANNS which include, Feed Forward and Feedback Networks. With Feed Forward Networks, signals travel in one direction, where each unit transmits information to a corresponding unit but does not receive any return information. These types of networks are typically used for pattern recognition and classification. Units are able to transmit information bi-directionally using a loop. Although Feedback Networks are extremely powerful, they are often complex. Figure 22 highlights a Feedforward Neural Network and its various layers.

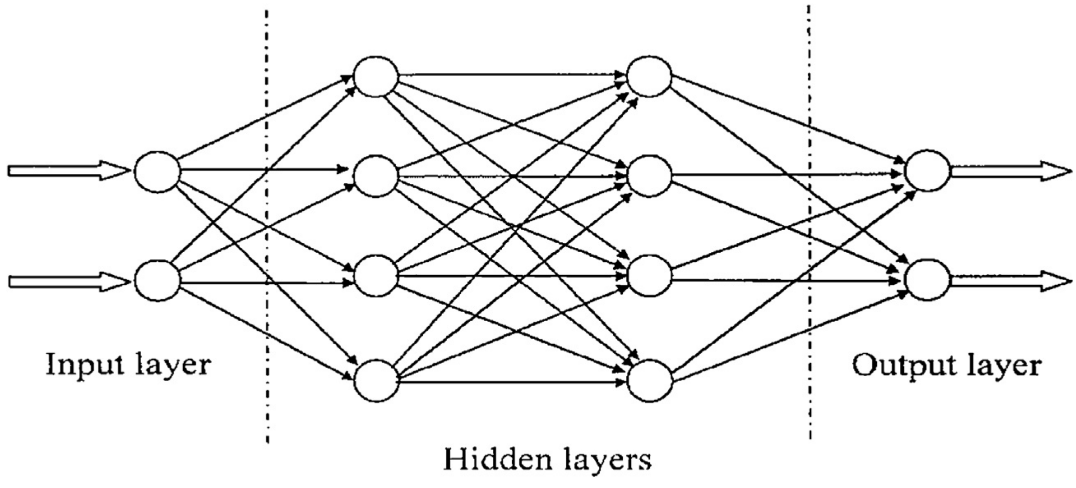


Figure 21: Multilayer Feedforward artificial neural network

ANNS are able to detect complex nonlinear relationships between dependent and independent variables. They also have the ability to detect all possible interactions between predictor variables and utilise various training algorithms [85].

However, there are disadvantages that are associated with ANNS. Firstly, there is a requirement for sufficient amounts of training data to facilitate a wide range of possibilities and predict the output. Additionally, ANNS work as black boxes, where they do not provide a descriptive model that depicts why a particular decision has been derived [85].

- **Bayesian Networks:** Bayesian networks belong to the family of probabilistic graphical models, which represent relationships between a set of random variables. A Bayesian network is a type of graph called a Directed Acyclic Graph (DAG). Essentially they model variables, dependencies and their probabilistic relationships. Bayesian Networks use a concept known as Bayes' theorem of probability theory [86]. This is used to propagate information between nodes. Bayes' theorem describes how prior knowledge about hypothesis H is updated by observed evidence E. Each node in the DAG represents a set of features such as parameters, values or states. Edges or links represent the relations between the various features where the direction of the edge indicates causality. Bayesian networks can be used for a wide range of tasks including prediction, anomaly detection, diagnostics, time series prediction and decision making. A Bayesian network is defined as follows [87]:

$$P\ (h|e) = \frac{p(e|h).p(h)}{p(e)} \tag{2}$$

  Where $p\ (h)$ is the prior probability of the proposed hypothesis; $p(e)$ is the prior probability of evidence $e; p(e|h)$ is the probability of e given h, while $P(h|e)$ is the probability of h given e.

  One the main advantages of a Bayesian network is that it can effectively handle missing data. Because of this feature, Bayesian networks are considered for use in our own system, in order to mitigate concerns surrounding periods of missing data.

- **Support Vector Machines:** Support Vector Machines (SVMs) are a supervised learning model, which functions by identifying the best hyperplane that separates all data points of one class from those of the other class. The superlative hyperplane for an SVM means the one with the largest margin between the two classes. The hyperplane can be linear, quadratic or polynomial depending on the kernel and complexity of the problem. Figure

23 highlights a linear SVM and its separating hyperplane. SVMs are used principally for classification, regression and outlier detection.

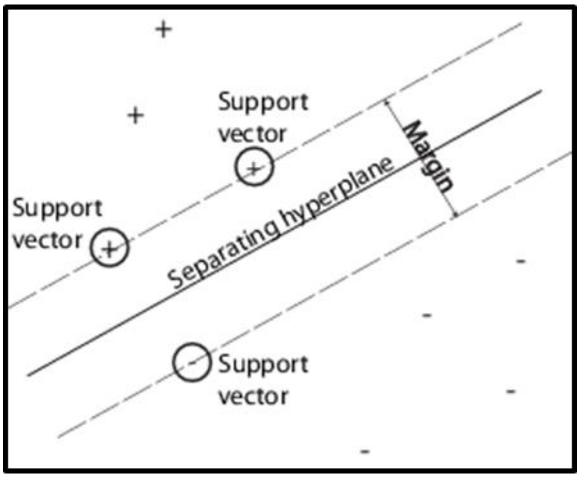


Figure 22: SVM with hyperplane

SVMs were originally designed for binary classification tasks. However, methods have been proposed to facilitate multiclass operations [88], which include one against one or one verse all approach. The use of SVMs are considered in our approach, as their kernel could be altered to match the complexity of the acquired smart meter data. Reducing the complexity of the hyperplane meant that computational requirements are reduced, as much as possible, resulting in decreased processing costs. In order to train an SVM, a distribution-free learning process is employed [89] and is defined as follows.

$$\mathrm{D} = \{(\mathrm{X}_i, Y_i) \in X\ x\ Y\}, i = 1, l \tag{3}$$

Where *l* is the number of training data pairs and is equal to the size of the training data set *D*. Y_i is the desired target value [90].

Decision Trees: Decision trees have been used for a number of years by a variety of researchers and are commonly used for classification tasks [91]. They have been applied to many research areas, such as detecting abnormalities, image classification and regression tasks. The Multiclass Decision forest functions by building multiple decision trees and the 'voting' on the most popular class. Voting is a form of aggregation, in which each tree in a classification decision forest outputs a non-normalised frequency histogram of labels. The aggregation process sums these histograms and normalises the result to get the "probabilities" for each label [92].

A tree consists of a set of individual nodes that are organised in hierarchical structure. Figure 23 highlights the structure of a typical decision tree, where the various internal nodes are represented as circles while the leaf nodes are represented by squares.

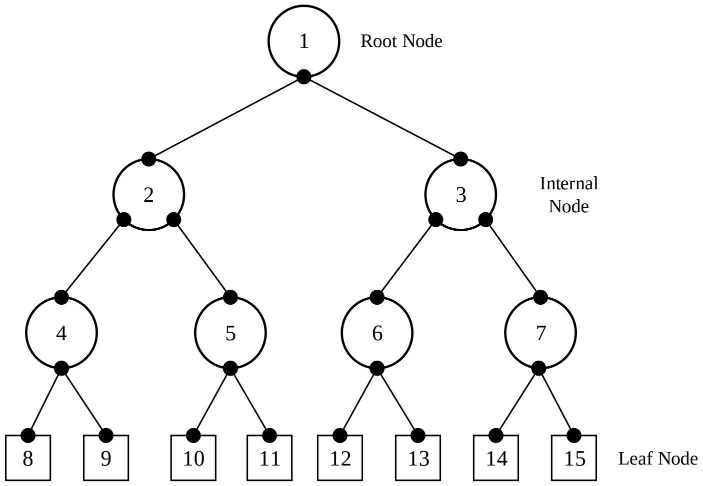


Figure 23: Random decision tree

Each internal node stores a test function, which is applied to the data; consequently each leaf node contains the predicted class. Decision forests are both scalable and flexible and can be adjusted for each classification task. For simple problems, they enable the user to select each of the individual node parameters manually. For tasks that are more complex the tree structure and parameters can be learned automatically by using training data. Decision Forests have a number of features and benefits [91] which include:

- They are naturally suited to classification tasks where multiple classes are present.
- They are efficient in computational tasks reducing the demand on both memory and the processor during training and predication.
- They support data with varied distributions.
- They provide much higher accuracy on previously unseen data (generalisation).

A Multiclass Decision Forest is configured with a variety of parameters. For example a parameter to determine how labelled training data is sampled. Randomness is introduced to the trees during the training phase by utilising a method known as bootstrap aggregating or bagging [93]. Bagging belongs to an ensemble method, which combines multiple predictions to generate an accurate model. Therefore:

$$\hat{f} = \frac{1}{B} \sum_{b=1}^{B} f_b\,(x') \qquad (4)$$

Where, f_b is the decision tree, B is the number of times bagging takes place and x is the training set. Each tree is trained on a new sample, which is generated by randomly sampling the training data; essentially each tree utilises a different training subset. Each output (prediction) is combined to generate an accurate prediction by majority voting or by averaging the results in order to obtain the greatest outcome. The main advantage of bagging is increased training speed and efficiency, while decreasing the variance of the model, without increasing the bias.

The machine learning pipeline includes the following:

- **Data Processing:** Preparing data for classification is used to remove any potential issues in the data. This includes missing data and unbalanced data sets. Missing data values are a common occurrence in real world dataset. Missing data can adversely affect the performance of the classifier which ultimately leads to unreliable results [94]. In addition, the use of a balanced data set is required for the classification process [95]. Imbalanced data typically refers to a problem in classification where the classes are not represented equally [96]. As a result the classifier does not have adequate examples of the positive class to learn from. This scenario can have a significant impact on the classification process, as classifiers are more prone to detecting the majority class. Many datasets are unbalanced; this is especially true for medical data as the number of observations belonging to each class can vary greatly [97]. This scenario is common and often introduces bias outcomes [98].
- In order to address this issue, the Symmetric Minority Over-Sampling Technique (SMOTE) technique can be used during model training. SMOTE functions by increasing the number of observations for the minority class. New instances are generated synthetically by taking samples of the feature space for each target class and its nearest neighbours. New examples are generated that combine features of the target case with features of its neighbours [99]. SMOTE has been used in variety of studies to effectively solve issues associated with imbalanced datasets and is defied in algorithm 1 [100].

Algorithm 1: SMOTE

---

1. Input: Minority data $D^{(t)} = \{x_i \in R^d\}$, ׀ = 1,2,…, T number of minority instances (T), SMOTE percentage (N), number of nearest neighbours (k).

2. For i = 1, …, T,

3. Find the k nearest (minority class) neighbours of x_i

4. $\hat{N} = \left[\frac{N}{100}\right]$.

5. While $\hat{N} \neq 0$

6. Select one of the k neatest neighbours, $\bar{x}$.

7. Select a random number $\alpha \in [0, 1]$

8. $\hat{x} = x_i + \alpha(\bar{x} - x_i)$

9. Append $\hat{x}$ to S

10 $\hat{N} = \hat{N} - 1$

11. End While

12. End For

13. Output: Return synthetic data S

Fergus *et.al.,* use SMOTE to address a class imbalance in their dataset. They note an overall improvement in classifier performance (sensitivity); however the models exhibit a 10% decrease in specificity. While the researchers note that using SMOTE is not ideal, it is an accepted technique in overcoming skewed datasets [100].

- **Feature engineering, selection and reduction:** Typically data undergoes multiple stages of transformation. These transformations are used to reduce the dimensionality of the data buy reducing the number of features to avoid overfitting. This is vital for building an effective predictive analytics system. Different dimensionality reduction techniques exist, the selection of the correct method depends on the data distribution. Selecting the correct method can have a direct impact on the accuracy of the classifier [101]. The accuracy of any classifier is dependent on the variables that are presented for classification. There are many domains where a high degree of dimensionality exists, for example time series and sensing networks [102]. This scenario adversely affects the performance of the classifier [103].

Principle Component Analysis (PCA) can be used to achieve dimensionality reduction on the obtained data. PCA functions by identifying directions in the data that have the largest variance thus archiving a lower dimensional dataset [104]. Examples of dimensionality reduction techniques beyond PCA include Fisher Linear Discriminant Analysis (FLDA) and a filter based technique called Spearman Correlation. FLDA achieves a more optimal result if variances between groups are similar and if the data has a normal distribution. FLDA obtains a linear combination of features that determines the direction the classes are separated most accurately. When considering various classes, the distance between the means of the classes is calculated in order to find a linear combination of features. This is defined as:

$$f(y) = W^\wedge T\, X + \alpha \tag{5}$$

Where α is the bias, *W* is calculated using Fishers LDA, and X is the training data without class labels. For a multiclass approach, a one-against-many method is employed. This is defined by Farag *et al.*, as follows [105]:

$$\textstyle\sum_W = \sum_{i=1}^{C} \sum_{x_k \in X_i} (x_k - \mu_i)(\, x_k - \mu_i)^t \tag{6}$$

Where *C* refers to the quantity of classes, X_i is the set of points in class *i*, μ_i is the mean of class *i*, and X_k is the *k*th point of X_i. The subsequent scatter matrix is the correlation of class means defined by Rao *et al.*, as follows [106]:

$$\textstyle\sum_B = \frac{1}{C} \sum_{i=1}^{C} (\mu_i - \mu)(\, \mu_i - \mu)^t \tag{7}$$

Where *C-1* is the principal eigenvalue, N_i is the values that belong to Class *i*, μ_i is the mean of Class *i*, and μ is the overall mean.

Spearman Correlation on the other hand utilises a non-parametric test, nonparametric tests do not assume a specific distribution in the data. Here a subset of features are generated with the highest degree of predictive power. Consequently, each column is scored and later utilised to build the predictive model. It assesses the relationship and statistical dependence between stochastic sequences in which the coefficient can be depicted using a monotonic function [107]. Here:

$$\rho = 1 - \frac{6 \sum_d 2}{n(n2 \quad -1)} \tag{8}$$

Where ρ denotes the Spearman rank correlation coefficient, *d* is the difference between the sequences, and *n* is the number of the sequences.

- **Machine learning algorithms:** The main objective for any machine learning application is to obtain a successful classification result. There are numerous classifiers available; however different classification algorithms are suited to different applications and data types. Typically machine learning algorithms can be divided into parametric and non-parametric algorithms. Parametric algorithms make particular assumptions which speed up the learning process, but can also limit what can be learned from the data. Non-parametric algorithms do not form strong assumptions about the mapping function. As a result they are free to learn any form from the data meaning they are often more flexible, achieve greater accuracy, but have longer training times. Classifiers are also selected for other qualities and are often used to address some of the issues previously discussed such as class imbalances, sample sizes and data distribution [108]. The selection and identification of the most effective classifier is usually an iterative process.

To perform statistical tests to ascertain if the data is normally or abnormally distributed, two common approaches are used. They include boxplots and Quantile Quantile (Q-Q) plots.

A box plot uses statistical measurements which include the minimum and maximum range values, the upper and lower quartiles, and the median. Box plots themselves are non-parametric, they show variations in data without making assumptions of the underlying statistical distribution. Additionally, box plots determine if the dataset contains any outliners that could adversely affect the performance of a classifier.

Q-Q plots provide a graphical illustration to determine if two datasets come from populations with a common distribution. The plot is created by plotting two sets of quantiles against one another. The Q-Q plot determines if sample $X_{1\ldots,}X_n$ has come from a distribution with a given distribution function $F\,(x)$. The plot displays the sample quantiles $X_{1\ldots,}X_{(n)}$ against the distribution quantiles $F^{-1}\,(p_1\,), \ldots, F^{-1}(\,p_n\,)$, where:

$$p_1 = \frac{i - 1/2}{n} \tag{9}$$

- **Validation:** Scoring and validating the results of the classification is an essential step in determining the algorithms suitability. The use of machine learning algorithms can introduce bias and variance. Bias is often introduced as algorithms make assumptions in an attempt to make the target function easier to learn. Results that are obtained during training often appear valid while demonstrating a high degree of accuracy. However, models often exhibit a reduction in accuracy when alternative data is used [109]. This scenario is known as variance and is used to estimate the error rate if different data is used. As a result, it is not uncommon to attain a 100% accuracy using training data and significantly less on test data. The selection of an appropriate validation method is required to overcome two fundamental problems; the first being the selection of an appropriate model and the second being performance estimation. If an algorithm is given access to an unlimited set of answers the problem of validation would not exist. This is because the lowest possible error rate for the entire population would be attained. However, real experiments only have access to a finite set of examples, often much lower than desired. The selection of an appropriate validation method requires careful consideration as numerous techniques exist. These typically include:

- Hold out validation: splits the data into two groups, one for training and one for testing. The training set is used to train the classifier were the testing set is used to estimate the error of the trained classifier. However this approach introduces two significant drawbacks. Firstly, setting aside a portion of the dataset for testing can be problematic for small datasets. Secondly, since it is a single train-and-test experiment, the holdout estimate of error rate can be misleading.
- Random sampling: is similar to K-Fold cross validation. However, instead of all the examples in the dataset being used for both training and testing. Random sampling selects a (fixed) number examples to train and estimate the error rate.
- K-Fold cross validation: The data set is randomly divided into *k* equal subsets; each subset contains approximately the same amounts of data. Of the *k* subsets, a single subset is retained for testing, with the remaining *k-1* subsets stored for the training. This procedure is then repeated *k* times, until every one of the *k* subsets is utilised exactly once as a testing set. The results are averaged to estimate the classifier's predictive performance. Specifically, the data is split into 5 folds, which provides a more accurate assessment of the classifiers performance, while reducing the risk of over fitting.
- Leave-one-out cross-validation: is a derivative of K-Fold cross validation, where K is chosen as the total number of examples. A dataset containing N examples we perform N experiments. Each experiment uses N-1 examples for training and the remaining example for testing.

2.6.1 CLASSIFER EVALUATION

For the validation method, a number of different metrics are used to measure the performance of a classifier [110]. Calculating sensitivity, specificity and accuracy are actively used in the medical field.

Each of the classifiers performance is calculated using a confusion matrix to assess the success of the classification or Area Under the Curve (AUC), sensitivity, specificity and error [110]. This can be expressed mathematically as shown below:

$$Sensitivity = TP / (TP+FN) \tag{10}$$

$$Specificity = TN / (TN+FP) \tag{11}$$

$$Accuracy = (TP+TN) / (TP+FP+FN+TN) \tag{12}$$

$$Error\ rate = 1 - Accuracy \tag{13}$$

Sensitivity measures the proportion of positives which are correctly identified in our system. This would be the detection of normal behaviour. Specificity measures the proportion of negatives identified during the classification. A confusion matrix is used for multiclass classifications. Receiver Operator Curve (ROC) visualises the performance of a binary classification to generate a graphic that highlights the cut off values for the false and true positive rates.

2.7 THE USE OF CLOUD COMPUTING FOR MACHINE LEARNING

The ability to undertake real time decisions using data is a fundamental requirement of many services. These are often beyond the capabilities of traditional on premise data centres and infrastructures. Therefore, to achieve this requirement, scalable data analytic services are required. These data analytical services are becoming increasingly prevalent in the cloud environment where organisations can leverage various services and resources to derive important insights and meaning from their acquired data.

Big data is frequently unstructured and is often difficult to process using conventional tools. Cloud based data analytics utilise complex and demanding algorithms, which require vast computational power [111]. By utilising a cloud infrastructure, the historical constraints associated with data analysis, such as vast storage is removed and a flexible computational resource is offered. Cloud providers have integrated dedicated hardware to aid in the machine learning process. Field-Programmable Gate Arrays (FPGAs) are used to decrease the computational time required for machine learning and other cloud services [112]. FPGA algorithms are directly written into the hardware and require reprogramming to take advantage of new machine learning developments. Additionally, cloud providers are open and extensible as they are compatible with a variety of existing languages and frameworks.

In order to facilitate services and create an effective system, the classification models need to be accessible to front end applications. Utilising cloud services enables the real time interpretation of data intelligence through the integration of front end applications. This can be achieved by deploying analytical services as ready-to-use web services. These web services facilitate the integration of apps which can be utilised to provide critical information to support the needs of the organisation. With the emergence of cloud analytics new and innovative ways for querying and interacting with big data have been developed. Natural language and proactive interaction enables the user to seamlessly interact with their data by utilising cognitive API's for speech, vision and text recognition.

2.8 INTERNET OF THINGS, EDGE COMPUTING AND SENSOR ANALYTICS

Although cloud computing provides scalable resources for processing large amounts of data, the ability to perform localised processing introduces numerous benefits, such as reduced costs and lower latency [113]. Traditionally, the role of edge computing involved storing, filtering and transmitting acquired data to centralised processing facilities such as the cloud. As these systems evolve, by introducing increased processing, storage and analytical power, the requirement for centralised processing has been reduced or removed completely.

Modern day edge computing is an extension of Content Delivery Networks (CDNs), which increase web performance by caching content locally to the caller. Edge computing extends this functionality by leveraging cloud computing functionality for computationally intensive tasks through a concept known as cloudlets [114]. Cloudlets provide computational services to mobile devices or sensors either through servers placed at the edge of the network or by requesting resources from a central datacentre. Edge computing can be used to effectively divide computational tasks between edge devices and centralised systems (such as Azure or Google cloud). Capabilities are largely dependent on the specification of IoT device that determines if processing is undertaken on the device, network edge or in the datacentre.

2.8.1 EDGE COMPUTING VS CLOUD COMPUTING

Edge computing is a relatively new concept, in which computational resources are placed at the internet's '*edge*' in close proximity to mobile devices or sensors [113]. With edge computing the processing of data is undertaken at the edge of the network. As a result, it has the potential to address data processing, bandwidth, data safety, privacy and response time issues surrounding the proliferation of IoT [115].

Cloud computing has revolutionised the way in which we process, store, access data and services. Offloading computing tasks to the cloud has proven to be an efficient method for large scale data processing and analytics since cloud computing outperforms the capabilities of edge devices. With the introduction of IoT, many researchers suggest technology is on the verge of a post cloud era [115]. The concept of edge computing was developed to address issues with applications and services that do not perform adequately with the cloud paradigm. These include the requirement for low latency, geographical distribution, and large scale resources.

It is estimated that by 2020 data captured by IoT devices will surpass 1.6 Zettabytes (ZB)[6]. Processing data at the edge of the network would introduce increased efficiency for network bandwidth, as the transportation of vast volumes of data is becoming impractical for cloud-based processing. Generally cloud providers construct a limited number of data centres that are geographically distributed. This introduces considerable separation between the infrastructure and end devices [116].

Although significant developments in cloud computation have been realised, advancements in network bandwidth have been slow and remains a significant challenge in the big data paradigm. In addition to big data, applications such as vehicular networks and augmented reality require low latency data processing, which is unavailable using cloud infrastructure.

In recent years, vast amounts of research has been undertaken to overcome existing limitations associated with cloud computing. Concepts such as edge, mobile cloud and fog computing are samples of emerging paradigms. The similarities in all edge computing platforms are the deployment of technology which can mimic cloud capabilities at the edge of the network. An overview for each of the edge paradigms and their applications are as follows:

- **Fog Computing:** is considered as an extension of cloud computing. It provides virtualised resources such as computation, networking, storage and applications between IoT devices and data centre. Fog computing (FC) is designed to work in conjunction with cloud infrastructure; essentially extending cloud computing services to the edge of the network. The main objective of fogging is to improve efficiency by reducing the volume of data being transported to the cloud. In a fog environment short term data processing is

[6] https://www.abiresearch.com/press/data-captured-by-iot-connections-to-top-16-zettaby/

undertaken using a smart hub or gateway where possible, while more intensive longer term analytics are sent to the cloud.

FC addresses the inadequacies of the cloud based model which include latency, network bandwidth and the need for geographic distribution. As a result, FC is popular in smart grid, smart city and smart home applications [117]. Shanhe *et.al.,* introduce both a design and implementation of a prototyping platform for FC. The researchers evaluate the platform for use within smart home environments by comparing both the latency and bandwidth between the FC and Amazon EC2. Each FC subsystem consists of one router and three servers, all of which are connected to Amazon EC2 through a Wide Area Network (WAN). The results show a round trip time (RTT) of 1.416 milliseconds (ms) for FC compared to 19.989 ms for EC2; while a reduction in bandwidth is noted. The researchers implement a face recognition application which is run from a smart phone. Each photo is uploaded to a remote server either in the FC or in the cloud. The response time for FC is 168.769 ms compared to 899.970 ms for the cloud. The researchers note that network bandwidth contributes the most to the difference in response time [118].

- **Mobile Edge Computing (MEC):** The concept of MEC provides services within the close proximity of mobile subscribers by introducing server infrastructure at each base station [119]. Similarly to fog computing, this approach reduces latency, while enabling features such as context aware applications and computation offloading. Typically, mobile devices, such as smart phones and tablets, exhibit multiple constraints in terms of computation and storage. In a MEC architecture computational resources are managed locally by the network operator; hosts are virtualised, while functionality is exposed through API's. Tran *et.al.,* introduce two significant use cases which illustrate the benefits of MEC, these include mobile edge orchestration and collaborative video caching and processing [120]. Here they present a novel framework, which is used to manage resources across the edge layer and the collaboration between end users, edge nodes and cloud nodes. Edge nodes analyse the data from nearby end users and notify the cloud node for further processing. By using a task allocation algorithm, the researchers compare the processing time of a smart phone with an edge computing device. They note that the performance of execution on a single MEC server is significantly improved when compared to the local device. The researchers note that even though the data was transmitted to the edge, there is an overall reduction in execution time of 40%.

- **Mobile Cloud Computing:** In mobile cloud computing (MCC), cloud servers provide a shared pool of high availability resources such as processors, software and storage. Typically mobile devices consume these resources through radio access network (RAN) or the internet. With MCC, computing resources can be either distributed or centralised, both the performance and adoption of MCC is largely reliant on the deployment of 5^{th} generation (5G) mobile networks. The use of 5G will provide improved performance in offloading both data and computational tasks to the cloud. By offloading computationally demanding tasks to the cloud applications such as mobile learning, healthcare and gaming can be efficiently undertaken on smart devices. Curevo *et.al.*, propose a system which facilitates fine grained energy aware offloading from mobile devices to the cloud. The researchers conduct a number or experiments to evaluate the amount of energy used in gaming applications. They state that instead of offloading the entire application for cloud processing, code could be partitioned at run time based on the costs of communication and CPU utilisation. The results demonstrate a 27% saving in energy usage while improving the games refresh rate from 6 to 13 frames per second [121].

With the emergence of narrowband IoT the proliferation and usage of low cost sensors is increasing. Companies deploy, manage and process sensor data for multiple applications while using platforms such as Azure IoT hub for data analytics. Typical applications include utility metering, environmental monitoring, event detection and parking sensors. The use of narrowband IoT directly compliments edge computing, where limited amounts of sensory data can be effectively processed on the network edge. Although narrow band IoT offers reduced costs and increased battery life, its transmission speed is limited to 100kbps, therefore restricting its range of applications. With the introduction of 5G, data transmission speeds range between 1 – 10Gbps therefore facilitating the use of cloud computing for data processing and analytics. The use of 5G, can facilitate low latency orchestration between IoT devices and cloud services providing scalable on demand computing. This approach is becoming increasing viable bringing into question the need for edge computing platforms.

2.9 SUMMARY

The implementation of the AMI and, in particular smart meters, enables the analysis of energy usage with a high degree of accuracy and granularity. Being able to utilise the collected data brings countless benefits to grid stakeholders and consumers alike. Due to its ability to integrate with third party services additional applications can be accommodated beyond its original intended use. Around the world a large-scale implementation of smart meters is underway, which is supported by a vast and complex infrastructure. The smart meter is regarded as more than a simple analogue to digital upgrade. It provides significant data collection abilities, which facilities many of the smart grids aim and objectives.

The emergence of the smart gird has introduced a number of complex computational challenges. The requirement for a reliable and scalable IT infrastructure has resulted in many researchers proposing the use of cloud computing to mitigate the numerous challenges facing the wide implementation of the smart grid. As discussed, cloud computing infrastructures are both scalable and adaptable, while overcoming the static limitations that are associated with traditional onsite datacentres.

The chapter introduced the concept of load disaggregation and how it can be exploited to identify the use of individual appliances. Specifically the methods and their associated benefits and limitations where discussed. Additionally the chapter introduced the concept of machine learning along with its individual steps and considerations. The chapter also introduced the concept of machine learning within a cloud environment. Many researchers and organisations are adopting the use of cloud based machine learning to overcome challenges in both computation and system integration. Although the use of cloud computing can alleviate many challenges associated with big data, it is clear significant limitations in both mobile and IoT applications exist. Challenges, such as bandwidth and latency, mean that cloud computing is becoming increasingly impractical for many mobile applications. The chapter introduced three specific edge computing concepts which are designed to address these limitations. Although Edge computing demonstrates potential, the technology is in early development with no clear technical standardisations. Limitations in hardware mean that there is still a requirement for large data processing to be undertaken in the cloud. However, by using edge and cloud computing, in a hybrid model, challenges with both technologies can be overcome.

CHAPTER 3 ASSISTED INDEPENDENT LIVING

This chapter provides a discussion on related work on technologies used to assist independent living. The various strengths and weaknesses of each are outlined, as a comparison to the approach presented in this thesis. Specifically, the chapter focuses on technology within the home and discusses the various sensors and concepts currently used to facilitate independent living. In addition, the chapter contains seven requirements for any solution to be considered effective in routine clinical practice. Finally the chapter outlines different behavioural considerations for selected health-related conditions to facilitate the identification of key behavioural patterns.

3.1 CURRENT ASSISTIVE TECHNOLOGIES

The term assistive technology covers a wide range of applications and tasks [122]. Assistive technology refers to devices or systems that support a person to maintain or improve their independence, safety and wellbeing [123]. Typically, existing technologies are divided into two distinct categories. Firstly, physical aids which assist the sufferer in performing specific tasks which include walking, eating and drinking. Secondly, monitoring and surveillance, whereby electronic devices keep track of a person's medical condition and automatically alert health care staff, outreach teams or family members of any changes when required. Although no official standardisation exists for assistive technologies, it is widely agreed that technology should be personalised, adaptive and non-intrusive.

Current assistive living technologies involve the deployment of various sensors around the home [124]. These include motion sensors, cameras, fall detectors and communication hubs. However, installing, maintaining and monitoring these devices is costly and technically challenging [125]. In addition, diverse wearable technology is also available. These include: Personal Emergency Response Systems (PERS), wearable body networks, electrocardiogram (ECG), pulse oximeter, blood pressure monitors and accelerometers. The main objective of these sensors is to obtain essential data to assist in the overall assessment of a patient's wellbeing. These readings enable clinical staff to evaluate the state of a patient remotely, whilst determining if there is a requirement for intervention or further treatment.

Even though some technologies enable patients to live independently for longer periods, there are concerns about their associated costs and benefits. It is estimated that by adding existing telemedicine solutions to standard care plans increases overall costs by 10%. More importantly, a recent study has shown that existing solutions provided only minimal gains in quality of life [126]. The cost per Quality Adjusted Life Year (QALY) was utilised in the study to measure the cost effectiveness of the solution. The QALY measurement combines the duration of life lived and adjusts it for quality of life. The study identified that the difference between intervention and non-intervention groups was only 0.012 QALYs. This margin equated to only a few additional days of quality health. In addition, the study identified that the resulting interventions from the trial was not cost effective and below the threshold recommended by The National Institute for Health and Care Excellence (NICE) [126].

Many areas of research and technology contribute to assistive solutions, with trials undertaken to assess their feasibility [127]. The application of several domains has been exploited to enable and improve the use of assistive technologies within the household. The collection and integration of such technologies is often referred to as Ambient Intelligence or Ambient Assistive Living (AML), which aims to support people by enabling them to achieve their everyday objectives [128]. Some of the different technologies that have been created and integrated into telehealth solutions are highlighted in figure 24 [129].

Assistive health technology can be divided into three distinct groups which include: enabling, preventative and responsive. Each group facilitates the unique requirements of the patient by leveraging different technologies and their associated features. Specifically, enabling technologies ensure that the patient can perform safely common everyday tasks such as controlling heating or lighting. Preventative technologies function by reducing or preventing certain dangers to patients by mitigating particular risks. This is achieved by ensuring that the patient undertakes specific ADLS, such as taking medication or eating and drinking. Responsive technologies react to certain events such as falls, triggered alarms and leaving the home. Responsive technologies rely on an effective escalation procedure, which is based on a predefined protocol.

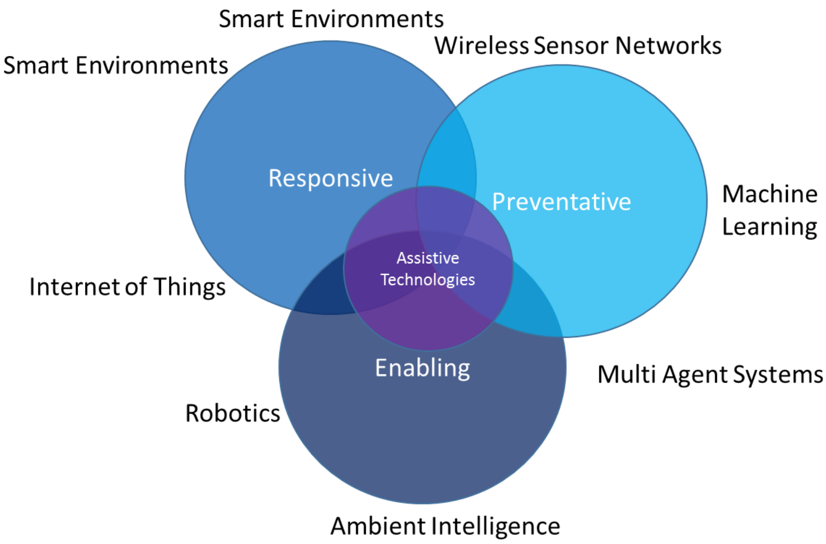


Figure 24: Assistive solutions related technologies an AML approach

AML is not only regarded as the integration of various technologies (i.e. sensors, computing etc.) and related domains (i.e. computer science, engineering, medicine and social sciences) but focuses on incorporation and applicability of such technologies. The main function of any system is for the ability to identify human activities from the acquired sensory data. This is achieved by applying meaning (which is usually in the form of medical insight) to observations.

Preventative and responsive AML technology is of particular interest to the medical profession and can be divided into two distinct applications; smart health and smart homes. Firstly, smart health involves the use of wearable technologies to collect and analyse important biomedical readings. Secondly, a smart home environment, which is the focus of our research, is used for improving or maintaining the health and wellbeing of the occupant [130]. The vast majority of existing solutions in the field focuses on the detection of ADLS, which was a concept first proposed in the 1960's[7]. The assessment of ADLS facilitates the monitoring of both the physical and psychological aspects of the patient. The process operates by identifying key aspects of a patient's routine, such as preparing food or sleeping. These activities are assessed through the use of multiple sensors or monitoring equipment, to ascertain any deviation or abnormal behaviour.

[7] Katz, S., Ford, A.B., Moskowitz, R.W., Jackson, B.A. and Jaffe, M.W., 1963. Studies of illness in the aged: the index of ADL: a standardized measure of biological and psychosocial function. *Jama*, *185*(12), pp.914-919.

3.2 TECHNNOLOGY IN THE HOME

Over 80% of people would prefer to stay in their own home in the later years of life[8]. This is beneficial to both the patient and service providers alike. Evidence suggests that enabling patients to live in their own home is more cost effective than any other setting [131]. Although many patients wish to live independently, it is crucial to find the right balance between independent living and unnecessary harm. The challenge we face is how to mitigate the main areas of risk to the patient while ensuring that an appropriate framework for escalation exists. Patient risk varies greatly depending on the condition and its overall severity. The normal ageing process and more serious conditions, such as dementia and psychiatric disabilities share many commonalities in terms of risk [132]. However, living with serious conditions increases the likelihood of an incident occurring. Additionally, with degenerative diseases the probability of incident increases over time due to disease progression and secondary complications. This is also true for patients suffering with various psychiatric conditions as certain events or periods may heighten the severity of the condition [133]. In recent years, there have been a variety of suggested assistive technologies and a number of research studies undertaken [134] [135] [136]. However, many solutions raise concerns regarding their feasibility and cost effectiveness.

It is an essential requirement for any patient monitoring system to take into account the specifics of each health condition and their associated risks. If a technology fails to meet the individual needs and requirements of the patient, the solution will be largely ineffective and may cause additional confusion and complications. Examples of some of the common risks that modern technology must address include:

- Adequately detect a reduction in food and fluid consumption, which directly contributes to the overall decline in a patient’s health and wellbeing [137]. Malnourishment increases the likelihood of immune deficiency, anaemia, pressure sores, poor healing and low blood pressure. Likewise, dehydration can result in urinary tract infections, pneumonia, hypotension and confusion. Complications from malnutrition can severely affect a patient’s cognitive and functional capacity. This ultimately impedes their ability to participate in normal activities of daily living. Additionally, researchers in [138] noted that there is a significant lack of research in the use of dietary interventions in older people.

[8] http://www.raeng.org.uk/publications/reports/designing-cost-effective-care-for-older-people

- Assess both the cognitive and physical health of the patient to assess significant risk. The identification of the physical functions and decision-making capacity aids in the overall assessment of the patient. Additionally, it can provide an understanding of the overall risk to the patient, while facilitating in their mitigation through the involvement of health care providers and family. However, early detection is vital for an effective outcome and must be considered one of the main objectives for any monitoring system [139].
- Assess the risk of falls due to an inappropriate environment, frailty or cognitive impairment [140]. Frailty is a common ailment among elderly patients, which carries increased risk of incidents such as fractures, breaks and mortality. Falls often result in increased hospital admission rates, which place additional strain on healthcare resources.
- Inappropriate use of medication can increase the overall risk of falls, as common side-effects include fatigue, confusion, perceptual disturbances, dizziness and altered muscle tone. Additionally, the introduction of new medication can increase the overall risk to a patient, as it can result in side effects.
- Wandering which is a common symptom in both the elderly and people suffering with dementia. This behaviour might occur due to environmental irritants, physical discomforts or psychological distress. Wandering introduces significant risk to the patient as it has the potential to result in injury and additional worry and concern for family members and carers.
- Fire and flooding which are a common risk to patients. Cognitive impairment can often result in burning of food or forgetting to turn appliances or taps off after use.

In addition, the compromise of any technical deployment could further endanger the safety and wellbeing of the occupant; specifically through the following:

- The patient being able to switch off or remove some or all of the installed equipment. Patients can easily become confused and forget what and why the solution is there. This problem is often exacerbated if the assistive technology requires the installation of multiple sensors. The environment should remain confinable and familiar, which can be adversely affected with the introduction of sensors.
- Alert escalation ensuring that there are efficient numbers of relatives, carers and care workers to respond to any alert within an acceptable time period and within a predefined protocol.

- Devices that require any interaction from the patient are particularly problematic. Many solutions require the patient to wear a device or manually interact with a device to trigger an alarm.

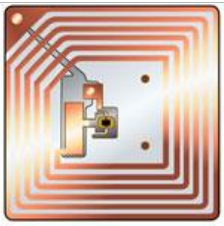
3.3 AMBIENT ASSISTED LIVING

The vast majority of telehealth systems fall into an area referred to as Ambient Assisted Living (AAL). Essentially, one of the main objectives for any AAL solution is to monitor the changing needs and risks of the patient. The system should provide alerts and facilitate improved responses to any of the identified needs or risks [141].

Remote patient monitoring solutions provide alternative ways of monitoring and support. In order to achieve this outcome a variety of different sensors are available which can be used singularly or in combination to achieve the desired objective. Table 9 highlights the various sensors and functions, which are commonly used in a smart home environment [142].

Table 9: Sensors deployed in a smart environment

Sensor Type	Measurement	Limitations
Passive Infrared Motion Sensor (PIR) 	Movement around the living environment.	Multiple sensors are required. Typically one for each room in a persons living environment. PIR solutions often struggle to detect key ADLS, as they can only verify location and not the occupant's activity. Sensors can have poor battery life, which requires ongoing maintenance and accurate detection of failing batteries.
Radio Frequency Identification (RFID)	Movement around the living environment.	Multiple sensors are required, which are distributed throughout the living environment. RFID often suffers from reduced

		accuracy due to interference from neighbouring sensors [143]. It is common for RFID solutions to experience contact sensing difficulties. For example, when a sensor is within the range of an antenna but is not detected.
Pressure Sensors / Smart Tiles 	Detects the presence of pressure on multiple items such as flooring, mats, bed and chairs.	Often inaccurate (sensing motion not presence) [140]. Equipment positioning often requires important consideration to obtain the best results. In addition they are often used in conjunction with other sensors [144].
Magnetic Switches 	Detection of door / cabinet opening and closing.	Multiple sensors required. Switches can be wired or wireless and are often used in conjunction with other sensors.
Cameras 	Tracks activity within the living environment.	Often considered unacceptable due to legal, privacy and ethical issues. Additionally the deployment of camera technology within the living environment is both expensive and intrusive [145].
Microphone	Used to record and	Microphones can be

	identify particular noises within the home.	deployed throughout the living environment and can be used to identify significant sounds. Noises can be utilised for the detection of ADLS or identifying if the patient is in trouble.
Physical Alarms 	Devices which are worn by the patient and can be triggered in the event of an emergency.	Systems that are solely reliant on a person's interaction to function pose many safety concerns. Dementia patients in particular may forget to activate the device or fail to identify if they are at risk.

There are numerous smart home projects, which utilise one or more of the above sensors in an attempt to create a smart living environment. Most solutions employ algorithms, with the aim of improving accuracy for monitoring indoor localisation, tracking, activity recognition, and anomaly detection. Numerous AAL solutions combine complex multidisciplinary technology, many of which are still in their infancy [146]. Currently, there is no agreed standardisation for AAL, while concerns surrounding high costs and complexity impede their adoption [147].

Indoor localisation, activity recognition and tracking are key components of AAL research and a consideration for any system. As such, it has become the focus of research studies. Machine learning and computational techniques have been applied to many solutions in human behaviour technology and activity recognition [148, 149]. Specifically, the vast majority of AAL solutions depend on supervised learning algorithms, which utilise labelled data for training. Examples of such solutions are categorised in table 10 below:

Table 10: Summary of various AAL solutions

Authors	Monitoring Type	Technology	Algorithm	Single / Multi Senor
Przybylo et.al [150]	Activity Recognition	Wearable Camera	Speeded Up Robust Features (SURF)	Single
Culmone et.al [151]	Activity Recognition	Distributed Sensing	Rule Based Logic	Multiple
Liu et.al [152]	Activity Recognition	Wearable Sensors (accelerometer)	Dynamic Time Warping Algorithm	Single
Große-Puppendahl et.al [153]	Activity Recognition	Distributed Sensing (capacitive proximity sensors)	Radial basis function (RBF)	Multiple
Hailong et.al [155]	Indoor Localisation	Radio Fingerprinting	k nearest neighbour (KNN) / naive Bayes classifier (NBC)	Multiple
Antonio Del Campo et.al [156]	Indoor Localisation	Radio Fingerprinting	None	Multiple
Bouchard et.al [159]	Indoor Localisation	Proximity Systems (Bluetooth)	Localisation Algorithm	Multiple
Hsu et.al [160]	Indoor Localisation	Proximity Systems (RFID, Accelerometers)	Genetic Algorithm	Multiple
Kovácsházy et.al [161]	Sleep Monitoring	Passive Infrared Motion Sensor (PIR)	None	Single
Yazar et.al [163]	Fall Detection	Vibration Sensors / PIR Sensors	Support Vector Machine (SVM) / Sensor Fusion	Multiple
Čavka et.al [154]	Fall Detection	Wearable Sensors	Threshold Based	Single

Activity Recognition: Przybylo *et.al.*, propose the use of a wearable camera to track the patient's movement around the home while identifying key activities [150]. The data collected is analysed in real time, which removes the need for recording equipment. Person localisation is achieved through the use of natural landmarks, which are obtained during the calibration procedure. They propose the use of the SURF algorithm, which attains results of 83% accurate classification. The researchers note, however, that further research is required in order to improve the speed of both the hardware and algorithm. They also advise that further testing in different environments is required to assess the robustness of the system. Meanwhile Culmone *et. al.,* propose an ontology-based framework to discover human daily activity [151]. The system works by identifying a set of specific actions and locations through the use of distributed smart sensors. These sensors consist of presence sensors in the bed, kitchen and doors. They define the flow of actions that usually represents the considered activity, also taking into account, when necessary the timing of user action. Currently, the proposed system employs a rule based logic approach, while the authors state that future work will include machine learning (Bayesian Networks) and Markov Models to model routine.

Liu *et.al.,* on the other hand utilise wearable wrist sensors, which communicate wirelessly to a hub [152]. This process enables the system to detect hand movements, while attributing the results to specific tasks. These tasks are limited to a small number of actions, which include cleaning tables, cleaning windows, sweeping and mopping the floor. The overall performance in precision, recall, and F1-socre is 89.0%, 88.6%, and 88.1% respectively. Research undertaken by Große-Puppendahl *et.al.,* is able to classify the posture of a person using proximity sensors embedded into the living environment [153]. The approach embeds eight capacitive proximity sensors into a sofa to produce an evaluation using eighteen individuals of diverse body height and weight. The authors report 97% accuracy in eight different postures using a Radial basis function (RBF) network based classifier.

Indoor Localisation: While out-door tacking is relatively rudimentary using GPS [154], indoor tacking is vastly more complex. In order to address the various challenges of indoor tracking, Hailong *et.al.*, [155] and Antonio Del Campo *et.al.,* [156], share a common method for location detection called Radio Fingerprinting. Essentially, they work by analysing signal properties, such as signal strength, and comparing them to a database of properties. The database is constructed from readings that are obtained from various locations, commonly referred to as a location map. The closest set of compared properties from both the sensor and database returns the estimated position of the occupant. A similar approach was proposed by *Fergus et. al.,* here similar approaches have been proposed in [157]. Additional research undertaken by *Fergus et. al.,* introduced how both physical activity and sedentary data can be collected from different environments. The researchers used TelsoB sensors to locate and measure the behaviours of a resident within their home environment. Sensor networks where installed throughout the home to track the physical location of the person by using signal strength indicator (RSSI) Values. Several static TelosB sensors were fitted, at fixed points, in the home environment while a mobile node was fitted to the resident being monitored. Additionally the wearable node was used to measure standing, sitting, and lying positions. The experiment was undertaken over a four day period. Overall the results showed an accurate account of activity for both location and body position [158].

Research undertaken by Bouchard *et. al.,* utilises a smart watch to track the patient's position within the home [159]. The smart watch transmits its position using Bluetooth, which is detected by low energy Bluetooth beacons deployed throughout the environment. In order for the localisation to occur, a localisation algorithm is used to receive and analyse a set of inputs. These variables are comprised of a beacon ID, a timestamp and the received signal strength indication (RSSI). To assess the performance of the system three different environments are used, each containing different amounts of sensors depending on its size. Samples are collected at two minute, one minute and thirty second intervals. The authors note that the sampling windows used for analysis, affects the overall performance of the system. The system obtained over 70% accuracy for a thirty second window and over 80% when sampling was increased to ~one minute.

Research undertaken by Hsu *et.al.,* utilises RFID to determine a person's position within the home [160]. The approach utilises RFID, in conjunction with accelerometers, to improve the accuracy of the system. By using the acceleration values the system identifies the walking routes while determining the number of steps taken by the occupant. The system uses the RSSI value from RFID sensors and the walking paths to approximate the position of the occupant using a genetic algorithm.

Sleep Monitoring: Non-intrusive sleep monitoring introduces various challenges but is one of the most important indicators of a person's health. Kovácsházy *et.al.,* deploy passive infra-red motion sensors to estimate the sleep quality of the occupant [161]. The authors point out that sampling rates between 10 and 20 hertz are required and advise that higher sampling rates have a detrimental effect on battery life (6 months of battery life was estimated). The node is positioned above the bed to monitor bed occupancy, and the overall movement of the person. The results highlight that small movements are detectable, which are used to identify disturbances in peaceful sleep periods.

Fall Detection: Fall detection technologies have become the focal point for many AAL solutions and often utilise a variety of different sensors. Most solutions focus on three sensor types; ambient sensors, wearable sensors and computer vision, which can be used singularly or in conjunction [162]. Research by Yazar *et.al.*, involves the deployment of vibration sensors, which operate by converting vibrations into electrical signals [163]. The system is supplemented by PIR sensors, as the paper identifies that vibration sensors alone are not robust enough to distinguish falls. The authors extract feature vectors from the acquired waveforms, which are later classified by an SVM. A second algorithm (sensor fusion algorithm) is deployed to analyse the acquired PIR data. Two PIR sensors are used; one to monitor the upper part of the body and one to monitor the lower part of the body.

Čavka *et.al.*, used a wireless fall detection sensor, which contains an accelerometer that attaches to the occupant's belt [164]. Signals are sent and processed using a communication gateway, home router, and server, which is used to notify a carer in the event of a fall. To evaluate the system, ten test subjects were asked to act out three types of fall on the mat (forward fall, fall on the back, and fall on the side) and three types of (ADLS) which include: sitting in a chair, sitting on a toilet and lying down in the bed. These activities are conducted twice. The experiment obtained results of 97% for sensitivity and 95% for specificity, demonstrating the system's ability to detect falls accurately.

All of the above methods present multiple limitations and restrict the ability for widespread adoption. Specifically three areas have been identified, which include sensor prevalence, personalisation and cost of ownership. The majority of research requires the deployment of sensors within the living environment. As such, their installation and ongoing maintenance introduces additional costs and complexity. It is clear from the literature review that existing approaches do not take these concerns into account during the devolvement phase of their AAL solution. Typically, any AAL solution should not rely on user interaction, nor should it be overly complex. Some of the solutions presented in the literature review require the user to wear one or more sensors in order for monitoring to occur. This approach relies heavily on the user's ability to correctly position the sensors on a daily basis. Additionally, related research is dependent largely on the user's ability to remember to use the sensors, while ensuring that the device is functional. The use of these technologies would be impractical for monitoring the vast majority of age related conditions making them largely unsuitable for AAL applications. Many people, in later life, struggle with memory problems that are often exacerbated by cognitive impairment. Relying on the user's ability to interact with the system can result ultimately in ineffective monitoring therefor putting the user at undue risk.

Many of the solutions, highlighted in table 10, require the use of sensors; either on the person or distributed throughout the living environment. The use of sensors in AAL solutions requires special consideration. Their intrusiveness, complexity, feasibility and reliability can limit their adoption. The associated financial cost of both implementation and ongoing maintenance make them impractical for large scale deployment. Many of the solutions listed above use different sensors with the aim of detecting the location of the person and their ADLs.

The majority of reviewed solutions fail to detect significant ADLs and only track the occupant around the home. This limits the assessment of cognitive function and hinders the system's ability to personalise over time. Personalisation is absent in current solutions leading to a generic approach that does not take the persons routine or medical condition into consideration. The absence of both personalisation and clinical knowledge limits the effectiveness of EIP while reducing the likelihood of preventing relapse.

3.4 AAL DEPOLYMENT AND PRODUCTION

Many AAL solutions have been adopted, developed and are now used in production. Here we examine solutions that are commercially available. Typically, technologies and offerings can be divided into the following categories:

- **Community Alarm Services:** This is a common offering within the telehealth field. This type of service has been utilised for many years and is often provided by social services, NHS Trusts and private companies. Typically, the system employs various sensors and alarms that communicate wirelessly to a community alarm. The patient can activate the alarm manually and raise an alert, usually from a pendant or watch that is fitted with an emergency button. The receiver, which is typically connected, to a phone line, transmits the alert to a central monitoring centre. When an event is triggered care staff can take appropriate action, which is outlined in a previously agreed protocol.

  There are a variety of companies, which offer this type of solution. LifeLine24[9] provides a wearable pendant alarm, which operates using the 869MHz European Social Alarm

[9] https://www.lifeline24.co.uk/pendant-alarms/

frequency. A receiver is fitted to the patient's phone line that is used to trigger an alert, which, is answered by a dedicated care team[10]. Likewise, Age UK offers a similar solution, whereby if an incident takes place an operator calls the occupant and where appropriate contacts a nominated key holder or emergency service[11].

- **Distributed Sensors:** These have become increasingly prominent in telehealth solutions and are often used in combination depending on the monitoring application. The types of sensors used differ greatly, each with their own benefits and limitations. Commonly deployed sensors include heat sensors, smoke detectors, flood detectors, unlit gas detectors, carbon monoxide detectors and fall/pressure detectors. Additional sensors exist, which include door sensors, passive sensors that track movement around the home and cameras. Tunstall is a reseller who provides a wide variety of sensors to detect specific events[12]. Sensors are placed in the living environment that can automatically raise an alert if a problem is detected, such as smoke, gas, flood or fire. Sensors are predominantly wireless and operate using a dedicated radio frequency. Sensors can be configured to raise an alert, which can be directed to a mobile phone or to a monitoring centre where trained operators follow predefined protocols.

3.4.1 LIMITATIONS AND REQUIREMENTS FOR AAL SOLUTIONS

Based on a review of the literature, and research carried out in this study, it has been determined that there are many limitations and challenges with existing solutions. Multiple barriers exist, which impede and restrict the wide implementation and adoption of many solutions. In many instances, AAL systems often fail to meet the complexity of environments, patients and objectives required to facilitate independent living [166]. These limitations and challenges are summarised as follows [166]:

- **Complexity and feasibility of technologies**: Systems are often dependant on complicated distributed hardware and software, which are required to seamlessly and reliably interact with each other. Many solutions rely on their ability to analyse complex data, which is obtained from a variety of different sensors. These distributed sensing models make use of a variety of communication technologies, which introduces unnecessary complexity.
- **Complicated installation, configuration and ongoing maintenance**: Multiple sensors and associated equipment can be challenging to install. Variations between buildings,

[10] https://www.lifeline24.co.uk/pendant-alarms/
[11] http://www.ageuk.org.uk/products/independent-living/
[12] http://www.tunstall.co.uk/solutions/products

infrastructure and environmental layout exist, which require careful consideration during the planning and installation phase. Additionally, battery replacement and ongoing calibration is often required to ensure the continuation and reliability of services.

- **The requirement for user training and education**: As various solutions require some form of interaction from the patient and often a response from a carer there is often an element of training required to ensure that the system is utilised correctly. For certain patient groups, such as those with dementia, the requirement for interaction impedes the overall safety and effectiveness of the solution. Any solution must facilitate the monitoring and escalation without the need for patient involvement.
- **Lack of communication standards and interconnectivity between different solutions**: Technology standards provide the basis to facilitate interoperability, integration, and scalability. However, many of the approaches previously mentioned use communication standards, which restrict their interoperability. This often leads to additional financial costs, while limiting their applicability and integration with other solutions and services. This type of problem is a common concern as there is no governance or agreed standardisation for AAL solutions.
- **High costs to both the care provider and the patient**: Typically, existing solutions require the purchase of expensive equipment and usually some form of ongoing subscription or licencing cost [167]. Expense restricts the possibility of widespread implementation, while also raising concerns regarding cost effectiveness.
- **Low acceptance due to usability and intrusiveness**: The acceptance of many solutions relies heavily on both the benefits of the system but also its level of intrusiveness [168]. They are often considered to be too intrusive and raise privacy and ethical concerns, especially for vulnerable patient groups. In addition, many AAL systems are plagued with usability issues [169]. The requirement for patients to interact with the technology or wear some type of sensor is a significant failing of existing AAL solutions. Often patients suffer from confusion and memory problems, which reduce their ability to use the device and impede the effectiveness of the solutions.
- **Inadequate understanding of conditions and patient needs**: The previously discussed solutions do not account for the specific characteristics and behaviours of the condition. This can result in the misclassification of important behavioural indicators.
- **Lack of adequate evaluation and validation (effectiveness and efficiency):** Evidence surrounding the benefits of telehealth on service use, costs, or cost effectiveness remains

scarce. As a result, service providers are often reluctant to offer solutions to their patients as the cost benefits of many services are unclear.

- **Absence or inability to adequately facilitate early intervention**: Many systems fail to identify early behavioural concerns, which could be indicative of a problem; while mechanisms, which enable escalation to a relative, are carer, are often absent.

From the related research, six specific areas have been highlighted which can directly impede the deployment and acceptance of any current solution. Here we discuss each of them in detail, all of which have been considered in our methodology.

3.4.2 CHALLENGES FOR AAL SYSTEM DEPLOYMENT

There are six considerations that need to be addressed if AAL systems are to be useful, viable and cost-effective:

- **Early Intervention:** Any remote monitoring system must facilitate EIP, enabling front line community services to intervene much earlier. If changes in a patient's condition are not dealt with early, the prognosis is often more severe and as a result the cost of treatment will undoubtedly be higher [170]. An early intervention approach has been shown to reduce the severity of symptoms, improve relapse rates and significantly decrease the use of in-patient care. Additionally, evidence suggests that a comprehensive implementation of EIP in England could save up to £40 million a year in psychosis services alone [171]. Being able to detect deteriorating conditions in dementia patients earlier enables physicians to better diagnose and identify stage progression for the disease. This helps individuals, and their families, when adapting to illness progression.
- **Cost:** There are numerous costs, which are related to the development, deployment and management of telehealth solutions. These costs largely consist of research and development; equipment, maintenance, communication and staffing. Any solution must be cost effective while ensuring long term sustainability. NICE recommendations for using health technologies in the NHS should range between £20 000 to £30 000 per QALY [172]. Previous solutions have been criticised for failing to adequately evaluate cost benefits, health outcomes and patient satisfaction [173].
- **Personalisation:** A person's habits and routines are clear indicators of their wellbeing. Yet, one of the most significant limitations with existing solutions is the absence of personalisation. The inability to learn the unique characteristics of each individual and each condition degrades the effectiveness of any solution. The ability to model routines,

and understand their significance, is imperative for any patient monitoring system. These limitations are the main contributors for the inability to provide effective interventions and limited gains in QALYs. Although customisation is an important requirement for any solution, it is often problematic to achieve, as patients are known to be unable to or are reluctant to assist in the development of customisation [174]. Additionally, many patient groups, such as dementia patients, are considered vulnerable, which introduces many challenges in terms of ethical approval and conducting patient trials where the condition is prevalent.

- **Condition Specific:** In order to derive a complete understanding of a patient's wellbeing, the solution must account for observations that are specific to the condition. Failure to identify and correctly classify key behavioural indicators can reduce the overall effectiveness of the system, while reducing the likelihood of EIP and gains in QALYs. Any solution should be trained using patient groups, which suffer from the specific condition ensuring that individual models are tailored to the ailment. To the best of our knowledge, current systems do not consider personalised, adaptive, and anticipatory requirements [174].
- **Alerting and notification:** Any AAL solution that does not facilitate the automatic escalation of abnormal behaviour impedes its overall effectiveness. Behavioural indicators should be classified and dealt with accordingly through a previously agreed protocol. Any alerts or notifications should be interpretable by the recipient, while identifying their importance and type of notification. Safeguards are required to ensure timely escalation if an alert is not dealt with in a predefined period of time. In addition, false alerts should be used to retrain the system to limit future reoccurrence. In other words the system should get more efficient over the duration of use.
- **Unobtrusiveness:** Most technologies are considered too intrusive [175]; the use of sensors and cameras within living environments are an example of this and raise both privacy and protection concerns. This often leads to a reluctance to use technology. Although privacy is important to the individual, it is also recognised in legislation and must be considered during the development of any solution. Concerns relating to privacy are one of the biggest limitations in current AAL solutions and directly impede their widespread adoption. Additionally, there should be minimal change and disruption to both the patient and the living environment. As many AAL solutions require the use of wearable or distributed sensors patients often decline their implementation.

3.5 BEHAVIOURAL ANALYSIS AND CONSIDERATIONS

A comprehensive understanding, of both the condition and their associated behavioural characteristics, is essential for remote patient monitoring [176]. This is imperative in determining the diagnosis and enabling an accurate evaluation of any changes. Table 11 highlights the main ADLs and behaviours, which are required for assessing the overall wellbeing of the patient. More specifically, it demonstrates the types of behaviours that can be detected through a patient's interactions with their electrical devices.

Table 11: Important ADLs and Considerations

Behaviour	Description
Eating patterns	For the purposes of detecting abnormal or altering changes in eating habits. These types of behavioural changes provide key indicators regarding the general health of the patient, while providing insights into condition progression.
Sleep patterns	Changes in sleep patterns provide insights into a patient's mental and physical wellbeing. Sleep disturbances are often key indicators for various mental health problems.
Behavioural changes	Provide important indicators for the detection of new conditions, while providing information about the progression of existing medical problems.
Changes in activity	Highlight possible periods of inactivity. These types of changes would require intervention to prevent additional complications and worsening of a patient's condition.
Routine alteration	Is vital for detecting changes in a patient's behaviour The identification of a routine change especially in more serious conditions, such as dementia, can indicate the need for immediate intervention.
Side-effects of medication	Drugs that are prescribed to certain patient groups, such as dementia sufferers, can have adverse side effects which increase a person's confusion. Patients can also be prescribed doses that are too high, or drugs that are no longer appropriate to their needs.

Loss of mobility	People with dementia gradually lose their ability to perform everyday tasks. They usually perform tasks at a much slower rate and are more likely to fall due to a reduction in mobility.

Being able to detect subtle changes early and predict future cognitive and non-cognitive changes facilitates earlier intervention. Often, dementia sufferers in hospital are admitted due to other poor health caused by other illnesses [177].

These illnesses are a result of reduced mobility in the patient. Most commonly, infections cause additional complications and can also speed up the progression of dementia [178]. Additionally, immobility leads to pressure sores, other serious infections and blood clots and an overall decline in their physical condition which can be fatal. With any of these complications, early intervention for both preventative care and early treatment is vital to ensure a good prognosis and safe independent living.

There are a common set of features for Alzheimer's disease and other dementias, which include agitation, anxiety, depression, apathy, delusions, sleep and appetite disturbance, elation, irritability, disinhibition and hallucinations [179]. The severity of each symptom differs at various stages of the disease so any system would need to be fully adaptable to these changes, as patient's progress through the different stages of the illness [180]; particularly, as later stages of the disease are regarded as significant (if not more significant) than earlier stages. Sufferers tend to harbour unique characteristics and events, which occur, affecting the lives of the patients and their carers; so it is essential to categorise these appropriately. Behavioural problems, such as agitation for example, become more pronounced in the later progressive stages of the disease.

Currently, the Mini Mental State Examination (MMSE) is used by clinicians to diagnose dementia and assess its progression and severity [181]. The 6 Item Cognitive Impairment Test (6CIT) is also used for similar purposes. This assessment is undertaken more in primary care due to copyright issues and time constraints associated with MMSE. After a patient's initial diagnosis ongoing evaluation is required. Typically, a patient is reassessed three months after diagnosis and subsequently twice a year. By monitoring a patient's ADLs through smart meter data, there are possibilities for disease progression to be identified much earlier. The characteristics being evaluated would need to change regularly, along with the algorithms used, in order to maintain system accuracy for each stage of the disease. Figure 25 highlights the MMSE in more detail, showing the need for changes in the monitoring techniques as the severity of the disease increases.

Severe depression exhibits many similar behavioural problems as dementia, e.g. memory problems and social disengagement. Additionally, depression can cause physical problems, such as chronic joint pain, limb pain, back pain, gastrointestinal problems, tiredness, sleep disturbances, psychomotor activity changes and appetite changes [182]. These changes can be reflected in how the sufferer interacts with people, their environment and their electric devices.

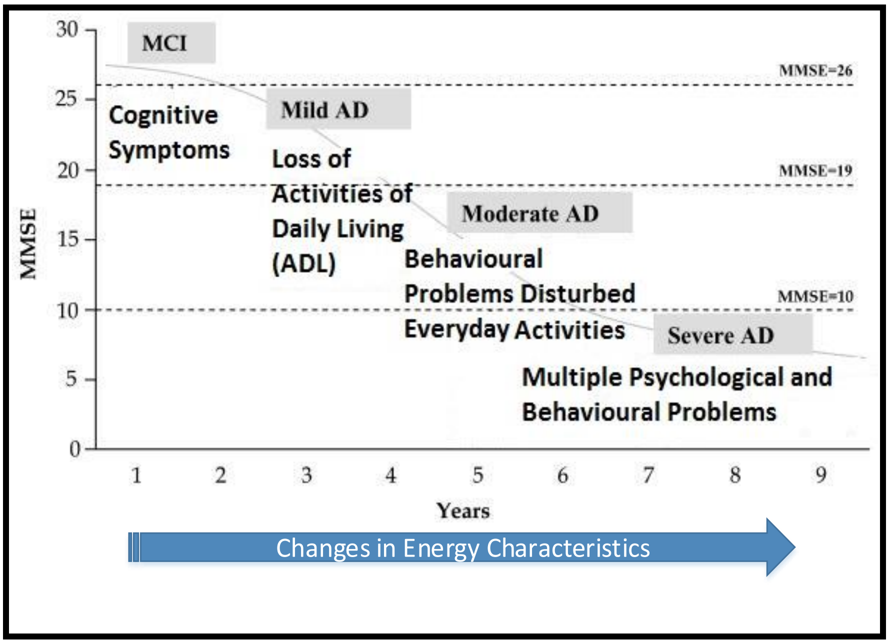


Figure 25: MMSE graph highlighting the various stages of cognitive change

For example, during periods of severe depression, the sufferer may interact less with their electrical devices; they may stay in bed for longer durations (insomnia or hypersomnia) or not cook meals (change in appetite) [183]. Changes in sleep behaviours and appetite are all reflected through energy usage. Such behaviour could be identified for further investigation where appropriate.

Being able to detect any erratic or sudden behaviour change early enables a better intervention process that could lead to an earlier diagnosis in psychosis. Each individual is different with their own set of symptoms and warning signs; however one or more indicators are likely to be evident. Many of these symptoms can be detected in the electricity usage patterns [184]. This includes memory problems, severe distractibility, severe decline of social relationships, dropping out of activities, social withdrawal, isolation, reclusiveness, odd or bizarre behaviour, feeling refreshed after much less sleep than normal, deterioration of personal hygiene, hyperactivity or inactivity, severe sleep disturbances and significantly decreased activity.

3.6 SUMMARY

This chapter, presents an overview of the current assistive technologies at the time of this research and their various approaches. In particular, the chapter focused on smart home solutions, which are deployed within the patient's home to facilitate independent living. It reviewed and discussed the main areas of AAL research, including activity recognition, indoor localisation, sleep monitoring, and fall detection. During the review it was established that current AAL research is not sufficiently focused on solving the most critical problems identified in this chapter. These issues include interoperability, usability, facilitating EIP, reliability, and the quality of the user experience. Most of the research presented deals with the isolated aspects of AAL and patient requirements. As a result, there are limitations and challenges with existing solutions, which means many of them are impractical. Affordability and associated costs with existing technologies mean they cannot be implemented on a large scale. This leaves a myriad of solutions inaccessible to NHS trusts, councils and social services. Often technical solutions are tailored to a specific application and do not meet the ongoing changing requirements of a patient. Current solutions fail to adequately identify trends in behaviour, which may indicate health problems and facilitate early intervention. The proposed solution presented in this thesis is foundational in character. It is a novel never seen before solution for independent living that addresses all of the problems and limitations discussed above that builds on the smart meter rollout, cloud computing platforms and advanced machine learning algorithms to monitor and model a person's routine behaviour in a persons preferred place of care – the home – that provides a real time personalised adaptive health monitoring system.

CHAPTER 4 - PERSONALISED INTELLIGENT HEALTH MONITORING USING SMART METERS

The need to provide a cost effective, non-intrusive and accurate solution leaves existing solutions impractical for widespread deployment. We propose an entirely foundational approach called Personalised Intelligent health Monitoring using Smart meters (PIMS) that facilitates the real time monitoring of routine behaviours exhibited by patients using energy readings obtained from smart meters in domiciliary settings.

4.1. SYSTEM ARCHITECTURE

Upon interfacing with a patient's smart meter, the system operates in three specific modes; device training mode, behavioural training mode and predication mode. The PIMS framework is used to learn a person's behavioural routines around the home. The unique energy signatures for each electrical device are identified in order to establish ADL routines.

Mode 1 (device training): power readings are obtained from the patient's smart meter and are recorded within a data store. These energy readings are used to train the system to identify autonomously the specific electrical devices from aggregated load readings. The training process achieves this using machine learning classifiers.

Mode 2 (behavioural training): data features are extracted for the data analytics involved in detecting abnormal behavioural patterns. The features are used to enable the system to recognise the daily routines performed by the patient, their particular habits and behavioural trends.

Mode 3 (prediction mode): the detection of both normal and abnormal patient behaviours is conducted in real time. The PIMS framework uses web services to facilitate machine to machine communication using a collection of open protocols and standards. During this process, the monitoring application interfaces with a web service to receive real time monitoring alerts about the patient's wellbeing.

Figure 26 provides a high level description of the end-to-end process; starting with the smart meter and ending with the monitoring applications. The processing components in the PIMS framework function exclusively within a cloud infrastructure ensuring scalability and integration with existing services. In order to obtain real time energy readings from the smart meter, the software is deployed onto a CAD, which exploits a local communications protocol to connect to the smart meter infrastructure.

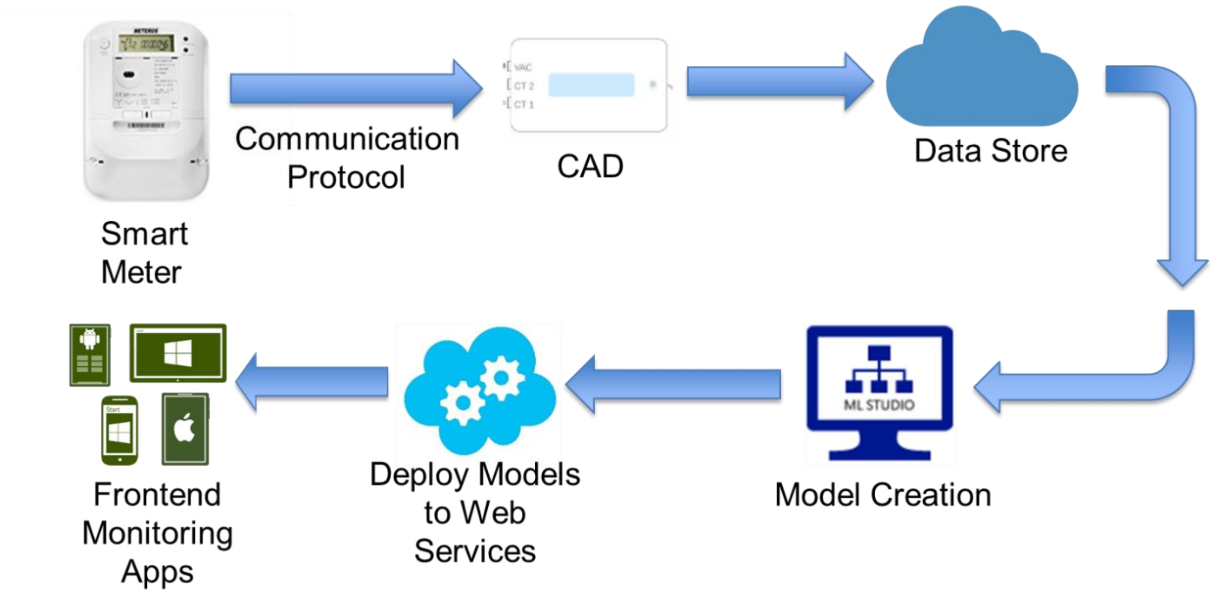


Figure 26: PIMS high level system process

4.2. PIMS ARCHITECTURE AND FRAMEWORK

Figure 27 highlights the system components along with their interactions. The framework is divided into three distinct sections, which reflects the specific modes of operation (device and behavioural training and prediction).

The framework is comprised of three core components, which include the consumer's home, the backend cloud computing infrastructure and the public gateway used by monitoring applications and other third-party systems, such as those provided by the NHS. PIMS offers an alternative approach to patient monitoring which does not require the installation or use of distributed sensors. Here the use of a single on premise CAD provides a comprehensive monitoring solution (you simply turn it on and it pairs with the smart meter using a personal area communications protocol). This is one of the novelties of our approach.

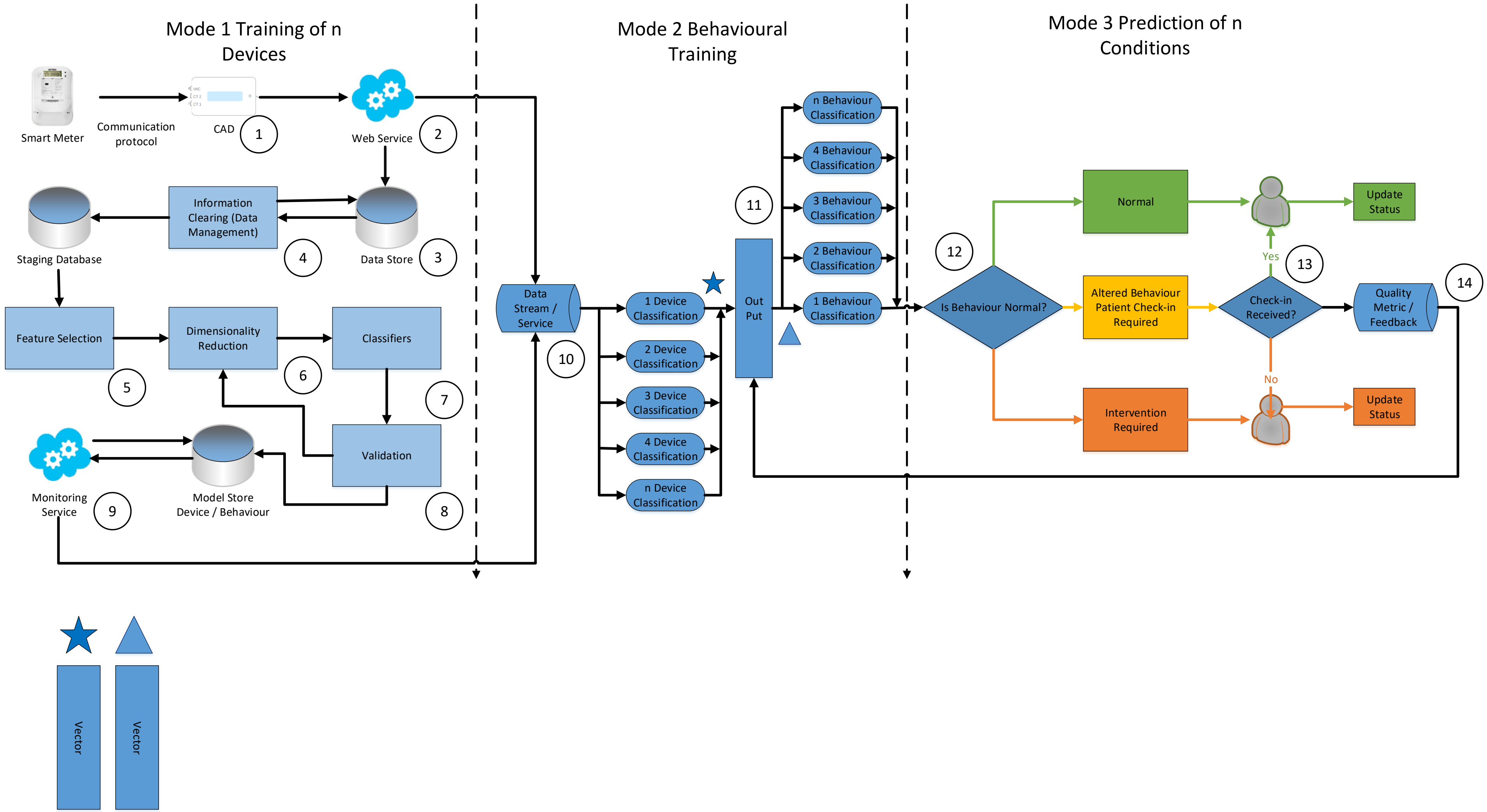


Figure 27: PIMS end-to-end system framework

4.2.1 MODE 1: INTERFACING WITH THE SMART METER DEVICE TRAINING

Figure 28 shows of the PIMS device training mode procedure.

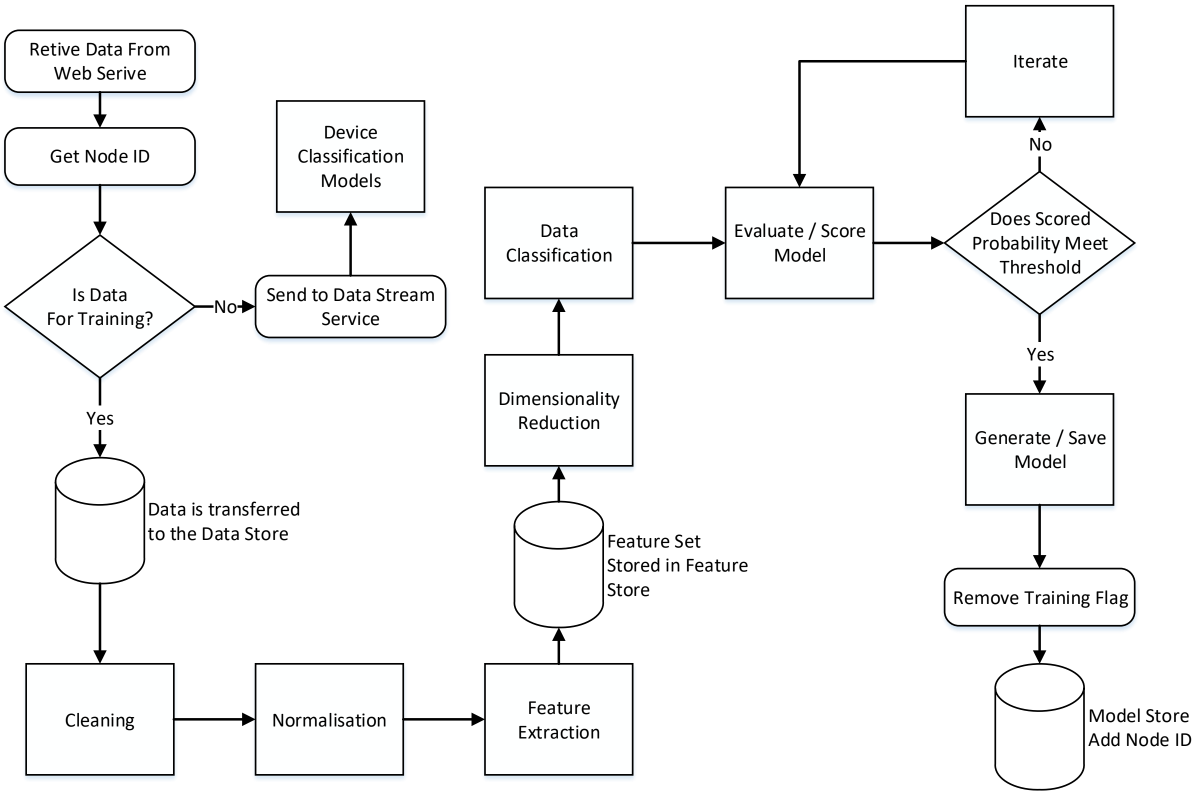


Figure 28: PIMS Training Mode UML

The process starts with the smart meter, which resides in the patient's home. Table 12 highlights example readings obtained from a smart meter at 10 second intervals (the higher data sample rate is achieved using a CAD system). The date time column describes the date and time of the reading while the reading column displays the amount of electrical load in watts (W).

Table 12: Smart meter data sample 10-second intervals

Date Time	Reading
01/03/2016 21:25	1217
01/03/2016 21:25	1224
01/03/2016 21:25	1220
01/03/2016 21:25	1213
01/03/2016 21:26	1147

The CAD securely exchanges data with a smart meter using a personal wireless communication protocol and joins the SMHAN through a predefined paring procedure.

As shown in figure 29, the CAD connects to the smart meter using a remote pairing procedure. Once connected, PIMS accesses the aggregated load readings in real time. Date Time, Energy Usage (Watts) and the Node ID are collected and transmitted wirelessly to the patient’s router using a wireless standards, such as 802.11 or by utilising a wide area networking technology, such as 3G.

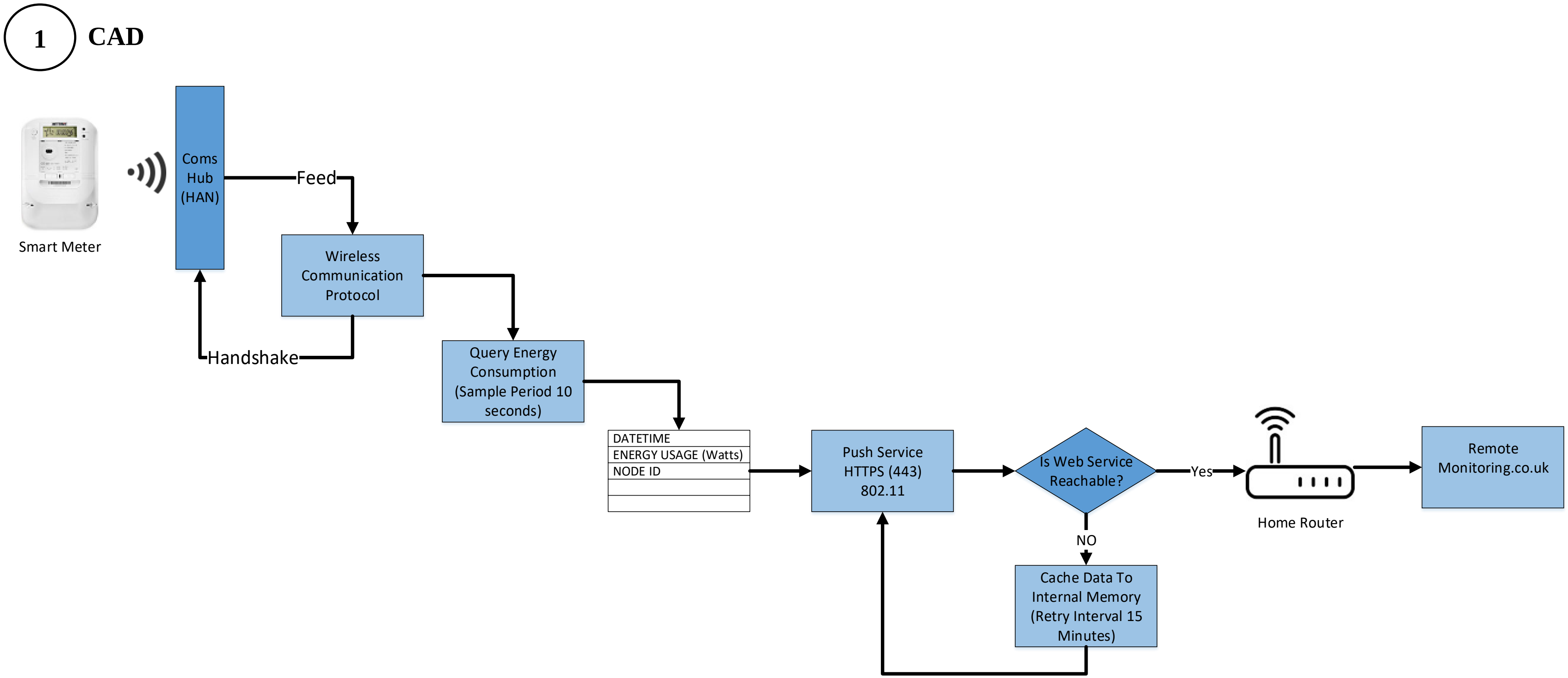


Figure 29: CAD data collection process

Once the pairing process is complete, the CAD deploys a push notification service to transmit all acquired data to a remote web service. If a connection cannot be negotiated, the data is cached locally to the devices internal memory and remote storage is re-attempted using a scheduled task. This ensures that important data is retained in the event of a network outage.

The remote web service, as highlighted in figure 30, is used to collect and process three specific variables from the CAD. They include the date time, aggregated energy usage in Watts and the node ID.

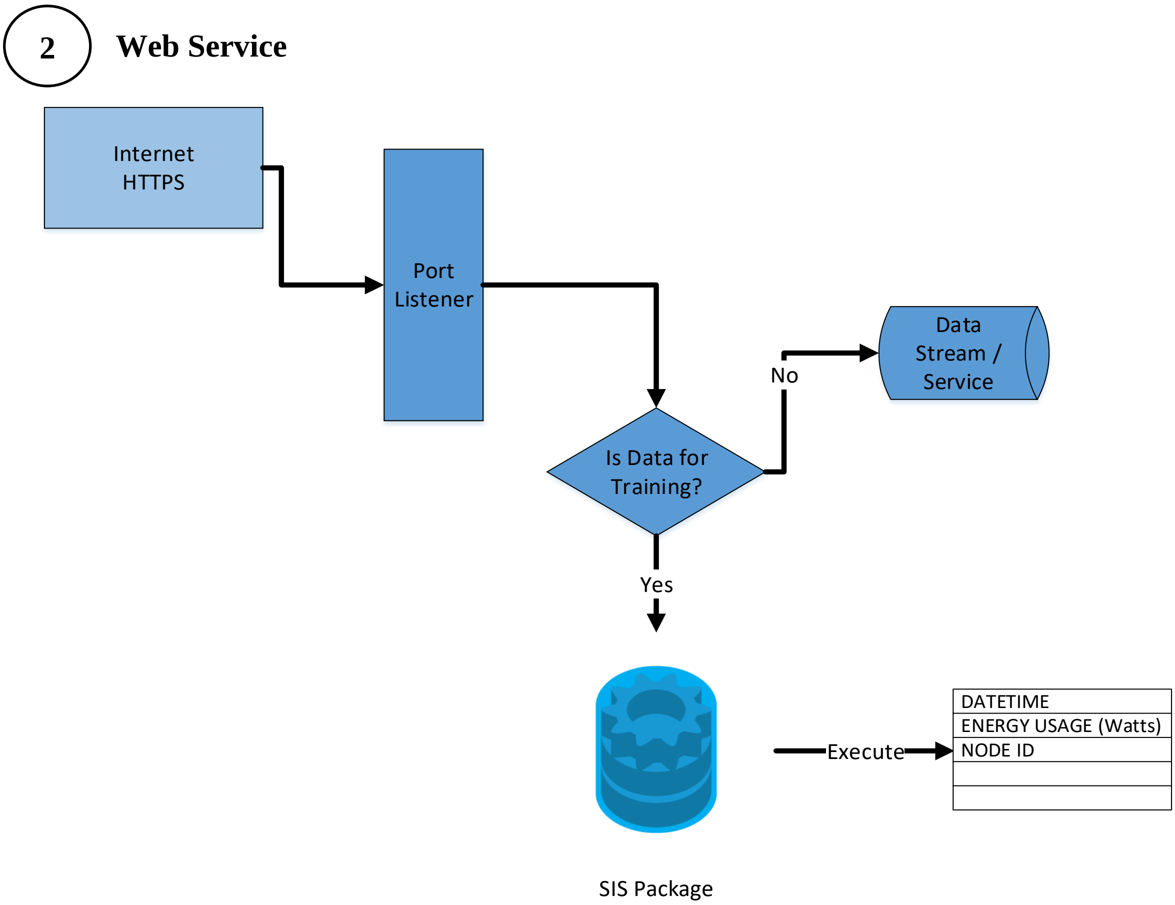


Figure 30: PIMS remote web service

The port listener identifies and responds to incoming requests that use protocols such as HTTPS and their associated port numbers. If the system is operating in training mode, the data is processed and sent to the data store. The web service checks the node ID and an associated flag to determine if the data collection process should be undertaken for training, or if the data should be processed by the data stream service. This verification process is highlighted in figure 31. All new nodes are automatically flagged for training but can be manually reset should the need occur.

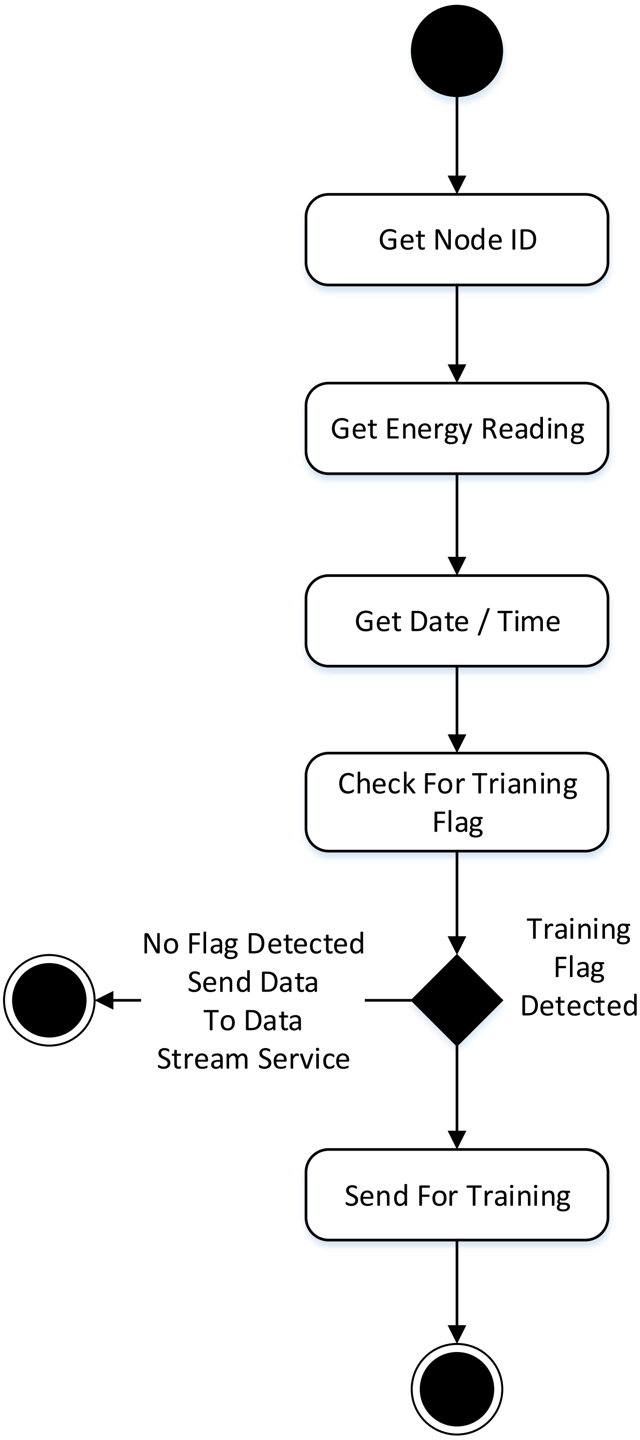
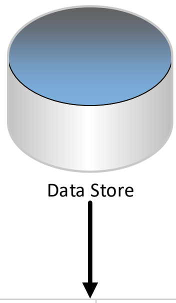


Figure 31: PIMS Training verification process

Here the data is collected over a predefined period, for example a week or month and is highlighted in figure 32. The period required alters depending on the application, condition and the category of electrical devices. Alternatively, if the system is running in prediction mode the data is transmitted to the data stream service, which is analysed by device classification models.

3 Data Store



DateTime	Reading	Node
01/03/2016 21:25	1217	Node 5
01/03/2016 21:25	1224	Node 5
01/03/2016 21:25	1220	Node 5
01/03/2016 21:25	1213	Node 5
01/03/2016 21:26	1147	Node 5

Figure 32: PIMS data store

Any data that is obtained from the smart meter requires pre-processing before feature extraction can occur. These processes are undertaken by the information clearing component, which is highlighted in figure 33. The system starts the data preparation process by retrieving the energy usage data from the data store.

In order to achieve a classification result the selected training data is cleaned, as highlighted in figure 33. This process starts by removing any missing or null values, as most algorithms are unable to account for missing data. Here the system deploys statistical replacement where any missing values are identified. Alternate values, such as median or mode replace any missing values [185]. The data cleaning process also provides an opportunity to exclude attributes, which are not required for classification. As highlighted the data is normalised to maintain the general distribution and ratios, ensuring that it confirms to a common scale. Example methods include: Zscore, MinMax and LogNormal [186]. The processed data is then written to a database.

4 **Information Clearing (Data Management)**

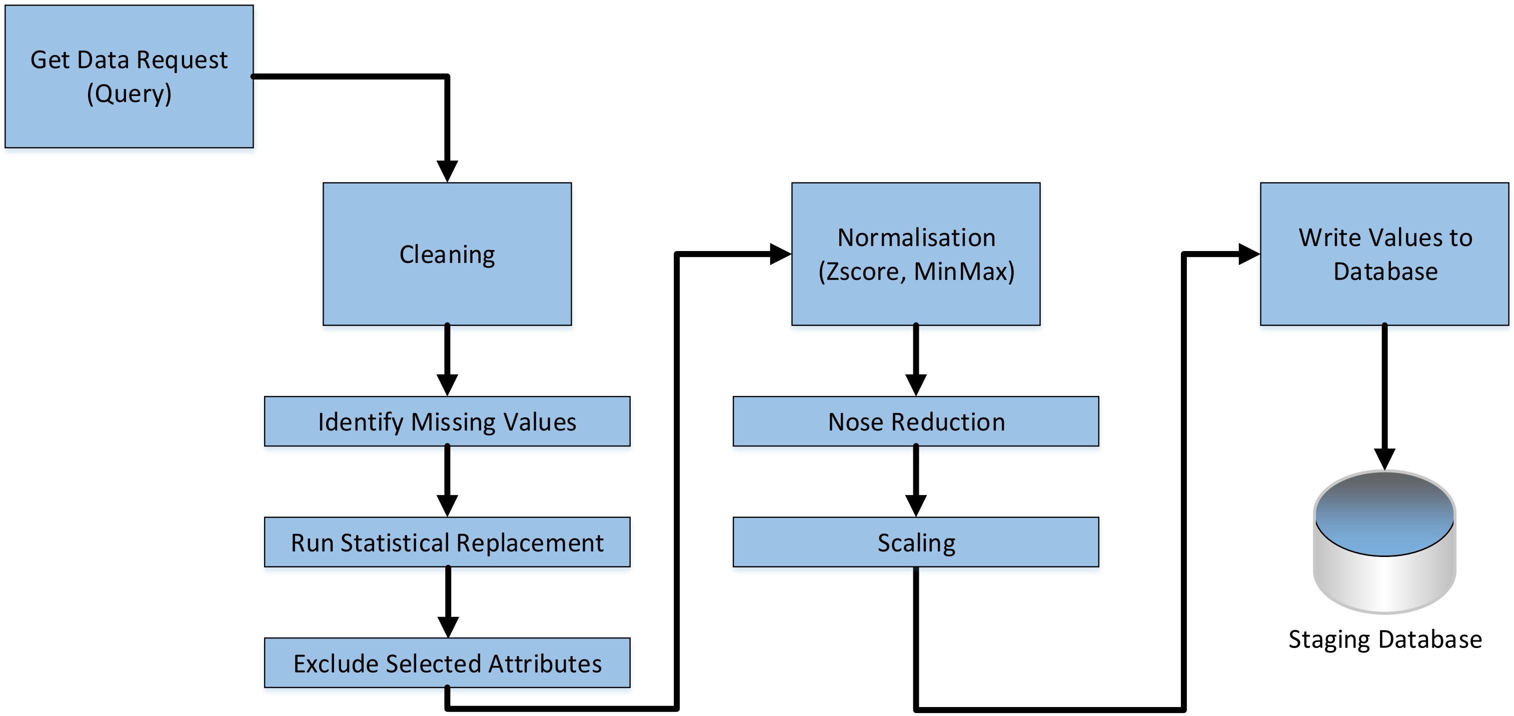


Figure 33: PIMS information clearing (data management)

Once the data cleaning stage is complete, the processed data is retrieved from the staging database for the feature extraction process. During the training mode, features of the data are extracted, which in later stages form feature vectors. Features are given aspects of the data, which provide an overall representation of the unique electrical signatures for each appliance type. Training data can be enhanced by the extraction of features from the raw dataset as they increase the efficiency of the training process. During the extraction process, statistical calculations are performed against each of the designated observations.

As highlighted in figure 34, each reading sample is assigned an ID and labelled '*ready*' for classification. During this stage the features for each device are extracted and placed into a data store. This process uses unique features that support device identification, which include energy, power and consumption levels. The system then extracts more complex features from the data such as min, max, mean, mode and standard deviation.

During training mode, the system deploys dimensionality reduction to improve the classification process while reducing the likelihood of overfitting. Figure 35 schematically illustrates this process. To ascertain the optimum features and the optimum variance for the classification, the method used depends on the distribution of the data, for example Linear Discriminant Analysis (FLDA) or Spearman Correlation. Dimensionality reduction is an essential requirement for the identification of specific electrical devices from within aggregated load readings. Figure 36 highlights the classification process. The appliance identification models are created using the processed training data. Supervised learning algorithms make predictions based on a set of training examples. Each example (observation) used for training is labelled to represent each appliance category enabling the algorithm to look for particular patterns in data. For appliance identification, a multiclass classifier is deployed. For behavioural classification, there are only two choices either normal or abnormal for the label. As a result, our classification is a two-class or binomial classification problem. After the algorithm has identified a candidate pattern, it compares that pattern with unlabelled test data to make predictions. All classification experiments are run against the test data set over thirty iterations. Each of the classifiers' predications are noted for the validation process.

5 Feature Selection

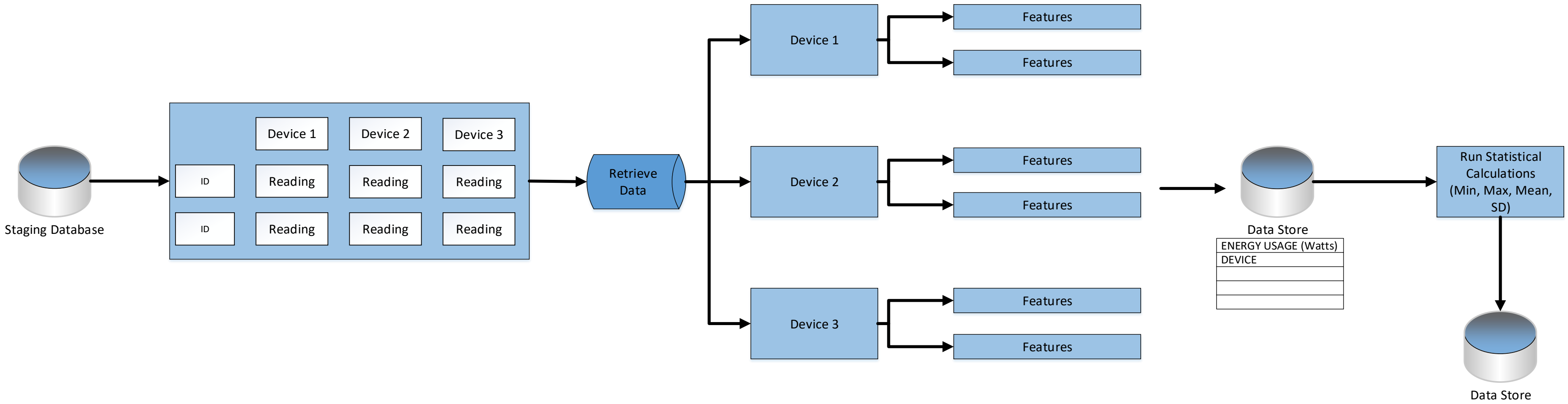


Figure 34: PIMS feature selection

6 Dimensionality Reduction

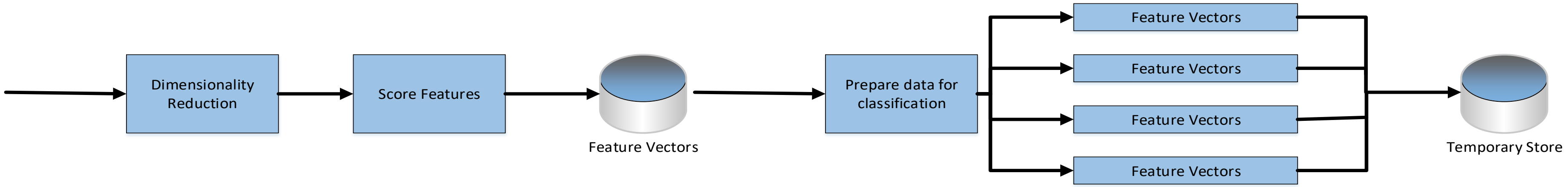


Figure 35: PIMS dimensionality reduction

7 Classifiers

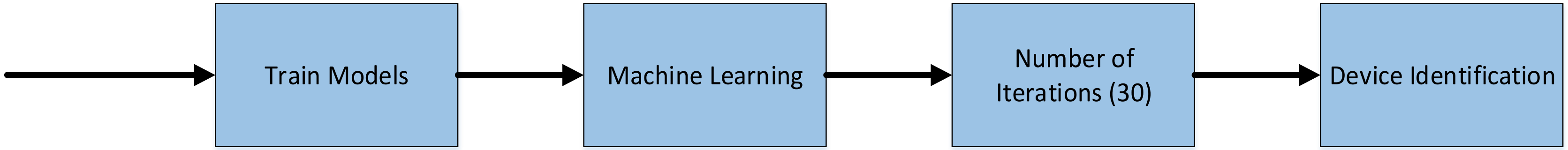


Figure 36: PIMS classification process

Figure 37 highlights the validation step, which is used to access the performance of the model.

The process is iterated to find the optimum model for each electrical device. As highlighted in step 8 in figure 37, the system determines whether the overall accuracy of the model is acceptable for the system. This is achieved by scoring and evaluating the model using mathematical techniques such as calculating the sensitivity, specificity, accuracy and error rate. If the minimum threshold is not met, the system selects new features to try and improve the classification result. If the score exceeds the minimum threshold, the model is stored in the model store for use in production by the real time data stream service.

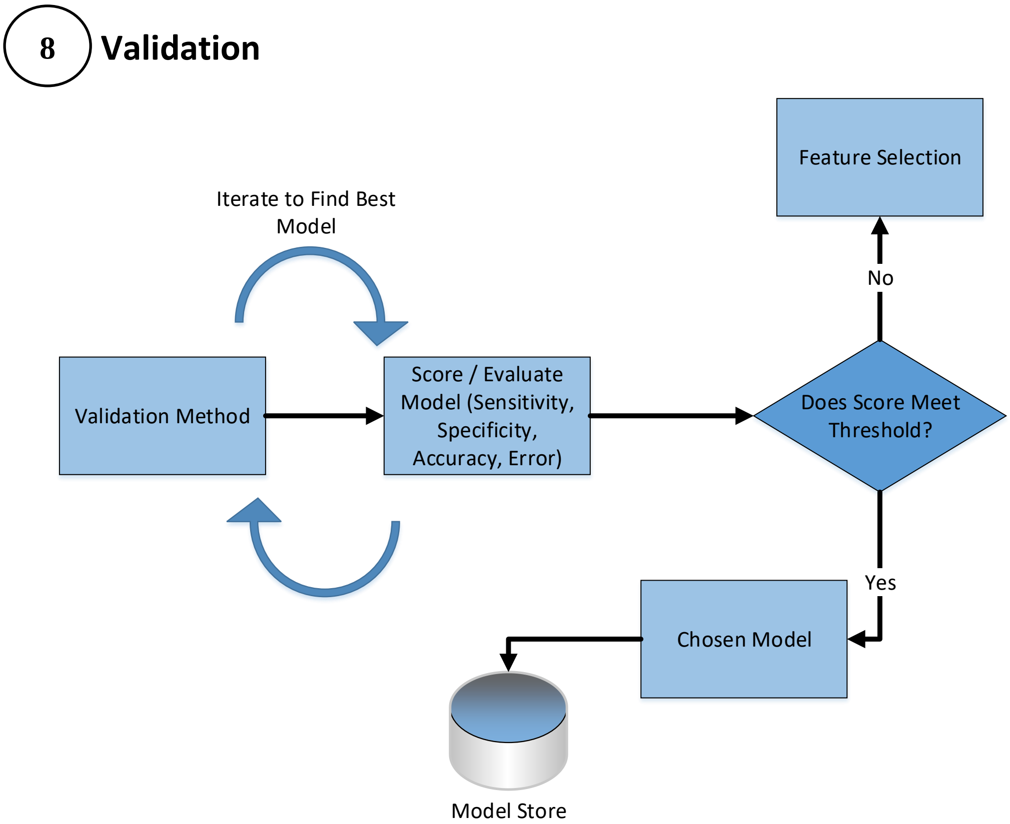


Figure 37: PIMS validation process

Figure 38 shows the validation process in its entirety. Once the classification meets or exceeds the validation threshold it is assigned a unique model ID, API access key and paired with the node ID for future prediction. Once these stages are complete the model is sent to the model store which can be accessed by the web service.

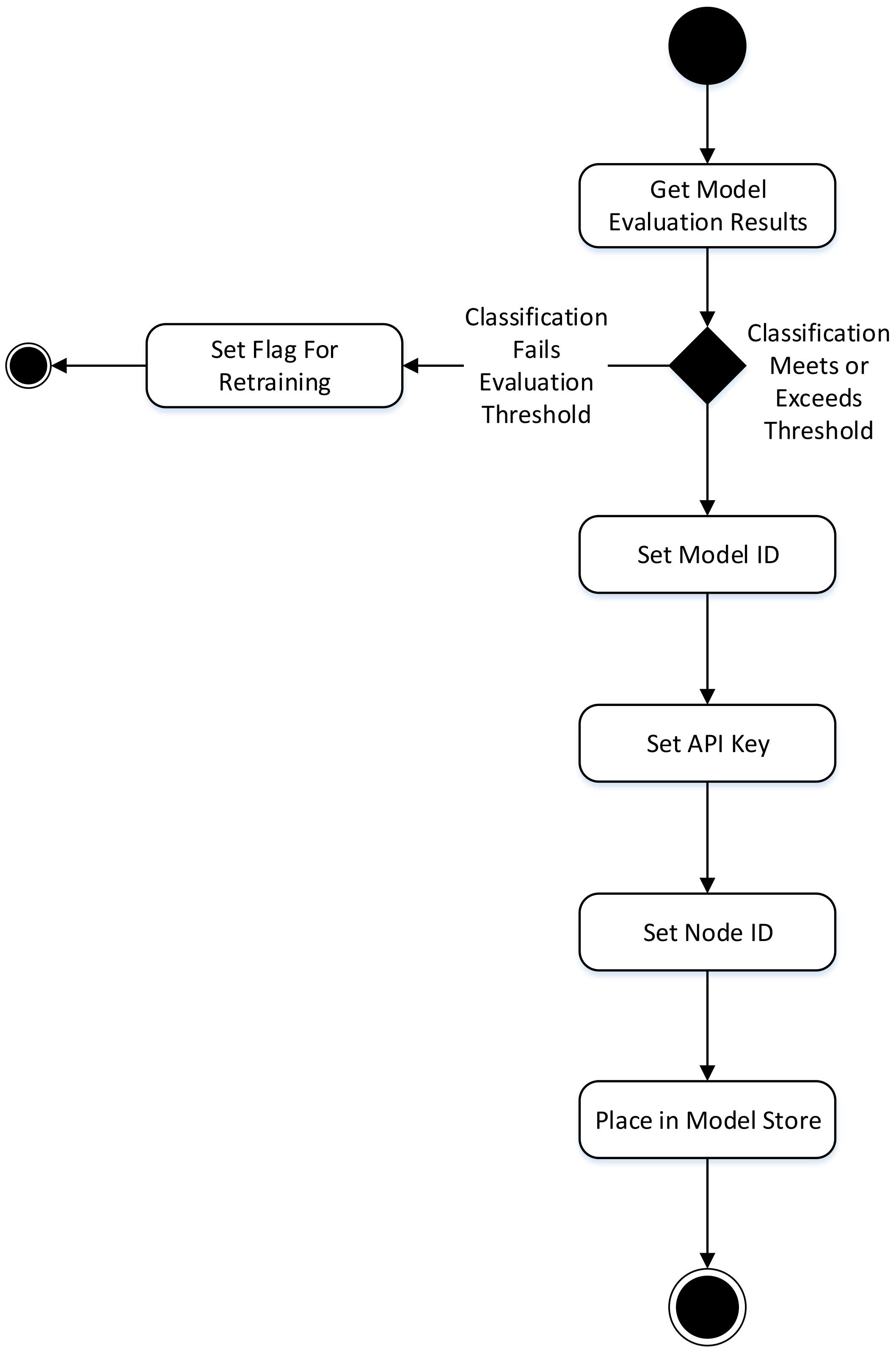


Figure 38: PIMS Model validation and generation process

Once the device classification models are generated, the next stage is to ensure that they are accessible to the data stream service. Figure 39 highlights the operations undertaken in the web service, which facilitates the exposure of the models' functionality. Specifically, an API communicates with the device classification model and configures the input and output schema for the service. The API exposes both a synchronous service for single requests and an asynchronous service for handling multiple requests.

As highlighted in figure 39 the service provides the following three parameters:

- The web service address, which enables access to the real time data for assessment. This is achieved by invoking the web service and sending the output data to operation 10 in figure 41.
- An API access key is generated and used by the CAD to access the models. The access key is a unique security identifier and must be presented on every service request to authenticate the caller. Using an access key not only improves the security of the system but also ensures that the CAD is accessing the correct models.
- Input / output schema, here the web address provides information on the input and output parameters, which include all of the variables and their associated data types.

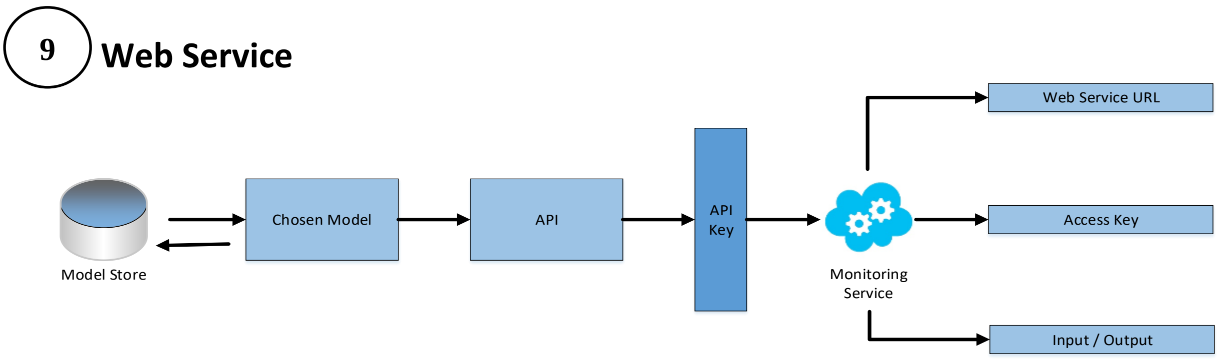


Figure 39: PIMS web service

Figure 41 highlights the data stream service, which is used to facilitate the integration of live data and the trained device identification models. This is achieved by exploiting the web service APIs previously discussed. Data describing energy usage is received from the patient's CAD. Data is only sent to the data stream service if the web service does not detect the presence of a training flag. Here the data is sent to the monitoring service URL using web protocols. Web based protocols, can be utilised for querying, updating and exposing data using a standardised syntax. Once a connection is made using web protocols, the service requests the headers. These headers contain the information regarding the content and datatypes expected by the web service. The body provides the exact input format, data columns and values which is passed to the monitoring service for prediction to occur. In order to correctly structure the data for the input parameters the web service contains a feed parser. Figure 40 highlights the process starting with the obtained data and ending with the parsed feeds.

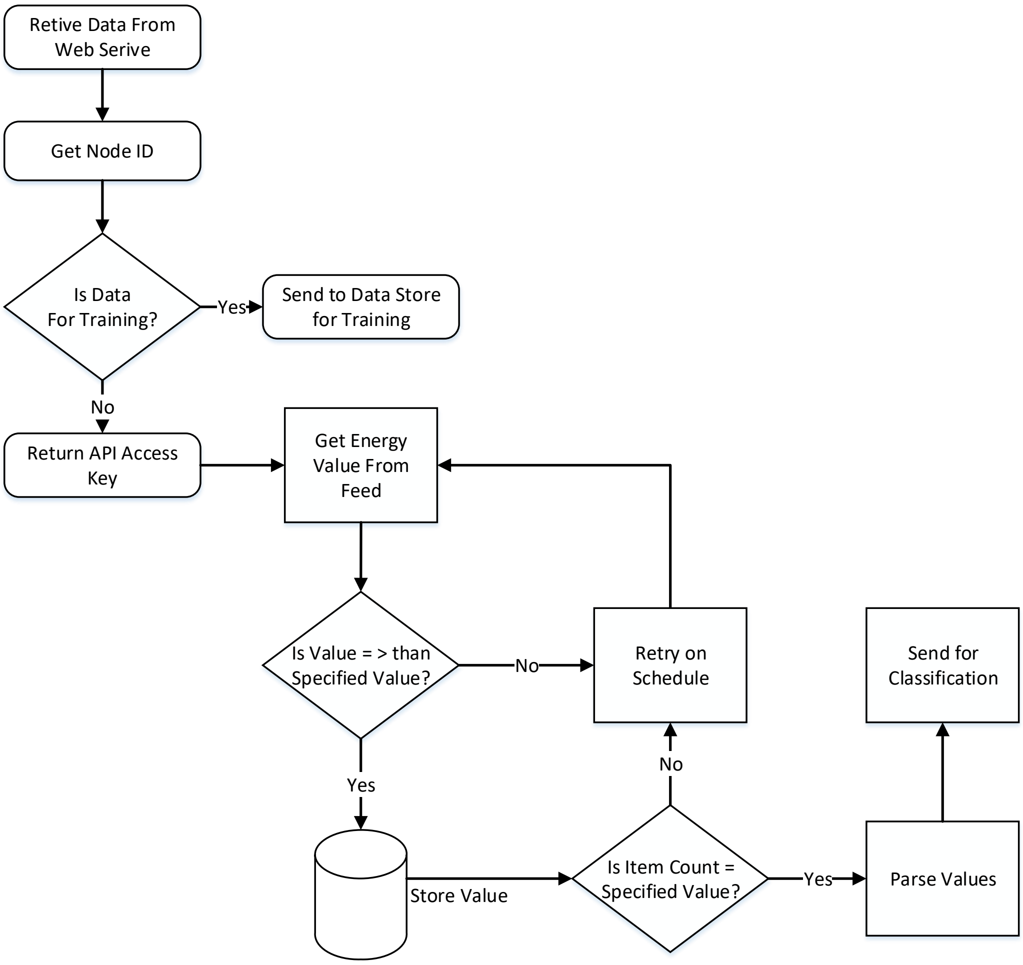


Figure 40: PIMS Web Service Feed Parser UML

As the service is required to be scalable to cater for multiple patients, the monitoring service is housed behind a load balancer. The header and body are sent and the service checks for a successful response code. If an error code is returned, it is transmitted to the web service and logged for investigation. If a successful code is returned, the data is transmitted for use in the device classification, as highlighted in operation 11 in figure 42.

10 Data Stream Service

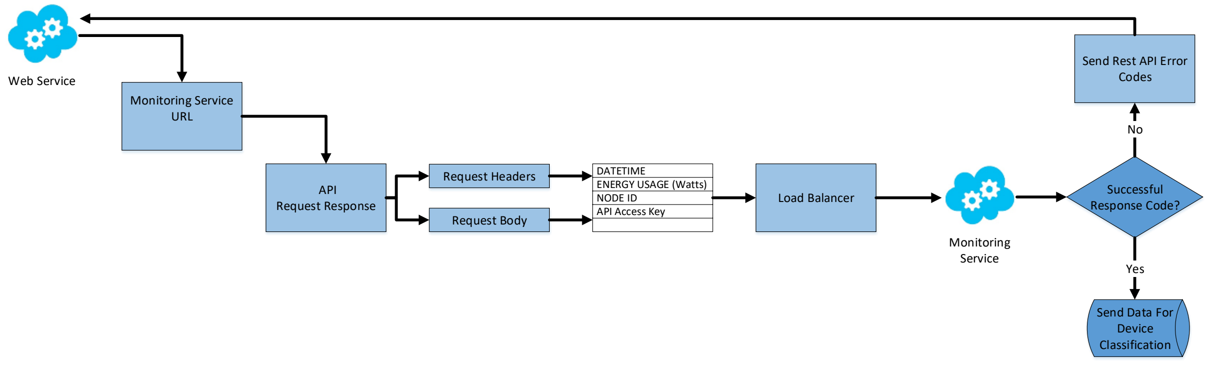


Figure 41: PIMS data stream service

In the next stage of the process, the system identifies specific electrical devices from the aggregated load readings. Figure 42 highlights the device classification process in detail. Here the aggregated load readings are obtained from the web service and passed to the classification models. The system identifies the individual electrical device patterns from the aggregated readings by predicting the device class. The system makes a prediction by using the trained device classification models.

The model is individually scored, providing the numerical probability (likelihood) of the class predication. The models prediction is examined by assessing the scored probability to ensure that it meets a minimum threshold. This ensures that the accuracy of the system and any information that is passed to the monitoring apps is accurate. Setting a probability threshold introduces a safeguard, which is vital for clinical decision support. If the probability score is below the expected threshold, the predication is rejected by the system.

Individual device detections are stored as feature vectors for use in the behavioural classification process. Here the predicted class is assigned a unique device ID for each appliance class. Each of the various device IDs are stored in the parameter ID database. Once the ID is assigned to the class prediction the device features are stored in the feature vectors store. These are later used to perform the correlation between expected user behaviour types and device behaviour patterns.

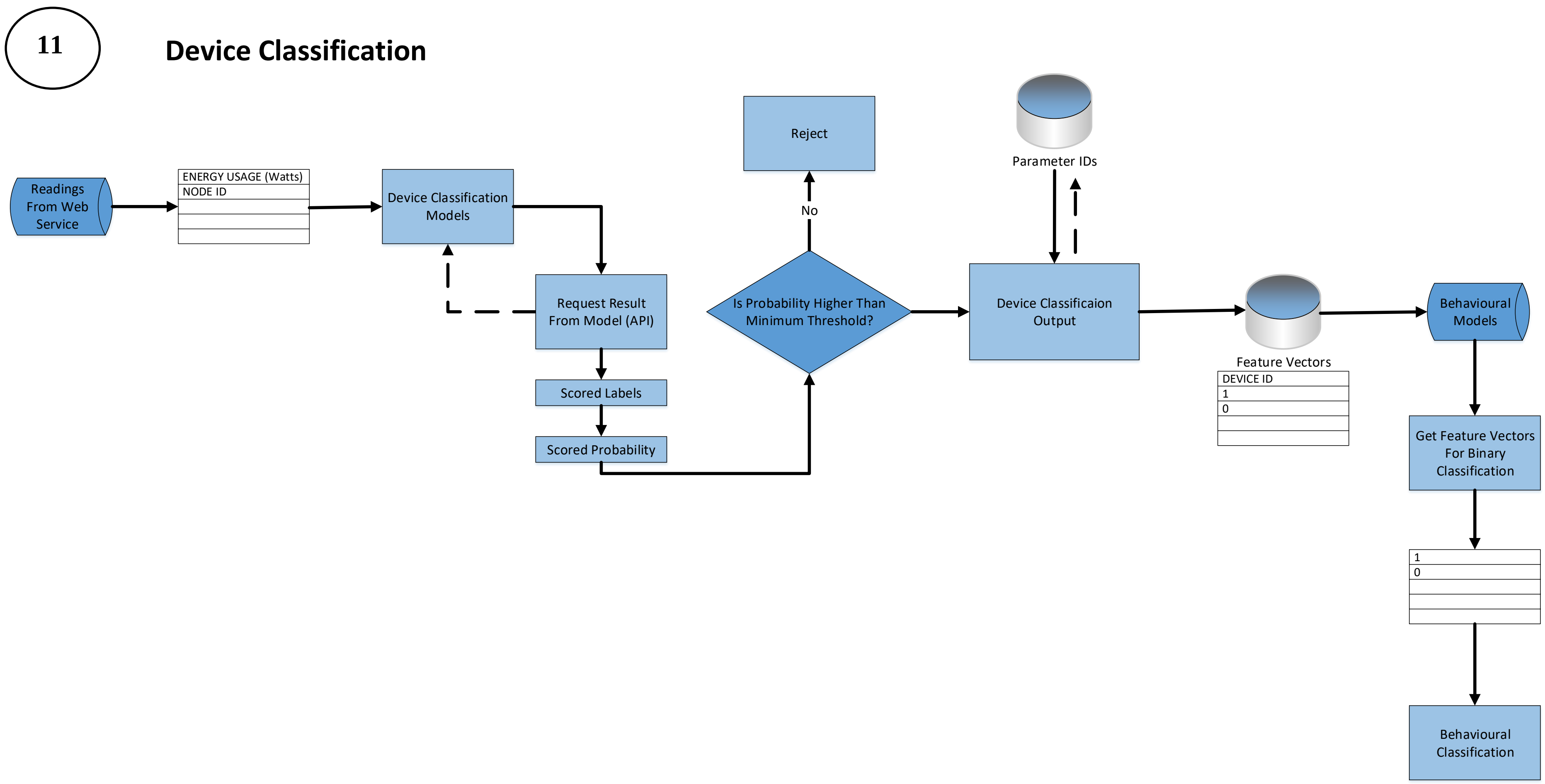


Figure 42: PIMS device classification

Figure 43 highlights the process for generating the vectors for the behavioural classification stage. Here each of the identified devices are labelled with a unique ID which corresponds to a specific device class for example: kettle (1), toaster (2) and microwave (3). Each of the individual predictions are assigned a date time value and placed in a data store for the behavioural models.

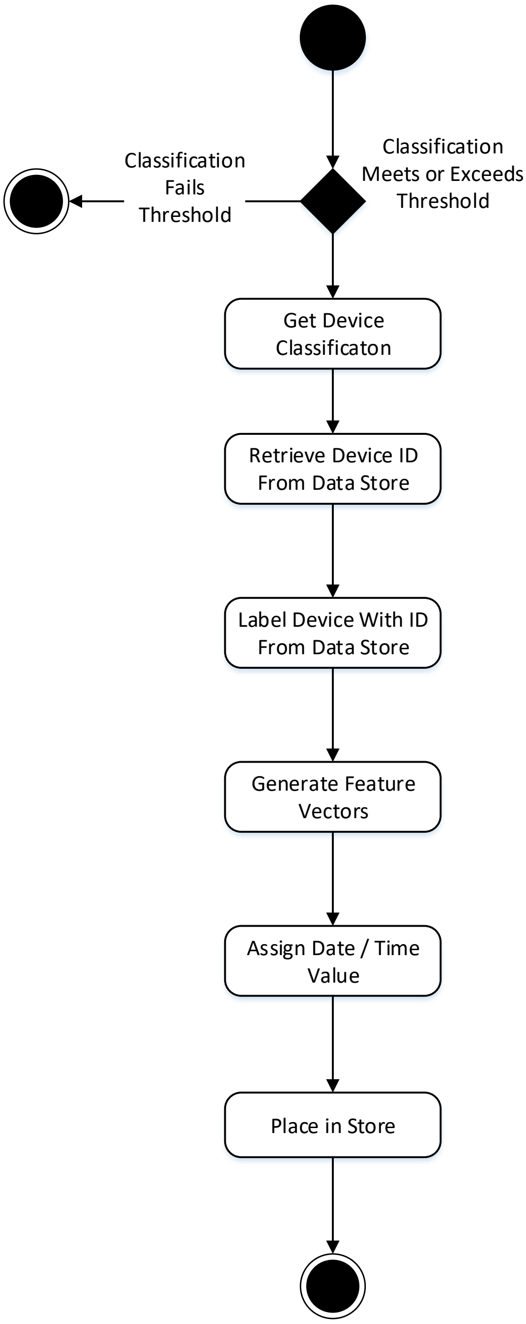


Figure 43: PIMS device feature vector generation

4.2.2 MODE 2: BEHAVIOURAL ANALYSIS

During mode two (behavioural training), the patient's behaviour is assessed, which enables PIMS to make a decision about the patient's welfare. During this process, a decision is made based on aspects of the patient's routine. A person's routines are blueprints of behaviour, which influences every aspect of their life. Usually routines are not fixed and can fluctuate and are regarded as normal. Figure 44 highlights the parameters that are presented to the behavioural models for behavioural analysis. Firstly, *P* represents the specific devices being used; here a unique value is assigned to the identified device. Secondly, *t* represents the time of utilisation, which is required for identifying unusual behaviour or a deviation from a patient's normal routine. *wd* records the day of the week, enabling the algorithm to construct detailed knowledge concerning the unique routines of the patient. *c* denotes the combination of devices over specified time periods e.g. hourly, morning, evening etc. Identifying normal device combinations provides insight to both the mental and cognitive functions of the patient.

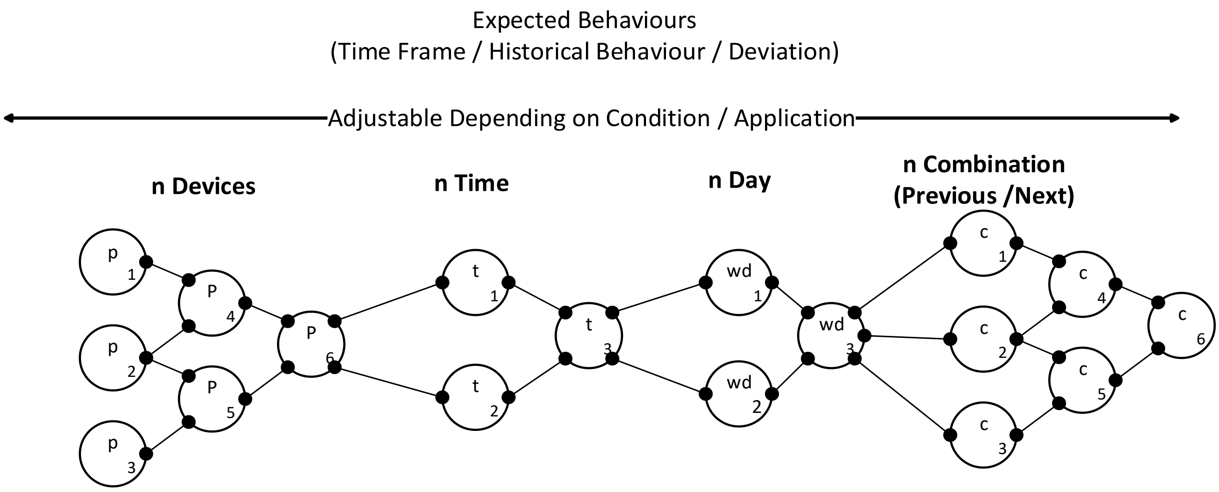


Figure 44: PIMS behavioural process

Table 13 highlights the different features that are assessed by the behavioural models. The types of devices and behavioural characteristics, which are considered key for patient assessment, are also shown.

Table 13: Behavioural features

Feature	Description
Device Usage (Activity)	Type of Device {Kettle, Microwave, Oven /Hob, Toaster, Washing Machine, Dryer, Dishwasher, Shower, Vacuum, Television, Computer, Radio / DAB, DVD / Blu-ray, HI-FI, Phone Charger, Lightings}
Time	Time of Activity {Time of Device Integrations}
Day	Day of the Week {M, T, W, TH, F, SA, SU}
Device Combinations	Devices used in combinations

The system categorises routines by determining the specific series of actions undertaken by the patient over a specified time period. This process is displayed in figure 45. Routines are stored in behavioural logs, which are converted into sequences of events. The system deploys the use of *T*-pattern analysis in order to obtain the temporal structure of the behaviour but also to generate a hypothesis regarding observations. The *T*-pattern represents the '*well-known characteristics*' of the behavioural patterns, which are extracted from the behavioural logs [187].

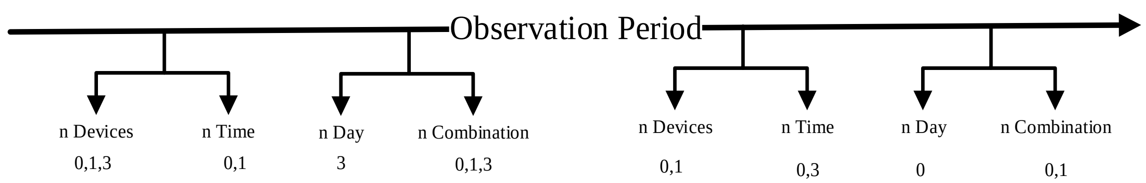


Figure 45: Discovering routines

This approach caters for patient personalisation. The behavioural classifiers take into account the unique characteristics of the patient and their particular routines. Different people develop their own distinctive routines and habits to deal with their individual situations. The timeframe and system parameters are adjustable based on the condition or application. More severe or later stages of a condition might require more finite monitoring. For example, the monitoring of depression requires the ability to monitor specific times; the evenings for detecting sleep disturbances.

The observation window can be adjusted based on the patient and condition while identifying abnormal behaviours. Additionally, it enables the PIMS framework to construct a personalised representation of the patient, as device usage can be assigned to specific observation windows. This approach improves the probability of identifying routine and behavioural alteration. Figure 46 highlights the 7 distinct observation windows for each 24 hour period. Here the individual values for each period and device class are displayed, which are used to generate the features for the behavioural classification models.

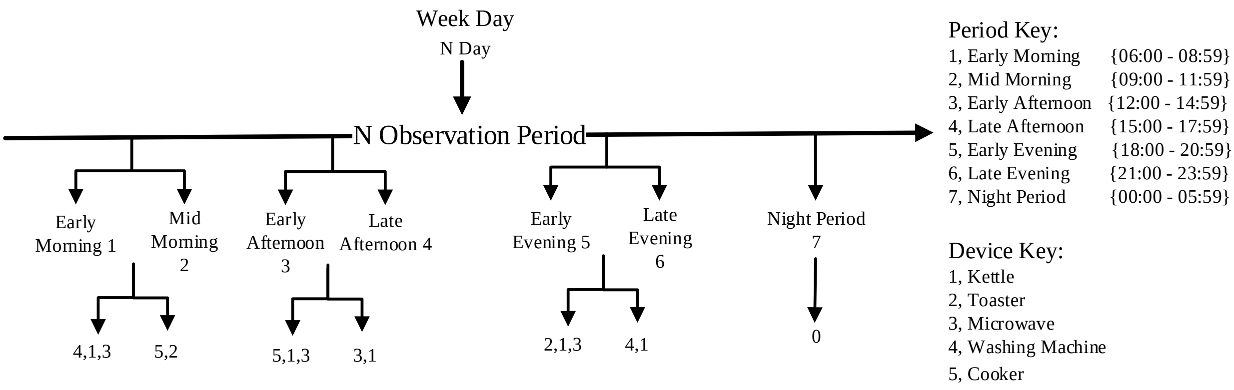


Figure 46: Behavioural observation construction

Figure 47 highlights the PIMS behavioural training process. Here the API access key from the device classification mode is sent to the web service. The service sets the period key as shown in figure 46 based on the selected monitoring window. The system checks for the presence of a training flag in a similar manner to that of the device training mode. If a training flag is absent the vectors from the device classification model are retrieved from the data store and sent to behavioural models for prediction. The date time stamps are verified to ensure the detected appliances consists with the selected monitoring window.

If a training flag is present the vectors are retrieved from the data store and labelled as normal or abnormal by either a clinician or carer. Once the labelling of the vectors is complete the behavioural classifiers are trained and validated using techniques such as K- Fold cross validation. The CAD node ID is assigned to the model and placed in the model store. Finally the training flag is removed to ensure new data is automatically sent for prediction.

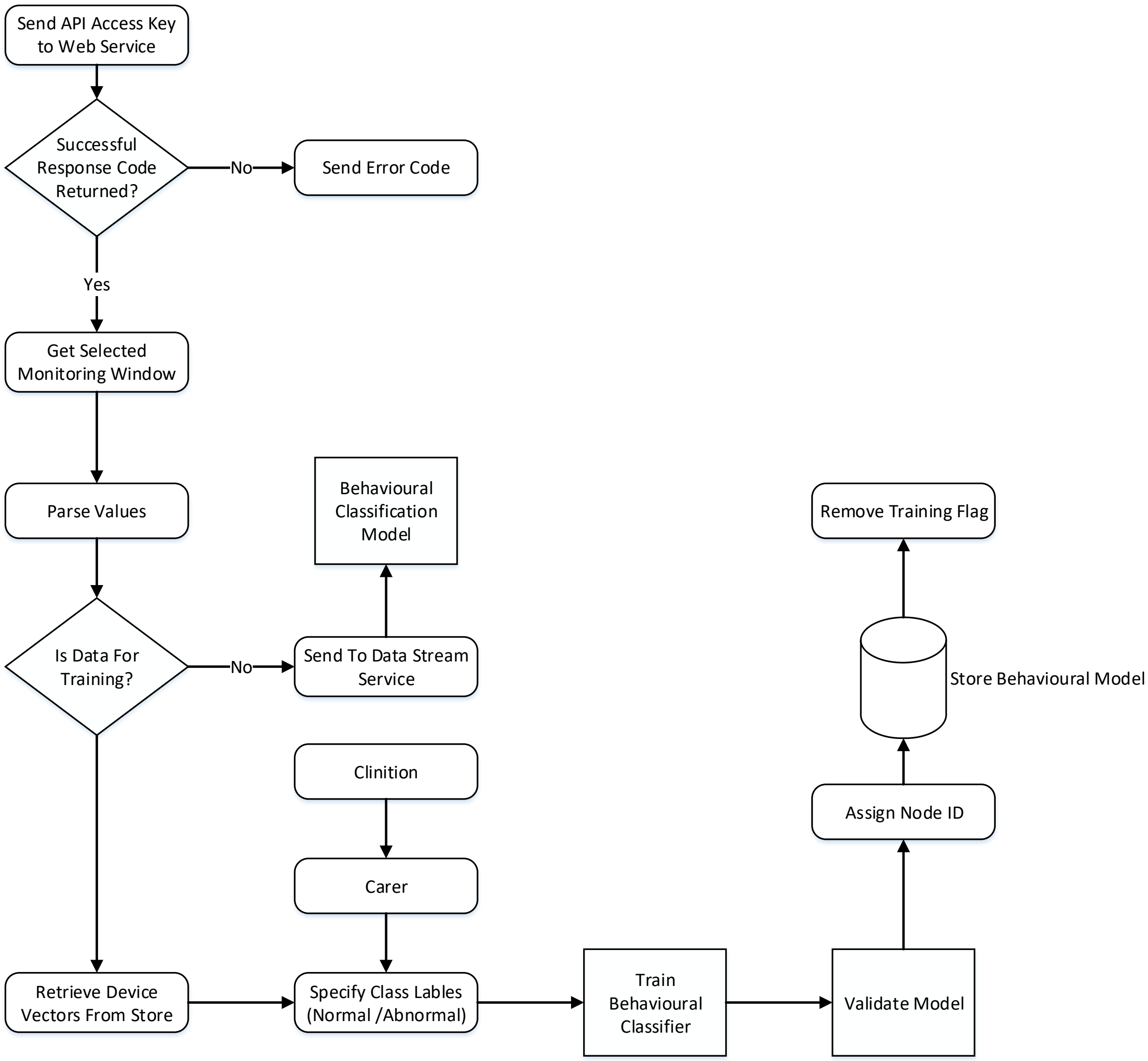


Figure 47: PIMS behavioural training

4.3 PREDICATION MODE ALERT PROCESS

In order to achieve a successful prediction, both the device classification and behavioural models are required to work in conjunction. The generated vectors from the device classification models are presented to the behavioural classification models to ascertain if the observed behaviour is normal or abnormal. Figure 48, illustrates this process.

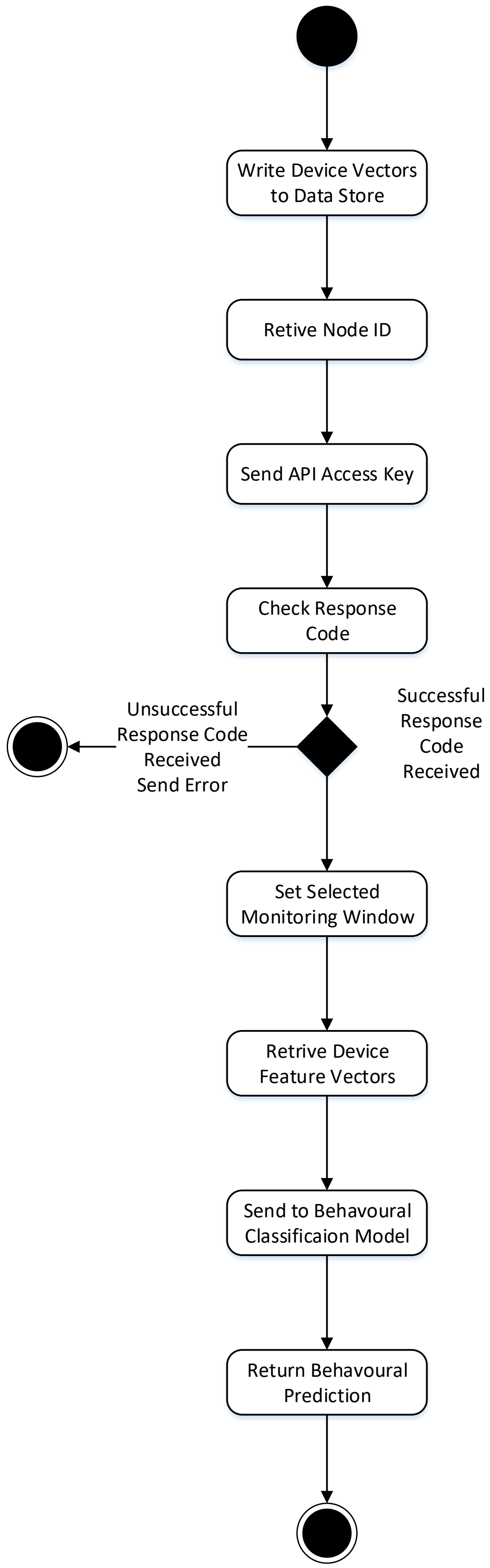


Figure 48: PIMS device and behavioural model interaction

During prediction mode, the PIMS framework formulates a decision regarding the patient's wellbeing. This is achieved by analysing both the device usage and behavioural features from the first two modes of operation. In step 12, as highlighted in figure 49, a binary classifier establishes the patient's behaviour. By exploiting the trained classifiers and the generated model, the system automatically detects both normal and abnormal patient behaviour in real time using web services. Where appropriate, the system alerts the patient's support network to a potential problem, if one is detected.

In the first instance, the system can be configured to alert the patient to check in, by performing a specific device interaction, as highlighted in step 13. This feature enables the system to reduce any possible false alarms and verifies that the patient requires no further assistance. However, this function largely depends on the type of condition being monitored and might be deactivated where it is believed to be unsafe or where a patient is deemed unable to interact. The system identifies if interaction has taken place; if not, an alert is communicated to a family member or a third party health care practitioner as highlighted in figure 44.

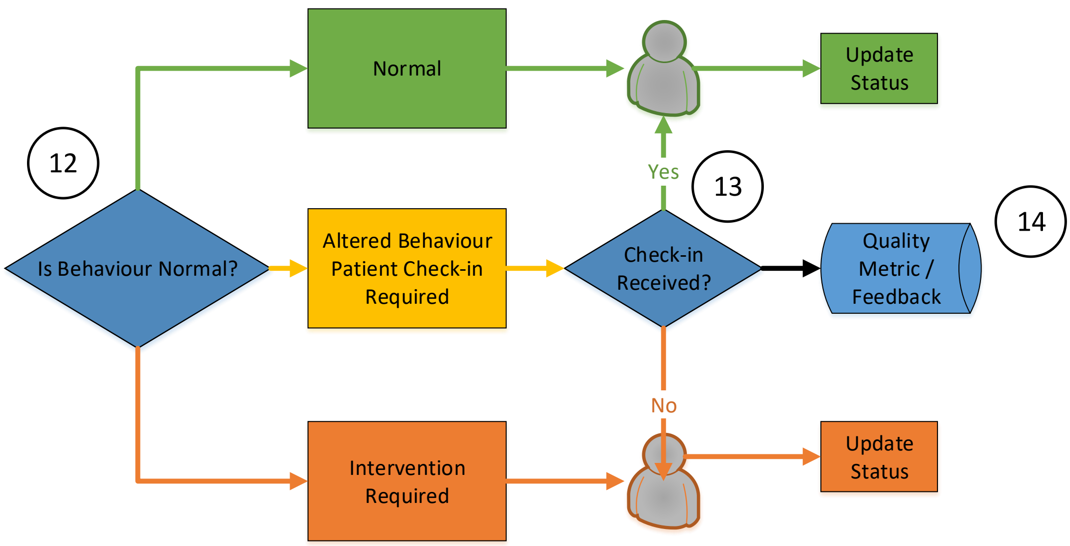


Figure 49: PIMS predication mode and alert process

The system also supports a sleep function, which deactivates the process and can be enabled from the monitoring application. This can be used if the patient is away from their premises for long durations, such as being on holiday, and reduces the likelihood of false alerts.

In order for PIMS to alert the registered user, a monitoring app communicates with the PIMS web service by utilising technology such as a Representational State Transfer (REST) API.

REST web services require low resources, are highly scalable and are commonly used to create APIs for web applications. A REST API facilitates the integration of multiple programming languages and platforms. Essentially, each app uses the same API to obtain, update and manipulate data, which ensures compatibility with existing services. By making use of a compatible API, the PIMS framework can be integrated with existing third party services, such as NHS services. Figure 50 illustrates the integration of the services with the PIMS system.

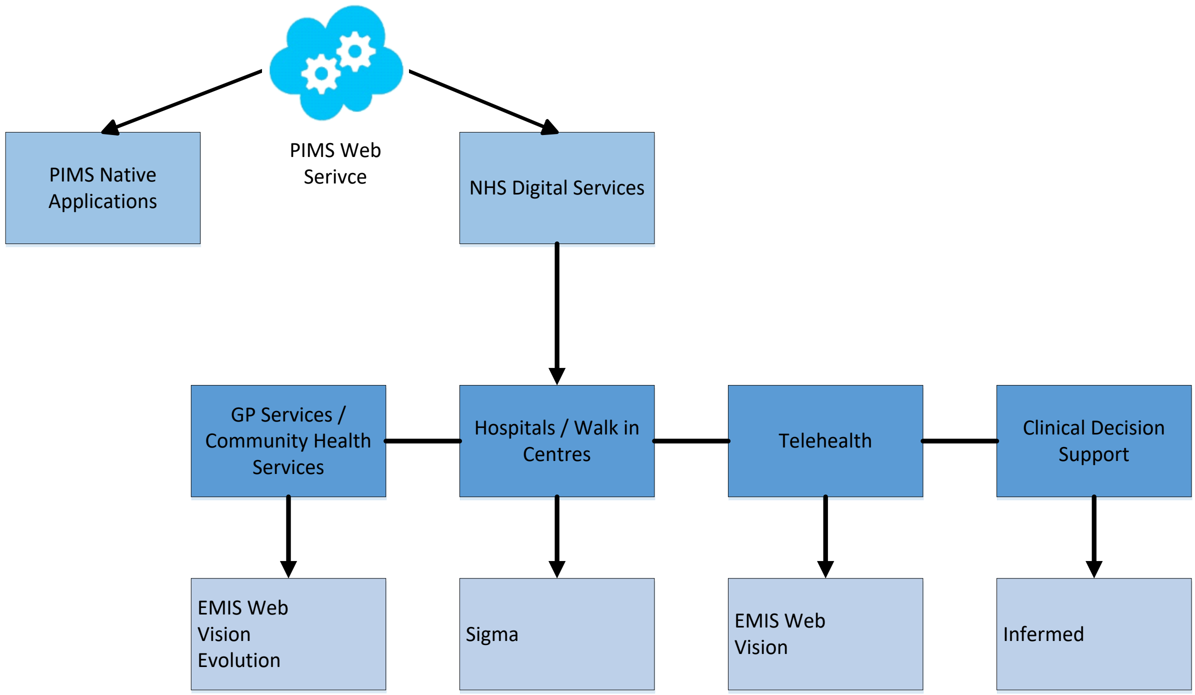


Figure 50: PIMS web service for integration with NHS Digital

Here the PIMS web service can expose model functionality to both native apps (ones which are specifically developed for the PIMS framework) and a selection of current digital services. Figure 51 highlights how the data supports different monitoring applications from within existing services.

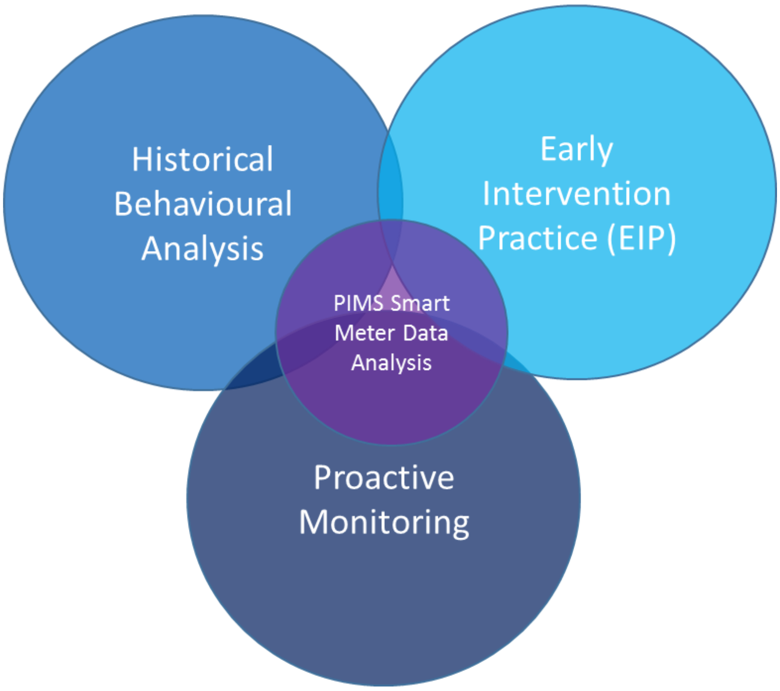


Figure 51: PIMS data analysis applications

To ensure that the system is adaptable and self-learning, a quality feedback metric is introduced in step 14. Here the system recognises if a previously identified behaviour has been incorrectly predicted by checking the update status. If an alert is cancelled the behaviour is reassessed and feedback is provided into the behavioural models, which are used to retrain the system. Figure 52 highlights the PIMS feedback mechanism.

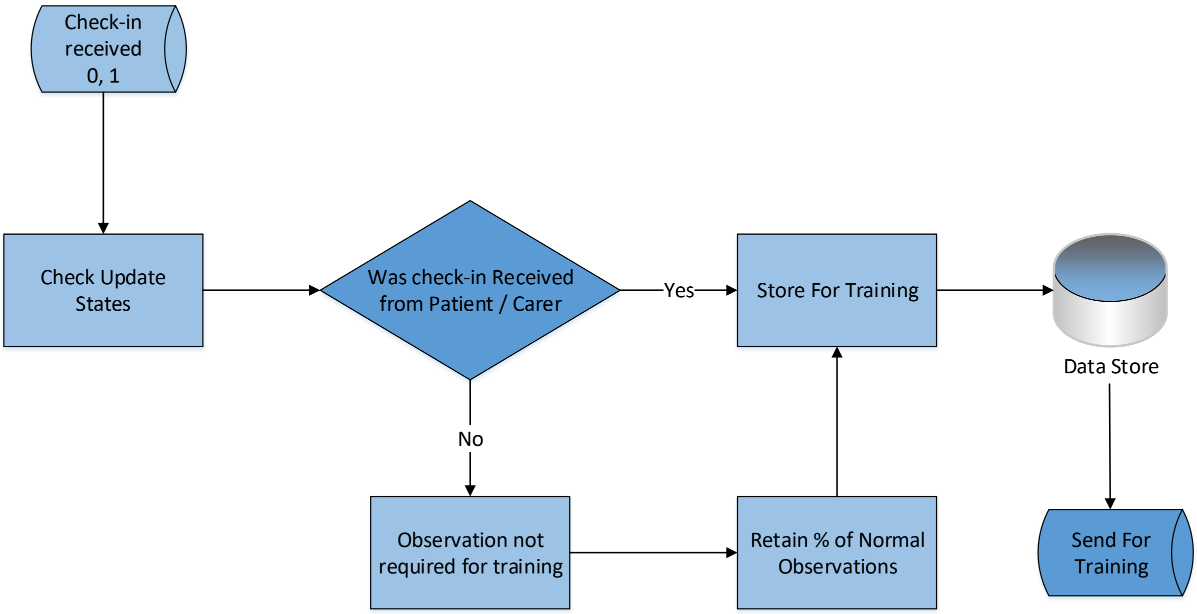


Figure 52: PIMS quality feedback process

Each notification is assigned a binary value, which identifies if the generated alert is valid. If an intervention is required and no check-in was received, the system assigns a binary value of 0 to the observed behaviour. However, if a patient check-in is received, or if the carer cancels the alert, the observation is assigned a binary value of 1. The system examines each generated status to ascertain if the alert was valid. If the query returns a value of 0 the system ignores the alert as the status is valid. However, if a value of 1 is returned the behavioural observation is retained in the data store, which can be used in future retraining. Figure 53, illustrates this procedure. Additionally the PIMS framework retains a number of normal observations so the models can be retrained over time as more behavioural data becomes available.

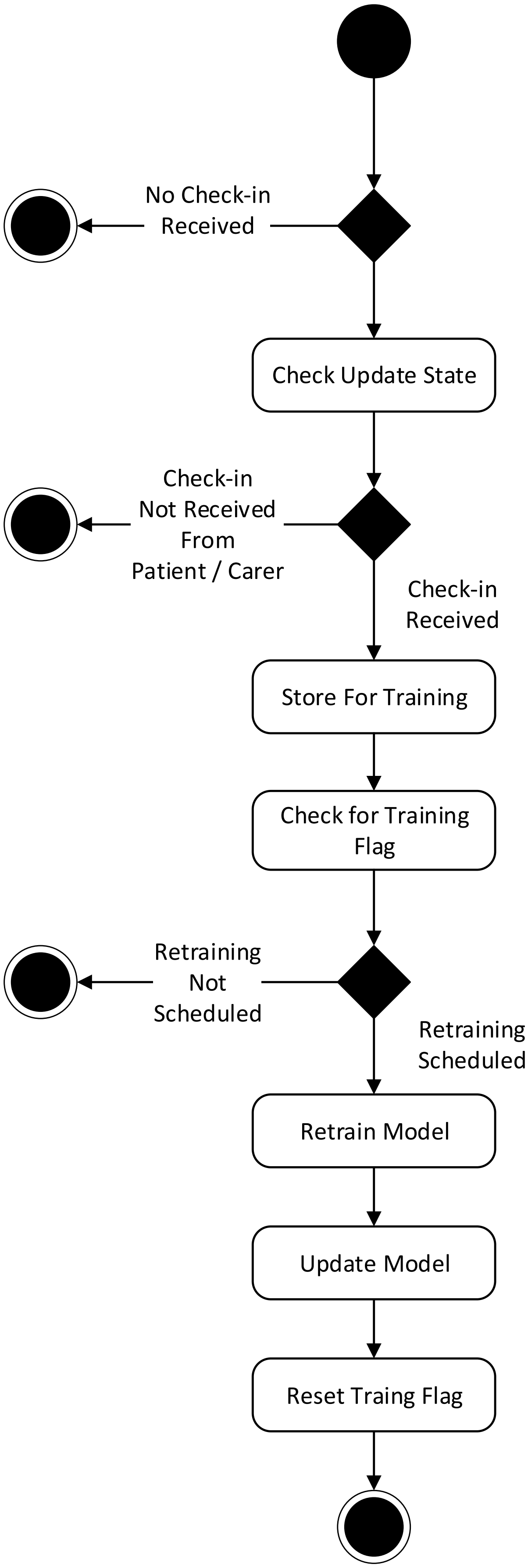


Figure 53: PIMS Retraining Procedure

4.3 SUMMARY

In this chapter, we presented the PIMS framework and highlighted the various functions and interactions it provides. The chapter discussed the three specific modes in which the system operates, in order to offer a personalised patient monitoring system. The chapter described the process for integrating with the patient's smart meter and the various data processing stages required for device identification and behavioural analysis. Essentially the PIMS framework can be described as a wrap-around system, which collects detailed electricity usage patterns to provide a non-intrusive stand-alone assistive device with rudimentary setup and configuration. It delivers ubiquitous and autonomous home monitoring for real time patient analysis that supports medical staff and social services. It facilitates a direct link between people at home and informal caregivers via a tool to monitor the patient. It also detects improvements and deteriorations in health conditions as they occur in real time. These features alone are not possible with other assistive technologies without the use of multiple and complex distributed sensors. This system design has been submitted for a GB, European and Worldwide priority patent application protecting the detailed system design and methodology (Aug 2016; Application no. 1613225.0).

Interpreting the vast amounts of data generated by smart meters is a significant challenge. The analytical work is therefore performed through a cloud-processing platform, such as Microsoft Azure. Additionally the use of a cloud platform facilitates exposure to the generated models, which can be integrated into high availability web services. Although the system would remain the same for each condition and application, the generated classification models can be altered in order to focus on the particular condition. Additionally, the chapter highlighted how the PIMS framework can be integrated with existing digital services through the use of a web service API. Here model functionality facilitates alternative monitoring applications ensuring that the system is both diverse and scalable.

CHAPTER 5 CASE STUDY

In this chapter a detailed case study is presented. An ongoing patient trial that is being conducted in partnership with Mersey Care NHS Trust is introduced. The case study introduces three individual patients. By monitoring the first patient over a six month period the acquired data and knowledge is used in both the implementation and evaluation of the PIMS framework. Additionally the case study outlines how the system currently monitors two additional dementia patients.

5.1 CASE STUDY INTRODUCTION

This research study involves testing the PIMS framework for people living with Dementia and other cognitive impairments. Dementia is selected, as patient's often exhibit complex and unexplained behavioural patterns. Dementia is one of the most challenging conditions for remote patient monitoring, hence its selection for this case study. PIMS detects a patient's interaction with specific electrical devices around the home. This is undertaken to identify their routine and habits, which enables the system to make a decision regarding their overall wellbeing based on their Activities of Daily Living (ADLs).

On the advisement of the NHS Research Ethics Committee (REC), participants must have the capacity to be able to consent to the study and the patient must live alone. If at any point during the study the patient loses the capacity to adhere to these requirements, the trial will be stopped and the sensor removed. Any data previously collected will be retained and used in accordance with the conditions outlined in the study.

The overall duration of the study is 6 months. During that time, energy usage readings are collected at 10 second intervals and logged to a remote server for analysis. This enables researchers to collect an adequate amount of data, while testing the performance of the algorithms used in system. For the purposes of this case study, an energy monitor is installed by a member of the research team for each patient in the trial. The primary outcome of the study is to assess the overall performance of the algorithms used by PIMS. This is achieved by generating both the training and test data for the implementation.

5.2 DEVICE INSTALLATION

In order to capture the required data an energy monitor is installed in each property. Figure 54 highlights the energy monitor that is used to collect the device signatures from one of the properties in the study. Here the CT clips is fastened around the neutral cable. At each 10 second interval the aggregated energy values are recorded and sent to a remote SQL data base.

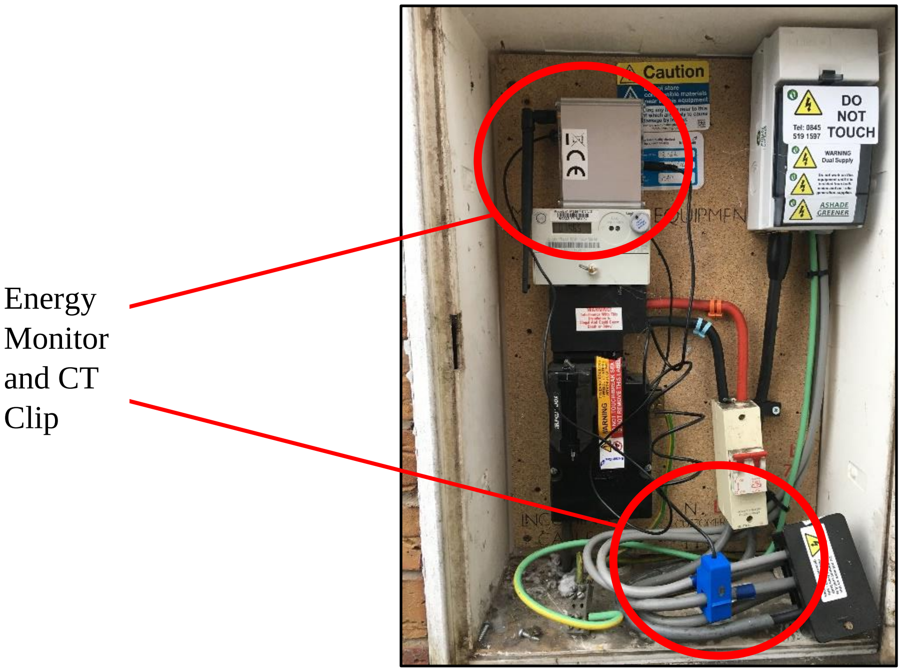
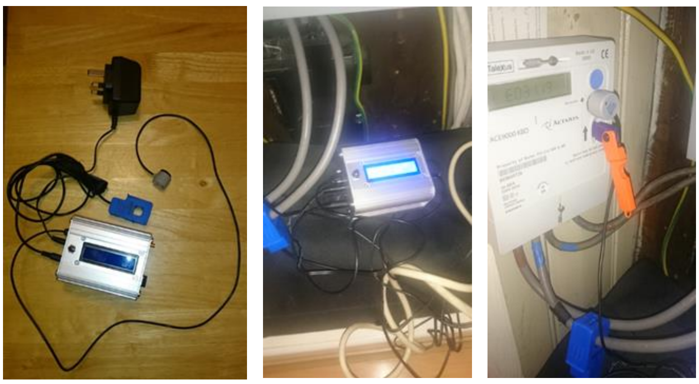


Figure 54: NITLM device for the collection of device training data

As smart meters are not widely available a sensor is fitted to the electricity meter. To implement the real time data gathering capabilities of a smart meter when used with a CAD, an energy monitor was installed in the person's home. Figure 55 provides an overview of the electricity monitor as shown in (a). The blue current sensor transformer clip (CT) is fastened around the live cable shown in (b) to measure the electrical load. Finally, the second white sensor, which is the Optical Pulse Sensor, as shown in (c), works by sensing the LED pulse output from the utility meter.



(a) (b) (c)

Figure 55: Energy monitor for behavioural classification

Each pulse corresponds to a certain amount of energy passing through the meter. By counting these pulses, a KWH value can be calculated. All of the acquired data is sent to a remote SQL server. Although the KWH are not available through a CAD, it has been recorded for use in future studies.

5.3 STUDY 1

The data obtained from the first patient in the trial is used to implement and evaluate the PIMS framework. Table 14 highlights the details of the patient.

Table 14: Patient 1 details

Patient Number	Condition	Sampling Rate	Start Date	End Date
1	Bipolar	10 Seconds	12/06/2016	15/12/2016

Over a 6 month period energy readings were collected at each 10 second interval to construct both the device and behavioural data. The installation is used to initially baseline a person's daily routine and to identify any noteworthy trends in device utilisation. During the installation the patient was asked to keep a record of each appliance used along with the date and time. Figure 56 highlights the initial device testing, here a kettle is shown.

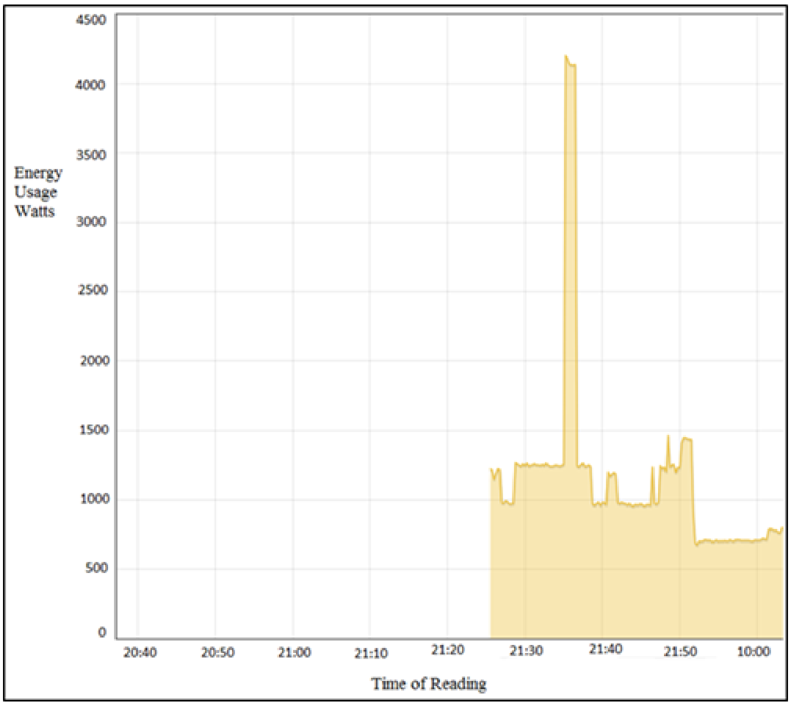


Figure 56: Patient 1initial energy readings

5.4 STUDY 2

Table 15 highlights the details of the second patient in the study.

Table 15: Patient 2 details

Patient Number	Condition	Sampling Rate	Start Date	End Date
2	Dementia	10 Seconds	03/04/2017	03/10/2017

As with the first patient the energy monitor will record energy values for a 6 month period. Figure 57 shows the energy readings obtained from the sensor. The y axis shows the energy readings in watts while the x axis highlights the time of utilisation. During calibration five devices are turned on to obtain a baseline for assessing the generalisation of the device classification models.

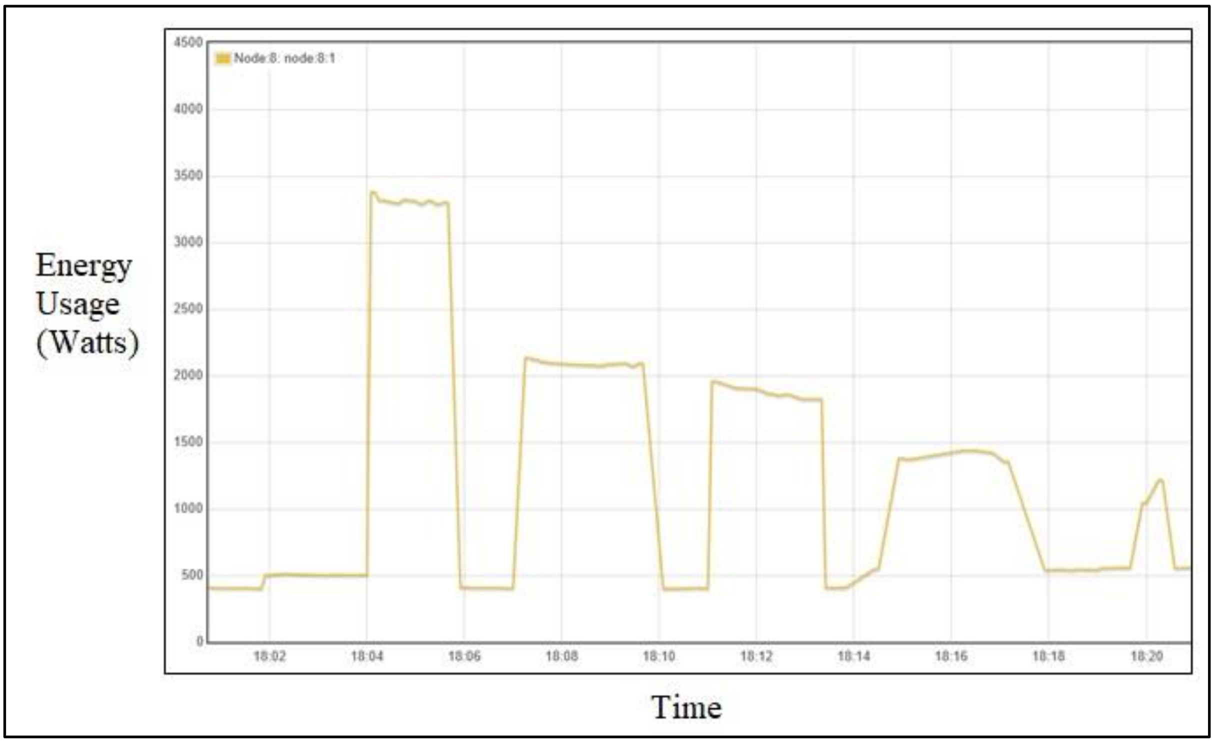


Figure 57: Patient 2 initial energy readings

Specifically in this trial the kettle, toaster, microwave, oven and washing machine where turned on for a period of 140 seconds each. These readings will later be processed by the device classification models during implementation to test their generalisation.

5.5 STUDY 3

Table 16 highlights the details of the third patient in the study.

Table 16: Patient 3 details

Patient Number	Condition	Sampling Rate	Start Date	End Date
3	Dementia	10 Seconds	10/04/2017	10/10/2017

Figure 58 highlights the energy readings taken from patient 3 during installation. However only the kettle, toaster and microwave where available for sampling.

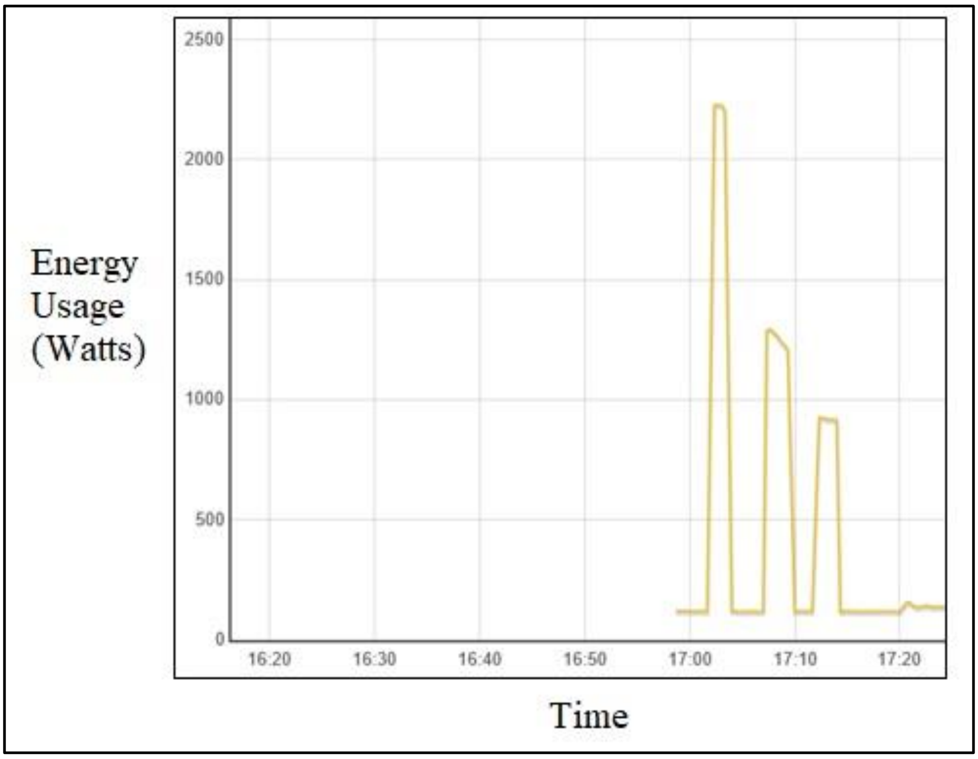


Figure 58: Patient 3 initial energy readings

During installation the energy monitors were configured to the patients Wi-Fi and each sensor was assigned a unique ID. The technical specifications of the energy monitor and its implementation is discussed in chapter 6. The installation time for each patient typically lasted between 30 – 40 minutes. During this period, patients where asked some basic questions regarding their routine such as when they typically get up and when they go to bed. This information can later be used to highlight deviations in their routine while determining if patient behaviour alters over time. By monitoring subtle behavioural changes over long observation periods, it may be possible to detect the progression of cognitive decline where patients suffer from certain diseases.

From the installations there are different types of appliances available which can be used for monitoring. Two patients highlighted restrictions in the use of certain appliances due to safety concerns: 1)Patient 3 had no access to a cooker due to safety reasons and was unable to provide a sample for the washing machine, 2) Patient 2 stated that although he owns a toaster it is never used due to difficulties in swallowing certain food types. The patients also stated differences in routine during questioning, this highlighted variations in key daily activities such as getting up and going to bed. It was also noted that patients attend reoccurring medical appointments and support groups that are unique to the individual. In addition the background noise from type 4 electrical devices differs significantly between the different patients by around 400 – 500 Watts (W). This supports the hypotheses that the behavioural models not only need to be unique to both the patient and condition, but in some cases also the environment.

Differences in both routine and available devices mean that the behavioural aspects of the PIMS framework cannot be generalised between patients. Certain aspects of the environment do however exhibit similarities. The energy readings sampled from patient 1 show comparisons to the test houses which are introduced in chapter 6. During installation the device, classification models identified all of the appliances from each property. This supports the hypotheses that the device classification algorithms can generalise across new installations, without the need to retrain the classifier. Although the classifiers exhibit acceptable levels of generalisation, the PIMS framework requires device signatures for each appliance class during new installations. This is needed to maintain accuracy and expand the signature database should the algorithm fail to correctly identify an appliance.

Although the use of only three patients limits the statistical relevance of the study, the objective is not to detect behaviours which are indicative to the patient’s condition. Instead the study focuses on the detection of abnormal behaviour, without attributing it to a specific condition or aliment. This ensures that a small number of patients can be used during the initial evaluation of the PIMS framework.

5.6 SUMMARY

In this chapter a case study was presented which involves the deployment of an energy sensor into the homes of 1 patient suffering with bipolar and 2 dementia patients. Here the energy readings are sampled at each 10 second interval to aid in the implementation and evaluation of the PIMS framework. The sensors used in the patient trial are configured to the same specifications to that of a smart meter when paired with a CAD. However there are clear differences in both the types of appliances available and the characteristics of the aggregated electricity load. The energy readings obtained from patient 1 are used in the PIMS implementation and are evaluated to determine its performance.

CHAPTER 6 IMPLEMENTATION

The chapter provides a comprehensive discussion of the implementation and the associated technologies used to implement the PIMS design.

6.1 DATA COLLECTION FOR DEVICE TRAINING

In order to construct an appliance signature database to train the classifiers an energy monitor was installed in three separate test homes which was highlighted in figure 54. The energy monitor has been configured to the exact standards of a CAD device by sampling the aggregated load. Here the real power value (Watts) are retrieved at each 10 second interval and sent to a SQL database for analysis.

The system is trained against a collection of known device signatures. Initially each system deployment involves the labelling of individual device readings. It takes up to 2 days to monitor individual devices to obtain an accurate enough assessment for the classifier [188]. This is achieved through the use of a patient companion application, as highlighted in figure 60. Patients are asked to record the type of device being used when a device interaction has taken place. The application logs the device type based on the patient's selection along with the date and time. The record is then matched with the aggregated power readings from the energy monitor to extract the appliance signature. Figure 59 highlights two of the feeds from the energy monitor.

Feeds

Id	Tag	Name	Process list	Public	Datatype	Engine	Size	Updated	Value
Node 7							374KB	14s	
12	...	node:7:1			REALTIME	PHPFINA	374KB	14s	100
Node 8							2MB	45s	
4	...	node:8:1			REALTIME	PHPFINA	2MB	45s	1051

Figure 59: Energy monitor feeds

The occupant is also asked to note whether the device is being used in conjunction with other appliances. This ensures that the training data includes observations where devices are used singularly or in conjunction with other appliances. In addition, the patient is also asked to log any unplanned interactions with medical services such as visits to GPs, A&E and Walk-in Centres. The app records the visit type and date; this is undertaken so the patient's energy reading can be assessed prior to the visit and to highlight any noteworthy changes in behaviour.

This application was constructed in Visual Studio 2015 using C# and Extensible Application Markup Language (XMAL). Here the Universal Windows Platform (UWP) application sends the data to a remote SQL database by consuming a RESTful API using JSON over HTTP.

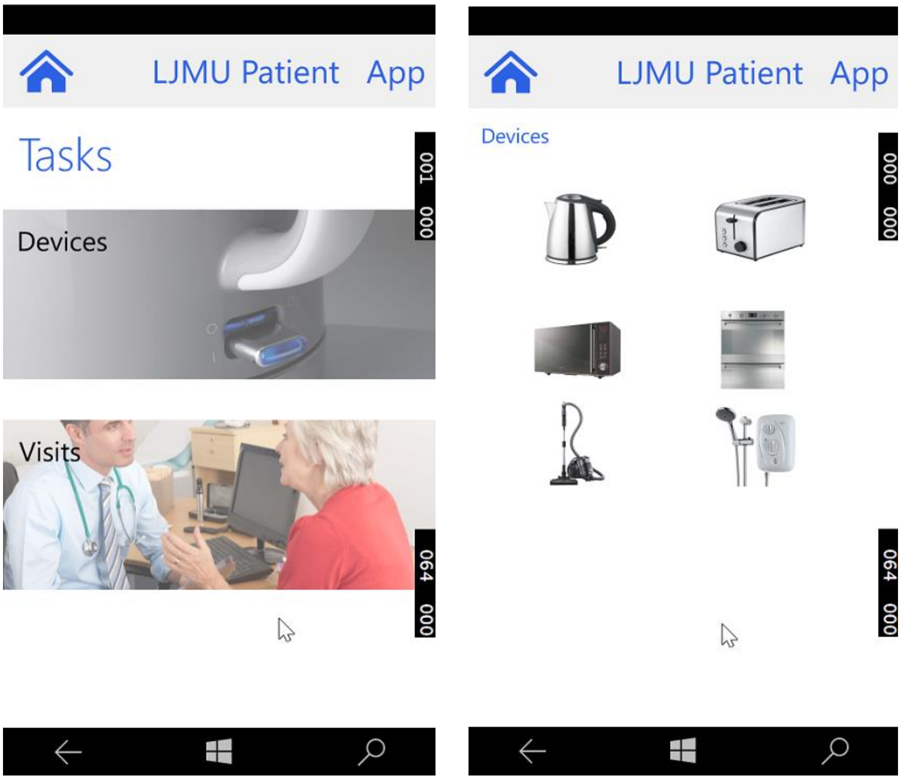


Figure 60: Patient companion app for class identification

Table 17 highlights the individual log files taken from the patient app. Here the date, time, device and load type is presented. Specifically, a single device utilisation is represented by a 0 and a multiple device usage is characterised by a 1.

Table 17: Patient companion app data sample

Date	Time	Device	Single Load
28/01/2017	13:29	Kettle	0
28/01/2017	15:46	Washing Machine	1
28/01/2017	17:29	Dryer	1
28/01/2017	18:01	Microwave	0
28/01/2017	18:28	Microwave	0
28/01/2017	19:34	Kettle	0
29/01/2017	07:06	Microwave	0
29/01/2017	07:41	Toaster	0
29/01/2017	08:39	Washing Machine	1
29/01/2017	11:09	Microwave	0

Once the database contains a sufficient range of signatures, the labelling stage in new deployments is no longer required. The device training dataset is constructed by installing an energy monitor into three separate properties and recording the device energy signatures. As a result, five distinct classes are generated, which include the kettle, toaster, microwave, washing machine and electric oven. The data set contains 25 individual samples from each property totalling 75 for each device class.

Table 18 highlights a sample of the training data obtained from the energy sensor. Specifically, eight individual aggregated kettle signatures are presented. The table shows the observations at each 10 second interval up to a maximum of 140 seconds.

Table 18: Aggregated device signatures

10	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**	**100**	**110**	**120**	**130**	**140**	**Class**
250	3319	3319	3176	3176	3182	3156	3189	3104	3142	3104	3104	3104	3169	Kettle
346	3334	3334	3334	3334	3334	3279	3259	3201	3143	3121	3073	3073	3111	Kettle
248	3313	3255	3255	3174	3174	3173	3140	3213	3216	3148	3216	3135	3218	Kettle
115	3066	2984	2984	2972	2972	2975	2975	3049	3037	3037	3030	3006	3042	Kettle
145	3054	3031	3063	3063	3063	3031	3084	3023	3077	3031	3069	2994	146	Kettle
278	3275	3230	3307	3246	3250	3213	3221	3221	3214	3222	3201	3211	3205	Kettle
291	3341	3341	3341	3341	3206	3282	3282	3201	3201	3223	3290	3290	3290	Kettle

6.1.1 DATA COLLECTION FOR BEHAVIORAL TRAINING

In the case study presented, the data obtained from the energy monitor used is logged to an SQL database as shown in Figure 61. The PIMS framework interfaces with the database directly.

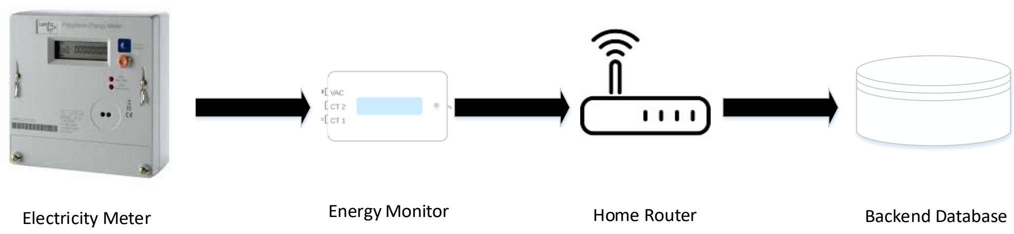


Figure 61: End to end data collection

In order to train the behavioural classification model the data obtained from the energy monitor is utilised to construct the behavioural features. The data is analysed by the device classification models using the web service which is described later in this chapter.

Figure 62 highlights the patient's energy usage taken at 10 second intervals. The y-axis shows the amount of energy being consumed in watts, while the x-axis shows a snap shot of the time. Specifically 00:00 has been chosen to highlight any night activities which could signify sleep disturbances. Additionally 12:00 has been selected to highlight midday activities. Each individual colour represents one week's electricity usage, which has been overlaid to show correlation over a four week period.

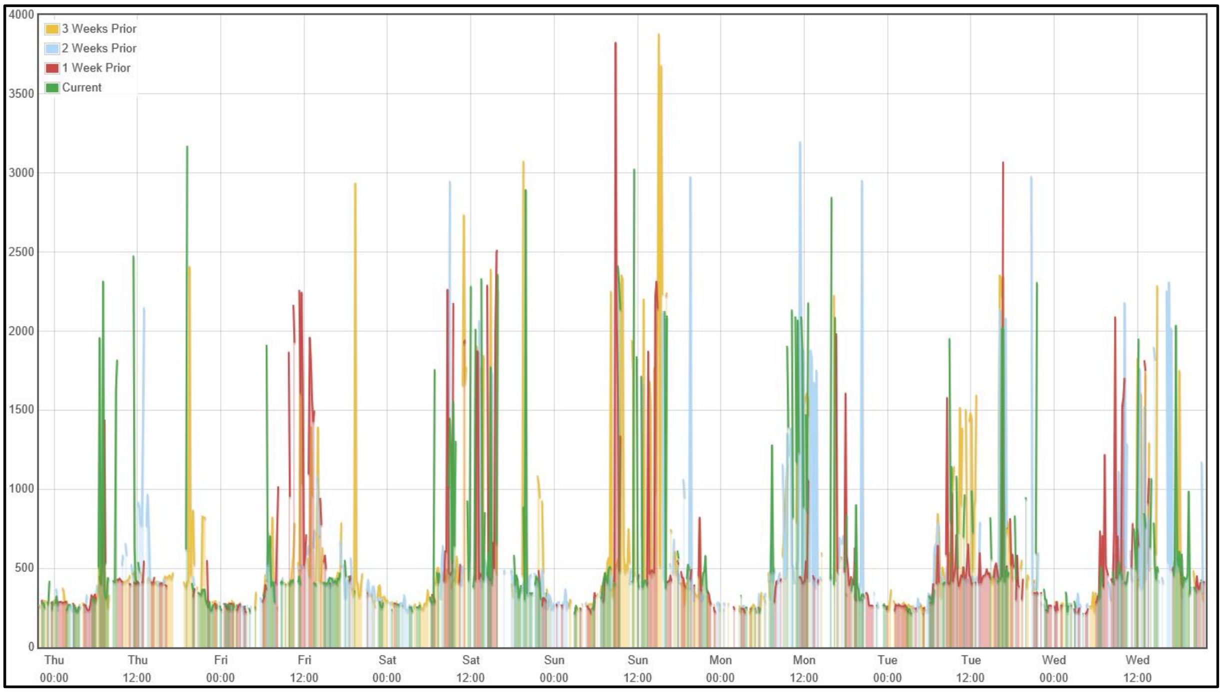


Figure 62: Overlaid energy usage four week period

Visualising the energy usage data enables background device noise from type 4 electrical devices to be quantified. As highlighted, the energy baseline does not peak above 500 watts during the entire 4 week period. Estimating the baseline could enable other homes with a similar distribution to use existing device classification models, removing the requirement for a home by home training period.

6.2 PIMS IMPLEMENTATION

The following section provides a detailed description of the PIMS implementation. Here the techniques and methods are discussed along with justification for their selection. Each of the different implementation stages required for the PIMS framework to operate, are broken down into their individual functions. Figure 63 highlights the system implementation in its entirety. The system is configured in a hybrid mode. Here the energy monitor used in the implementation is highlighted in figure 64. The monitor posts the readings to an on premise web server which in turn processes the data for classification in the cloud using a RESTful API.

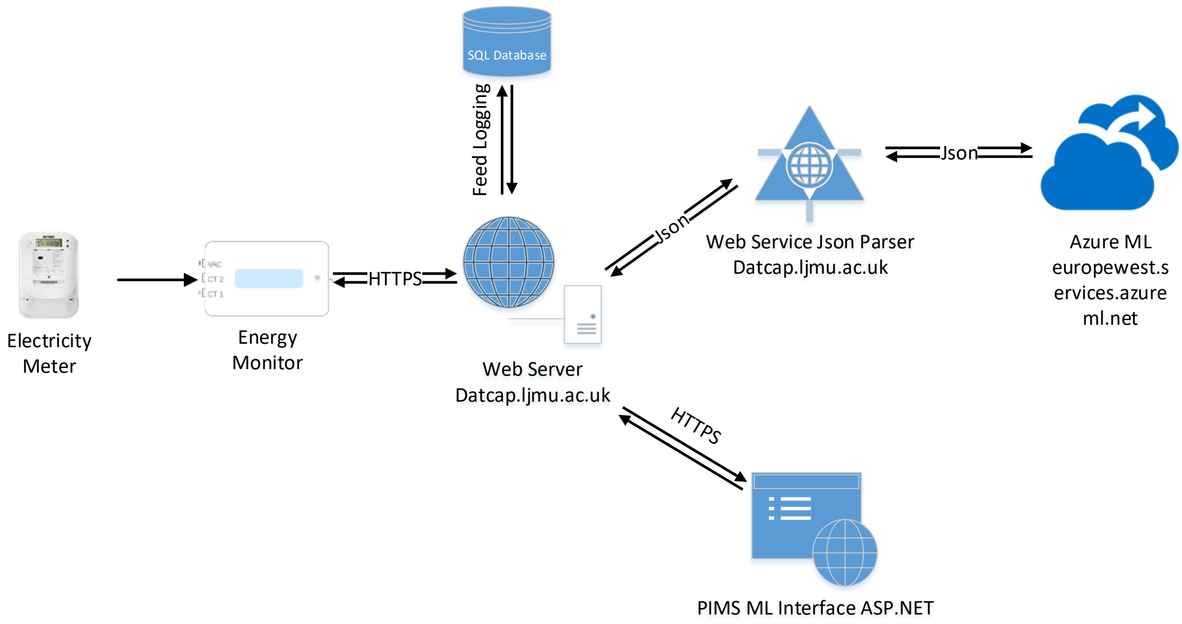


Figure 63: PIMS Implementation

Figure 64: Energy Monitor and CT clip

Using both the energy monitor and CT clip the energy value (W) and an associated date time stamp are logged to a remote web server at each 10 second interval. Feeds are generated for each energy monitor and logged to a database. Data received from RFM69Pi is decoded and published to Message Queue Telemetry Transport (MQTT) service. Figure 65 presents an overview of the energy sensors architecture.

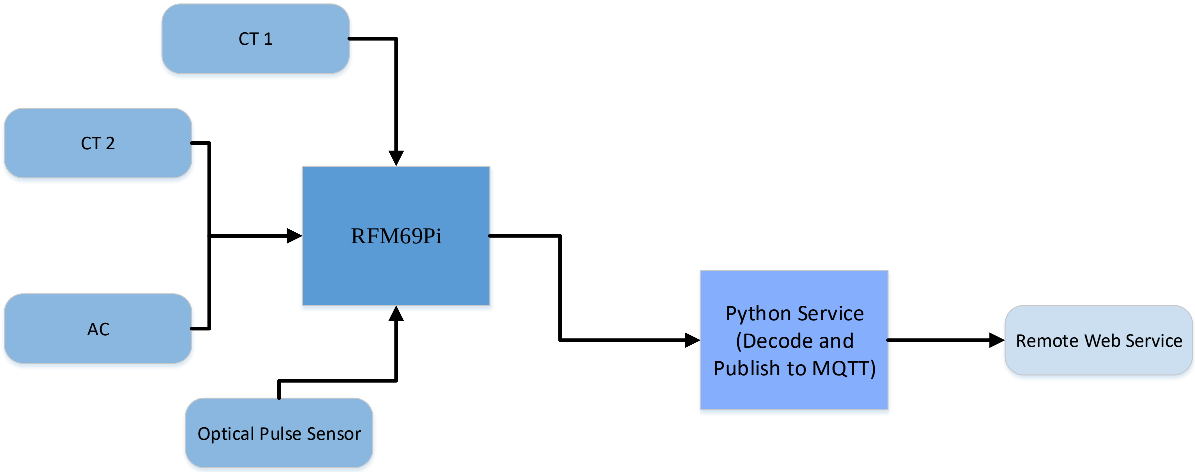


Figure 65: Overview of energy sensor architecture

All of the acquired data is logged directly to a time series feed which is used to explore historical data. Figure 66 highlights the logging process while figure 67 shows the login page for the website.

Key	Name	Process list	Updated	Value
power1		Log to feed Power to kWh	6s	479

Figure 66: Logging values to time series feed

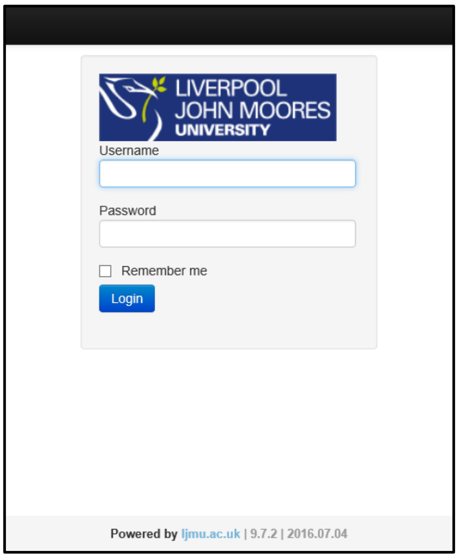


Figure 67: Login page

In order to send the obtained energy values to azure for classification the JSON feed needs to be parsed. How the JSON parser functions is outlined later in this chapter. Figure 68 highlights a data sample from the JSON feed for one of the energy monitors used in the trial, both the time and energy value are shown.


```
[[1494763200000,2602],[1494765000000,991],[1494765900000,871],[1494766800000,652],[1494769500000,1797],
[1494770400000,1522],[1494771300000,591],[1494772200000,1265],[1494773100000,1091],[1494774900000,562],
[1494775800000,664],[1494776700000,616],[1494777600000,490],[1494778500000,410],[1494779400000,418],
[1494781200000,400],[1494782100000,461],[1494783000000,422],[1494784800000,372],[1494785700000,402],
[1494786600000,427],[1494788400000,465],[1494789300000,447],[1494790200000,517],[1494792000000,479],
[1494793800000,467],[1494794700000,341],[1494796500000,329],[1494797400000,1140],[1494798300000,271],
[1494799200000,268],[1494801000000,346],[1494801900000,270],[1494802800000,273],[1494805500000,261],
```


Figure 68: JSON time and energy value

Figure 69 highlights the device classification training process stating with the device signatures and ending with the trained model. The entire process is undertaken within the Microsoft Azure Cloud platform, which has been selected for its scalability and for its ability to expose the PIMS functionality.

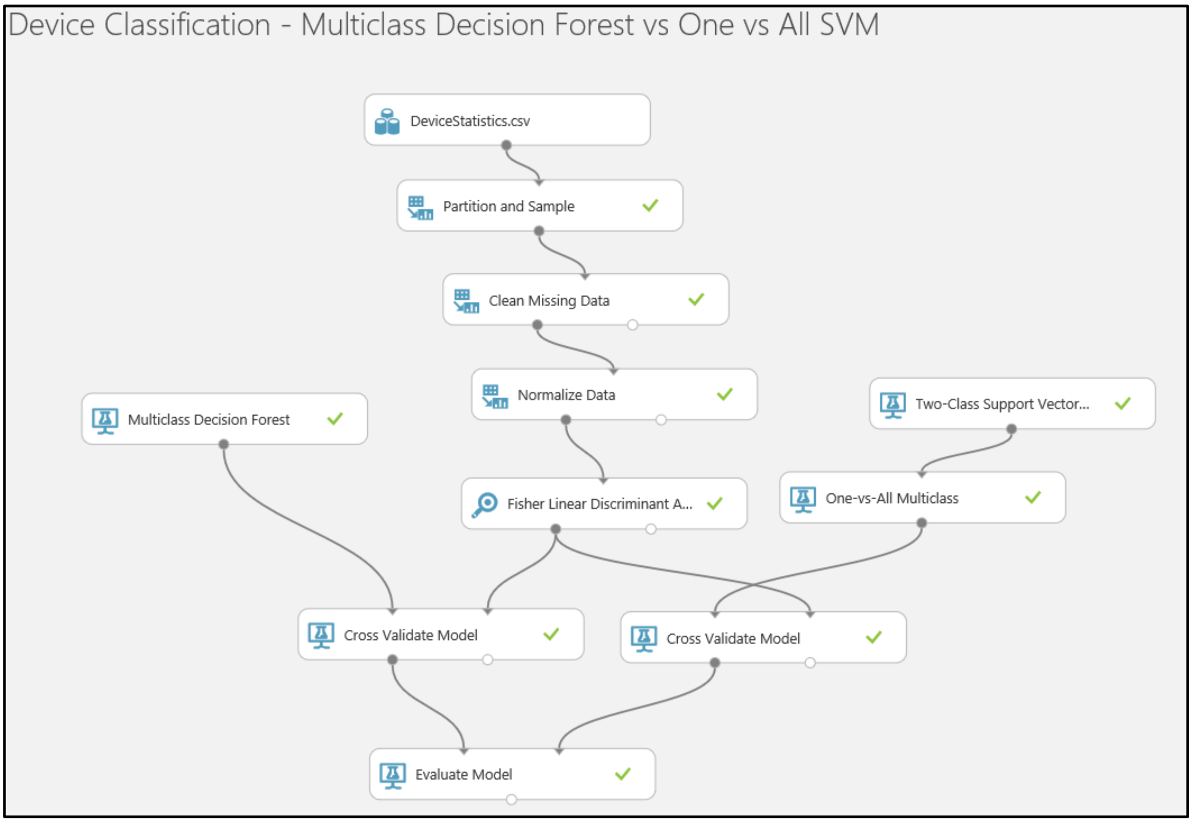


Figure 69: Device classification training process

6.2.1 DEVICE CLASSIFICATION

For the device classification process two classifiers are chosen for testing, which include a Multiclass Decision Forest and a Two Class (SVM). Here the SVM has been adapted to support a multiclass operation through a one verse all mode as shown in figure 70, therefore facilitating the detection of multiple devices. An SVM has been selected for evaluation as they have been used in a number of existing NILM algorithms with varying degrees of success [189]. One of the main benefits of using a Decision Forest for the device classification is that they are unaffected by scale, therefore removing the requirement for normalisation. Energy data does not conform to a common scale, which could adversely affect the performance of certain classifiers. In addition, by using a Random Decision Forest, the likelihood of overfitting can be reduced without the need to use regularisation techniques. The generalisation of the device classification models is an important requirement for the PIMS framework.

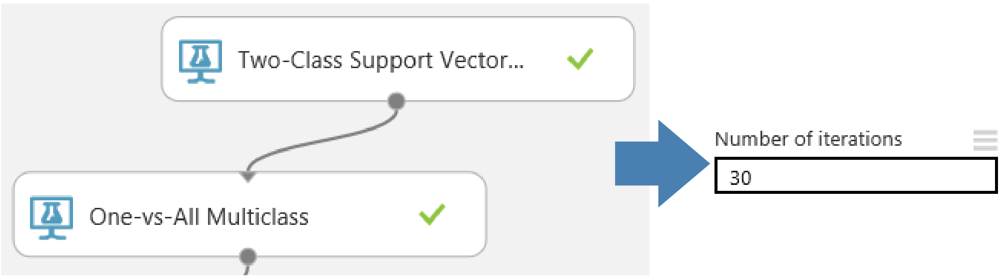


Figure 70: Azure SVM Multiclass Module

6.2.2 MUTLICLASS DECISION FOREST CONFIGURATION

The Multiclass Decision Forest is implemented using Azure and can be configured with a variety of parameters. The first configurable parameter specifies how the labeled training data is sampled. Randomness is introduced to the trees during the training phase by utilising a method known as bootstrap aggregating or bagging [190]. Bagging belongs to an ensemble method, which combines multiple predictions to generate an accurate model. Here each tree is trained on a new sample, which is generated by randomly sampling the training data; essentially each tree utilises a different training subset. Each output (prediction) is combined to generate an accurate prediction by majority voting or by averaging the results.

The next configurable parameter to consider when utilising bagging decision trees is the number of trees to include. This parameter is selected by increasing the number of trees after evaluating each training cycle until the accuracy shows no improvement. Increasing the number of trees facilitates more coverage but larger models take longer to run and require more computational resources.

The final configurable parameter to specify sets the number of samples, which is required to generate a leaf node. Here the value dictates the threshold for generating a new rule. Here the model is iterated and tuned using the above parameters in order to attain the optimum result. Each iteration is evaluated using *k* fold cross validation. Figure 71 highlights the Azure decision forest configuration.

Figure 71: Azure ML Decision Forest Configuration

Each of the configurable parameters are tested, where the results of each iteration are evaluated to ascertain the optimum configuration.

6.2.3 FEATURE ENGINEERING

This section describes the feature engineering methods used to prepare the data for device classification. Each device has varying durations of use, for example a kettle boils over different durations, depending on the volume of water. In addition, devices are often used in combination with others, typically when preparing meals. This situation could adversely affect the performance of the classifier as the boundaries between certain devices classes become harder to distinguish. Figure 72 (a) highlights an example of devices being used in conjunction or in close succession; while figure 72 (b) presents evenly distributed single device interactions.

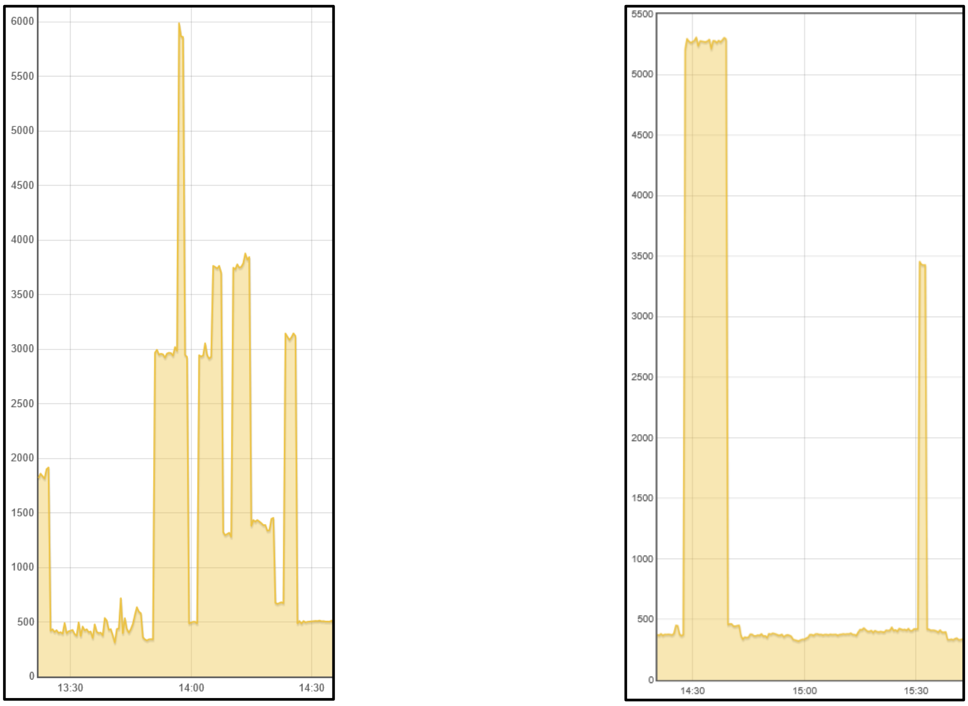


Figure 72: (a) multiple overlapping devices (b) Single devices

Models must correctly identify devices, including when they are being used in combinations. This is achieved by training the models, using only the minimum number of observations possible. By identifying the appliance in the shortest possible timeframe, devices can be classified before additional devices are used. Additionally, our research demonstrates that reducing the number of observations enables the classifier to identify type 2 electrical devices (MSD). As MSDs consume similar amounts of energy during start-up they are identified before variations in the energy usage signal begin. In addition, power consumption levels vary depending on the device utilisation as illustrated in figure 73. Here a boxplot highlights the distribution of the individual device classes. Typically, the device usage duration in our data set ranges between 10 – 360 seconds. The number of observations for each device is reduced to the first 14 samples equating to 140 seconds of device usage. The classifiers are scored until the lowest possible number of observations can be used to accurately identify the device.

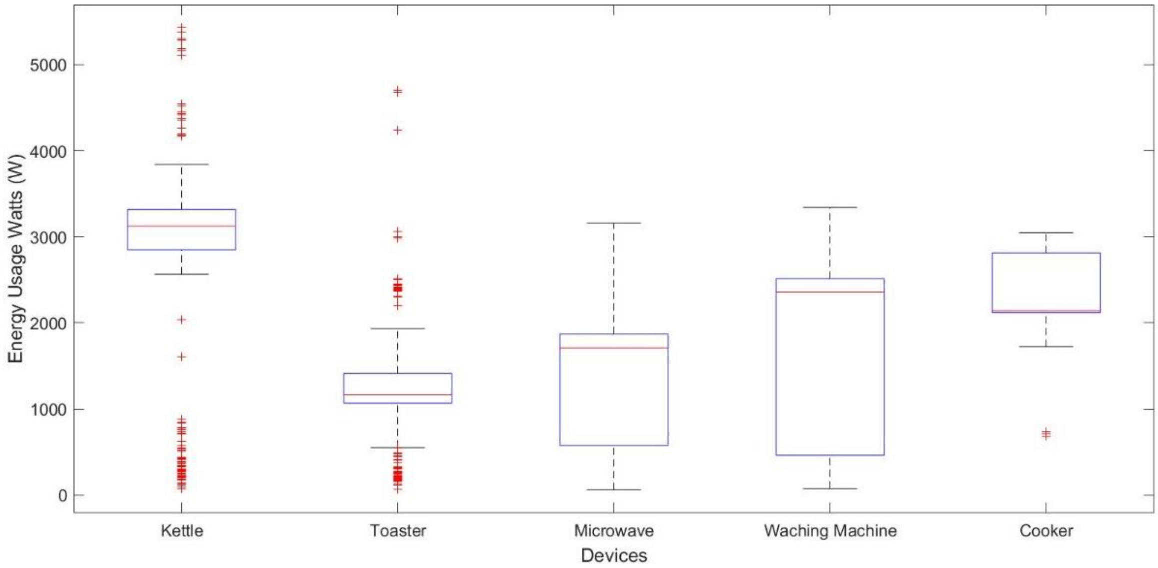


Figure 73: Power consumption distribution during device utilisation

As discussed previously, device signatures that are obtained from aggregated loads pose particular challenges for classification. This is because of varying levels of background noise from type 4 electrical devices. Type 4 devices remain active for a considerable duration, while consuming energy at a constant rate. The level of noise varies for each home as it depends on the number of devices being used. Therefore, the specific method used for data pre-processing is the statistical replacement method. This involves using the arithmetic mean as the replacement value for each missing value in the dataset (14). Figure 74 highlights the data cleaning process in the Azure ML portal.

$$\bar{x} = \frac{x_1 + x_2 + \cdots + x_n}{n} \tag{14}$$

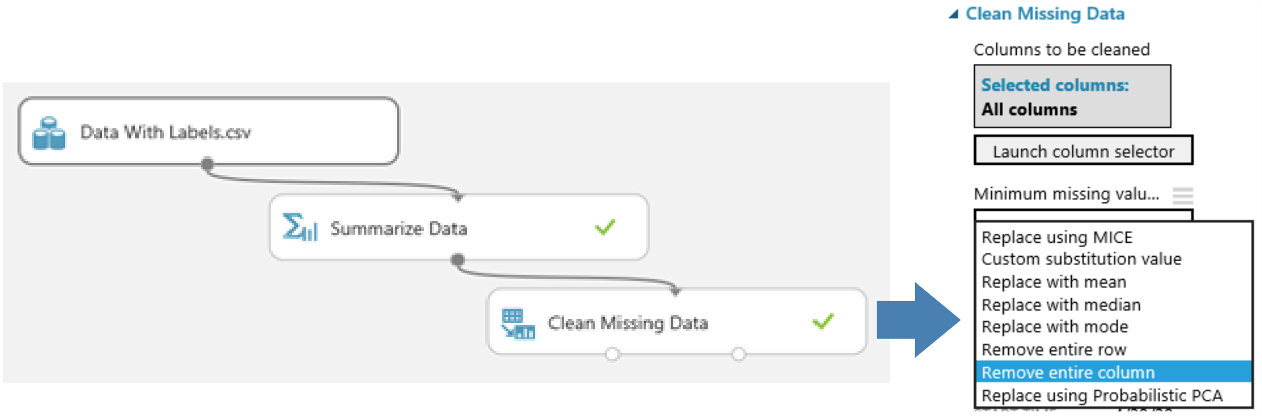


Figure 74: Azure ML device cleaning process

Some classifiers require data to be normalised depending on the data structure. SVMs exhibit a level of improvement when the data conforms to a common scale. However, normalising data for other classifiers, such as a decision forest, is not required, as the criterion splitting is not sensitive to scale. Normalisation is used to eliminate bias due to differences in data scaling.

The normalisation technique deployed by the PIMS framework for the SVM is the Min-Max scaling approach, where data is scaled to a fixed range 0-1 and is defined as:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{15}$$

The normalisation process in the Azure ML portal is highlighted in figure 102 in the appendices.

Figure 75 presents the effects of the normalisation process on the processed data. The non-normalised data is presented on the left, while the normalised data is presented on the right. Here the effects of the normalisation process are shown the x and y axis where the fixed range of 0-1 has been applied.

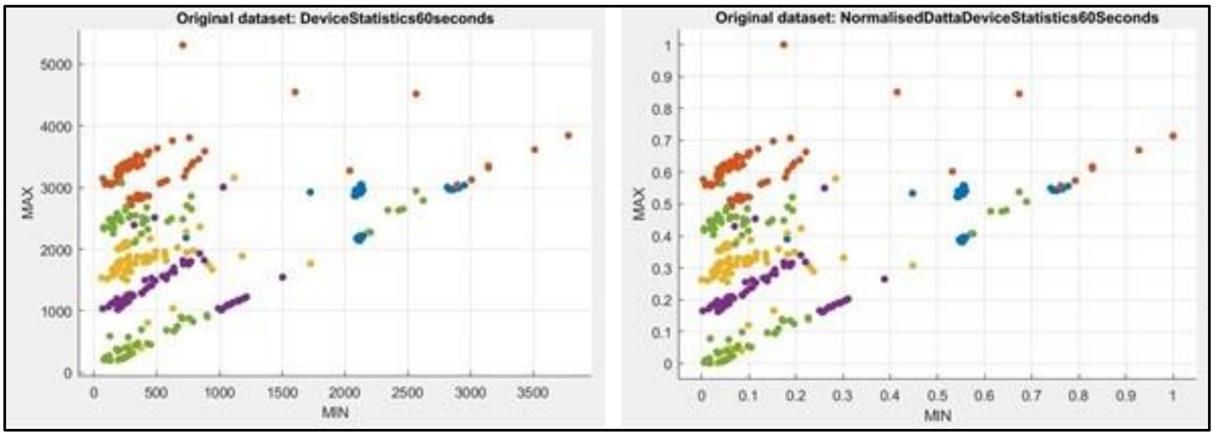


Figure 75: Data normalisation plot

For the purposes of this implementation, a steady state feature selection method is deployed. The features used in the study are presented in table 19. True Power (*P*), where (*P*) is the active power in watts for each device utilisation:

Table 19: Statistical feature extraction utilised by the PIMS framework

Measure	Feature
True Power (*P*) Aggregated Load	(*Psd*) standard deviation
True Power (P) Aggregated Load	(*Pav*) average
True Power (P) Aggregated Load	(Pmax) maximum
True Power (P) Aggregated Load	(Pmin) minimum
True Power (P) Aggregated Load	(Pmean) mean

In this implementation two feature selection techniques are evaluated. Firstly, Fisher Linear Discriminant Analysis (FLDA) and secondly, a filter based technique called Spearman Correlation.

Nonparametric tests do not assume a specific distribution in the data, as such the method is utilised in the PIMS framework. Here subsets of features are generated with the highest degree of predictive power. Consequently, each column is scored and later utilised to build the predictive model.

Figure 76 highlights the distribution of the device training data using a probability plot, which is also known as a Quantile – Quantile Q – Q plot. As presented none of the device signatures conform to a normal distribution.

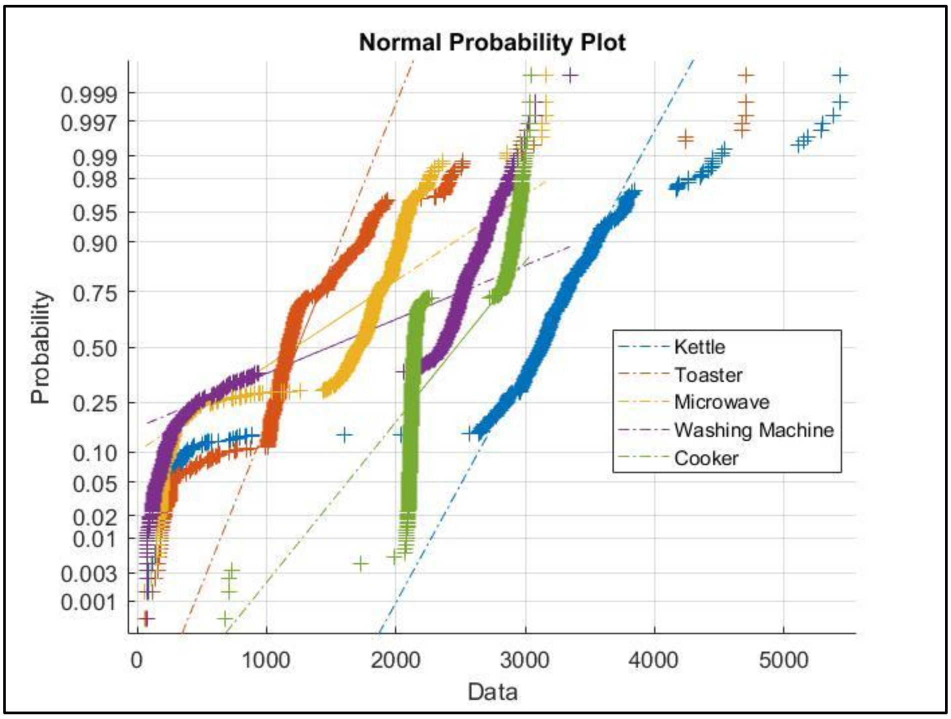


Figure 76: Normal probability plot device distribution

6.2.3 WEB SERVICE IMPLEMENTATION

Figure 77 shows the PIMS web service used to expose the models functionality. Here the input and output services are created in order for the web server to transmit the parsed data and receive the classification response.

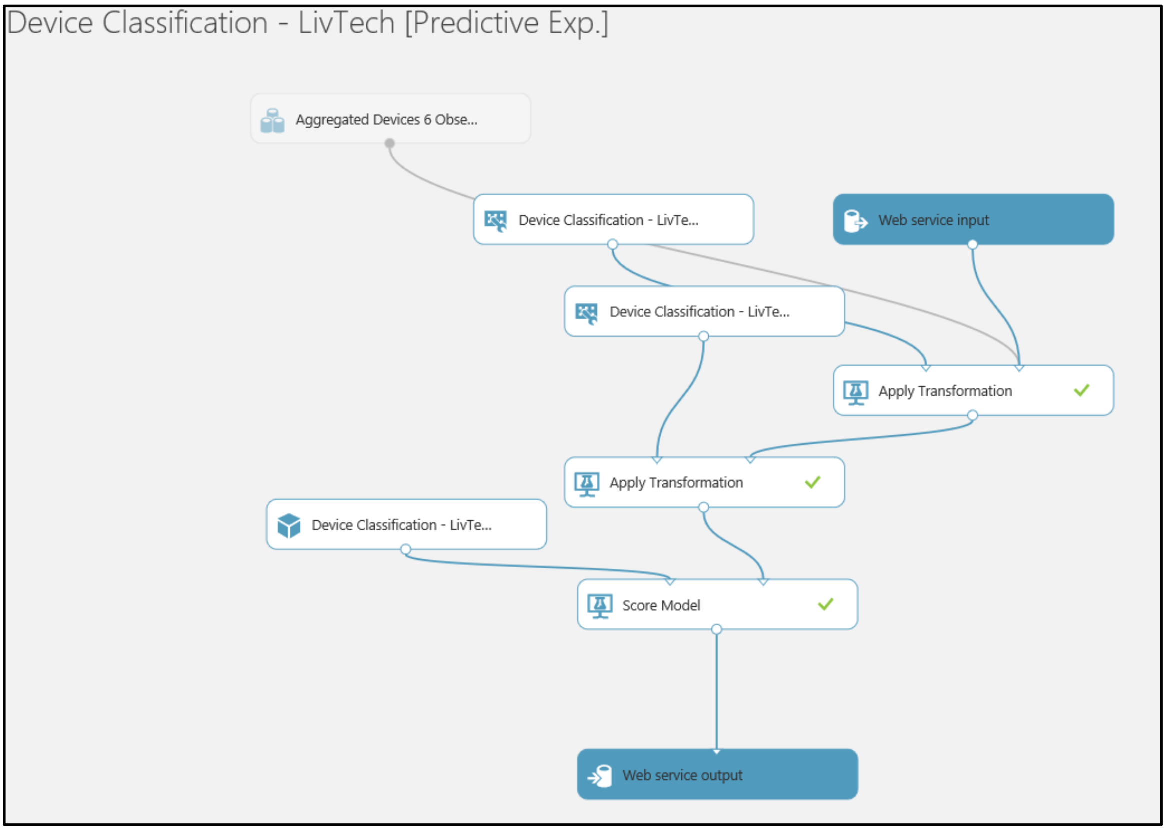


Figure 77: PIMS Web Service Implementation

The PIMS web service expects 6 integer values from the energy monitor, representing the first 60 seconds of appliance usage. Once the classification is undertaken the predicted class label is returned along with the scored probabilities. The input output schema is presented in figure 98 in the appendices section. A Request-Response Service (RRS) parses both the input and output values for the PIMS framework. The code for the RSS web service and the JSON parser can be found in figures 104 - 111 in the appendices section.

6.3 BEHAVIOURAL CLASSIFICATION

The second model in the PIMS framework is used to classify both normal and abnormal patient behaviour. This is achieved by constructing a feature set utilising the PIMS device classification models. The method proposed is based on T-Pattern analysis, which identifies the temporal structure of the data. As a result reoccurring sequences of behavioural events can be categorised and described [191]. Relationships between events are identified by taking into account various metrics, such as the simultaneously, order, relative and real timing and frequency of the observed events, as well as their hierarchical structure [191]. Figure 78 highlights the behavioural classification process.

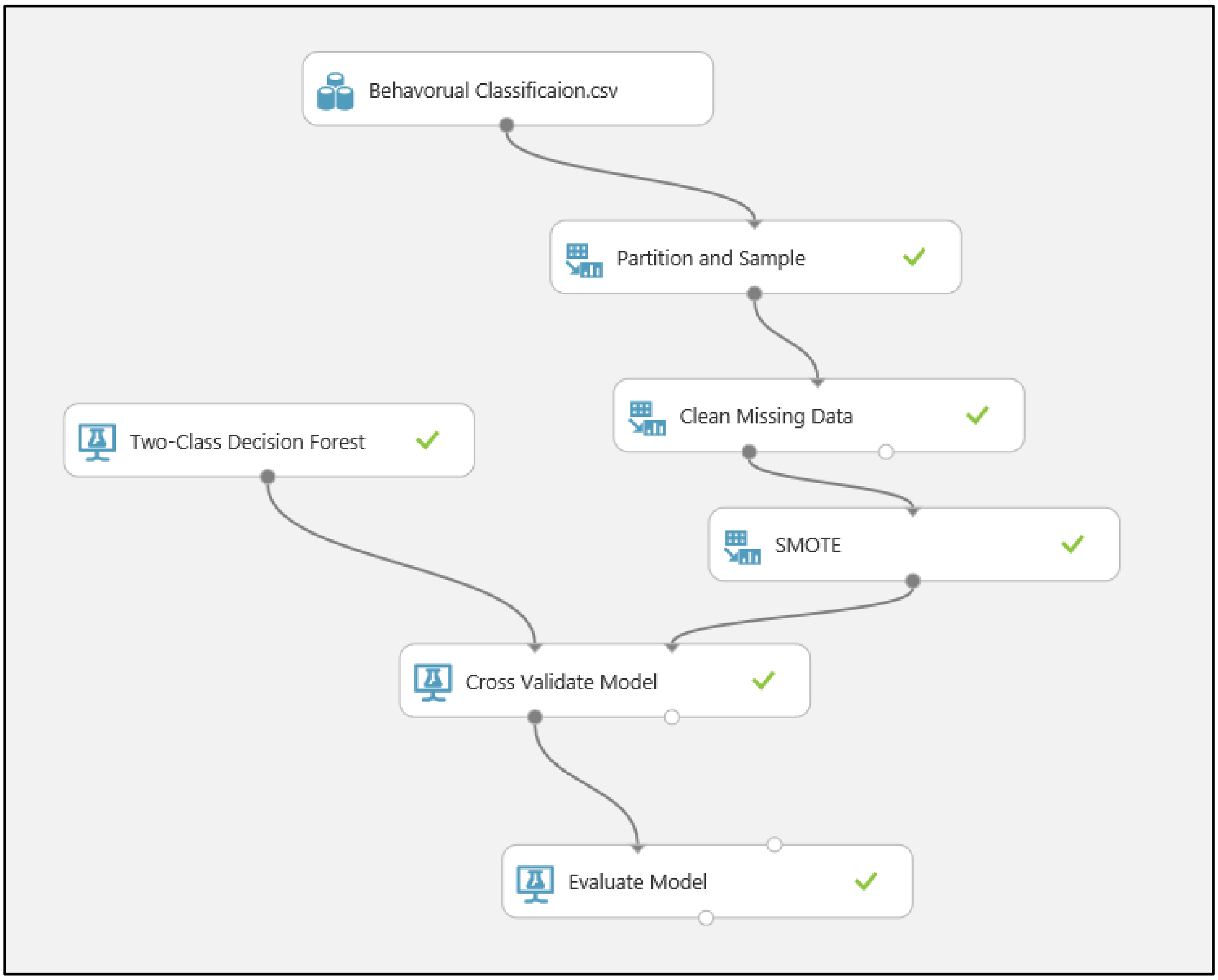


Figure 78: Behavioural classification training process

Similarly to the device classification models, both an SVM and Decision forest are evaluated for use within the PIMS framework.

6.3.1 BEHAVIOURAL FEATURES

Figure 79 highlights the web interface used to call the web service API for device prediction.

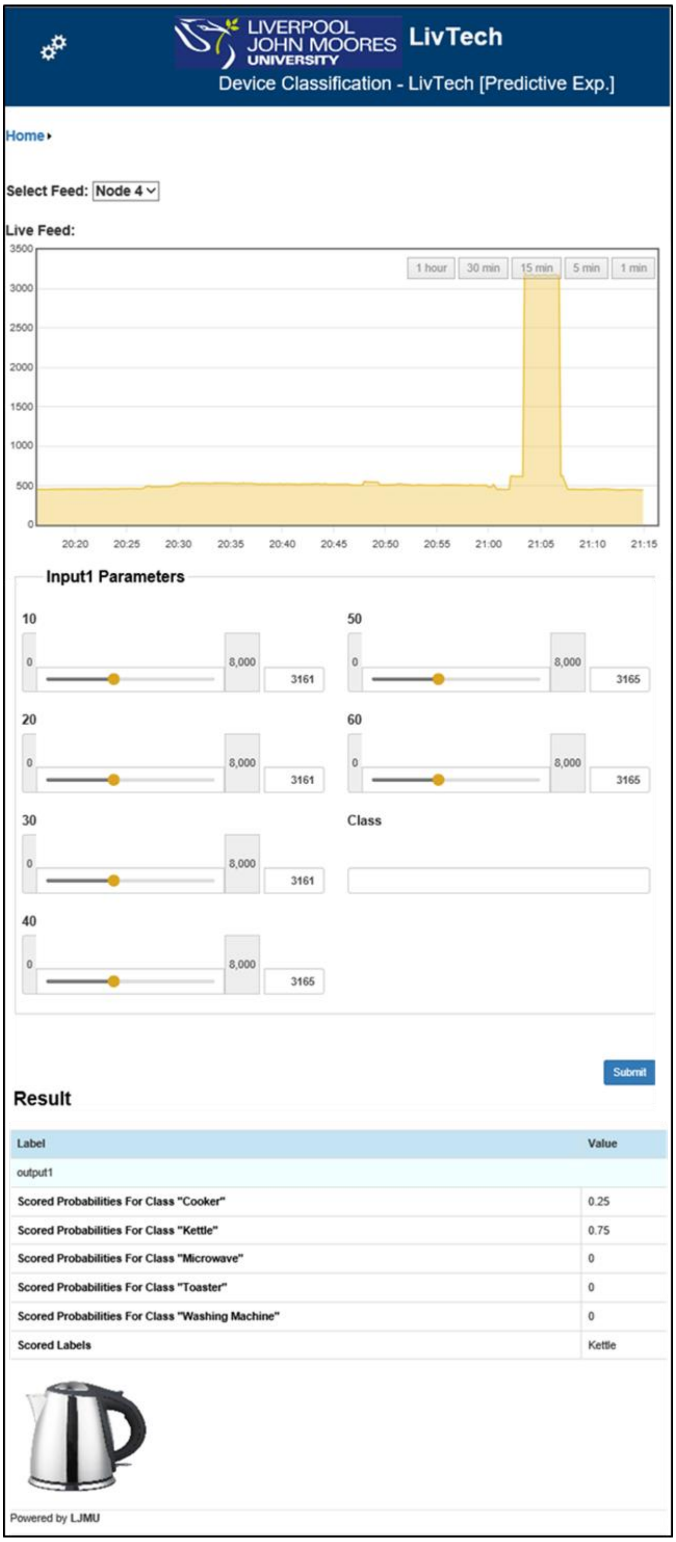


Figure 79: RSS web interface for device prediction

Each of the models predictions are scored. Any probability scoring lower than 0.70 is discarded and excluded from the behavioural dataset. Table 20 highlights the behavioural log files. It presents five device classes which are used over a 48 hour period.

Table 20: Behavioural logs 24 hour period

Time	**Event**	**Day**
07:06	Microwave	SUN
07:41	Toaster	SUN
08:39	Washing Machine	SUN
11:09	Microwave	SUN
12:11	Kettle	SUN
14:01	Kettle	SUN
14:03	Oven	SUN
17:56	Microwave	SUN
18:28	Microwave	SUN
19:52	Kettle	SUN
20:00	Microwave	SUN
06:49	Kettle	MON
07:13	Kettle	MON
10:55	Toaster	MON
15:41	Kettle	MON
16:14	Oven	MON
16:57	Microwave	MON
18:30	Microwave	MON
19:28	Kettle	MON
20:40	Toaster	MON

The PIMS framework monitors a set of specific observation windows to ascertain the behavioural structure of the patient. These windows can be used singularly or in combination up to a maximum of 24 hours depending on the application or condition. Certain observation periods are considered more significant than others [192]. For example, detecting device interactions during the night can signify sleep disturbances. Likewise no device interactions in the morning could signify that a patient has not awakened.

Table 21 highlights a sample of the behavioural features used to train the behavioural classifiers. Each of the observations represents the identified devices over a combined s 24 hour period. The first row in the table represents each of the device interactions.

Table 21: Behavioural features 25 hour period

D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D14	D15	D15	Class
3	2	4	3	1	1	5	3	3	1	3					Normal
1	1	2	1	5	3	3	1	2							Normal
3	2	1	5	3	3	3	3	3	2	1	1				Abnormal
3	2	1	5	3	3	1									Abnormal

In most real world datasets normal data vastly outnumbers abnormal data causing an imbalanced dataset. The same is true for the behavioural data presented to the PIMS behavioural models. Small imbalances within a dataset do not generally cause an issue. Class imbalance in our dataset is not only common but expected. For example normal patient behaviour will likely be more prevalent than abnormal behaviour. During the first 48 days of the patient trial no abnormal behaviour was identified for any of the patients. In order to generate abnormal behavioural patterns, data containing both a reduced number of device interactions or device usage in contrast to the patient was generated in the trial homes.

In one of our datasets 34 samples represent normal observations, while 14 samples represent abnormal observations. In total, 48 days were used in the training dataset. Figure 80 highlights the SMOTE process in the Azure ML portal.

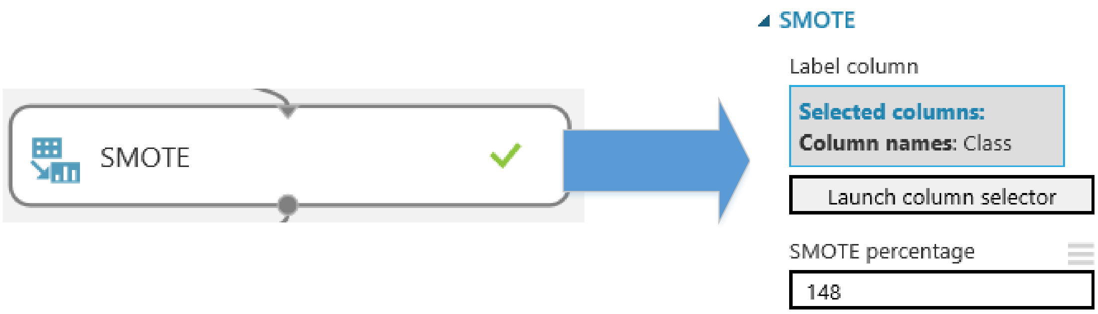


Figure 80: Azure ML SMOTE Configuration

By utilising SMOTE the number of abnormal observations is increased from 14 to 34 hence creating a balanced dataset.

The approach presented in this implementation provides an end-to-end infrastructure for hosting both the PIMS framework and the patient trial outlined in chapter 5. The acquired sensory data can be transmitted to the cloud using web service API's, thus providing access to the machine learning models for classification and evaluation. Using cloud services for the PIMS implementation enables scalability, reliability and interoperability through redundancy, hosted services and associated API's. Although this approach has many benefits, organisations such as the NHS are reluctant to use cloud infrastructure for data storage and processing. This is largely due to concerns surrounding both data security and governance. In order to overcome these concerns, a hybrid approach is undertaken to ensure only anonymous energy usage data is sent to the cloud for classification. By using a hybrid method additional costs are introduced as duplicated resources are created on premise. Although other cloud providers such as Google cloud and Amazon Web Services (AWS) offer similar services, Azure is selected for its close integration with the .NET framework and its selection of machine learning resources.

6.4 SUMMARY

Analysing the vast data that is collected from the smart meter creates detailed energy usage profiles. These profiles facilitate the identification of reoccurring patterns and trends in behaviour. In this chapter, the data collection process was described. By deploying an energy monitor into three different households and recording their device interactions an appliance signature database was created which is used to train the device classification models.

In order to assess the behavioural routine of the patient in a manner that is both scalable and personalised the PIMS framework was implemented using the Microsoft Azure platform. This approach facilitates the detection of individual devices from a single non-intrusive sensor which is vital for detecting specific ADLs. However, such analysis introduces a variety of different complications. This is due to the wide diversity of different devices which are used with an aggregated load. Additionally, the limited parameters that are available from the CAD impedes the selection of features which can be obtained from the data.

Specifically, the reading frequency of the CAD introduces significant challenges for load disaggregation. Hence the chapter introduces a novel load disaggregation method specifically designed for smart meter CAD data.

CHAPTER 7 EVALUATION AND DISCUSSION

In this chapter the results for both the device and behavioural classification are presented. The PIMS framework is assessed using electricity data, which is sampled at 10 second intervals. This approach provides a more granular assessment of the patient's wellbeing by identifying specific ADLs through device interactions within a predefined time period. Due to the flexibility of the decision forest, parameters such as tree numbers and depth are altered and evaluated to determine their optimal configuration. The chapter also discusses the results from the implementation. The performance of the PIMS framework is the result of numerous key stages including, data processing, feature engineering and classification. In this chapter a discussion regarding the justification of the results during the evaluation process is presented.

7.1 PIMS CONFIGURATION AND EVALUATION

The evaluation is conducted in two separate stages, firstly the device classification models where the performance of the Decision Forest and SVM are compared. Here the various configurable parameters and dimensionality reduction techniques are evaluated to ascertain the optimum configuration. We start by reducing the number of observations to the minimum amount possible while aiming to maintain accuracy. This is undertaken so that the device can be classified in the shortest timeframe possible. The complexity of the classifiers is adjusted to find both the highest attainable accuracy and their optimal efficiency. In the second stage, the evaluation of the behavioural models is presented. Data obtained from the device classifiers is used to classify both normal and abnormal behaviour.

7.1.1 REDUCING THE NUMBER OF OBSERVATIONS FOR DEVICE TRAINING

Table 22 highlights a sample of device observations and their associated class. Here all 14 observations are included and equate to 140 seconds. The observations are reduced by 4 observations each iteration to a minimum of 60 seconds (6 observations) in the final iteration. The full data set contains 375 distinct observations, a sample of which can be found in the appendix.

First iteration all observations

Second iteration reduced by 4 observations

Third iteration reduced by 4 observations

Table 22: Device observations - two examples per class

10	20	30	40	50	60	70	80	90	100	110	120	130	140	Class
250	3319	3319	3176	3176	3182	3156	3189	3104	3142	3104	3104	3104	3169	Kettle
346	3334	3334	3334	3334	3334	3279	3259	3201	3143	3121	3073	3073	3111	Kettle
1109	1103	1103	1091	1091	1092	1093	1094	1092	1093	1105	1085	1084	1084	Toaster
1096	1100	1097	1101	1101	1115	1101	1095	1097	1097	1097	1097	1097	1101	Toaster
735	2279	2271	2271	2248	2248	2272	2235	2239	2258	2238	2296	2298	2244	Microwave
1943	1943	738	738	737	742	1963	1963	1975	1975	1975	1994	1930	1950	Microwave
704	714	708	900	707	694	2482	2554	2479	2479	2539	2478	2494	2547	Washing Machine
2222	2222	2188	2188	2278	2212	2212	2185	2185	2228	2257	2147	2147	2235	Washing Machine
2154	2166	2149	2157	2112	2141	2108	2113	2152	2116	2117	2116	2119	2124	Cooker
2149	2143	2152	2150	2121	2126	2111	2110	2112	2125	2113	2111	2119	2110	Cooker

For the evaluation, both the raw energy data and the generated features are assessed. Table 23 highlights a sample of the generated feature dataset, which is presented to the individual classifiers. The dataset is regenerated to reflect the reduction in observations and resubmitted to the classifiers for evaluation. We hypothesise that the generated features will help to maintain a higher degree of accuracy while reducing the number of observations when compared to the raw data.

Table 23: Generated features on all fourteen observations

P **MIN**	***P*** **MAX**	***P*** **MEADIAN**	***P*** **STDDEV**	***P*** **MEAN**	**Class**
2038	5184	3199.5	895.7511	3532.571	Kettle
3008	3124	3035	31.41371	3044.5	Kettle
1084	1109	1092.5	7.636179	1094.214	Toaster
1095	1115	1097	4.776644	1099.429	Toaster
735	2298	2253	393.5894	2152.286	Microwave
737	1994	1946.5	552.4232	1611.857	Microwave
694	2554	2478.5	876.8858	1748.5	Washing Machine
776	2647	2544.5	612.1363	2295.5	Washing Machine
2110	2152	2120	15.72467	2125.143	Cooker
2808	3003	2868.5	60.10077	2875.429	Cooker

7.1.2 DEVICE CLASSIFICATION RESULTS OF RAW DATA

In this section the results for the classification experiment, which is undertaken on the raw energy data as described in table 19, is presented. Figure 81 highlights a confusion matrix, which presents the classification results for the raw data. Here all 14 observations are presented to the classifiers for training. The results for the Decision Forest are presented on the left where the SVM is presented on the right.

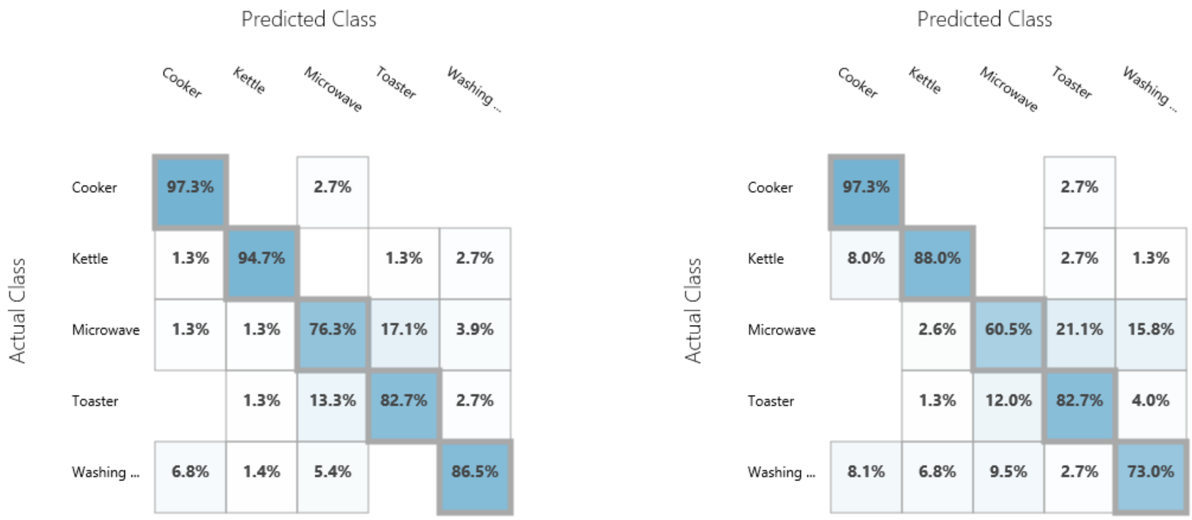


Figure 81: Confusion matrix Decision Forest vs SVM all observations using raw data

The Decision Forest attained an accuracy above 76.3% across all device classes with the cooker class achieving the best accuracy of 97.3%. The SVM matched the performance of the Decision Forest for both the cooker class and toaster class. However, the SVM exhibited reduced accuracy across the remaining classes with 88% for the kettle, 60.5% for the microwave and 73% for the washing machine. The SVMs least performing class was the microwave were 2.6% of the observations were incorrectly classified as kettle, 21.1% as a toaster and 15.8% as a kettle.

Figure 82 highlights the results from the same configuration with the number of observations reduced to 6, which represents the first 60 seconds of device usage. It is obvious that by comparing the two sets of results that there is a reduction in accuracy across the majority of classes for both algorithms.

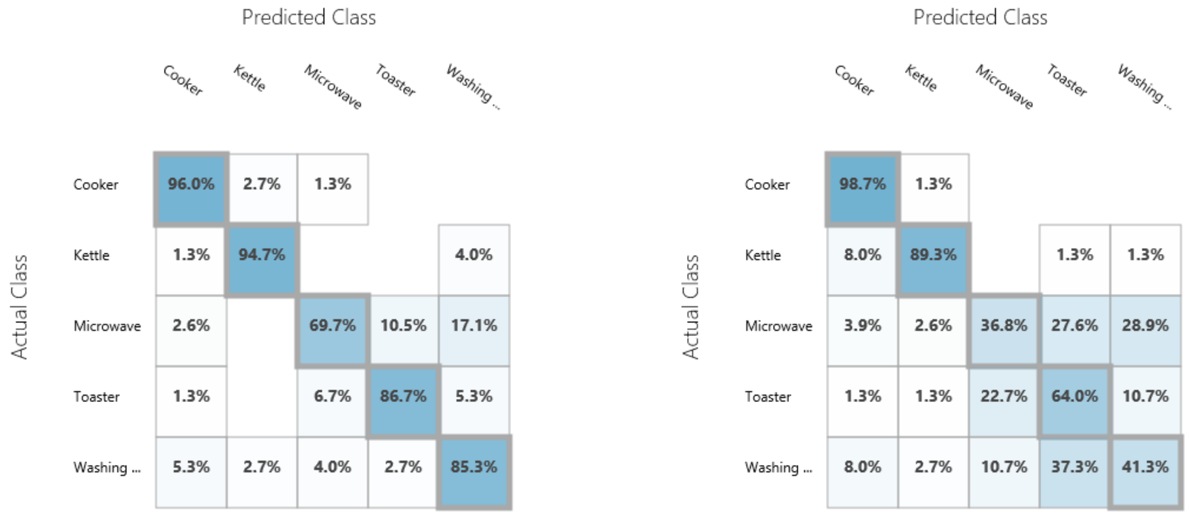


Figure 82: Decision Forest vs SVM first 6 observations using raw data

The Decision Forest presents a reduction in accuracy for the cooker, microwave and washing machine. However, it maintains accuracy for the kettle and improved accuracy for the toaster class. In contrast the SVM exhibits a reduced accuracy for the washing machine, toaster, microwave and kettle. Nevertheless, it improves accuracy for the cooker class from 97.3% to 98.7%. The least accurate class for both algorithms across the two iterations was the microwave. This highlights a close correlation between the microwave and toaster energy signatures were the misclassification prevalence was more prominent for the SVM.

As the PIMS framework is required to identify a device class in the shortest possible time period it is evident that the use of raw data for device identification is not feasible due to the adverse classification performance.

7.1.3 DEVICE CLASSIFICATION RESULTS USING STATISTICAL FEATURES

This section presents a diverse range of results using the generated statistical features as described in table 23. The aim is to reduce the device observation period while maintaining a high degree of accuracy. To establish a baseline all 14 observations are used. Figure 83 highlights the confusion matrix for both the Decision Forest and SVM using FLDA. Figure 84 presents a confusion matrix replacing FLDA with Spearman Correlation. Here the number of trees and tree depth in the Forest is set to 32 with 128 random splits per node.

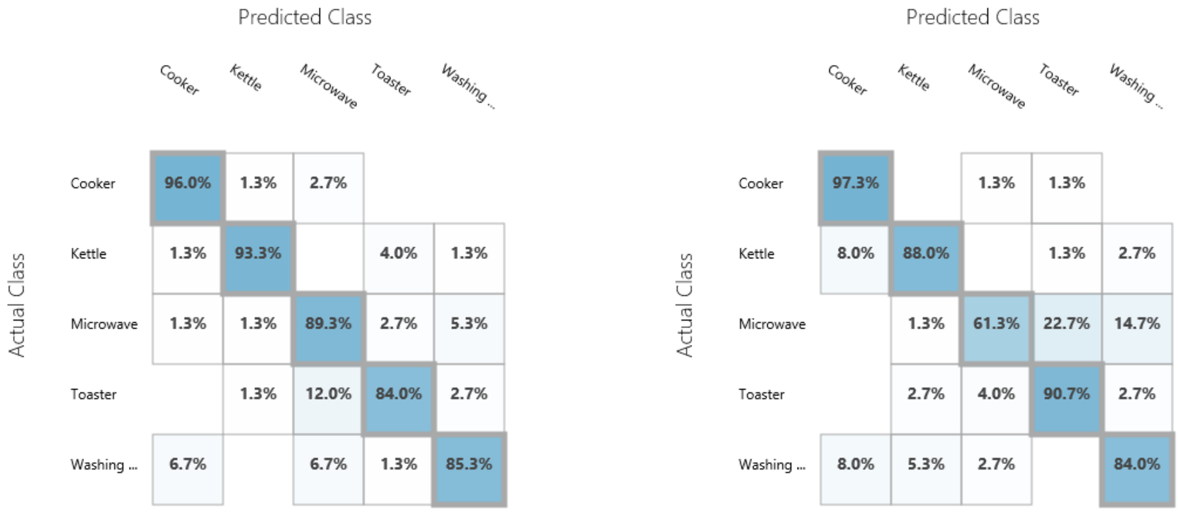


Figure 83: Initial confusion matrix Decision Forest vs SVM all observations using FLDA

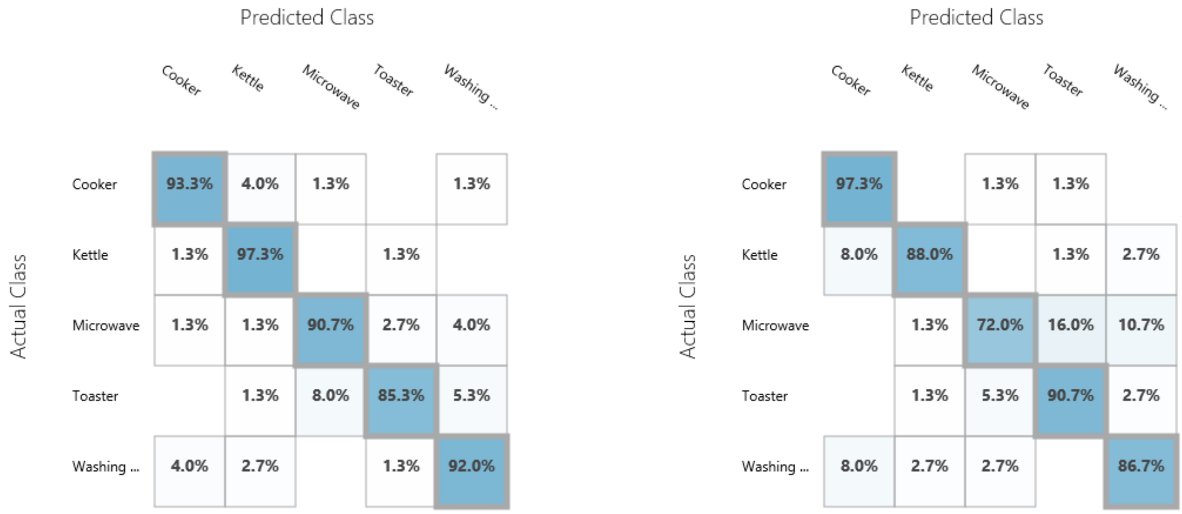


Figure 84: Initial confusion matrix Decision Forest vs SVM all observations using Spearman Correlation

When comparing the results to the raw data, the Decision Forest presents, a reduction in accuracy across the cooker, kettle and washing machine class as highlighted in figure 83. Accuracy was improved for both the microwave and washing machine classes. The SVM displays the most improvement using the statistical features maintaining accuracy across the cooker and kettle classes and improving accuracy for the microwave, toaster and washing machine class.

By using Spearman Correlation, as highlighted in figure 84, the Decision Forest shows improved accuracy across the kettle, microwave, toaster, and washing machine classes. There was a notable reduction in the cooker class, where 4% of the observations are incorrectly classified as the kettle class. An additional misclassification of 1.3% for the washing machine class is presented. The SVM exhibited the most overall improvement using Spearman Correlation. Here the accuracy improved across the microwave and washing machine class, while maintaining accuracy for the cooker, kettle and toaster classes. However as with the raw data, the microwave class presented the poorest accuracy.

Figure 85 highlights a bar chart, which presents the classification results across all classes and techniques. It is clear that the Decision Forest and SVM obtain similar accuracy for the cooker class but have their own individual strengths and weakness with certain device classes. For example an SVM would not be selected for the microwave class due to its reduced accuracy. However it shows higher accuracy for the toaster and cooker class.

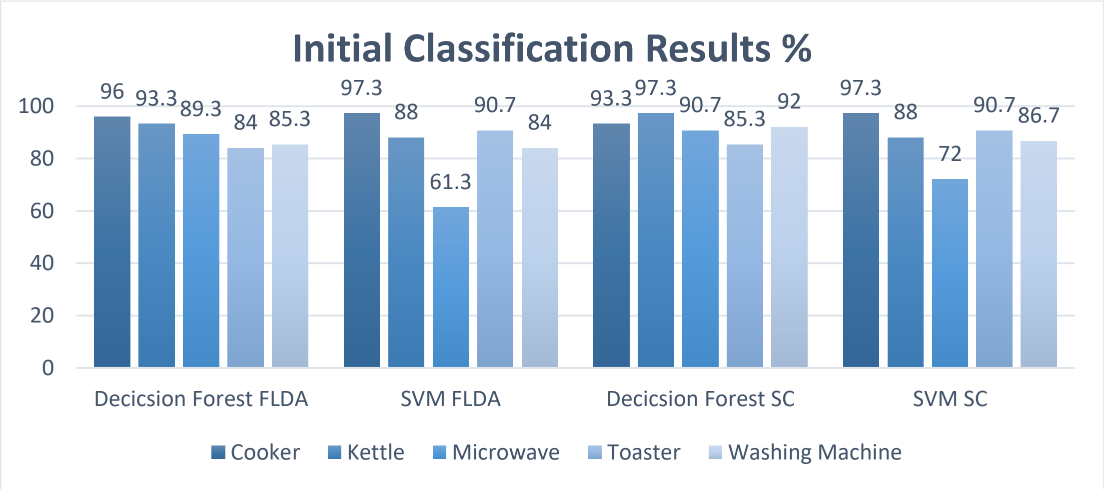


Figure 85: Initial classification results across all observations

To determine if the accuracy of the Decision Forest could be improved its complexity was altered and evaluated by increasing the number of trees. Figure 86 highlights the accuracy of the Decision Forest using both FLDA and SC. Here the number of trees in the forest was increased to 64 and reduced by half in each training epoch. The configuration that exhibited the highest accuracy was SC when configured with 64 trees. Here both the kettle and microwave class presented an improvement in accuracy while the worst performing configuration was FLDA with 8 trees. The experiment was re-evaluated to ascertain if the algorithm presented a higher degree of accuracy by altering both the tree depth and number of random splits. Here the tree number was set to 32 with both the tree depth and random splits being doubled to 64 and 256 respectively. The accuracy across all device classes presented no change with FLDA. However a slight reduction of 2.7% for the microwave class was noted using SC and a minor improvement of 1.3% for the washing machine class.

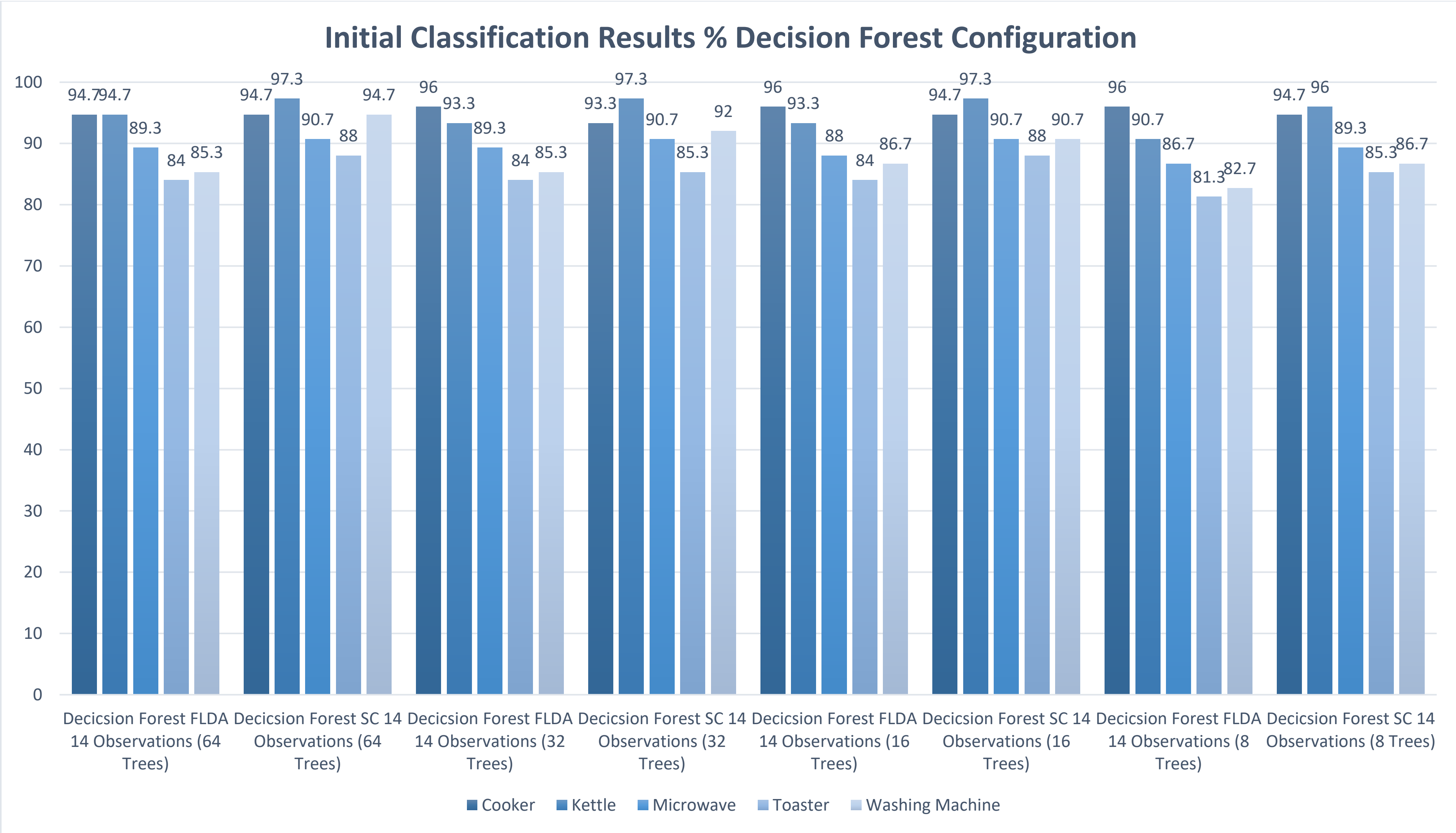


Figure 86: Initial classification result across different Forest configurations

Following the process above the observations are systematically reduced by 4 for each epoch, while assessing the classification performance. Figure 87 highlights the accuracy for FLDA after the first iteration. Using all observations the Decision Forest presented a reduction of 1.3% for the cooker class, 2.7% for the toaster class and 2.7% for the washing machine. However accuracy for the kettle was maintained and an improvement of 7.7% was noted for the microwave class. The SVM presented a reduction across all device classes except for the microwave class which showed an improvement of 7.4%.

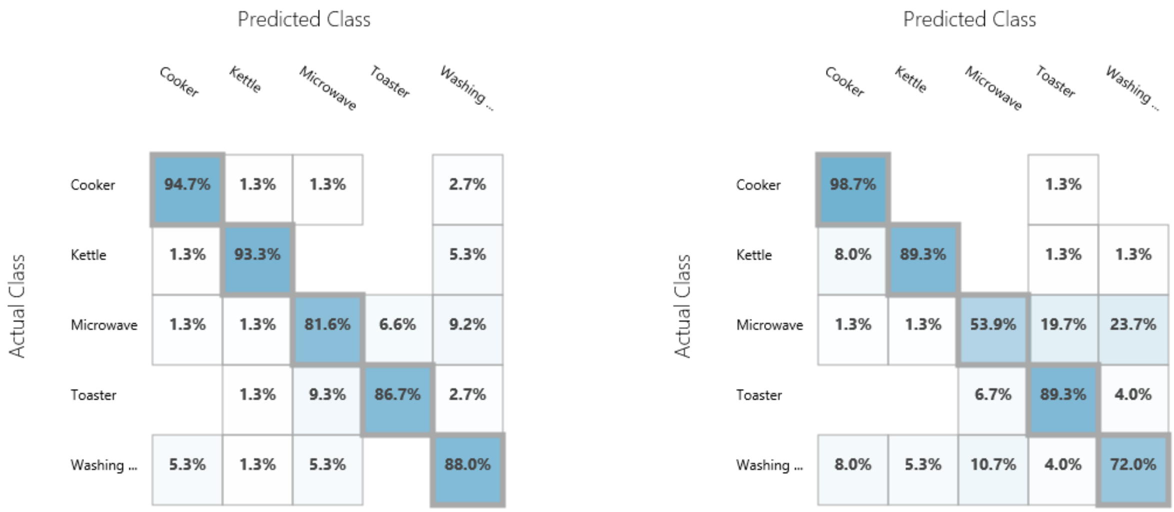


Figure 87: Decision Forest vs SVM first 100 seconds (10 observations) of device usage observations using FLDA

Figure 88 presents the results for the SC after the first iteration. Comparing the results to all observations the Decision Forest presented a reduction in accuracy of 1.4% for the cooker, 4% for the kettle, 9.1% for the microwave and 1.4% for the toaster. However an increase in accuracy of 4% was noted for the washing machine class. The SVM presented a reduction in accuracy for the cooker of 1.4% and 1.3% for the kettle. The accuracy for the microwave exhibited an improvement of 18.1%, 1.4% for the toaster and 14.7 for the washing machine.

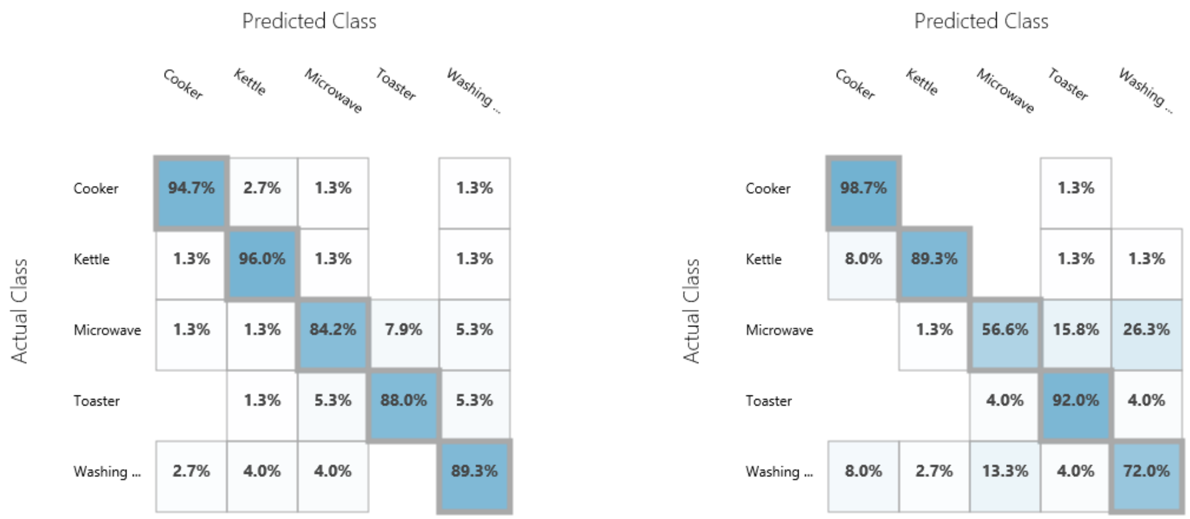


Figure 88: Decision Forest vs SVM first 100 seconds (10 observations) of device usage observations using SC

Figures 89 and 90 present the confusion matrix for the final reduction in observations using the generated statistical features. The Decision Forest and SVM using FLDA is highlighted in figure 89. Comparing the results to the previous iteration, the Decision Forest improved accuracy for the cooker by 4%, the toaster by 1.3% and maintained accuracy for the kettle. However a reduction in accuracy of 5.3% (microwave) and 9.3% (washing machine) was noted. The SVM maintained accuracy for the cooker class and presented an improved accuracy for the kettle (1.3%) and microwave (2.3%). However, a reduction in accuracy was exhibited for the toaster (9.3%) and the washing machine (37.3%) where 41% was misclassified as a toaster.

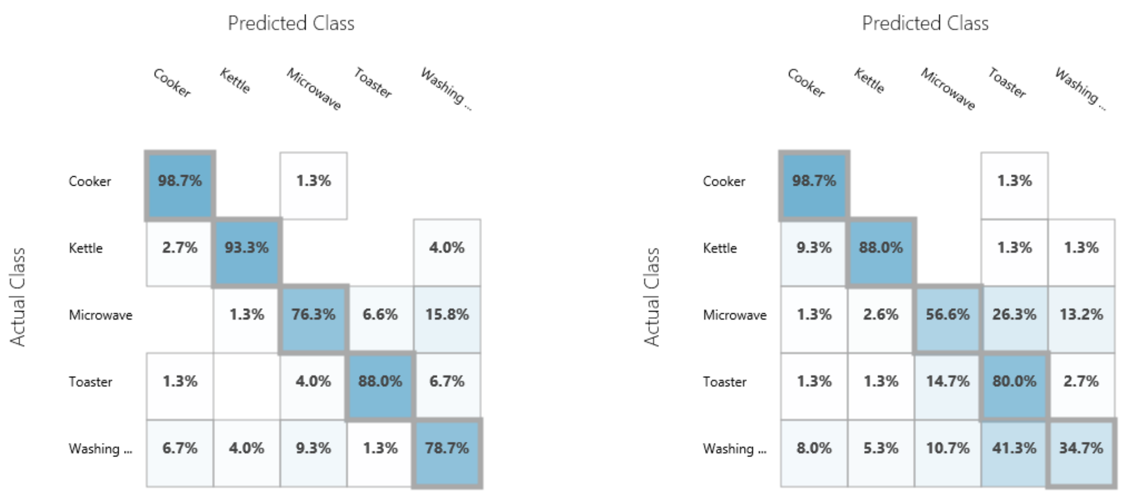


Figure 89: Decision Forest vs SVM first 60 seconds (6 observations) of device usage observations using FLDA

Figure 90 highlights the confusion matrix for SC. Here the results are compared to the previous iteration as presented in figure 86. The Decision Forest presented an accuracy reduction of 1.4%, 6.6% and 4% across the cooker, microwave and washing machine classes respectively. However, accuracy was maintained for the kettle and toaster classes. The SVM exhibited a reduction across the kettle, microwave, and washing machine but improved accuracy of the toaster by 13.3%. Accuracy for the cooker was maintained at 98.7%.

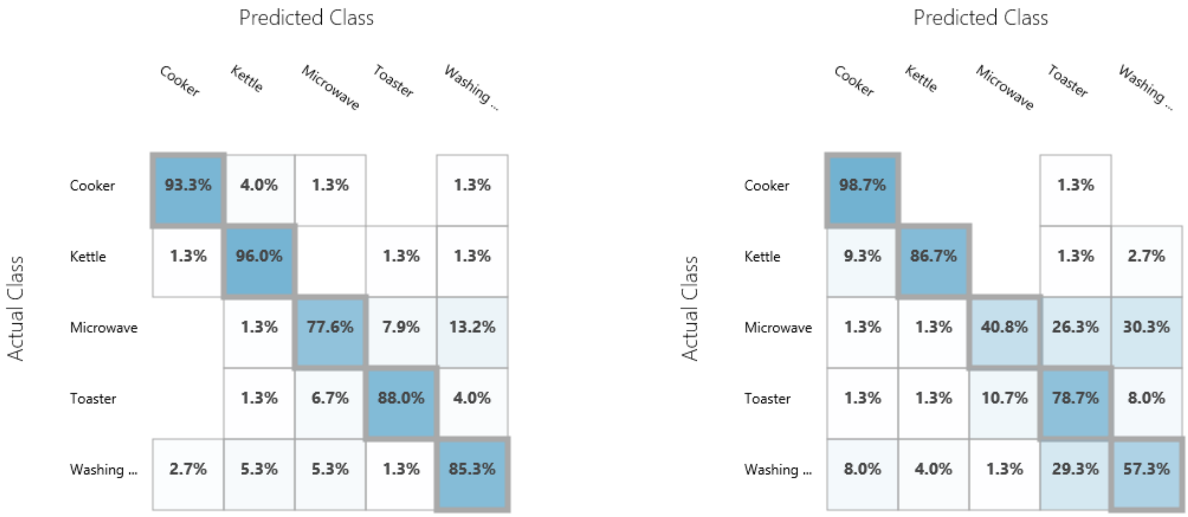


Figure 90: Confusion matrix Decision Forest vs SVM first 60 seconds (6 observations) of device usage observations using SC

Figure 91 highlights the accuracy using 6 observations for both the raw data and the generated features. The minimum threshold for the PIMS acceptance criteria of 70% is represented by a red horizontal line. Only three configurations met the acceptance criteria for each device class. These include the Decision Forest SC raw data, Decision Forest FLDA statistical features and the Decision Forest SC statistical features.

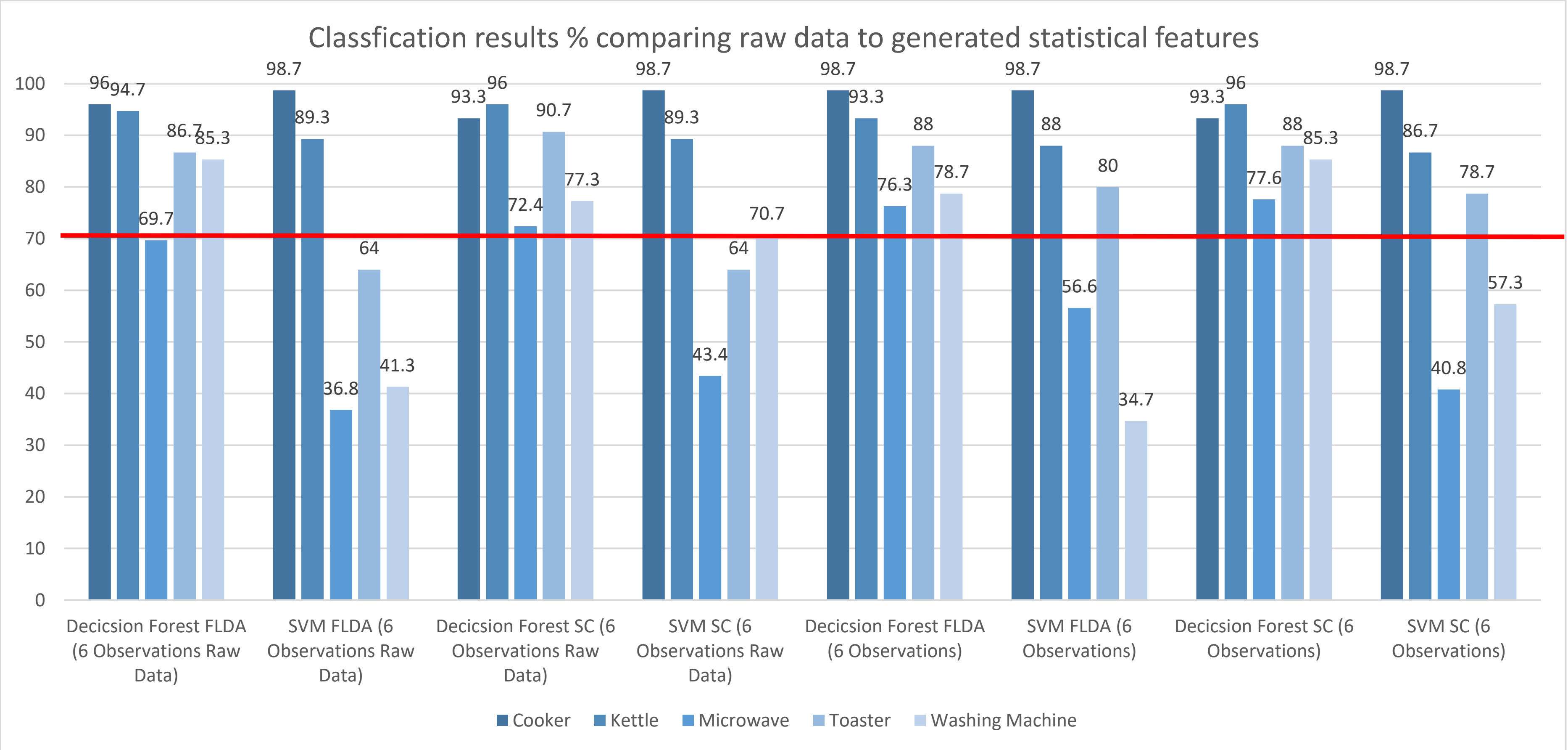


Figure 91: Classification results comparing raw data to generated statistical features

7.1.4 BEHAVIOURAL CLASSIFICATION RESULTS

In the following section the evaluation of the behavioural classification process is presented. Specifically, the predicted appliance interactions from the device classification models are recorded for each of the patients outlined in chapter 5. In total 48 days of device interactions were assessed for each patient in the trial. 48 days were chosen as this is a feasible amount of time for training before the system is moved into prediction mode. Training the system for longer periods would introduce unacceptable delays in patient monitoring. Although the initial training period is limited, the PIMS formwork facilitates the continuous training of the behavioural models as outlined in chapter 5.

Abnormal days are identified where there is a notable reduction in device interactions. As with the device classification model, the number of trees and the tree depth in the Forest is set to 32 with 128 random splits per node. A linear SVM has been introduced to establish if the accuracy is of an acceptable level using a less computationally expensive algorithm. For the SVM, the data has been normalised using Min Max. Any missing values in the training data have been replaced with a 0 to represent the absence of a device interaction. By using two contrasting algorithms, the study investigates the level of model complexity required to obtain an acceptable behavioural classification.

Patient 1: 34 days where identified as normal while 14 were identified as abnormal. In order to balance the dataset SMOTE was used to synthetically increase the number of abnormal observations to 34. Table 24 presents the confusion matrix for the Decision Forest while table 25 highlights the confusion matrix for the SVM.

Table 24: Confusion matrix Patient 1 Decision Forest behavioural model

	Estimated Labels		
True Labels	1 (Normal)	2 (Abnormal)	Totals
Class 1 (Normal)	30	4	34
Class 2 (Abnormal)	1	33	34
Totals	31	37	68

Table 25: Confusion matrix Patient 1 SVM behavioural model

True Labels	Estimated Labels		
	1 (Normal)	2 (Abnormal)	Totals
Class 1 (Normal)	24	10	34
Class 2 (Abnormal)	6	28	34
Totals	30	38	68

Figure 92 highlights the ROC curve for the behavioural classification for patient 1 using the Decision Forest, while figure 93 presents the ROC curve for the SVM.

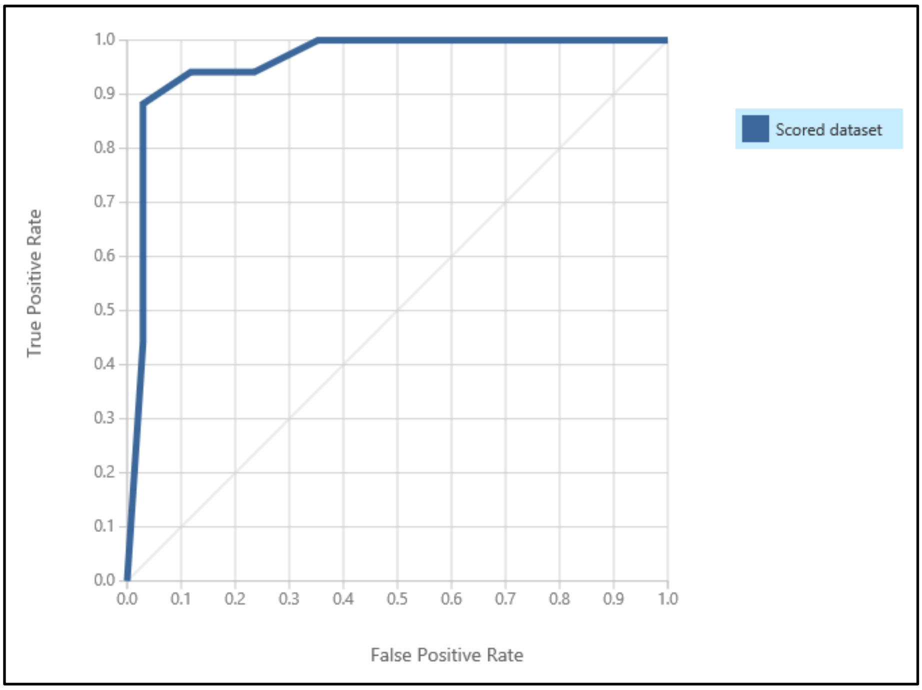


Figure 92: ROC behavioural classification patient 1 decision forest

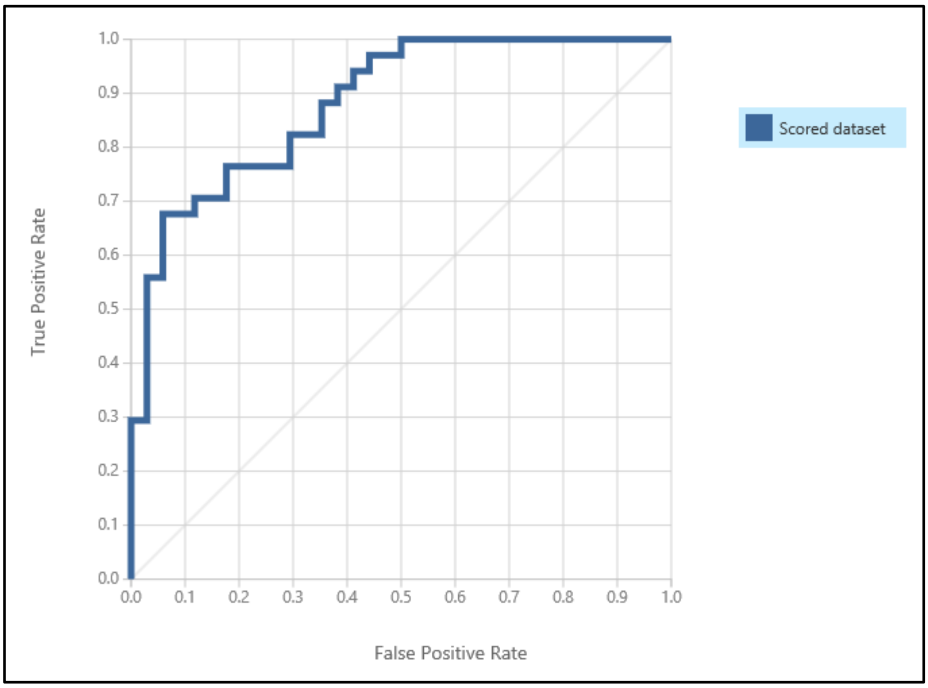


Figure 93: ROC behavioural classification patient 1 SVM

Patient 2: exhibited 37 days of normal behaviour while 11 days where identified as being abnormal. SMOTE is used to balance the dataset by synthetically increasing the number of abnormal observations to 37. Table 26 highlights the confusion matrix for the Decision Forest while the confusion matrix for the SVM is presented in table 27.

Table 26: Confusion matrix Patient 2 Decision Forest behavioural model

	Estimated Labels		
True Labels	1 (Normal)	2 (Abnormal)	Totals
Class 1 (Normal)	32	5	37
Class 2 (Abnormal)	3	34	37
Totals	35	39	74

Table 27: Confusion matrix Patient 2 SVM behavioural model

True Labels	Estimated Labels		
	1 (Normal)	2 (Abnormal)	Totals
Class 1 (Normal)	29	8	37
Class 2 (Abnormal)	2	35	37
Totals	31	43	74

Figure 94 highlights the ROC curve for the behavioural classification for patient 2 using the decision forest, while figure 95 presents the ROC curve for the SVM.

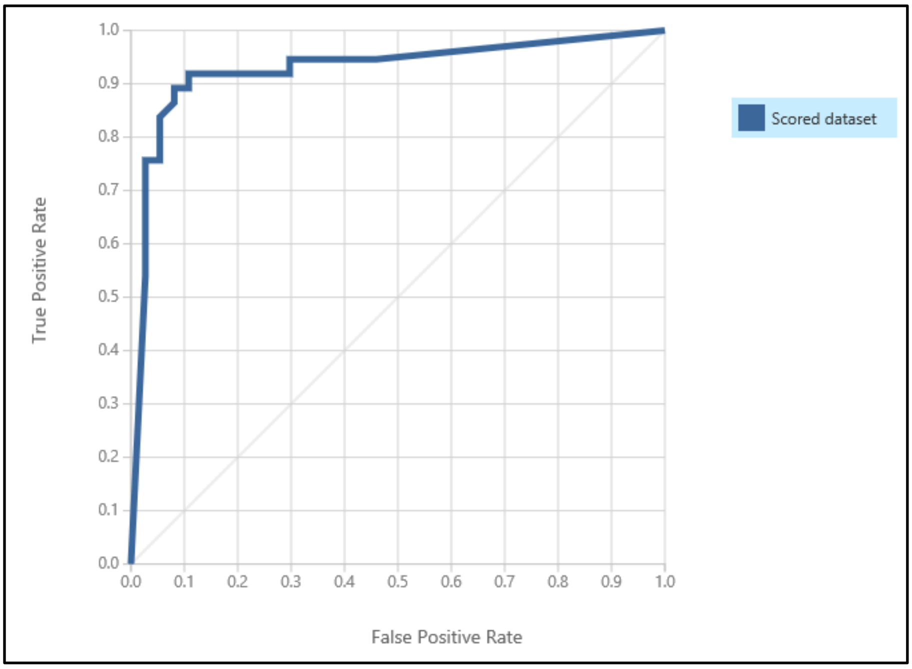


Figure 94: ROC behavioural classification patient 2 decision forest

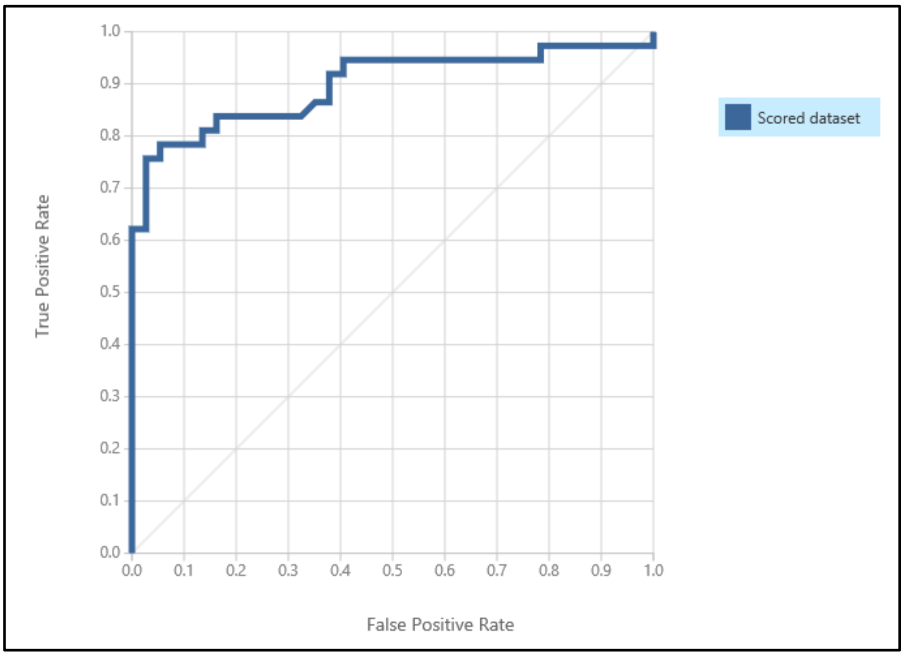


Figure 95: ROC behavioural classification patient 2 SVM

Patient 3: During the first 48 days of monitoring patient 3 presents 36 days of normal behaviour while 12 days are identified as abnormal. As with the previous patients, SMOTE is used to synthetically increase the number of abnormal observations to 36. Table 28 presents the confusion matrix for the Decision Forest while table 25 highlights the confusion matrix for the SVM.

Table 28: Confusion matrix Patient 3 Decision Forest behavioural model

True Labels	Estimated Labels		
	1 (Normal)	2 (Abnormal)	Totals
Class 1 (Normal)	33	3	36
Class 2 (Abnormal)	3	33	36
Totals	36	36	72

Table 29: Confusion matrix Patient 3 SVM behavioural model

True Labels	Estimated Labels		
	1 (Normal)	2 (Abnormal)	Totals
Class 1 (Normal)	30	6	36
Class 2 (Abnormal)	1	35	36
Totals	36	36	72

Figure 96 highlights the ROC curve for the behavioural classification for patient 3 using the decision forest, while figure 97 presents the ROC curve for the SVM.

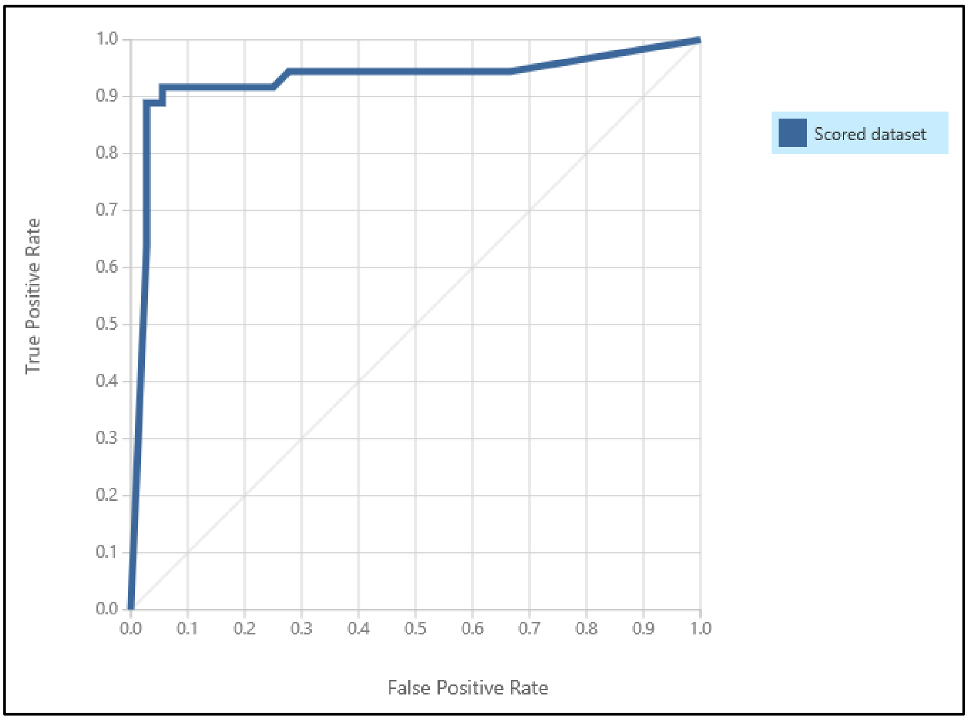


Figure 96: ROC behavioural classification patient 3 decision forest

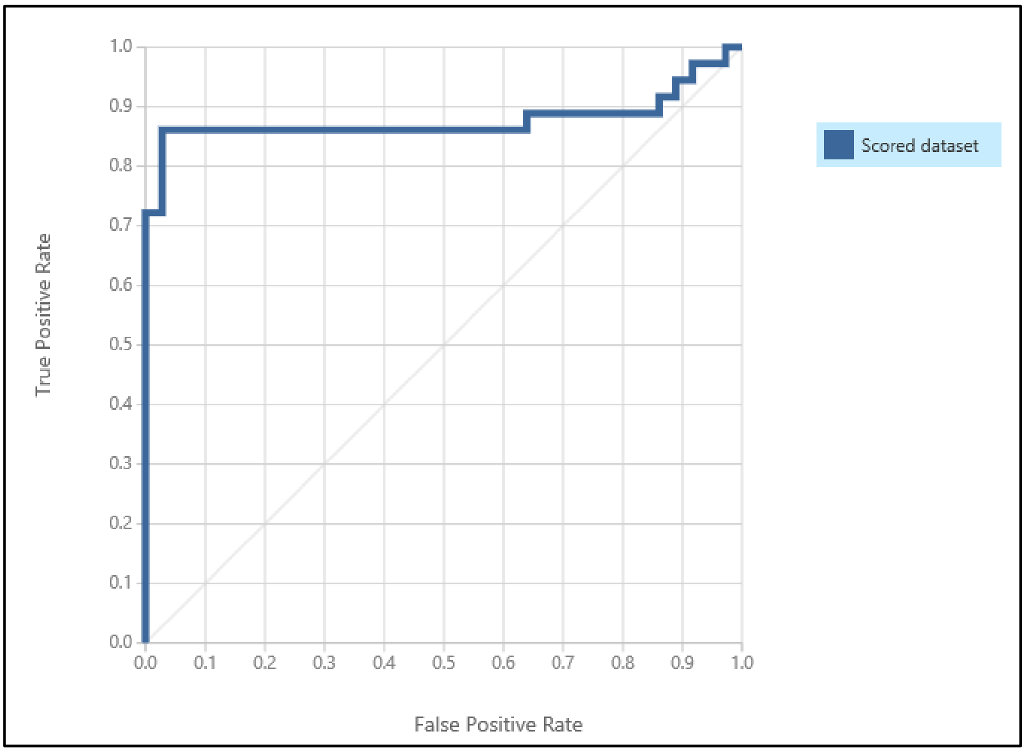


Figure 97: ROC behavioural classification patient 3 SVM

Table 30 displays a comparison between the success rate; error rate; sensitivity; specificity and Area Under Curve (AUC) for each classification experiment. Of all the experiments, the Decision Forest presented the best results achieving an accuracy of 92.64% and an error rate of 0.0736 for patient 1. The worst performing classifier is the SVM for patient 1 with an accuracy of 76.47 and an error of 0.2352. The best performing classifier across all patients is the Decision Forest achieving an average accuracy of 91.16 compared to the SVM of 84.3.

Table 30: Classification results comparison Decision Forest vs SVM

Patient	Classifiers	AUC (%)	Sensitivity	Specificity	Error
Patient 1	Decision Forest	92.64	0.882	0.970	0.0736
Patient 1	SVM	76.47	0.705	0.823	0.2353
Patient 2	Decision Forest	89.18	0.864	0.918	0.1082
Patient 2	SVM	86.48	0783	0.945	01352
Patient 3	Decision Forest	91.66	0.916	0.916	0.0834
Patient 3	SVM	90.2	0.833	0.972	0.098

7.2 PIMS EVALUATION

Using both the methodology, and an iterative approach, the minimum threshold for the PIMS framework was achieved and in some cases exceeded across all devices classes. By generating an accurate device classification model the behavioural classifiers can be deployed to identify both normal and abnormal behaviours.

The devices selected for this implementation not only have good prevalence in UK homes, but their usage signifies the undertaking of essential ADLS. Although these devices provide significant representation of the activities undertaken, the inclusion of additional devices will undoubtedly provide an enhanced assessment of the patient. However, adding additional appliances could impact the accuracy of the classifier while leading to increased costs. Before additional devices are added to the PIMS framework consultation with clinicians must be undertaken to ascertain its effectiveness.

It is evident from the device classification results that both the Decision Forest and SVM achieve reasonable results using both the raw data and the generated statistical features. However, obtaining a higher degree of accuracy from the raw data required the use of all 14 readings. Between the two classifiers the Decision Forest attained a higher degree of accuracy when compared to the SVM. The SVM presented a reduction in accuracy for the microwave class suggesting the presence of a strong relationship between the microwave, toaster and washing machine class. This trend was also reflected in the results for the Decision Forest although the reduction in accuracy was not as significant.

A clustering algorithm as illustrated in figure 98 is used to obtain an overall visualisation of the raw data and to find any natural boundaries or relationships between the different device classes. Identifying the boundaries between the different classes aids in the selection of the classifier for example: linear, quadratic or polynomial. The algorithm selected for this task is the Yifan Hu, which belongs to the category of force-directed algorithms [193]. These algorithms use specific formulas to calculate both the attraction and repulsions forces. The repulsion F_r formula is mathematically defined as $(F_r = k/d^2)$ while the attraction F_a formula is expressed as $(F_a = -k \cdot d)$ where d represents the distance between the two nodes. One of the main benefits of this approach is that the algorithms function by calculating the specific structure of the data using only information contained within the structure of the graph. This removes the need for domain-specific knowledge [194]. Specifically, the Yifan Hu algorithm uses the repulsive forces on one node from a cluster of distant nodes, which are approximated by a Barnes-Hut calculation scheme for grouping together bodies that are sufficiently nearby [195].

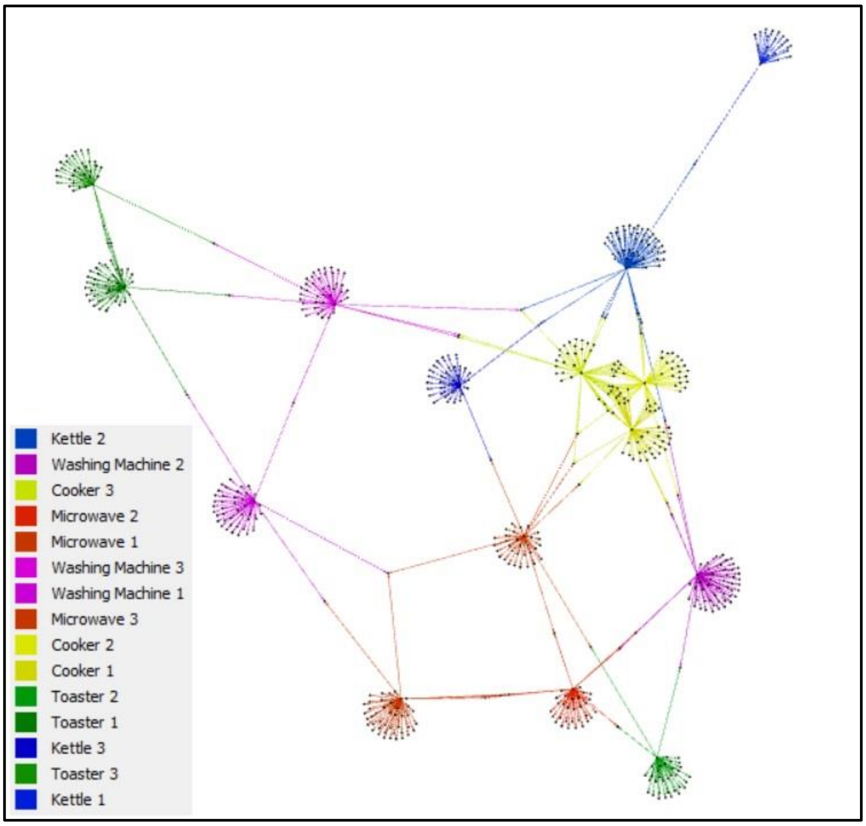


Figure 98: Cluster analysis of the different device classes highlighting device relationships

The results presented in figure 98 confirm the presence of a quadratic boundary between the different device classes. However, a clear relationship between the toaster and microwave classes exists, which could impede the performance of the classifier. The limited sampling frequency of the smart meter impedes the classifiers ability to separate certain device classes. As a result the introduction of more complex algorithms might be required depending on the desired accuracy. Using the first six readings of the device enabled the classifier to identify the appliance based on its unique start up signature. By using this technique the algorithms achieved reasonable success even though the device boundaries are complex.

The PIMS framework is required to classify the use of an appliance in the shortest possible timeframe. Reducing the number of readings from 14 to 6 using the raw data presented a significant reduction in accuracy for the SVM across three device classes. However the Decision Forest presented a notable reduction in only a single device class. By using the raw data and a reduced observation period only the Decision Forest FLDA configuration archived the minimum probability threshold for the PIMS framework.

In order to ascertain if the use of statistical features could improve the accuracy of the classifiers the experiments where iterated. Applying all 14 observations to both the Decision Forest and SVM presented an overall improvement using FLDA and SC. The class that presented the most significant improvement for both algorithms was the microwave. Out of the 4 results 3 configurations met or exceeded the minimum threshold. These include the Decision Forest FLDA, Decision Forest SC and the SVM SC. The results confirm that the method out lined in this thesis can be used to effectively identify electrical appliances from aggregated load readings.

By using the first 6 readings two configurations exceeded the minimum threshold. These include the Decision Forest FLDA and the Decision Forest SC. By reducing the number of observations from 14 to 6 both the Decision Forest and SVM presented an overall reduction in accuracy. In particular the Microwave class exhibited the most significant reduction for both classifiers. However, by deploying the statistical features and reducing the number of observations to the target value it was possible to obtain an overall accuracy in excess of 70% using the Decision Forest.

To investigate whether increasing the complexity of the Decision Forest improved the classification accuracy, the experiment was repeated. Increasing the tree count, depth and splits presented no significant improvement in accuracy using both FLDA and SC. Using all 14 observations each device class presented an accuracy in excess of 80% across each configuration, therefore exceeding the minimum threshold. Deploying a configuration that maintains accuracy while reducing computational requirements is a principal consideration for production. Increasing the Forest complexity introduced extended training times while gaining only a minimal increase in accuracy. Typically cloud platforms charge using a per transaction cost model consequently, increasing the complexity of any algorithm could introduce higher processing costs therefore decreasing the overall cost benefit of the solution.

To improve upon previous classification performance the use of two techniques were deployed and evaluated. FLDA and SC presented varying degrees of success depending on the dataset, device class and the type of algorithm deployed. Overall both methods achieved an accuracy in excess of 70% using both the Decision Forest and a reduced number of observations. Across all experiments SC improved the accuracy of both the microwave and washing machine class but presented an adverse effect on the cooker class using the Decision Forest. As discussed in the methodology there was an expectation that SC would exhibit a higher degree of accuracy due to the distribution of the data. However FLDA attained similar results while increasing the overall accuracy of the SVM by the greatest margin.

The Decision Forest presented the highest degree of accuracy using both the raw data and statistical features. While the SVM did not attain the required accuracy across both the microwave and washing machine class it exceeds the threshold across the remaining classes. Although the data was normalised therefore benefitting the SVM, altering the kernel from linear to a more complex decision boundary such as quadratic improved the overall performance. Figure 99 presents the true positive rate for both the linear SVM and the quadratic SVM. Here the two classifiers used FLDA and SC for the 6 observations from the statistical features.

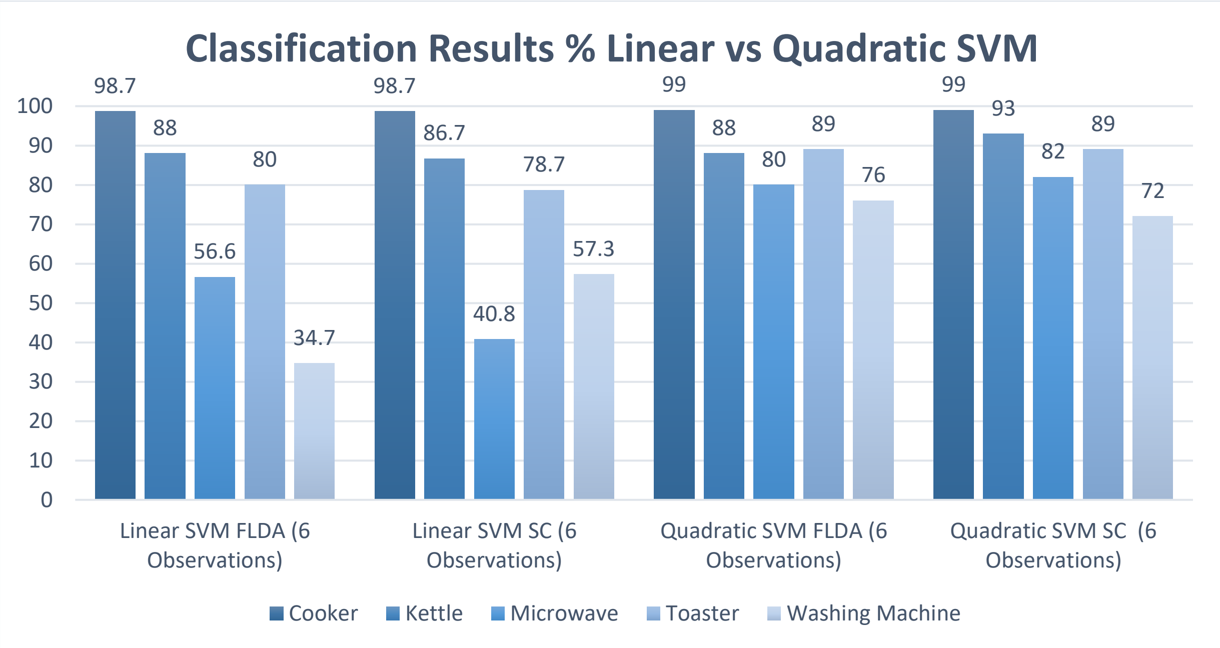


Figure 99: Classification results linear vs quadratic SVM

By increasing the complexity of the SVM the quadratic kernel exceeded the minimum threshold achieving comparable results when compared with the Decision Forest.

Using both the Decision Forest and SVM the behavioural classification presented an accuracy in excess of 76% across all patients in the trial. Out of the two classifiers the Decision Forest obtains the best accuracy of 92.64% for patient 1. The results from all experiments exhibit adequate accuracy for use in PIMS and can be used to formulate a decision regarding the patient's wellbeing. The balance between specificity and sensitivity requires careful consideration to ensure that both the false positives and false negatives are adjusted accordingly. The decision on which factor is of more importance lies with the medical profession but warrants adjustment on a case by case basis. The flexibility of the PIMS framework facilities the integration of medical knowledge thus facilitating personalisation based on both the needs of the individual and their condition.

Although the implementation uses an entire 24 hour period this approach can be scaled to assess finer periods. By using the identified devices as behavioural indicators the classifiers are able to determine the absence or presence of the individual devices along with any change in usage frequency. The amount of behavioural data available for training the classifiers will always be limited as collecting large amounts of data during the implementation phase is not feasible. Once the CAD is installed the initial training phase will be short so the system can start monitoring the patient. However, the PIMS framework retrains over time using a feedback mechanism. The enables the system to adjust as increasing volumes of data become available.

The outcomes from the patient trial present promising results for its use as an AAL technology. By using both the energy readings from a smart meter and a machine learning approach, limitations with existing AAL solutions can be overcome. The results demonstrate that specific ADLs can be identified by detecting interactions with electrical appliances. This approach offers significant improvements over existing AAL technologies where ADL detection is often absent. The results from behavioural classification demonstrate that the use of machine learning algorithms can be used to provide a personalised assessment of the patient's wellbeing.

7.3 SUMMARY

In this chapter, the PIMS framework was evaluated using different configurations to ascertain the performance for both the device and behavioural classification models. The evaluation highlighted strong relationships between certain device classes which can impede the overall performance of the system. However, it was noted that particular classifiers exhibit high performance for certain device classes providing the notion of combining them to improve accuracy. The need to balance accuracy with computational requirements was discussed. This balance is imperative when moving the system into production as extended processing time introduces higher financial costs. As previously discussed higher financial costs are likely to impede its acceptance. In addition the results from the behavioural classification were presented. The results demonstrated that the detection of both normal and abnormal patient behaviour is possible using PIMS.

By using the PIMS framework, the ability to monitor the behavioural characteristics of the patient is possible. However further medical insight is required to define the importance of both the observation windows and the observed behaviour.

CHAPTER 8 CONCLUSIONS AND FUTURE WORK

8.1 INTRODUCTION

In this chapter the thesis is concluded and a summary of the work is put forward. In addition the novel contributions to knowledge are highlighted. The chapter also discusses the importance of both the research for overcoming limitations with existing solutions. Additionally future work is discussed while outlining the different future directions the project might take. The chapter is concluded with a summary of the future challenges.

8.2 THESIS SUMMARY

The research outlined in this thesis provides a foundation to a novel and emerging concept, where smart meter data can be used to address the variety of limitations with existing solutions. By using a novel approach the research presented was able to identify the use of 5 distinct electrical appliances. By detecting the use of electrical appliances the identification of specific ADLs is possible. The advantage of using such an approach means that patient activities can be accurately identified, opposed to just detecting that an activity has occurred. As demonstrated in this thesis our approach requires the use of a single non-intrusive sensor which requires no patient interaction to operate. This single feature removes numerous limitations with existing solutions which relay on either a complex distributed sensing network or manual intervention from the patient. By using a machine learning approach the identification of abnormal patient behaviour is possible. This method facilitates the construction of a personalised solution which takes into account the complex patterns of human behaviour.

Although the primary objective for the AMI is to balance grid load and demand. The infrastructure and its data collection capabilities are also beneficial in a variety of health and care applications. However, there are still advancements that need to be made in identifying a wide range of electrical devices from aggregated energy readings. These advancements would heighten both the adoption and usefulness of smart meters for an assistive living technology. However, these improvements rely on additional data features and improved sampling rates, beyond the current default readings of 10 second intervals. Although this limitation is not a technical restriction, the modification to any smart meter function is a policy decision which is specified by both utility companies and government.

In conclusion, chapter one provided an introduction to both smart meters, there capabilities and the concept of the AMI. Additionally, the motivation behind the research was introduced and the various health and social challenges facing the UK were outlined. As well as an overview of the challenges, the various aims, objectives and novelties were presented, which were deployed and developed to overcome the research problem.

The background has been presented in chapter two. This included an overview of the motivation, technical detail and the multiple components that sit within the smart grid. Specifically the AMI is broken down into its three distinct layers, highlighting their functions and interoperability. The chapter introduces the data challenges, which are associated with the AMI and the related infrastructure used to process and manage the collected data. Here a detailed technical discussion of smart meters is provided along with their data collection capabilities. The chapter discussed the concept of load disaggregation focusing on both ILM and NILM and their associated benefits and limitations. Additionally the chapter introduced the concept of machine learning along with its challenges and mitigations. The chapter was concluded with an insight into cloud computing and how it is used in both smart grids and machine learning.

Related research detailed in chapter 3 discussed an emerging concept known as AAL. Here numerous fields and disciplines have been integrated to provide a variety of different technical solutions aimed at overcoming existing monitoring problems. However, as identified, there are a plethora of different issues and limitations, which are associated with existing solutions. Complexity, cost, maintenance and the lack of personalisation and integration are just some of the reasons for limited deployment and adoption.

The design and functionality of the PIMS framework was introduced in chapter 4. Here the end-to-end system was described starting with the smart meter and ending with the generated alert status. Through the use of web services, the functionality of the generated models could be exposed and integrated with both native applications and existing services. As a result, the research in this thesis introduced a novel approach achieving a cost effective, nonintrusive and personalised solution.

Chapter 5 presented a case study involving 3 different patients. Here the study was used to satisfy both the implementation and evaluation of the PIMS framework. By conducting a patient trail it facilitated the generation of the behavioural training data and assed the generalisation of the device classification models.

In chapter 6, a detailed description of the data gathering techniques used in the approach was presented. Specifically, an energy monitor was installed in three properties to create both the appliance signature database and behavioural data. The data collection undertaken to generate and validate both the device and behavioural models was described along with the data preparation for classification. In addition the chapter presented the implementation of the PIMS framework using a hybrid approach. By using the Microsoft Azure platform a work space was generated for the PIMS framework. Here the trained classification models where created and configured to facilitate the real time detection of both normal and abnormal patient behaviour. In order to expose the functionality of the generated models, two web services where created to facilitate the real time classification of both device usage and patient behaviour.

In chapter 7, the results for the device classification models were presented using the raw data, statistical features and altering the observation window. Both a decision forest and SVM where used to classify each of the 5 electrical devices. Additionally the behavioural models were scored using the evaluation methods outlined in the methodology. In Addition the implementation and evaluation of the approach was discussed. The chapter highlighted strong relationships between certain devices classes and what effect these relationships posed for classification. The chapter discussed how the accuracy could be improved by increasing the complexity of the classifier while highlighting concerns surrounding increased computational requirements.

8.3 CONTRIBUTIONS TO KNOWLEDGE

In this thesis, a wide variety of health applications were proposed for the PIMS framework. These include monitoring incapacity (such as falls), sleep disturbances, memory problems, changes in activity patterns, inactivity, occupancy and the identification of ADLs. The research presented in this thesis identified a number of benefits where smart meters provide advantages when compared to other AML approaches, such as wearable, distributed sensors and Internet of Things devices (IoT). As smart meters will reach high prevalence by 2020 exploiting this low cost, accurate and maintained infrastructure for health applications arguably provides an attractive proposition to health and social care providers alike. Whilst these benefits provide the opportunity to alleviate many issues associated with current telehealth solutions there are also significant challenges.

As a result, the proposed methodology offers a significant contribution for both the advancement of AAL and load disaggregation. In the UK, the effects of an ever aging population are becoming increasingly harder to manage. Consequently a variety of challenges for both health and social care providers have been introduced. Using our methodology, an automated machine learning approach which is both adaptable and personalised is provided, which can be applied to a variety of medical domains and uses. Proposed applications include issuing alerts to carers when unusual activity patterns are recognised, identifying significant events such as sleep disturbances, inactivity and monitoring the progress of conditions (to inform treatment needs).

The ability to identify usage patterns of individual appliances facilitates a greater understanding of the behavioural patterns of occupants. PIMS can accurately identify kettle, toaster, microwave, cooker and washing machine usage. Interaction with these devices and the models generated facilitates the detection of significant ADLS, and are used to ascertain the overall wellbeing of the occupant. Studying the usage patterns (and changes in usage patterns) of individual appliances provides the ability to detect abnormal patterns of behaviour linked to various health conditions. For example, unusual energy use overnight may be evidence that an occupant is experiencing sleep disturbances.

Furthermore, analysis of the combination of appliance usage, and variations in these, offers the potential to infer different forms of EIP. Such combinations can be used to identify whether somebody is simply getting up in the night to go to the toilet, or whether they are getting up in the night to eat or make a cup of tea. It is the interpretation of these 'activities of daily living' that has the strongest potential for smart energy data to support health and care lies. However, such applications would be just a small part of the much wider domain of digital health. The research presented in this thesis is validated through the implementation of the PIMS framework and a unique patient trial. This study is the first of its kind and does not increment the technological successes of any other solution; this makes the approach unique and foundational in character within remote health monitoring solutions. As a result the research provides a novel approach for using energy data for both patient monitoring and assistive technologies. The proposed solution requires minimal installation, as it utilises the already installed smart meter infrastructure. It is truly non-intrusive in that it requires no user interaction beyond the normal usage of common household devices and services. The system costs are therefore very low given that the user is not required to wear or use any custom devices for the solution to work. This approach is a never been seen before technology that addresses many fundamental healthcare needs, for a safe and sustainable independent living home-care and Early Intervention system.

Although the research offers significant benefits to the AAL domain, its applications are far reaching especially in the field of NILM. Historically smart meter load disaggregation has been restricted by the quality of data provided by the smart metering infrastructure. By using the novel approach presented in this thesis a method is provided for the disaggregation of electrical appliances using only smart meter data. Using the start up signatures for each appliance class and a single obtainable parameter a machine learning approach was used to identify 5 distinct appliance classes. This approach offers a number of contributions to NILM by overcoming the challenges with smart meter disaggregation.

8.4 FUTURE WORK

The work conducted in this thesis can be adapted to provide a more granular assessment of the patient's wellbeing while being applied to different medical conditions and use cases. In this subsection an overview of the future work and considerations are presented.

- **Combining device classification models:** As demonstrated in chapter 6, different classification models and dimensionality reduction techniques presented increased accuracy for certain device classes. The possibility of using the device classification models in combination and selecting the classifier with the highest probability score could enhance system accuracy. In future work, the web service could be altered to present the electricity observations to multiple classification models while scoring them individually. The prediction with the highest scoring probability would be used to identify the device. Figure 100 highlights the concept of an enhanced PIMS web service:

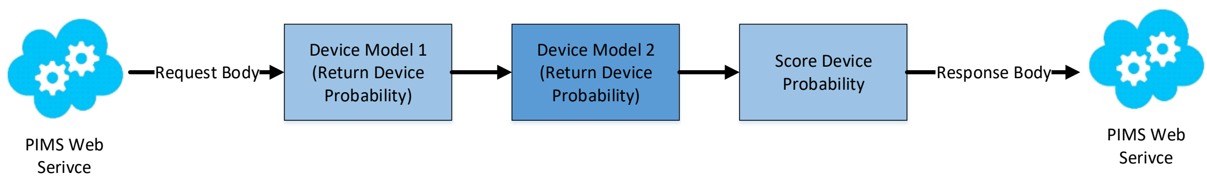


Figure 100: PIMS cross model scoring

Although cross modelling could improve the device classification accuracy careful consideration is required when assessing computational requirements. Each model will use additional compute hours which will incur additional costs.

- **Increasing device signatures:** In this thesis, the device classification models were trained to identify five distinct device classes. Any future work would benefit from an expanded device classification model, in particular profiling the lighting, which would enable the detection of a patient's location within the home. Lights, light fittings and bulbs create specific profiles based on the type of light and the amount of bulbs fitted. This type of monitoring is extremely beneficial in assessing a patient's wellbeing. Determining how often a patient visits the bathroom during the night can provide useful insights into their current health. For example, frequent visits may indicate a urinary tract infection or prostate problems if they are male.

- **Multiclass behavioural model:** In future work a multiclass model will be deployed during step 12 replacing the existing binomial model. This will enable the system to identify various behavioural patterns, which require more tailored responses. By utilising a multiclass approach, it permits the system to be more granular by facilitating the detection of additional behavioural patterns and altering the required response to match the identified behaviour. However, generating additional behavioural classes beyond both normal and abnormal requires medical insight. Each training sample will require labelling to train the classifier to identify the significance of the observation. Additionally behavioural models could be generated which are specifically targeted at particular medical conditions enabling personalisation to both the patient and their associated condition.
- **Monitoring additional utilities:** By monitoring the use of additional utilities such as gas and water the detection of additional ADLS is possible. Cooking equipment such as gas ovens and hobs can be identified in a similar manner to electrical devices. Likewise the identification of water consumption can be used to detect bathing habits such as using a bath or shower.

  Combing observations from multiple utilities facilities the construction of a more detailed behavioural pattern which could be used to detect concerning behaviour. For example if the use of a bath was detected but no subsequent electrical devices are used this may signify the patient has not gotten out of the bath. Figure 101 highlights how the PIMS framework could be developed to assess the usage of additional utilities. Here the use of electricity, gas and water can be combined to assess usage patterns and combinations.

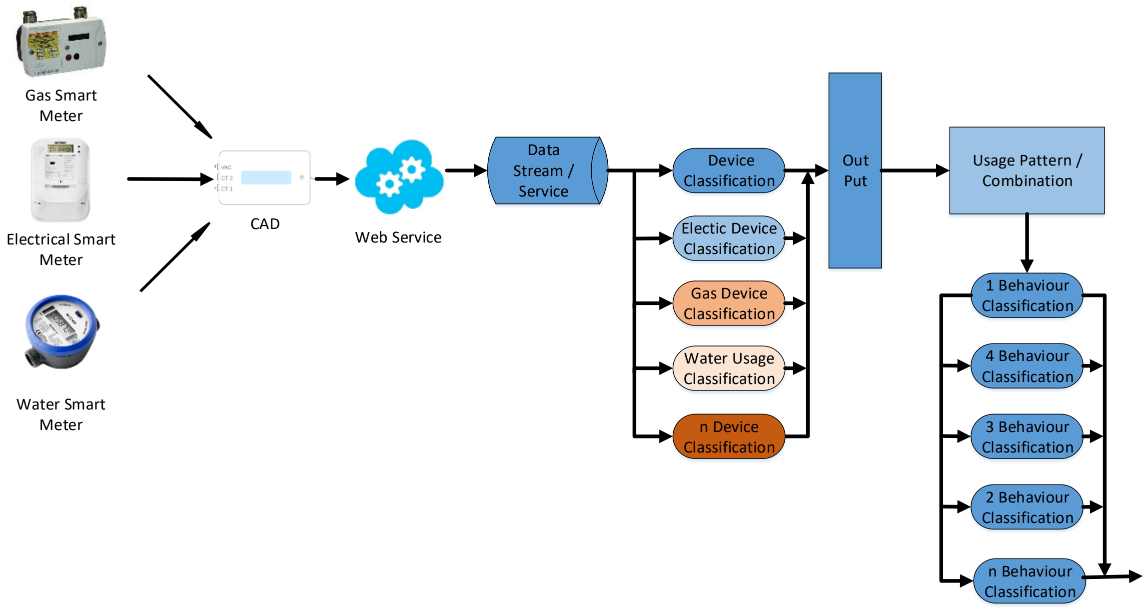


Figure 101: Monitoring additional utilities through the PIMS framework

- **NHS collaboration:** In order to best exploit the data generated from the PIMS framework a close partnership with the medical profession is essential. Currently the methodology presented in this thesis is being deployed in a number of patients suffering with early stage Dementia. Using both the PIMS framework and the expertise from the NHS future behavioural models will be more refined and tailored to the condition. By understanding the significance of the observed behaviours future training data can be used to detect more subtle changes in behaviour while branching out into other medical uses.
- **Work outside the medical domain:** The ability to detect specific devices within a home obviously inspires other areas of research outside a medical setting. Such avenues include balancing grid load and demand, building management and automation and energy conservation.
- **Expanding the appliance signature database:** Due to the limited number of device signatures there is a requirement to retrain the device identification models for each new deployment. This process requires manual labelling using the patient companion application. To remove this limitation the signature database should be expanded to include additional samples therefore improving mode generalisation.

8.5 CONCLUDING REMARKS

The approach presented in this thesis introduces an alternative methodology to existing patient monitoring solutions. As a result, many of the existing limitations associated with current technologies are removed. By using the data collected from smart meters the methodology outlined in this thesis was able to accurately identify the use of individual electrical devices. This novel approach provides numerus enhancements over existing solutions by facilitating the detection of specific ADLS independently form the patient. By using this data a personalised decision regarding the welfare of the patient can be derived.

Using smart meter data in a medical context is likely to involve taking it out of the regulated smart meter infrastructure to share it with third parties. By deploying a CAD sharing smart meter data has been facilitated. However, current pairing procedures impede the scalability of the solution and close coordination between healthcare providers and DECC will be important for mass implementation. Given the sensitive use of the acquired data and the associated intelligence that can be derived from it, various privacy concerns have been highlighted. Ensuring good data security and privacy after data has left the currently regulated system is likely to be a key concern of both the regulators and health care providers.

The level of failure tolerance for health critical usage is also likely to be lower than for standard energy metering applications, with potential implications for how the system is regulated. Questions will also need to be considered about where responsibility lies when systems fail (with potential health consequences). All medical devices are tightly governed and the need to maintain an adequate Service Level Agreement (SLA) is an important consideration. Smart meters which are being used in a medical context will require high priority should a fault occur.

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APPENDIX

Figure 102 highlights the normalisation process undertaken in the Azure ML platform. Here the PIMS framework normalises the energy values to ensure they conform to a common scale.

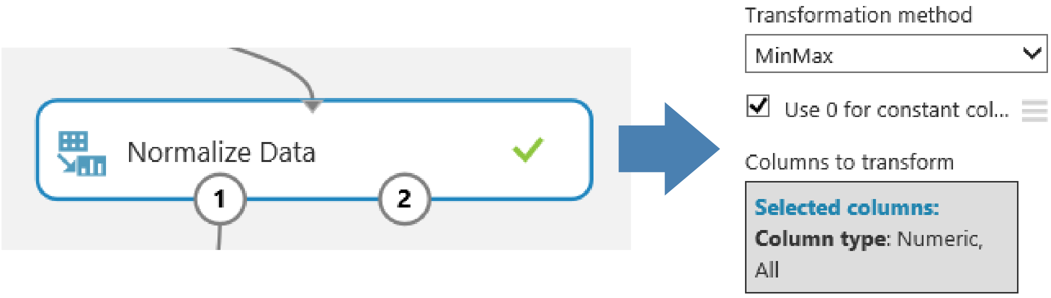

Figure 102: Azure ML Normalisation Configuration

Figure 103 presents the expected input and output schema for the PIMS web service. Specifically 6 input values are expected representing the first 60 seconds of device usage. Once the classification is complete the output schema returns the predicted class along with the scored probability for the prediction.

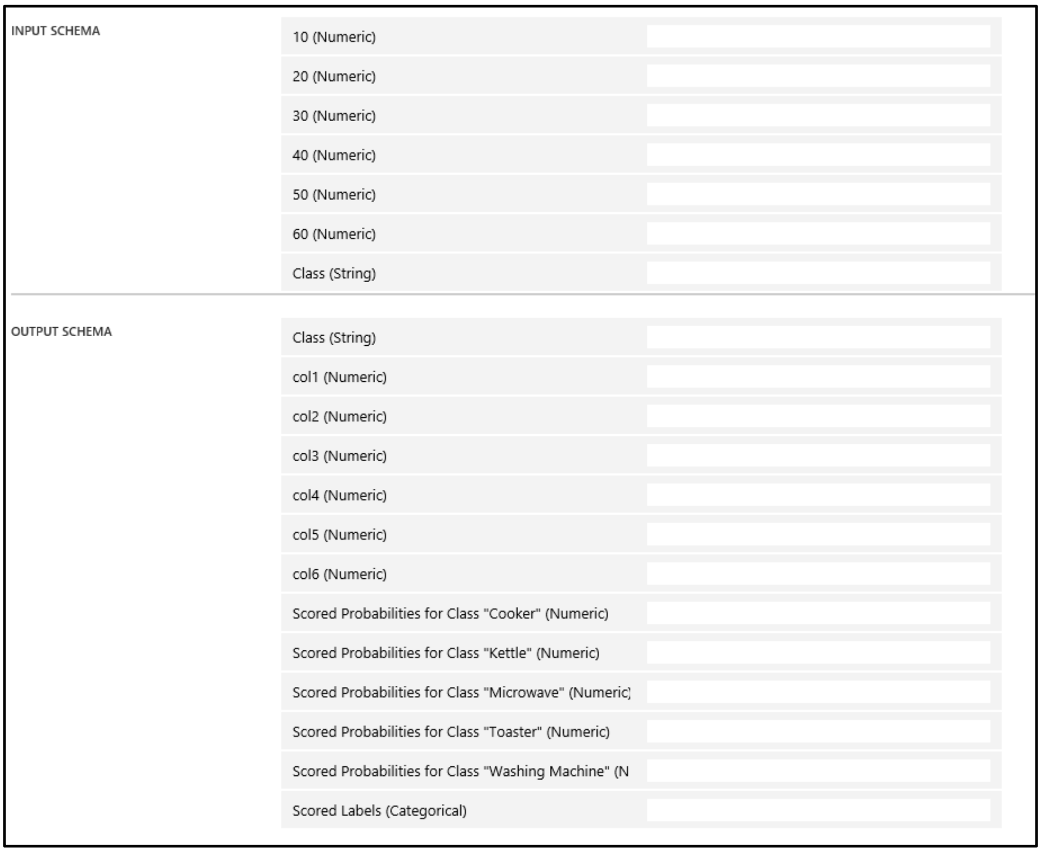

Figure 103: PIMS Input Output Schema

Figure 104 highlights the code used to generate the values for the RSS web service. In figure 105 a break point was added to highlight the 7 column values for the input schema. Here 6 integer values and one string value is expected by the web service.

```
async Task InvokeRequestResponseService_A(Dictionary<string, string> columnsDictionary)
{
    ServicePointManager.ServerCertificateValidationCallback = new RemoteCertificateValidationCallback(delegate { return true; });

    //var strtable1 = getColumnsAndValues("input1");

    var listInputs = new Dictionary<string, StringTable>();

    foreach (var groupName in paramObj.listInputGroup)
    {
        StringTable strparam = getColumnsAndValues(groupName);
        listInputs.Add(groupName, strparam);
    }

    var globalParameters = getGlobalParameters();

    using (var client = new HttpClient())
    {
        var scoreRequest = new
        {

            Inputs = listInputs,
            GlobalParameters = globalParameters
        };
```

Figure 104: Code for generating input values

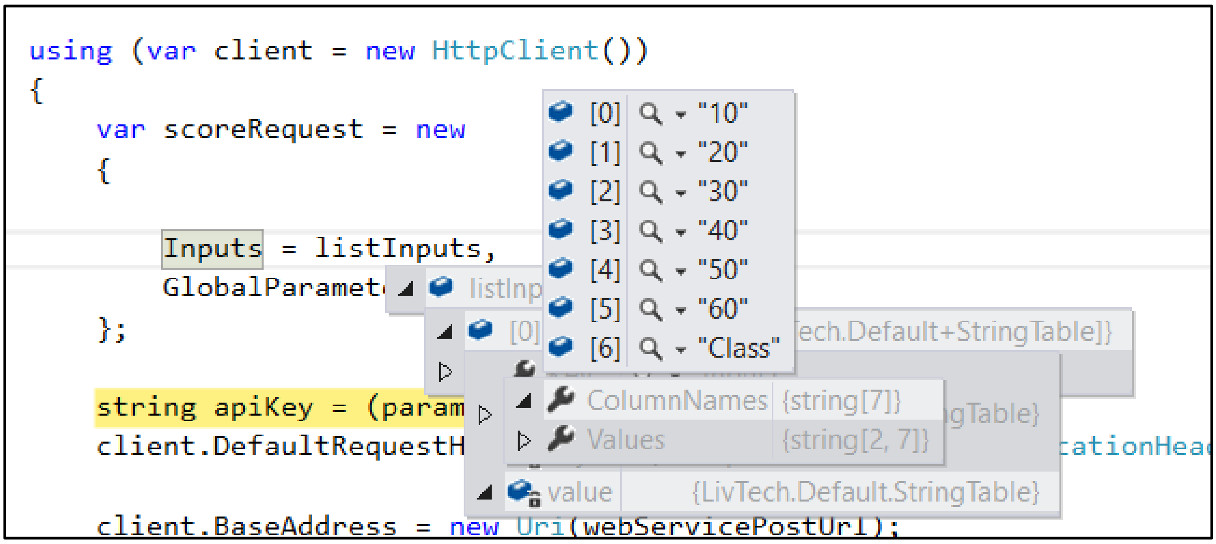

Figure 105: Break point highlighting input schema

In figure 106 a break point was introduced to highlight the 6 expected integer values from the energy monitor.

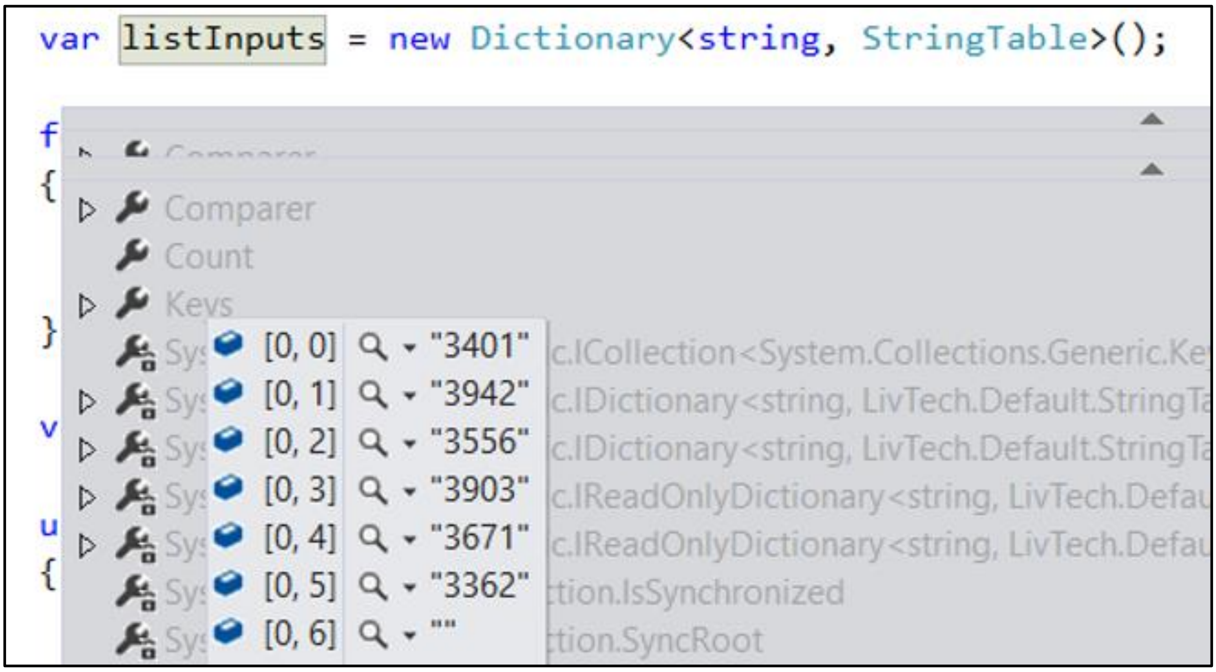

Figure 106: Break point highlighting input values

Figure 107 shows the web interface for the JSON parser. Here the feed value is checked at each 10 second interval. If the feed value is equal to or greater than 700W the vale is stored in a data list until there are 6 values for classification.

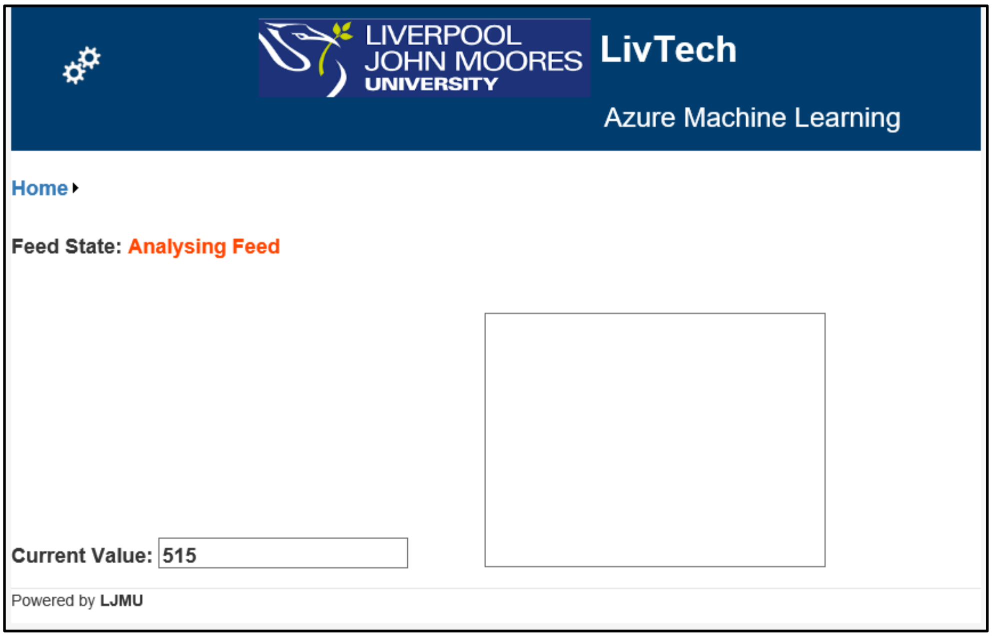

Figure 107: PIMS Web Interface JSON Parser

Figure 108 shows the JSON parser storing each of the acquired values for classification. Once 6 values are obtained the data is sent to the PIMS webserver. Figure 109 presents the code behind the JSON parser.

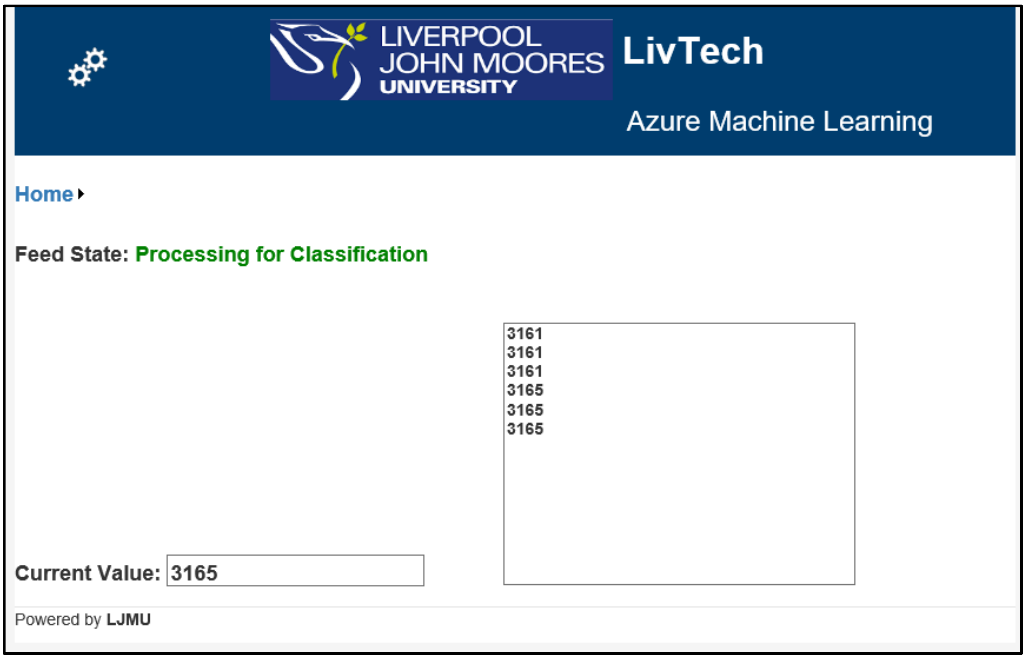

Figure 108: PIMS JSON Parser Processing For Classification

```
public void Timer1_Tick(object sender, EventArgs e)
        {
            //Parse data from data feed at each 10 second interval
            var url = "http://datcap.ljmu.ac.uk/xxxxxxx/value.json?id=4";
            var wc = new WebClient();
            var rawFeedData = wc.DownloadString(url);

            rawFeedData = rawFeedData.Replace("\"", "");

            int feedValue = int.Parse(rawFeedData);

            //Test Output
            OutPut_tb.Text = rawFeedData;

            //Add Value to list if over 700 watts
            if (feedValue >= 700)
            {
                StateLabel.ForeColor = System.Drawing.Color.Green;
                StateLabel.Text = "Processing for Classification";

                SaveVals.powerValue.Add(feedValue);

                Session["List"] = SaveVals.powerValue;
                PowerList_lb.DataSource = SaveVals.powerValue;
                PowerList_lb.DataBind();

                //Check
                if (SaveVals.powerValue.Count == 6)

                    //Call Web Service
                    SaveVals.powerValue.Clear();
            }
        }
```

Figure 109: PIMS JSON Parser Code

In order for the values to be passed to the web service both the URL and API Access key need to be provided. Figure 110 highlights the code used to connect and authenticate with the web service.

```
string apiKey = (paramObj.APIKey);
client.DefaultRequestHeaders.Authorization = new AuthenticationHeaderValue("Bearer", apiKey);

client.BaseAddress = new Uri(webServicePostUrl);
```

Figure 110: Web service connection and authentication code

Figure 111 presents the code for processing the response from the web service.

```
HttpResponseMessage response = await client.PostAsJsonAsync("", scoreRequest).ConfigureAwait(false); ;

if (response.IsSuccessStatusCode)
{
    string apiResult = await response.Content.ReadAsStringAsync().ConfigureAwait(false);
    //List<string> listValues = ExtractValues(apiResult);
    //GenerateControl.ShowOutput(OutputPlaceHolder, bottomsciprtPlaceHolde, paramObj.listOutputParameter, listValues, this);

    List<OutputObject> listOutputObject = ExtractValuesObject(apiResult);
    GenerateControl.ShowOutput(OutputPlaceHolder, bottomsciprtPlaceHolde, paramObj.listOutputParameter, listOutputObject, this);

    string lastItem = listOutputObject[0].Values[listOutputObject[0].Values.Count - 1].ToString();

    if (lastItem == "Kettle")
    {
        ImageResult.Attributes.Add("src", "/Resources/Kettle icon.png");
    }
    if (lastItem == "Toaster")
    {
        ImageResult.Attributes.Add("src", "/Resources/Toaster icon.png");
    }
    if (lastItem == "Microwave")
    {
        ImageResult.Attributes.Add("src", "/Resources/Microwave2 icon.png");
    }
    if (lastItem == "Cooker")
    {
        ImageResult.Attributes.Add("src", "/Resources/Oven icon.png");
    }
    if (lastItem == "Washing Machine")
    {
        ImageResult.Attributes.Add("src", "/Resources/Washing Machine icon.png");
```

Figure 111: Web service response code