Identifying behavioural changes for health monitoring applications using the Advanced Metering Infrastructure

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Abstract- The rising demand for health and social care, and around the clock monitoring services, is increasing and are unsustainable under current care provisions and legislation. Consequently, a safe and independent living environment is hard to achieve; yet the detection of sudden or worsening changes in a patient's condition is vital for early intervention. The use of smart technologies in primary care delivery is increasing significantly. However, substantial research gaps remain in non-invasive and cost effective monitoring technologies. Where such technologies are used, they are considered too intrusive and often incapable of being personalised to the individual needs of patients. The inability to learn the unique characteristics of patients and their conditions seriously limits the effectiveness of most current solutions. The smart metering infrastructure provides new possibilities for a variety of emerging applications that are unachievable using the traditional energy grid. Between now and 2020, UK energy suppliers will install and configure of 50 million smart meters therefore providing access to a highly accurate sensing network. Each smart meter records accurately the electrical load for a given property at 30 minute intervals, 24 hours a day. This granular data captures detailed habits and routines through the occupant's interactions with electrical

devices, enabling the detection and identification of alterations in behaviour. The research presented in this paper explores how this data could be used to achieve a safe living environment for people living with progressive neurodegenerative disorders, such as Dementia.

Keywords- Health Monitoring, Advanced Metering Infrastructure, Smart Meters, Profiling, Assistive Technologies, Early Intervention Practice, Machine Learning.

1. Introduction

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 (G.Lanzieri *et al.,*). 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[1]. 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 (K.Kaare *et al.,*). The success of modern medicine has completely transformed our health and care requirements as a result of an ever increasing ageing population. Ultimately, health and social care has failed to adequately adapt to this dramatic demographic shift (M.Green *et al.,*). 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 numerous challenges, which need to be addressed. In recent years, there has

[1] Office for National Statistics, Overview of the UK Population, https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/articles/overviewoftheukpopulation/february2016

been rapid development in monitoring technologies for independent living, early intervention services and outpatient condition management. However, research in non-invasive and cost effective monitoring technology lag far behind (P.Rashidi *et al.,*). Affordability and associated costs with existing technologies mean they cannot be implemented on a large scale. Additionally, Assistive Technologies (AT) often neglect both socio-economic and ethical considerations therefore affecting their widespread implementation and adoption (M. Bächle *et al.,*). The need to detect sudden or worsening changes in a patient's condition is vital for early intervention. Community mental health groups, home resolution teams and assistive outreach teams, all play a key role in preventing costly inpatient admissions. If any changes in a patient's condition are not dealt with '*early*' the prognosis is often worse and, as a result, costs for treatment will undoubtedly be higher (S.P.Singh *et al*.,). An early intervention approach has been shown to reduce the severity of symptoms, improve relapse rates and significantly decrease the use of inpatient care (L.N.Gitlin *et al.,*).

The Advanced Metering Infrastructure (AMI) 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. As the research in this paper demonstrates, analysing a patient's electricity usage through the use of smart meters can provide accurate around the clock monitoring of patients; not only for safety but also for enabling immediate, mid and long term prognosis. The challenge is how to interpret and make use of the data collected by smart meters, to develop applications for remote patient monitoring. Smart meters provide a highly accurate and low cost sensing mechanism for monitoring people within their homes.

As such, the investigation outlined in this paper covers the use of smart meters for monitoring the wellbeing of individuals with dementia. Dementia was chosen for two reasons; firstly due to the complexity of behaviours and secondly, being able to detect specific behaviours of interest, which include sleep disturbances and Sundowning Syndrome. The research presents various initial energy usage profiles, taken from a dataset containing over 78,000 individual households. A technique for establishing a patient's daily routines and habits is detailed. The data highlights the behaviour of a patient and how this information can be leveraged for both early intervention practices and detecting alteration in routine. In particular, the research aims to demonstrate how normal and abnormal behaviour can be detected through the patient's use of electrical devices. The remainder of this paper is as follows. Section 2 presents a background on smart grids, smart meters and the Advanced Metering Infrastructure, which includes the data types and its supporting technologies. In section 3, we discuss existing assistive technologies while highlighting challenges around their feasibility and implementation. In addition, examples of dementia characteristics and associated behaviours of individual patients and how they can be detected through electricity monitoring is introduced. In section 4 a case study, which focuses on electricity usage, behaviours and changes in habits, is documented. Initial results are also presented, highlighting the detection of behavioural routines and concerning behaviours such as sleep disturbances. In section 5, the proposal of a novel proprietary system design is outlined. Here the system describes the process for analysing smart meter data and how the acquired intelligence can be presented to the patients care team. The paper is concluded in section 6 where the future direction of the work is discussed.

2. Background

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 (JA.Momoh *et al*.,). 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. 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 (V.C.Gungor *et al.,*). One of the key differences over the existing grid is the introduction of the Advanced Metering Infrastructure. The AMI is not a single piece of technology, but a complex infrastructure which integrates with a variety of different technologies (R.R.Mohassel *et al.,*). 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.

2.1 Advanced Metering Infrastructure

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 (J.Zheng *et al.,*). 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. Figure 1 highlights the UK AMI layout.

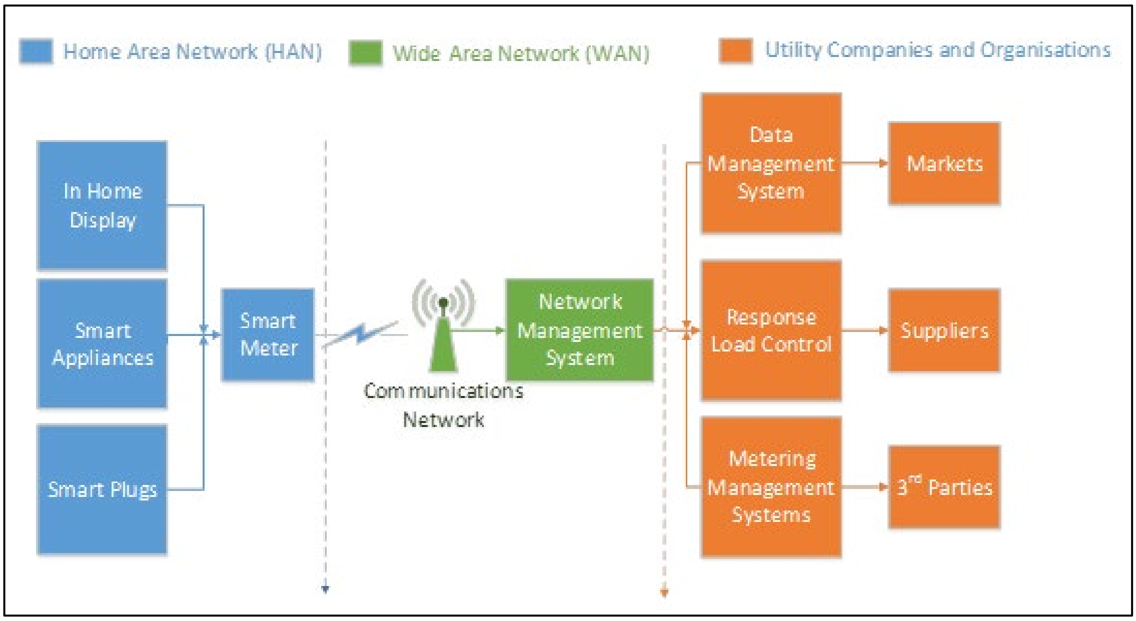


Figure 1. Advanced Metering Infrastructure

The Home Area Network (HAN) is located inside the consumer premises and is made up of different devices. Firstly, the in home display unit (IHD), which is the most visible and accessible part of the AMI. It provides the consumer with real-time electricity usage data. Secondly, the smart meter provides real-time energy usage to both the consumer and the energy provider. Smart meters are able to store 13 months of data, keeping a record of total energy consumption.

The Wide Area Network (WAN) communicates between the HAN and the utility companies. The WAN is responsible for sending smart meter data to the utility companies and other grid stakeholders using a robust backhaul network, such as Carrier Ethernet, GSM, CDMA or 3G. The geographical location of the smart meter may dictate they type of WAN technologies implemented, due to the constraints of certain communication technologies.

The utility companies and service users are a group of organisations that have access to the data for analysis and management purposes. Energy suppliers communicate remotely with the smart metering equipment in order to perform a number of tasks, such as taking meter readings, updating price information on the in-home display and identifying readings on a change of tenancy. Consumers can permit other organisations to have access to the data from their smart meter. For example, energy switching sites could use accurate information to advise on the best tariff based on personalised energy requirements.

2.2 Smart Meters

Fundamentally, smart meters are a new generation of gas and electricity meter. They deliver vast amounts of additional information that cannot be obtained from a conventional analogue energy meter (S.Shekara *et al*.,). 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 (L.Wang *et al*.,). 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. Smart meters in the UK collect and transmit energy usage data at 30 minute intervals using their default setting (P.Siano *et al.,*). However, smart meters are able to report energy usage as low as 10 second intervals through the use of a Consumer Access Device (CAD); even though this is not currently deployed due to the vast amount of data it would generate (A.Vojdani *et al*.,).

As Figure 2 highlights, the data sampling rate is relevant when identifying individual devices and their duration of use. The additional information obtained from increasing the frequency of reading has a significant impact on the accuracy of individual devices identification.

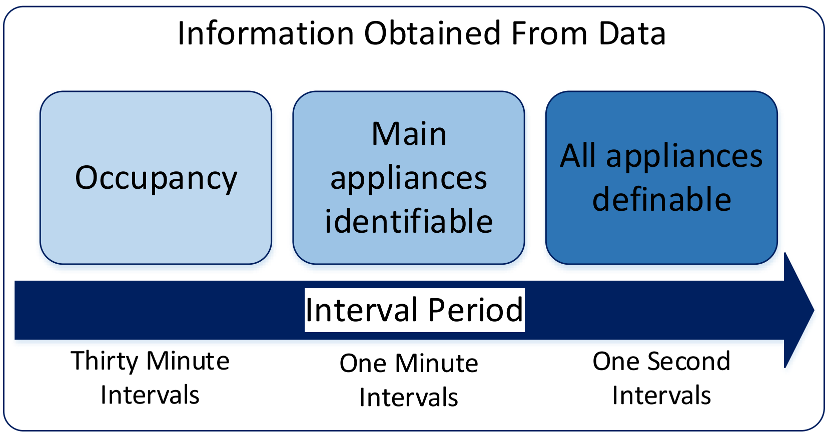


Figure 2. Information obtained by increasing interval reading of the smart meter.

Table 1 shows a data sample taken from a smart meter during a single period. This sample shows the granularity of the data collected compared to traditional meters where the readings are submitted collectively over a much larger period. It displays the data parameters obtained at each 30-minute interval collected in a 24-hour period (5 readings are shown as a sample). The Customer Key is the unique identifier for each individual smart meter device within the AMI. In other words, it acts as the unique identifier for the owner of the smart meter. Time of Reading indicates the time and date of the reading collection; while General Supply highlights the amount of on peak electricity being used in (Kilowatt Hour) KWH.

Table 1. Single Smart Meter data Sample showing the total aggregated load for each thirty-minute interval.

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

2.3 Challenges

The research put forward in this paper proposes using smart meter data to examine the behaviours of dementia patients. The aim is to enable patients to live independently, while safe in the knowledge they are being monitored both actively and remotely. This, however, presents many technical, ethical and privacy challenges. Firstly, the scale and size of data collected from smart meters and the AMI introduces real and complex challenges in terms of storing, structuring and analysing the acquired data (P.D.Diamantoulakis *et al.,*). New methods for analysing and modelling data should focus on using cloud platforms and data centres for processing. Cloud platforms, such as Microsoft Azure, have the ability to analyse large datasets and assign significant resources to process the data in a timely manner. Secondly, due to the scale of the smart grid infrastructure, ensuring standards, interoperability and continuity throughout the system is a challenge. This is largely due to the integration of interchangeable components from a variety of different providers (V.C.Güngör *et al*.,). Thirdly, there are many ethical and privacy concerns associated with the smart meter role out, which could potentially leave consumers vulnerable to exploitation (S.Zhou *et al*.,). For example, criminals could process data that is generated by the AMI to identify when households are unoccupied, helping to facilitate burglary or some other crime. Additionally, being able to identify appliances, would aid burglars to target households with the most expensive electronic devices.

3. Assisted Independent Living and Behavioural Considerations

Current assistive living technologies involve the deployment of various sensors around the home (J.Doyle *et al*.,). These include motion sensors, cameras, fall detectors and communication hubs. However, installing, maintaining and monitoring these devices is costly and technically challenging (A.Grguric *et al*.,). 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.

3.1 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. 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. 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 (P.Barsocchi *et al*.,), (G.Appelboom *et al.,*). Specifically, the vast majority of AAL solutions depend on supervised learning algorithms, which utilise labelled data for training. 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 (A.Bygholm *et al*.,). These limitations and challenges are summarised as follows (A.Bygholm *et al*.,):

- **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.
- **Complicated installation, configuration and ongoing maintenance**: Multiple sensors and associated equipment can be challenging to install.
- **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.
- **Lack of communication standards and interconnectivity between different solutions**: Technology standards provide the basis to facilitate interoperability, integration, and scalability.
- **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 (A.Dasion *et al*.,).

- **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 (F. Carinaux *et al*.,). They are often considered to be too intrusive and raise privacy and ethical concerns, especially for vulnerable patient groups.

The analysis of smart meter data enables active, in-home, monitoring of patients living with a range of conditions. By analysing past personalised behaviours, the detection of abnormal behaviours is made possible. This facilitates early intervention and a bespoke outcome for the patient by ensuring their medical and care needs are sufficient.

3.2 Active monitoring for behavioural changes with dementia

A comprehensive understanding, of both the condition and their associated behavioural characteristics, is essential for remote patient monitoring (V.Osmani *et al.,*). This is imperative in determining the diagnosis and enabling an accurate evaluation of any changes. The performance and undertaking of basic Activities of Daily Living (ADLs) is a significant challenge for patients living with progressive neurodegenerative disorders, such as dementia . Studies have shown that measuring the ability to undertake ADLs can be used to gage the decline of the patient cognitive abilities (M.Giebel *et al.,*) Table 2 highlights the behaviours, which are useful 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 2: Important Activities of Daily Living 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. Eating abilities and

	patterns are a key measurement in estimating the patients ability to undertake ADLs (T.Lima-Silva *et al.,*).
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 while negatively impacting on the person's ability to undertake ADLs (C.Nascimento *et al.,*).
Behavioural changes	Provide important indicators for the detection of new conditions, while providing information about the progression of existing medical problems (K.Hu *et al.,*).
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.
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. Falls and resulting loss in mobility are frequent in dementia patients, especially in the advanced stages (A.Laboni *et al.,*).

Being able to detect changes in a patient's habits, routines and features as highlighted above, ensures the active monitoring of their wellbeing. The vast majority of these behaviours can be accurately mapped using smart meter data therefore providing a nonintrusive and cost effective method for remote patient monitoring.

4. Case Study

In this section, a case study is presented, which highlights an individual's habits and routines using smart meter data. The data used in this case study was provided by the Australian Department of Industry as part of a recent trial. The research outlines how the use of granular smart meter readings can be used to establish individual's routines and identify any sudden changes in behaviour. To demonstrate this, a sample of the data profiling is presented in Figures 3 to 5. Each displays a morning period, between 05:00 and 12:00, the data is recorded at 30 minute intervals. Initially, an overview, highlighting three individual mornings, is presented. The energy usage, in KWH, is shown in the y-axis while the reading time is shown in the x-axis.

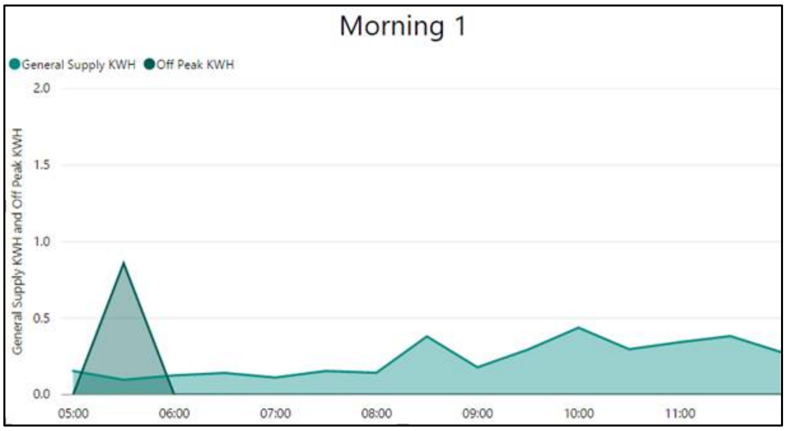


Figure 3. Morning 1 between the hours of 05:00 and 12:00.

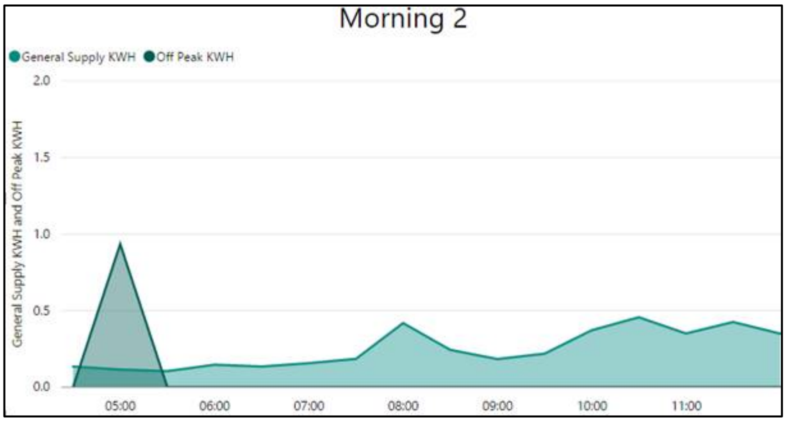


Figure 4. Morning 2 between the hour of 05:00 and 12:00.

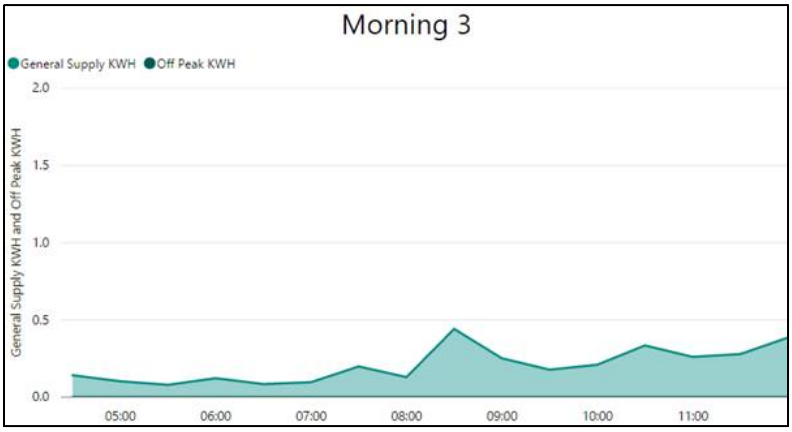


Figure 5. Morning 3 between the hours of 05:00 and 12:00

The individual used for the case study was selected at random from the data set, where the individual constrained to the criteria of there is a single occupant in the premises, living in a standard dwelling that does not have gas cooking or heating. These criteria were chosen to demonstrate the process for monitoring independent living. Gas cooking and heating are not included in the dataset, yet could be incorporated into future work. Knowledge of the type of heating and cooking equipment being activated facilitates an understanding of the devices responsible for the energy peaks. If no gas cooker is present, then the electricity readings at certain periods of the day would relate to eating preparation using an electric cooker.

It is also vital to establish what devices reside in premise, as different devices affect the amount of electricity being used. As Figures 3 and 4 highlight, the behaviours exhibited on morning 1 and 2 are comparable. The graphs show that the individual commences their daily activities at roughly the same time on both mornings, with the electricity consumption having comparable total-usage values. This type of behaviour can be attributed to normal behaviour, such as getting breakfast and having a shower for example. However, Figure 5 shows a clear change in routine and behaviour during the same period on morning 3. This type of behaviour might indicate that the consumer has merely stayed in bed, or it could be an indicator of a more serious problem. Due to the vulnerability of the patients being monitored, in our case this type of behaviour would require further immediate investigation to ensure patient safety.

Recognising changes and patterns in behaviour, such as in the example above, insures a personalised healthcare package is constructed. Individuals who suffer mental illness exhibit certain behavioural changes during periods of heightened severity. One of these more usual changes are alterations in sleep patterns as a patient typically awakens much earlier than normal (J. Murphy *et al*.,) Figure 6 shows the total energy consumption between the hours of 1:30am and 4:00am for the same individual over a duration of 10 months. Each of the larger peaks displays an increase in electricity during the early hours of the morning, meaning the occupant is awake during the night. This type of result highlights any changes in the person's sleep patterns, which provides an indication to a healthcare professional where intervention is required.

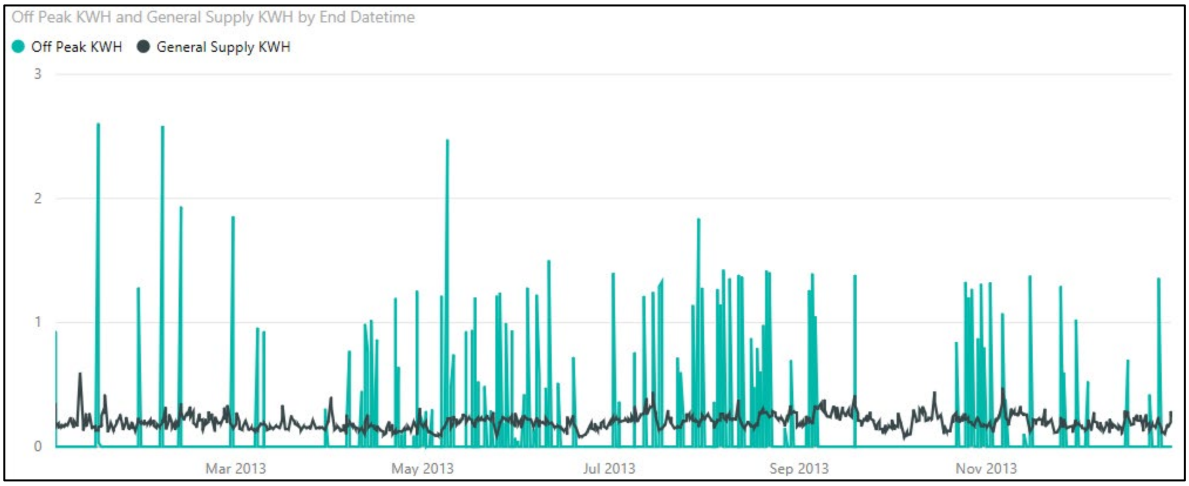
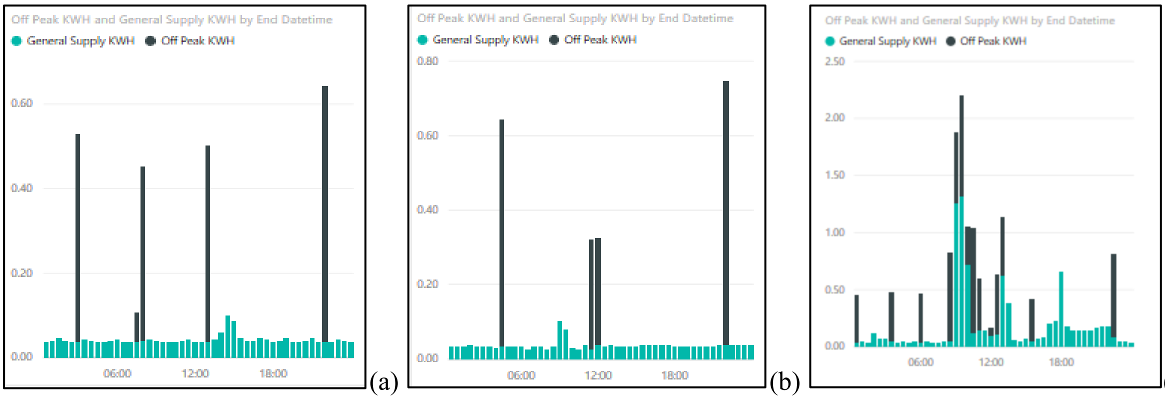


Figure 6. Energy usage over a one-year period between the hours of 1:30 and 4:00

Figure 7 demonstrates this process to a more granular level. Day 1(a) and Day 2(b) display electricity usage below 0.80 KWh; whereas Day 3(c) shows an increase in activity, with a significant electricity utilisation that peaks at over 2.00 KWh. The inactivity shown in Day 1 and 2 would require intervention if the occupant was a known to be living with progressive neurodegenerative disorders or any of the conditions previously discussed.



(a) (b) (c)

Figure 7. Daily comparison of activity (a total of three days shown).

5. Approach

In this section, a novel data analysis approach for the autonomous identification of abnormal behavioural patterns, which are the result of deteriorating health conditions, is presented. In this case study there is a specific focus on detecting the behavioural changes that are associated with both dementia and severe depression; where sleep disturbances are key indicators of a decline in a patient's health.

5.1 System Design

The system proposed in this paper identifies different patterns of behaviour based on historical energy profiles and where periods of abnormal activities are identifiable through known abnormal behaviour trends (relapse indicators). Additionally, the system can detect abnormal usage patterns based on customisable parameters. The system has a modular design in order to cater for different circumstances of healthcare monitoring. Smart meter data is collected in an unstructured way, which is unsuitable for the needs of the system so the data first needs to be adapted in order to ascertain the necessary features from it. For that reason, the proposed system is retrofitted to the data set. Figure 8 presents the system design, highlighting the main flow of data and the collection of data from three different sources:

- Half-hour consumption and generation, which contains the half-hourly usage readings.
- Device utilisation identification, along with its behaviour.

- The household demographics providing information relating to the occupancy of the household.

The module containing the health data is used to select the relevant features based on the patents condition or stage. As previously discussed, regular medical review would be required to assess the condition were appropriate. This could alter the required features, depending on the outcome of the review, which in turn highlights the expected behaviour and features. Should an abnormal usage be detected, an automatic message is sent to a healthcare professional, relative or carer for further investigation.

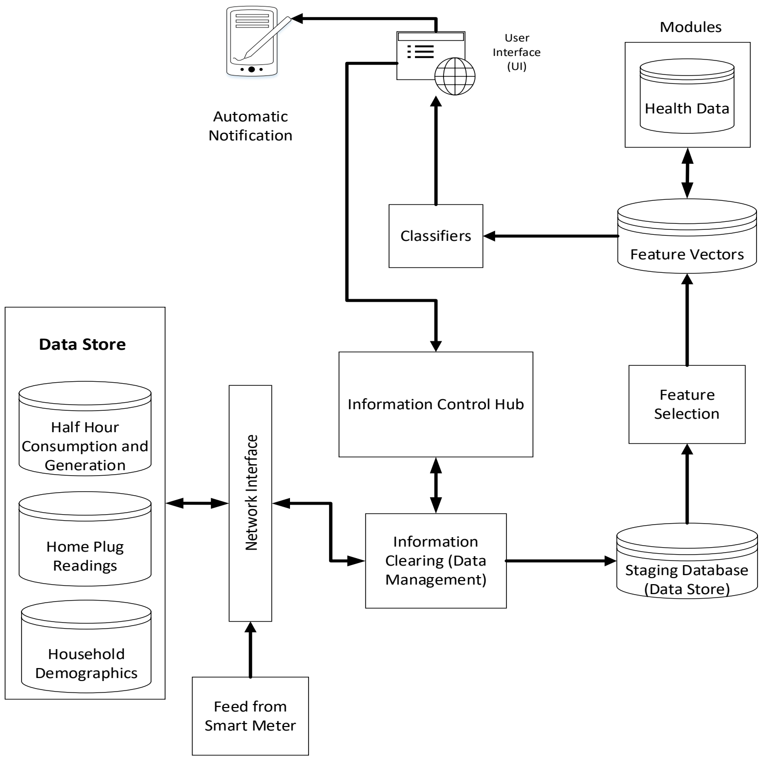


Figure 8. Proposed System Framework

In order to collect the energy usage readings from the smart meter, a Consumer Access Device (CAD) is required. Smart meters utilise ZigBee smart energy. The UK Department of Energy & Climate Change (DECC) has announced Smart Metering Equipment Technical Specifications (SMETS) 2, which cites the use of ZigBee Smart Energy 1.x. The processes, by which the CAD operates is shown in figure 9. 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 acquired data is parsed and transmitted to the network inference of the proposed system.

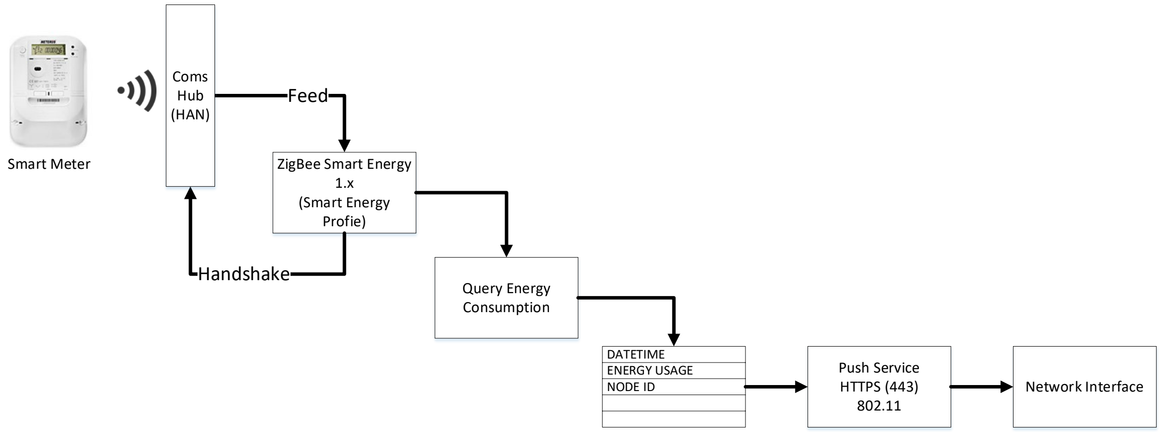


Figure 9. CAD Pairing Process

For the purpose of this case study, we focus on the data processing component of the proposed system. Figure 10 shows the methodology for the data processing component of the system, as shown in the information clearing component.

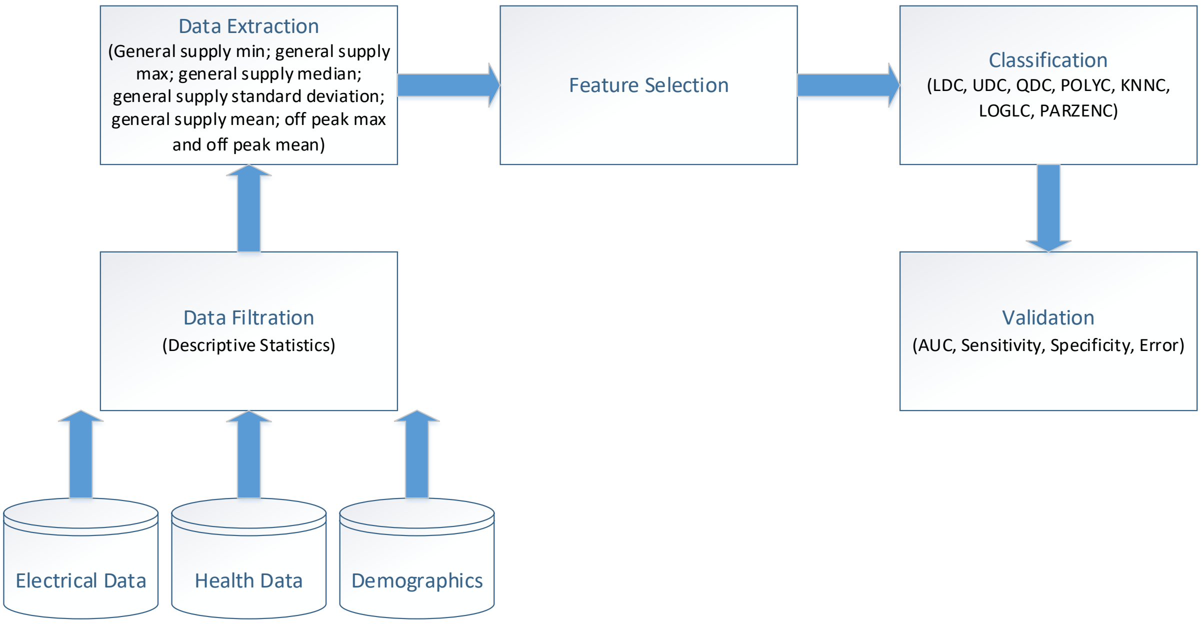


Figure 10. Data Processing Methodology

5.2 Data Collection

For the following analysis, one year's worth of energy usage readings for eight different smart meter users was selected. The eight consumers were selected as a sub group of the population as this approach is more practical for the initial data analysis. The consumers provided their consent for data access during the initial smart meter trail. Each of consumer's energy readings were taken every half hour equating to 48 readings per 24-hour period, totalling 17520 individual readings per consumer per year. Out of the eight consumers selected, four have normal readings and four have abnormal readings. The subjects with normal readings were classified as having no energy usage readings greater than 2 Kwh between the hours of 1:30 and 4:00 for the entire year period (signifying the absence of sleep disturbances). Abnormal subjects were classified where they exceeded 2 Kwh between the hours of 1:30 and 4:00 on 3 or more occasions in a one-year period (signifying the presence sleep disturbances). As discussed the detection of sleep disturbances within both dementia and mental health can be important relapse indicators to both cares and clinicians. All households in the experiment have one occupant to ensure accurate results. Initially seven features per consumer were derived for each 24-hour period totalling 8760 results for each of the following features: General supply min; general supply max; general supply median; general supply standard deviation; general supply mean; off peak max and off peak mean.

Figure 11 shows the data processing component for the proposed system starting with the data retrieval stage and ending with the generation of the feature vectors for both normal and abnormal patient behaviours. The process flow highlights the processes undertaken for the application of classifying sleep disturbances.

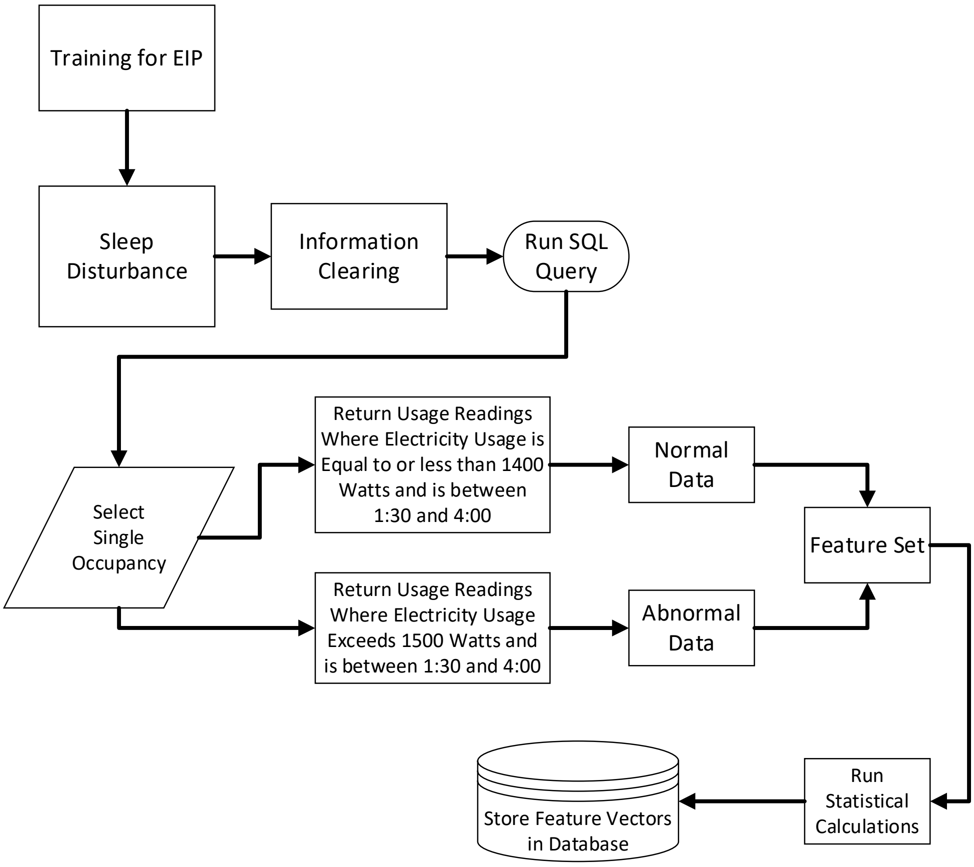


Figure 11. Data processing methodology sleep disturbance

5.3 Data Classification Process

The specific classifiers used in this analysis include the linear discriminant classifier (LDC), quadratic discriminant classifier (QDC), uncorrelated normal density based classifier (UDC), polynomial classifier (POLYC), logistic classifier (LOGLC), k-nearest neighbour (KNNC) and parzen classifier (PARZENC). Each of these classifiers is chosen because they have the ability to learn how to recognise abnormal values in a dataset. They also employ a supervised learning approach, which is a key part of the system design.

The linear discriminant classifier functions by sorting or dividing the data into groups based on a set of characteristics in order to perform the classification (A.J.Izenman *et al.,*). A discriminant function is obtained by monotonic transformation of posterior probabilities. In other words, it performs an ordered transformation of unknown quantities, which are separated by a linear vector. Again the quadratic discriminant classifier operates by dividing the data into separate groups based on a set of given characteristics. The data is divided up using a quadratic surface instead of a one dimensional data set. QDC makes no assumptions that covariance are alike instead it assumes that the changing of two random variables are not be the same. The polynomial classifier is a linear based classifier and essentially sorts the data by evaluating the weighting, using a linear combination of features and considering the variables of the objects (P. Fergus *et al*.,). The logistic classifiers are linear-based classifiers, which predict class labels based on weighted, linear combination of features or the variables of the objects. K-Nearest Neighbour includes the training data when building up the classifier, it predicts values based on the '*k-closest*' values from the training set. In other words, data is classified by a majority decision by identifying '*k-objects*', which are nearest to its neighbours (P. Fergus *et al*.,). The parzen classifier functions by including aspects of the training data when the classifier is built up. It is a non-linear classifier and it has the benefit that its parameters can be user supplied or optimised (P. Fergus *et al*.,).

5.4 Results and Discussion

Each of the classifiers performance was calculated using a confusion matrix to assess the success of the classification or Area Under the Curve (AUC), sensitivity, specificity and error (Ahmed J. Aljaaf *et al*.,). This can be expressed mathematically as shown below:

$$Sensitivity = A / (A+C) \tag{1}$$

$$Specificity = B / (B+D) \tag{2}$$

$$Accuracy = (A+B) / (A+ B +C + D) \tag{3}$$

Where A is the True Positive values, B is the True Negative Values, C is the False Negative values and D is the False Positive values. The KNNC and PARZENC classifiers were the most accurate with both classifying over 93% of the data accurately. The KNNC classifier was able to categorise the data with an accuracy of 94.81% with an error of 0.0519. For the KNNC 4074 out of 4379 normal behaviours were correctly classified whereas 4230 out of 4379 abnormal behaviours were accurate. All of the results from the classification are shown in Table 3.

Table 3. Classification Results Comparison

Classifiers	AUC (%)	Sensitivity	Specificity	Error
LDC	78.64	0.932	0.640	0.2136
UDC	74.29	0.884	0.600	0.2571
QDC	74.59	0.874	0.617	0.2531
POLYC	79.16	0.932	0.650	0.2084
KNNC	94.81	0.930	0.965	0.0519
LOGLC	85.40	0.893	0.816	0.146
PARZENC	93.92	0.923	0.955	0.060

It is clear from the results that the classifiers where able to identify the different behaviours with a high degree of accuracy. Figure 12(a) shows a scatter of the most accurate performing classifier while Figure 12(b) shows the least effective performing classifier. Normal behaviour is represented by blue crosses, while abnormal is displayed as red dots. The contour line generated highlights the division between the individual datasets which in figure 10 shows the enhanced classification results. These results demonstrate that by analysing the data generated from smart meters it is possible to detect changes in an individual's behaviour and routine.

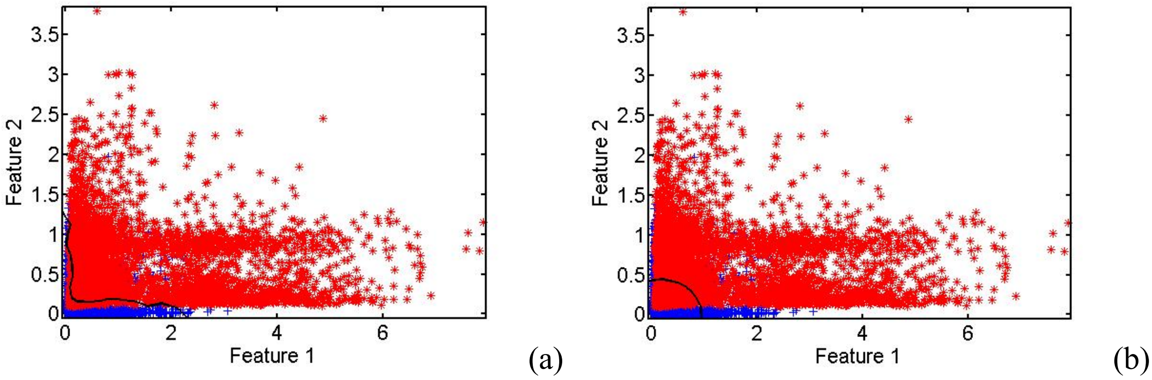


Figure 12. (a) KNNC Electricity (b) UDC Electricity - both over 1 Year Period

6. Conclusion and Future Work

With the implementation of the AMI, it is possible to monitor actively a consumer's wellbeing while providing insight into an individual's daily habits and routines. Analysing the vast data that is collected by smart meters enables detailed energy usage profiles to be created and reoccurring patterns and trends in behaviour can be identified. Being able to detect any deviations in behaviour is vital to enable safe independent living, early intervention and predicting changes in dementia. This paper discusses how these applications can be used to reduce costs and ensure a better outcome for the patient.

The case study put forward in this paper details how different deviations in routines can be identified using our novel system design and health-monitoring concept. This type of monitoring may provide healthcare professionals with a more detailed insight into their patient's behaviour permitting the patient's support network to intervene should any problems arise.

Dementia patients can often become confused and potentially provide incorrect information about their wellbeing to healthcare professionals. This type of monitoring helps to provide accurate information to determine if there are any changes that the patient might not be aware of, ensuring that the current treatment and situation is suitable for the patient. Monitoring an individual in this manner also promotes independent living for the patient. While this research has both social and monetary benefits, it also presents obvious privacy concerns. As such, the system would operate as an ‘opt-in’ approach for monitoring patents and strict data protection mechanisms. Additionally, 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. Given the sensitive use of the acquired data and the associated intelligence that can be derived from it, various privacy concerns have been highlighted by a number of researchers and governing bodies. 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.

Our future work will involve expanding the above case study to include a larger number of patients. Additional research will be undertaken to understand the correlation between energy usage and the progression of dementia. It important to ascertain the degree in which energy usage can alter as patient’s progress with their condition while potently uncovering new behavioural anomalies. In order to improve the classification results the use of a larger data set will enable the collection of additional features. Refinements in the feature extraction process can improve the outcomes of the classification; this can be achieved by ensuring only the optimum features are used. In order to achieve this outcome Horns parallel analysis can be used to select the most appropriate features and offers improvements over the more traditional K1 Kaiser’s method. Additionally, using a larger data set would ensure enhanced classifier training which helps to ensure a more accurate classification. This is significant, as different features and data classification techniques will be needed to realise the applications outlined in this paper.

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