Profiling Users in the Smart Grid

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***Abstract*— The implementation of the smart grid brings with it many new components that are fundamentally different to traditional power grid infrastructures. The most important addition brought by the smart grid is the application of the Advanced Metering Infrastructure (AMI). As part of the AMI, the smart meter device provides real time energy usage about the consumer to all of the smart grid's stakeholders. Detailed statistics about a consumer's energy usage can be accessed by the end user, utility companies and other parties. The problem, however, is in how to analyse, present and make best use of the data. This paper focuses on the data collected from the smart grid and how it can be used to detect abnormal user behaviour for energy monitoring applications. The proposed system employs a data classification technique to identify irregular energy usage in patterns generated by smart meters. The results show that it is possible to detect abnormal behaviour with an overall accuracy of 99.45% with 0.100 for sensitivity, 0.989 for specificity and an error of 0.006 using the Linear Discriminant (LDC) classifier.**

Keywords*— Smart Meter, Profiling, Advance Metering Infrastructure, Data Classification, Critical Infrastructure.

I. INTRODUCTION

Smart meters are one of the most significant components of the smart grid [1] and they are seen as the foundation of any future smart electricity network. Their introduction brings with it the ability for consumers to accurately monitor energy usage in real-time. By showing consumers their current energy usage, along with its associated cost, a more informed decision can be taken on when electricity consumption would be at its most cost effective. In addition, smart meters provide the gateway and monitoring for allowing consumers to generate their own electricity, selling any excess electricity back into the smart grid. This removes the traditional top down distribution, implementing a bidirectional energy flow [2]. The result is a bidirectional communication and power exchange between suppliers and consumers, transforming the traditionally passive end-users into active players.

The deployment and use of the smart meter generates large amounts of valuable data. For example, the amount of energy being consumed at set times and intervals. Additionally, smart meters can securely communicate many different real-time consumption values including: voltage, phase angle, frequency and any home generated energy. This produces accurate information about the amount of energy used so customers can be better advised on billing and consumption. In addition, it allows utility companies to plan future energy requirements based on past usage trends. This is achieved by analysing the data and identifying reoccurring patters of usage. As the roll-out proceeds, devices, including smart appliances, can be automatically controlled in order to better balance grid demand.

Smart meters have already been trialled in a number of countries, such as the USA, Australia, Netherlands, Italy and the UK, with future planned expansion [3]. In 2008, less than 4% of the electricity meters in the world were smart meters. By 2012, the percentage had grown to over 18% and it is expected to rise to 55% by the end of 2020.

In this paper, we present a case study into the data generated by three households. The households where selected from 78,720 individual smart meters in Australia. Using the data an approach for profiling consumers is put forward. We address how the development of a system, using advanced data analysis techniques, can be employed to assess consumers and detect abnormal behaviour. A discussion is also put forward on the benefits and challenges that smart meters bring with their implementation. The remainder of the paper is as follows. Section 2 presents a background on the Advanced Metering Infrastructure (AMI) and smart meters, section 3 defines the data collected from our smart meter case study. Section 4 discusses the methodology and techniques used for profiling users. The paper is concluded in Section 5.

II. BACKGROUND RESEARCH

The implementation of the smart grid has brought with it significant developments in technology such as the ability to remote read meters, allow bidirectional generation and distribution etc. Its introduction has enriched the way in which electricity usage data is produced and collected. This comprehensive data access is fundamentally different when compared to traditional grid infrastructures [4] and, for the first time, operators are able to gather highly detailed information about how their individual customers use electricity in real-time [5]. In this section, the focus is on the technologies which enables access to the data.

A. Advanced Metering Infrastructure

The AMI offers bidirectional communication between the consumer and the rest of the smart grid stake holders and replaces the traditional need for energy usage readings to be

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collected manually [6]. There are a number of advantages associated with Automated Meter Readings (AMR) these include:

- Reduced costs for meter readings.
- The possibility to access meters otherwise difficult to attend due to position or security reasons.
- Support for real-time pricing.
- Increased fraud detection.
- Reduced read-to-bill time allowing utility companies to learn more about consumer power consumption.
- More informed choices about energy usage based through the use of in home displays and smart devices [7].

Specifically, the AMI can be broken down into three main areas: The Home Area Network (HAN), Wide Area Network (WAN) and the utility companies. Figure 1 shows the interaction between the different components that comprise the AMI. Each of the layers is subsequently explained.

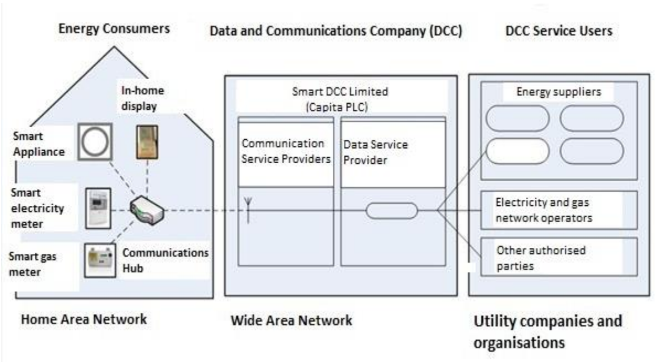

Figure 1. End To End Smart Meter Infrastructure

The Home Area Network (HAN) is housed inside the consumer's premise and is made up of a collection of devices. The in-home display unit (IHD), is the most visible and accessible part of the AMI. It provides the consumer with up-to-date information on electricity usage, as well as the units of energy being consumed. Secondly, the smart meter provides real-time energy usage to both the consumer and all of the stakeholders. This builds detailed energy usage profiles of its consumers. Smart appliances also react to peak events within the smart grid eco system. Adapting to these events enables a reduction in demand on the grid and energy costs for the consumer [8]. These smart appliances can effectively contribute to load management in future energy systems.

The Wide Area Network (WAN) handles the communication between the HAN and the utility companies. The sending of polled meter data to the utility, using a robust backhaul network such as: Ethernet, GSM, CDMA or 3G, is controlled by the WAN.

Organisations and utility companies have access to the data for analysis purposes this may include energy suppliers or energy networks. Enabling them to have detailed and accurate information. This improves management and planning of activities. In addition, grid reliance and performance is enhanced, as demand can be better provisioned.

B. Smart Meter Benefits

As previously discussed, the smart meter is an advancement on existing traditional meters [9]. Many of the advantages outlined below can be attributed to smart metering. These include lower metering costs; energy savings for customers; more reliability of supply through detailed monitoring and easier detection of supply problems and fraud. Its communication and data gathering capacities offer vast improvements and advancements over the traditional meters.

Electrical data, such as voltage, frequency and energy consumption information is recorded in real-time and reported every 30 minutes. Additionally, consumers are able to interact with their smart meters in order to interpret the data that is collected. Overall, smart meters can perform a wide variety of tasks including:

- Accurately record and store information for defined time periods (to a minimum of 30 minutes). This enables remote, accurate meter-readings with no need for estimates [10]. As these meters become more sophisticated, they are able to measure household power consumption at ever finer time-scales.

- Offer two way communications to and from the meter so that, for example, suppliers can read meters and update tariffs remotely [11].

- Allow customers to collect and use consumption data by creating a home area network to which they can securely connect data access devices [12].

- Enable other devices to be linked to the home area network, allowing customers to improve their control of energy consumption [13].

- Support time-of-use tariffs, under which the price varies depending on the time of day at which electricity is used [14]. Energy prices are more expensive during peak times. Billing consumers by time, as well as usage, will encourage them to change their consumption habits.

- Support future management of energy supply to help distribution companies manage supply and demand across their networks [15]. This is achieved automatically through previously agreed Demand Response (DR) actions.

- Allow remote enabling/disabling of supply by energy suppliers [16].

- Measure electricity exported from micro generation equipment to the network [17]. Having sensors capable of measuring a multitude of consumption generation parameters, rewards the consumer for adopting green technologies.

- Communicate with micro generation, home appliances and equipment within the property [18]. Smart meters will be able to control smart home appliances and communicate with other smart meters within reach. This allows devices to be switched on when grid demand is low and turned off when demand is high.

The implementation of smart meters undoubtedly brings many benefits. However, there are also many challenges which need to be addressed.

C. New Technology Challenges

One of the main concerns is for the privacy of the consumer. Smart meters enable detailed profiling of consumers' energy usage and household activities. Patterns can be identified without prior knowledge of the consumer. It is possible to extract detailed usage patterns and consumer habits from the data as readings are at granular intervals.

Work undertaken by Andr´es [20] highlights the privacy concerns associated with smart meters. Their research demonstrates how complex usage patterns, can be obtained from smart meter data using off-the-shelf statistical methods. Specifically, their investigations focus on identifying trends in energy usage. However, none of the data was taken from actual smart meters. While energy readings were taken every second, in order to identify usage patterns, this does not accurately reflect real world smart meter usage. Typically smart meters report energy usage at 30 minute intervals. This is unlikely to change to due to the size of the data that is generated.

Storing, processing and analysing all of the data generated from smart meters, and the wider smart grid is also a challenge, due to its size and complexity. This is due to the variety of data and parameters from consumer usage to power generation some of which are shown in table 1.

TABLE 1. SMART METER DATA PARAMETERS

Reading	Description
Generated interval data kW	Half hourly interval held on meter for 13 months – average kW demand over half hour period.
Generated Kilovolt-Ampere-Reactance (kVAr)	Reactive power measurement in half hourly interval held on meter for 13 months – average kVAr demand over half hour period.
Generation Technology Type	e.g. Solar PV, micro CHP, wind, hydro, Anaerobic Digestion.
Import demand kW	Load being drawn from grid.
Export kW:	KW being exported to grid.
Total consumption today (kWh)	Import + Generated –Export.
Cost of energy imported (£/hr) and £ today	Net cost of imported energy less value of exported energy. Pushed to the IHD via SMS for the consumer.

The implementation of the smart grid represents a huge technical challenge. Aspects such as, networking, security, communication and data management require careful planning. For example, the integration of Supervisory Control and Data Acquisition (SCADA) networks with other commercial networks has made control systems vulnerable to various threats. Possible refinement, or creation of new and existing technology standards, has now become a necessity [21].

D. Profiling Consumers

Creating detailed energy profiles with associated data has a variety of benefits to the grid stakeholders. Some of which include: predicting future energy requirements based on historical data; establishing a detailed correlation between energy usage, weather conditions and social events; the refinement of more accurate demand and response systems using historical data; anomaly detection within the smart grid and, as our research focusses on, the detection of abnormal user behaviour.

By observing and analysing readings from the AMI and smart meters it is possible to detect anomalies, cyber-intrusions and factors that affect energy distribution. This requires the incorporation of data sets which include: weather/environmental; household demographics; social events; home generation; distribution of Plug-In Hybrid Electric Vehicles and home plug readings data.

E. Discussion and Summary

There are a number of large scale smart meter deployments in various countries. These include: France, Italy, Netherlands, Norway, Australia and the United States. Each of these counties have different policies and regulations governing their smart meter implementation programs. Such as: if smart meters are voluntary or compulsory; the frequency of readings and whether they have full function of automatic meter readings. The United States has one of the largest smart meter deployments [22]. In 2012, 533 U.S. electric utilities had 43,165,185 AMI installations. About 89% were residential customer installations. In the UK, the objective is to install smart meters for both gas and electricity by the end of 2020. The UK government estimates that the installation of smart meters will provide £6.2 billion net benefits to the United Kingdom.

The detail and granularity of the data collected can be used to address many of current and future challenges faced by the grid. One of the main challenges is being able to meet future energy demands in an efficient and environmentally safe way. The International Energy Agency expects worldwide energy demands to increase at an annual rate of 2.2 percent, eventually doubling the global energy demand. Analysing historical data can help plan the provision of future energy needs. It is noteworthy that the introduction of new green technologies, such as plugin electric vehicles, will put additional strain on the grid [23].

There has been little research effort to investigate the benefits of user profiling in the smart grid. The level of granularity in the datasets allows for accurate modelling and prediction of an individual's behaviour. This is beneficial both for predicting how the power-grid can accommodate the integration of new technologies, such as plug-in vehicles or assessing an individual's well-being.

III. APPROACH

By analysing the rich dataset provided by smart meters, the research in the paper aims to identify patterns and behaviours which can be used to profile users; predict future energy requirements; detect faults in the grid and identify compromised meters. In this section, a system framework which is able to process the significantly large datasets generated by smart meters is presented. A case study into three different consumers, and a demonstration on how an individual's behaviour can be profiled through their electricity usage, are also put forward.

A. System Framework

The proposed system shown in Figure 2 is adaptable and can be applied to a variety of functions some of which are shown in table 2.

TABLE 2. POTENTIAL SYSTEM FUNCTIONS.

Functions
Predicting future energy requirements based on historical data.
Establishing a detailed correlation between energy usage and weather conditions.
Aid in the detection of illegal activates through energy usage monitoring.
Accurately plan for the use of Plug-In Hybrid Electric Vehicles (PHEVs) based on historical gird load fluctuations.
Analyse what effects social events such as football matches, concerts etc. have on energy usage to better plan grid requirements for large events.

The system operates autonomously and identifies anomalies, energy usage, distribution patterns and trends. Figure 2 illustrates the proposed system along with the dynamics and correlations that the system monitors.

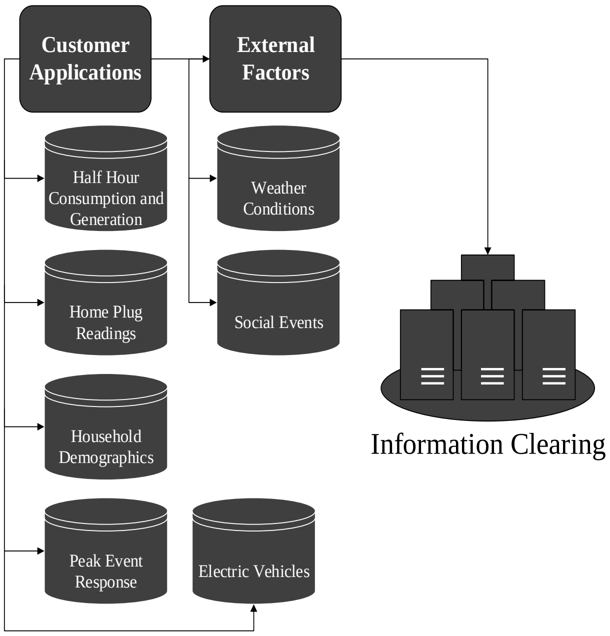

Figure 2. Proposed System Along With Associated Factors

The system provides detailed information about consumer consumption, which aids in the provisioning of future energy requirements and improving grid design and reliability.

B. Data Sample

As a demonstration of the functionality of the system, a case study is presented which focuses on an individual user taken from a large dataset during an extensive smart meter trial. Specifically, the data set generated by the trial contains smart meter readings taken from the 78,720 individual consumers over a six year period from 2008 to 2014.

For example, an individual user, selected at random from the data set, has 52560 rows of data. A typical sample of the data collected over a three hour period is displayed in Table 3.

TABLE 3. INDIVIDUAL SMART METER DATA SAMPLE (IN KWH)

Time (05/03/2013)	General Supply	Off Peak	Total Usage
07:29	0.014	No Usage	0.014
07:59	0.064	No Usage	0.064
08:29	0.107	1.132	1.239
08:59	0.155	0.169	0.324
09:29	0.092	0.563	0.655

The data shows the amount of electricity being used for each 30 minute interval (starting on the hour or half-past the hour) at each service location in the customer trial. Power consumption is reported as either normal domestic load or controlled load (i.e. off-peak - switched in or out by network control).

IV. USER PROFILING

To highlight how this data can be used to profile individuals, in this section we present a case study of the behaviour of two individual smart meter users. By analysing the dataset it is possible to develop a pattern of behaviour over one year and profile the behaviour of an individual. To enrich the dataset, household demographics taken from national census records for each consumer in the trial are included as above. This includes information about working patterns, household income and electrical devices that reside in the premise. For the initial profiling, the focus is on one years' behaviour data.

A. Profiles

In order to present a case study into profiling users in the smart grid, two individuals are randomly selected from the dataset as a sample, one with a normal energy pattern and one with an abnormal pattern. However, both users are within the same energy usage range. The census records detail that there is one occupant living in each of the premises selected for analysis. The residents are also known to be absent from home during the day.

Figure 3 and Figure 4 show a scatter plot of the daily max energy readings over 365 days of two individual consumers.

The energy usage is displayed along the x-axis. The y-axis refers to the day of the year.

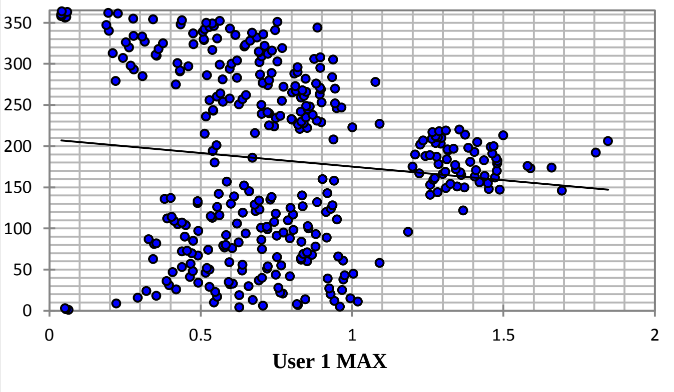

Figure 3. User 1 Max Energy Usage Kwh

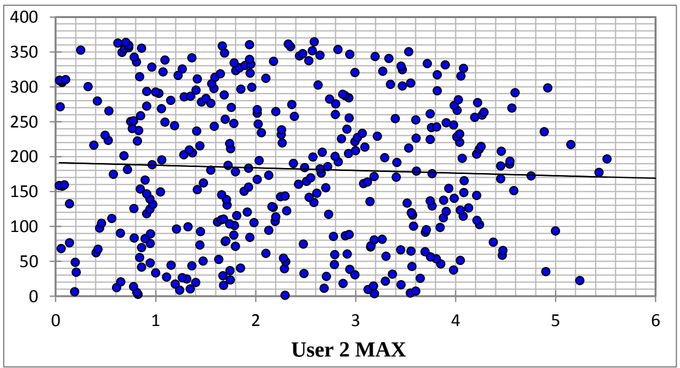

Figure 4. User 2 Max Energy Usage

The full profile of both consumers was evaluated over a one year period. This was undertaken to discover if any reoccurring patterns or habits could be identified based on their energy usage. Both figures also show the linear division of the data. As the division shows, the consumers have a tenancy to use more energy overall. Each 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. As shown in Figure 3 and Figure 4, clear divisions in the usage patterns can be clearly identified. Both households in this experiment have 1 resident who is out during the day.

B. Methodology

Figure 5 shows two users, comparing one with normal behaviour against a single individual expressing abnormal electricity usage patterns. Normal behaviour is represented by blue crosses, while abnormal is displayed as red dots. There is a clear visible difference in behaviour when comparing the usage.

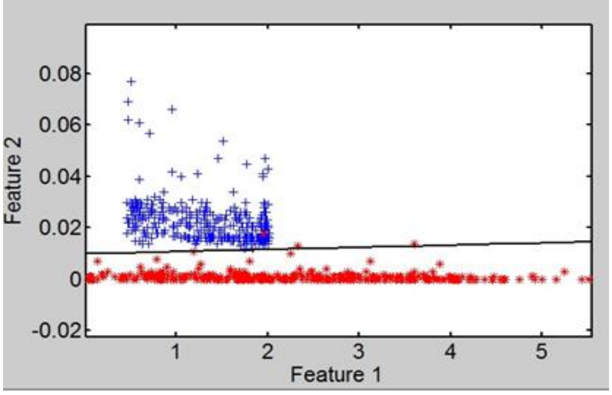

Figure 5. LDC Total usage per consumer over 1 year period

However, differences in behaviour are problematic to detect in the extensive datasets generated by smart meters. For this reason, our approach employs six different supervised machine learning classifiers: Uncorrelated Normal Density based Classifier (UDC), Quadratic Discriminant Classifier (QDC), Linear Discriminant Classifier (LDC), Polynomial Classifier (PLOYC), k-Nearest Neighbour (KNNC) and Support Vector Classifier (SVC). 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. Table 4 presents the results of the classification.

TABLE 4. CLASSIFICATION RESULTS COMPARISON

Classifiers	AUC (%)	Sensitivity	Specificity	Error
LDC	99.45	0.100	0.989	0.006
UDC	98.90	0.100	0.978	0.011
QDC	98.90	0.100	0.978	0.011
SVC	78.29	0.100	0.565	0.217
POLYC	99.45	0.100	0.989	0.006
KNNC	65.93	0.598	0.719	0.341

LDC and UDC were the most accurate, with both classifying over 98.90% of the data accurately. The LDC, is able to categorize the dataset with high accuracy (99.176%) with an error rate of 0.006.

LDC is shown in Figure 5 where the classifier is able to predict 99.45% of the data accurately. The KNNC classifier as shown in Figure 6 was the least accurate with an accuracy of 65.93%. As the graph displays, samples of the data from the abnormal set (red dots) is misclassified inside the KNNC contour grouping.

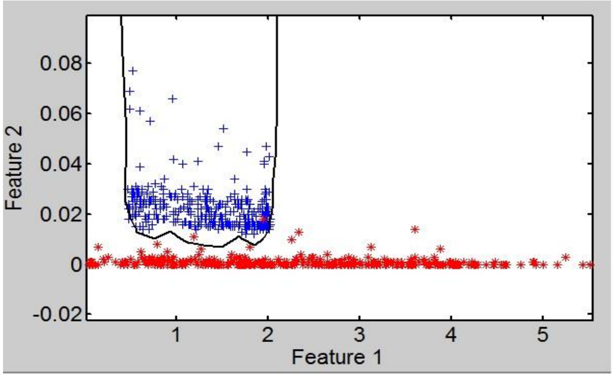

Figure 6. KNNC Total usage per consumer over 1 year period

C. Discussion

Despite selecting two users within the same energy usage range, clear deviations can be seen in the data sets. This change in usage patterns reflects an individual's unique behavioural characteristics. However, Figure 5 shows how the second consumer's behavioural patterns are not as clearly identifiable and there is no obvious visible trend in the usage pattern.

Profiling consumers with fine grained measurements brings many applications and benefits. For example, when comparing a third consumer's energy usage to the initial case study is it apparent that behavioural patterns are unique to the individual consumer. This data can therefore be analysed to give an accurate account of the customers' habits, characteristics and expenditure.

V. CONCLUSION AND FUTURE WORK

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 the grid's stakeholders and consumers alike. In order to meet future energy needs and be able to incorporate home generation and distribution, it is clear that changes in the current grid model are needed. The smart grid addresses the constraints imposed by the current power infrastructure by allowing detailed grid monitoring and involving the consumer. Being able to collect and analyse sufficient amounts of usage data makes it possible to identify reoccurring patterns and trends which can be used to address gird problems by profiling users of current and future grid implementations.

The results have shown that it is possible to identify and categorise individual user patterns generated by smart meters. Using the classification techniques presented in this research, it is possible to establish both normal and abnormal consumer behaviour based on granular energy usage data. The classifiers achieved high results. However, the main errors in classification are seen in the misclassification of normal user behaviour (sensitivity). This results in the false positive identification of abnormal user behaviour. This will be addressed in the future work by including the inclusion of more case studies to expand the dataset. Our future work will involve incorporating additional datasets, including home plug readings showing how much energy each electrical device has used at 30 minute intervals. The use of the additional data will create a more detailed profile of a user and allow us to make accurate assumptions about an individual's behaviour patterns.

REFERENCES

[1] A. Molina-Markham, P. Shenoy, K. Fu, E. Cecchet and D. Irwin, "Private Memoirs of a Smart Meter," Proceedings of the 2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building, 2010, pp 61-66.

[2] A. Mengolini and J. Vasiljevska, "The social dimension of Smart Grids," Joint Research Centre of the European Commission, 2013

[3] J. Zheng, D. Wenzhong Gao and L. Lin, "Smart Meters in Smart Grid: An Overview," Proceedings of IEEE Conference on Green Technologies Conference, 2013, Pages 57 -64.

[4] D. J. Kerrigan, L. Gamberini, A. Spagnolli and G. Jacucci, "Smart meters: A users' view," PsychNology Journal, 2011

[5] S. O. Hurtado and P. Parmenter, "The Green Grid Energy Savings and Carbon Emissions Reductions Enabled by a Smart Grid," Electric Power Research Institute 2008.

[6] M. Popa, "Data Collecting from Smart Meters in an Advanced Metering Infrastructure," Proceedings of 15th International Conference on Intelligent Engineering Systems, 2011

[7] A. Faruqui and L. Wood, IEE Releases: "The Benefits of Smart Meters," NARUC Winter Meetings. Institute for Electric Efficiency, Washington, D.C. 2011.

[8] R. Stamminger, "Synergy Potential of Smart Appliances, Project report within the Smart-A project," v2, November 2008

[9] R. van Gerwen., S. Jaarsma and R. Wilhite., "Smart Metering," IDC-Technologies, 2006

[10] F. Benzi, N. Anglani, E. Bassi and Lucia Frosini "Electricity Smart Meters Interfacing the Households," IEE transactions on Industrial Electronics, Vol 58, No10, 2011VOL. 58, NO. 10.

[11] C. Bennett, D. Highfill, "Networking AMI Smart Meters," November 2008, IEEE Energy2030.

[12] T. Krishnamurti, D. Schwartz, A. Davis, B. Fischhoff, W¨and i Bruine de Bruin, L. Lave and J. Wang, "Preparing for smart grid technologies: A behavioral decision research approach to understanding consumer expectations about smart meters," Energy Policyc41, 2011.

[13] M. Venables, "Smart meters make smart consumers," Engineering & Technology, Volume: 2, Issue: 4, 2007.

[14] L. Olmos, S. Reuster, S. J. Liong and J. M. Glachant, "Energy efficiency actions related to the rollout of smart meters for small consumers, application to the Austrian system," Energy Volume 36, Issue 7, July 2011.

[15] M. Anas, N. Javaid, A. Mahmood, S. M. Raza, U. Qasim and Z. A. Khan, "Minimizing Theft using Smart Meters in AMI," Seventh International Conference on P2P, Parallel, Grid, Cloud and Internet Computing, 2012.

[16] H. Farhangi, "The path of the smart grid," Power and Energy Magazine, IEEE (Volume:8 , Issue: 1), February 2010.

[17] J. Zheng., D. Wenzhong Gao and L. Lin., "Smart Meters in Smart Grid: An Overview," Proceedings of IEEE Conference on Green Technologies Conference, 2013, Pages 57 -64.

[18] S. S. Sreenadh, R. Depuru, L. Wang and V. Devabhaktuni, "Smart meters for power grid: Challenges, issues, advantages and status, Renewable and Sustainable Energy Reviews 15," February 2011.

[19] A. Molina-Markham, P. Shenoy, K. Fu, E. Cecchet, and D. Irwin, "Private Memoirs of a Smart Meter," BuildSys '10, 2010.

[20] Á. MacDermott, Q. Shi, M. Merabti and K. Kifayat: "Intrusion Detection for Critical Infrastructure Protection," June 2009, Neural Networks, 2009. IJCNN 2009, Pages 14-19.

[21] U.S. Energy Information Administration, March, 2015 [Accessed online at: http://www.eia.gov/]

F. Bouhafs., M. Mackay and M. Merabti "Links to the Future," IEEE Power & Energy Magazine, 2012.

