

A SERVER BASED LOAD PATTERN ANALYSIS OF SMART METER SYSTEMS USING INTERNET-OF-THINGS

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Abstract— *The electricity demand is increasing with the growth of population and with the use of different appliances in the households. So, there is a need for consumers to track their daily usage and understand the consumption patterns to save and control these resources. Smart meter along with Advanced Metering Infrastructure (AMI) is a pragmatic and efficient solution for this. This project aims at analyzing the performance of the proposed smart meter systems, efficient transmission and how utilities explore new developments for the benefit of consumers. The methodology followed to analyze the outcome is Power Line Communication(PLC) and Internet-of-Things. This is achieved by using PLC modems and Raspberry pi for remote monitoring and control of energy meters, as well as user friendly mobile App for consumers which is linked with utility server for constant updates. Smart grids collect large volumes of smart meter data in the form of time series or so-called load patterns. This project outlines the applications that benefit from analyzing this data and propose a load pattern clustering with prediction. The first stage is performed per individual user and identifies the various typical daily power usage patterns consumer exhibits. The second stage takes those typical user patterns as input, to group users that are similar. To improve scalability, fast wavelet transformation (FWT) of the time series data is used, which reduces the dimensionality of the feature space where the clustering algorithm operates in. The consumption patterns are studied and load analysis is made at the server side so that this can help in maintaining other systems associated with energy management.*

IndexTerms—*Smart Meter, Smart Grid Advanced Metering Infrastructure (AMI), Power line communication (PLC), Raspberry pi, Internet-of-Things(IoT), Load Pattern Clustering, Wavelet Features.*

I. INTRODUCTION

Now-a-day people expend electricity without care about the availability of power. As a result, the production ability does not match the demand. The global energy crises are increasing at an alarming rate and has the attention towards more and more energy production. Developing countries are facing acute problem of power theft and unorganized power management due to lack of sufficient and efficient past energy consumption data. This has led to huge losses to power companies or unbearable high electricity costs for customers. The utilities have made much more energy efficiency efforts as the price of energy and public pressure to lower carbon emissions is increasing. Since one becomes wiser in using electricity one can instantly know how much to use and consume. Hence a lot of new technology has been introduced to satisfy the user demands.

India is growing with an intense rate and it is striving to be a developed country by 2020. India with 32,280MW is the fourth biggest capacity in the world after China, the U.S and Germany. India's power requirement would increase to a target level of 60GW by 2022. The deployment of advanced metering Infrastructure(AMI) or Smart Metering satisfies the basic technique of Smart Grid (SG) concept. This will avoid the situations like blackout and shortage of power.

The motive of this work is to obtain a better understanding of the viability which are provided by the modern energy meters and their communication via PLC and IoT, an study on the functions and their communication protocol is needed.

The energy providers are in need to know the accurate information on the actual behaviour of the electricity customers. Effective results are obtained based on the classification of consumption pattern similarity. Various clustering techniques have been tested on electrical load pattern data to create customer grouping based on similarity aspects. Clustering algorithms are helpful for data mining, compression, probability density estimation, and many other important tasks

II. RELATED WORK

Smart Meter is an friendly energy meter that measures the electrical energy in terms of KWh. It is a simple device that benefits the consumers who want to save money on their energy consumption bill. They are associated with Advanced Meter Infrastructure and are accountable for permitting meter readings automatically to the energy providers[1]. Benefits of smart meter over traditional Electromechanical meters:1. Smart meters are less error prone. 2. Readings can be sent remotely over the web to the utility providers. 3. Tampering of these meters can be easily detected by the authorities[2].

A technique for effectively identifying patterns and clusters in high dimensional time-dependent functional data is given in [6]. It is based on wavelet based similarity measures since wavelets are absolute for detecting highly peculiar local time and scale features. Some basic ideas of the wavelet analysis are explained. A tightly supported WT uses a orthonormal basis of waveforms derived from scaling and translations of a compactly supported scaling function ϕ and a compactly supported mother wavelet ψ .

Parts of Advanced Metering Infrastructure (AMI) are developed to facilitate bi-directional communication using a variety of media and technology between the central database and consumer's meter. This permits remote configuration, receiving or sending control messages[9].

The project is based on data transmission over the power line. As the communication medium Power Line Modems (PLM) uses the power line cables. A communication cable that can be controlled and operated through a central unit. It is favourable as it eliminates the need to lay additional cables. Data transmitted at carrier frequencies in the range from 50 kHz to 500 kHz [11].

III. AN IDEA ON SMART GRID AND SMART METERS SYSTEMS

The Smart Grid is not just a group of smart meters, wind, solar, or plug-in electric vehicles, also, it is a series of technologies that allows utilities to integrate, interface with all supply, grid, and demand elements linked to a digital upgrade of power grid. The Smart Grid will provide real-time information and near-instantaneous balance of supply and demand. The Smart Grid will allow a bi-directional electricity flow and information that is capable of monitoring everything from power plants to customer preferences as the technology grows.

A smart meter should be capable of showing the total cost of the consumed energy. Smart Meter Systems are an integral part of the Smart Grid infrastructure in data collection and communications. These meters must be able to provide proper communication ports to respond to requests for collecting necessary data.

AMI consists of a set of equipment, networks, computer systems, protocols and organized processes which are employed to collect and send data related to electricity suppliers using power and distribution grid. By making use of AMI technology several functions can be done accurately at the utility.

Communication networks are able to send the control commands emerged from the station to the smart meter and to pass on the data collected by the meter to the central server. This can reduce the annual expenditure of utility to a great amount.

Deploy tele-protection services over its entire network. Using the new upgraded system, we are able to receive instant updates of any fault in its infrastructure and re-route power through alternative lines to minimize the dis-reputation to the end consumer. The system connects all our grid stations and ensures there is tele-protection.

IV. CONCEPT OF AMI

AMI is a configured infrastructure. It includes smart meters, communication networks at different levels of the infrastructure hierarchy to connect two ends, Meter Data Management Systems (MDMS), Customer Information System (CIS), Outage Management Systems (OMS), Distribution Management Systems (DMS) and the means to integrate the gathered data into software application platforms and interfaces at head end.

A sensor that can be clamped on to low tension distribution lines and can be detected lack of load balance, thus avoiding electricity theft. The sensors to transmit the data to the distribution company's central server so that the utilities can gauge that something is wrong.

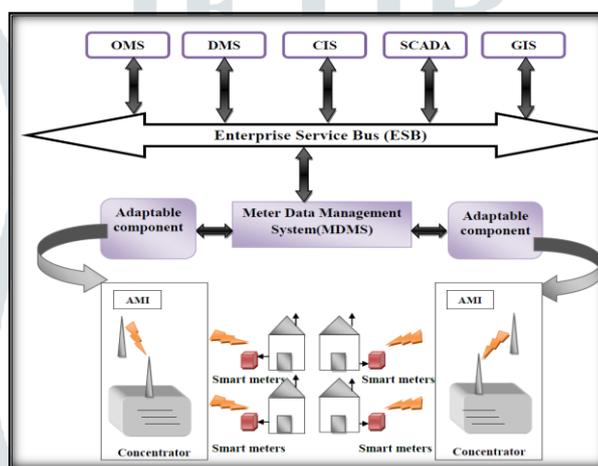


Fig.1: Smart Meter System Architecture

V. POWER LINE COMMUNICATION SYSTEMS

Power line communication also known as Power line carrier makes use of the existing electrical network for communication. Power line communication allows consumers to use their already existing wiring system to connect home appliances to each other and to the Internet. Existing AC power lines is used as a medium to transfer the information, which becomes easy to connect the houses with without installing new wirings. First data is modulated & filtered and then by using couplers, it is sent over the power lines.

A. PLC Modulation

PLCC needs a technique that can tolerate unpredictable attenuation and phase shifts. OFDM is the modulation technique that is used in HomePlug specification. In OFDM, information is modulated on to multiple carriers, where each carrier occupies its own frequency in the range of 4.3 to 20.9 MHz. Incoming bit stream is demultiplexed into N number of parallel bit streams each with 1/N of original bit rate which are then modulated on N orthogonal carriers.

B. PLC in Meter Reading

The meter reading system is made up of three components, MFNs function is to take reading of the meter on an hourly basis and store it in a memory chip. CNN is another part which manages all MFNs within a particular area and collects meter readings from all MFNs. All the data and meter readings from CNNs are managed at the server computer installed with Operation and Management System.

VI. INTERNET-OF-THINGS

Considerably large developments in the field of internet and technologies have made everything digital. Technologies discovered recently come into this state of being fully informed as Internet-of-Things (IoT). Internet-of-Things is a network made up of many electronic devices and sensors which are joined together to exchange some information over the web. We can analyze and control the objects anytime, anywhere from the world. One of the applications of IoT is smart meter. Computing and communications has its future in the technological transformation brought by the IOT, rapid technical changes are accountable for the further development of IOT. Each object will be marked for identifying, automating, monitoring and controlling.

VII. EXISTING SYSTEM

AMR devices just collected meter readings electronically (handheld devices or driven-by) and matched them with accounts.

A. Disadvantages

- Digital meter-one way communication
- Driven by m
- meter reading (kW) – manually
- Inaccurate billing and Increased power theft

VIII. PROPOSED SYSTEM

AMI is created to constitute the networking technology of fixed network meter systems that go beyond AMR into remote utility management. Some of the advantages are digital meters – two way communication, Remote meter reading and monitor, Daily meter reading(kWh), Demand(kW), Voltage(V), Reports Outages and Power Restoration, Connect/Disconnect Device and Special Pricing , Improved billing and tacking of usage.

The Hardware Module is divided into measurement circuit, Arduino Board along with PLC modem, Internet-of-Things and Mobile APP. The Software Module involves load pattern analysis and prediction for the real-time input data implemented in MATLAB software.

A. Block Diagram

1) Meter session

The meter session is used to measure the electrical energy consumed in one's house. This is constructed by connecting loads in series along with power supply and an Arduino board used for programming. It is programmed to take in consumed power as input values and the amount is calculated for units used and displayed in LCD. The PLC modems connected to Arduino board transfers this value to stand alone server(PLC modem) through the power lines.

2) Stand Alone Server To Main Server

The PLC modems transmit data through power lines from the house to stand alone server (sub server) having PLC modems and Raspberry pi. The data is then passed through IoT to main server at the utility where load pattern analysis is made for further energy management and maintenance. On the other hand the data is also updated in Mobile App of the user which is linked with Utility Profile so that user is able to have a knowledge of his consumption and can control excess usage of electricity.

The key learning platform for IOT is raspberry pi. Raspberry pi is connected to the PLC modems and the internet. Once the wifi connection is set then login to raspberry pi to start developing IoT platform. The programming language is used here is python. Raspberry pi send energy information to the internet connected server for monitoring energy usage information of individual device. Cloud storage and web hosting is useful for storing real-time energy data and permits other programs to access and monitor the data. The control signal send to raspberry pi using same server to turn on/off the device.

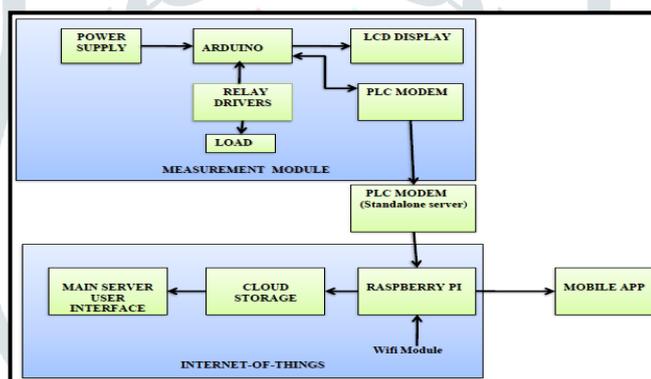


Fig.2: Proposed Block Diagram

IX. SYSTEM HARDWARE

A. Arduino UNO

Arduino is an open-source prototyping platform where both hardware and software is easy-to-use. Arduino boards read inputs - activating a motor, turning on an LED, publishing something online. The Arduino programming language and the Arduino Software (IDE) is used to achieve this. The calculation on the duration, load and units of consumption is coded using Arduino software. The Arduino software is easy-to-use for beginners, yet flexible enough for advanced users. It runs on Mac, Windows and Linux. 300,000 source code lines per sec can be executed at once.

B. PLC Modem

Power line modem is used over existing power lines to send and receive serial data. The modem is capable of providing low rate bi-directional half-duplex communication of any voltage up to 250V AC and for frequency 50hz or 60hz with 9600 baud rate. Byte by byte transmission takes place. Highly resistant to electrical noise and built in error checking are available so it never gives out falsify data and also AC isolated coupling circuit are built-in on board.

C. Raspberry pi

The raspberry pi is small sized and cheap computer which is launch by raspberry pi foundation with the help of Broadcom and university of Cambridge laboratory. The raspberry module also called microcomputer and this microcomputer is stand on Broadcom SoC unit. SoC means system on the chip in which all configuration of microprocessor is included. So there is RAM, ROM, CPU, and also ADC and DAC converter in addition serial interfaces. The thing that is distinct SoC from microcontroller is that, SoC devices are directly connected with CPU so huge computational capability which build it practicable to run operational manner.

X. SYSTEM SOFTWARE

A. Load Pattern Analysis Application

The proposal is to cluster daily load patterns for low voltage residential customers: (i) first cluster similar daily load patterns per user to find each user's classic daily patterns, (ii) cluster the whole set of classic user patterns over all users together. The clustering is done in a space of lower dimensionality (than the original time domain) by transforming the time series data using fast wavelet transformation.

Another benefit of FWT is that patterns that are similar in shape but just differ in a time shift still end up in the same cluster. This detailed examination of power consumption of individual users can be helpful in providing feedback on,

- 1) Electricity demand analysis
- 2) Customer segmentation, tariffs, billing and markets
- 3) Power system planning and operation
- 4) Demand response and demand side management
- 5) Load forecasting

B. Clustering Algorithms

1) **K-means**

K-means clustering directs to partition n observations into k clusters in which each observation is a member of the cluster with the nearest mean, representing as a prototype of the cluster.

K-means iteratively computes cluster centroids for each distance measure in order to reduce the sum with respect to the detailed measure. K-means algorithm directs at minimizing squared error function given in (1) as follows:

$$J(\mathbf{X}; \mathbf{V}) = \sum_{i=1}^n \sum_{j=1}^k D_{ij}^2 n_{j=1}^{ci=1} \quad (1)$$

Where, D_{ij}^2 is the chosen distance measure which is generally in Euclidean norm: $\|x_{ij} - v_{il}\|^2, 1 \leq i \leq c, 1 \leq j \leq n_i$. Where n_i represents the number of data points in i th cluster.

For c clusters, K-means is based on an iterative algorithm minimizing the sum of distances from each object to its cluster centroid. The objects are passed between clusters until the sum cannot be reduced any more. K-means algorithm involves the following steps:

- a) Centroids of c clusters are chosen from \mathbf{X} randomly.
- b) Distances between data points and cluster centroids are calculated.
- c) Each data point is assigned to the cluster whose centroid is closest to it.
- d) Cluster centroids are updated by using the formula in (2):

$$v_i = \frac{\sum_{j=1}^n x_{ij} n_{i=1}^{j=1}}{n_i}; 1 \leq i \leq c \quad (2)$$

- e) Distances from the updated cluster centroids are recalculated.
- f) If no data point is assigned to a new cluster the run of algorithm is stopped, otherwise the steps from (c) to (e) are repeated for probable movements of data points between the clusters.

Certain drawbacks are noticeable. The number of clusters K must be specified as input parameter, which is a non-trivial problem in most applications. The final clusters will be spherical i.e., an assumption that the data is distributed in spherical clusters.

2) **G-means**

The g-means algorithm can be seen as a cover around the k-means algorithm, that finds the best number of clusters and makes less assumptions about how data points are distributed within clusters. G-means iteratively increases the number of clusters as it advances. In each iteration, every current cluster whose member data points do not appear to come from a Gaussian distribution is split into two. K-means is executed on the entire dataset using the current cluster centroids between each round of splitting to treat the solution. The statistical test, for checking whether data within a cluster is Gaussian, is based on the Anderson-Darling statistic, a powerful one-dimensional normality test. Thus, the user only has to decide on the significance level α of the test, instead of specifying K .

G-means(\mathbf{X}, α) Algorithm involves the following steps :

- a) Let C be the initial set of centres (usually $C \leftarrow \{\bar{x}\}$).
- b) $C \leftarrow kmeans(C, \mathbf{X})$.
- c) Let $\{x_i | class(x_i) = j\}$ be the set of data points assigned to centre c_j .
- d) Use a statistical test to detect if each $\{x_i | class(x_i) = j\}$ follow a Gaussian distribution (at confidence level α).
- e) If the data look Gaussian, keep c_j . Otherwise replace c_j with two centres.
- f) Repeat from step (b) until no more centres are added.

The method is executed for k-means multiple times (up to k times when finding k centres), so the time complexity is at most $O(k)$ times that of k-means.

C. Adequacy Measures

To rate the performance of the clustering algorithms and to compare them with each other, six different adequacy measures is put to use. Their purpose is to obtain well-separated and compact clusters to make the load curves self explanatory. Below are the following measures :

i) The clustering algorithm actually aims to minimize the cost function J (also called distortion function/ Error function/Mean Square Error):

$$J = \frac{1}{N} \sum_{k=1}^K \sum_{x_i \in C_k} \|x_i - \mu_k\|^2 \quad (3)$$

Where new cluster centroids are calculated as the average over current cluster members:

$$\mu_k = \frac{1}{|C_k|} \sum_{x_i \in C_k} x_i \quad (4)$$

ii) The Mean Index Adequacy (MIA) is used to measure the compactness or homogeneity of the clusters:

$$MIA = \sqrt{\frac{1}{K} \sum_{k=1}^K d(\mu_k, C_k)^2} \quad (5)$$

Other indicators consider not only the compactness of the cluster, but also the separation of clusters or distance between clusters.

iii) The Cluster Dispersion Indicator (CDI) is:

$$CDI = \frac{1}{d(R)} \sqrt{\frac{1}{K} \sum_{k=1}^K d(C_k)^2} \quad (6)$$

iv) The Davies-Bouldin Index (DBI) represents the system-wide average of the identity measures of each cluster with its most similar cluster:

$$DBI = \frac{1}{K} \sum_{k=1}^K \max_{i \neq j} \left\{ \frac{d(x_i, C_k) + d(x_j, C_k)}{d(R)} \right\} \quad (7)$$

v) The Similarity Matrix Indicator (SMI) is given as the maximum off-diagonal element of the symmetrical similarity matrix, whose elements are computed using logarithmic function of the Euclidean distance between pairs of cluster centroids (i.e., representative load patterns):

$$SMI = \max_{\substack{i > j \\ i, j \in \{1, \dots, K\}}} \left\{ \left(1 - \frac{1}{\ln d(\mu_i, \mu_j)} \right)^{\wedge} - 1 \right\} \quad (8)$$

Compactness and cluster separation show opposing trends, e.g., compactness increases with the number of clusters, but separation decreases.

vi) The ratio of “within cluster sum of squares to between cluster variation” (WCBCR) is the ratio of the sums of the square distances between each input vector and its cluster’s centroid vector and the distances between the clusters’ centroids:

$$WCBCR = \frac{\sum_{k=1}^K \sum_{x_k \in C_k} d(\mu_k, x_k)^2}{\sum_{1 \leq p < q \leq K} d(\mu_p, \mu_q)^2} \quad (9)$$

For the study and evaluation of classification algorithms the following distance forms are defined,

vii) Euclidean Distance,

$$\text{Cluster}(x_i) = \arg \min_{k \in \{1, \dots, K\}} \|x_i - \mu_k\|^2 \quad (10)$$

between two n-dimensional vectors (e.g., load patterns):

$$d(x_i, x_j) = \sqrt{\frac{1}{n} \sum_{k=1}^n (x_{i,k} - x_{j,k})^2} \quad (11)$$

between a vector x_j and a cluster C_j :

$$d(x_j, C_j) = \sqrt{\frac{1}{|C_j|} \sum_{x_k \in C_j} d(x_j, x_k)^2} \quad (12)$$

within a set (e.g., cluster) C_j :

$$d(C_j) = \sqrt{\frac{1}{2|C_j|} \sum_{x_i \in C_j} d(x_i, C_j)^2} \quad (13)$$

D. Process Flow

The four main stages of the process are as follows,

1) Data pre-processing and feature extraction

The aim is to cluster load patterns into tightly packed and unique groups. It is dealt with time series data representing energy consumption of low voltage customers, e.g., households. Such measurements are typically performed on a 30 minutes basis, resulting in load patterns of 48 samples per day (i.e., a 48- dimensional vector x).

The Fast Wavelet Transform (FWT) with Haar wavelets is adopted to transform a time series data vector x . Instead of using the time series data itself (as is the common approach), it is converted to a lower dimensional representation (i.e., with fewer features). Wavelets get the general trend of the input data in an approximation component, while the localized changes are kept in the detail components. Wavelet representation shows the time series in both time and frequency domain. In our example, a 48-dimensional original time series vector x is transformed to a 128- dimensional up sampled vector X^u .

2) Typical load patterns per user

This stage comprises two steps: (a) clustering of the daily patterns of individual customers, and (b) selection of representative patterns (to be used as input for this stage).

3) Overall load pattern clustering

The input for this stage, after range normalization, is clustered using the same approach as in previous step. The resulting clusters group similar patterns from multiple users, after which each user can be represented in terms of how many of his day patterns belong to what global cluster.

4) Load Forecasting and Prediction

For the management of power systems electricity demand forecasting is of great importance. The need for exact load forecasts will increase in the future because of the sudden alterations occurring in the formation of the utility industry due to deregulation and competition.

In general, the load forecasts can be grouped into short-term, mid-term, and long-term forecasts. Short-term load forecasts are essential for the control and scheduling of power systems. Short-term forecasts are also essential by transmission companies when a self-dispatching market is in operation. The short-term forecasts refer to hourly prediction of the load for a lead time ranging from one hour to several days out. The quality of short-term hourly load forecasts has a significant impact on the economic operation of the electric utility since decisions such as economic scheduling of generating capacity, transactions such as ATC (Available Transmission Capacity) are based on these forecasts and they have significant economic consequences.

Artificial neural networks (ANNs) have a specific kind of importance in the load forecasting literature. NNs are able to give better performance in dealing with the non-linear relationships among the input variables by learning from training data set. The ARIMA modelling designed and trained for the given input. After the successful completion of the training process three plots were made which include:

a) The regression plots

- b) The performance function Vs epochs plot
- c) The training state plot

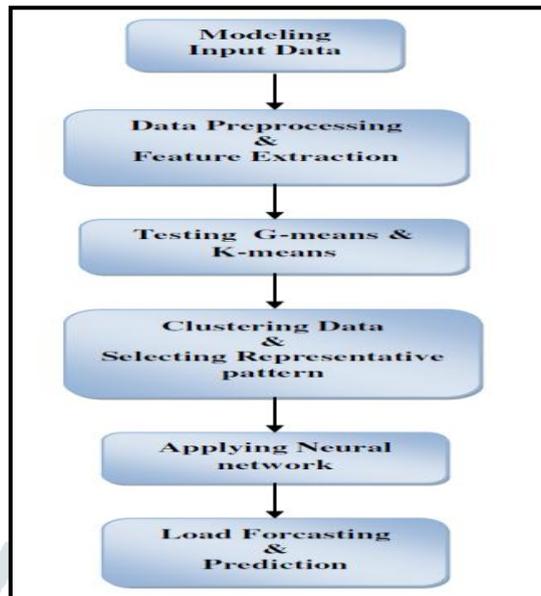


Fig.3: Flow diagram of the load pattern clustering analysis

XI. RESULTS

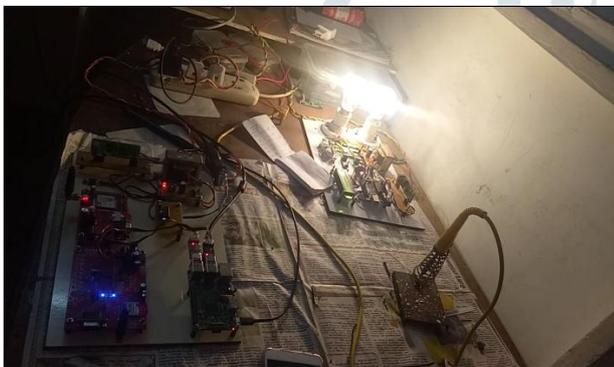


Fig.4: Overall hardware setup of Smart meter communication



Fig.5: PLC with Raspberry module for IoT communication

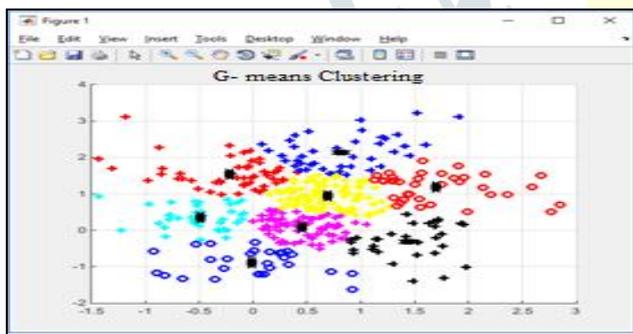


Fig.6(a): Overall G-means Clustering with $\alpha = 0.01$

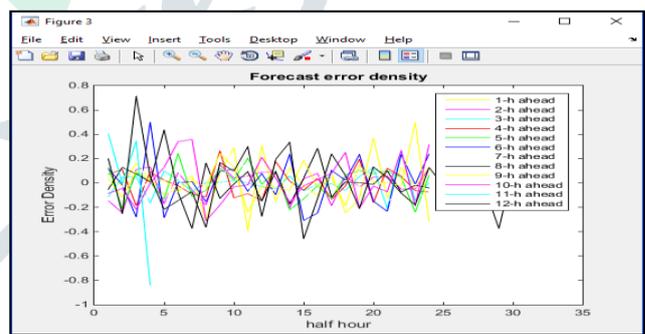


Fig.6(b): Error values featured from the dataset

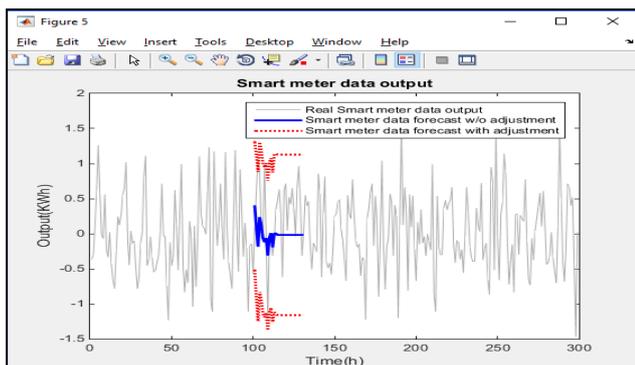


Fig.6(c): Load pattern shape analysed through G-means at $\alpha = 0.01$

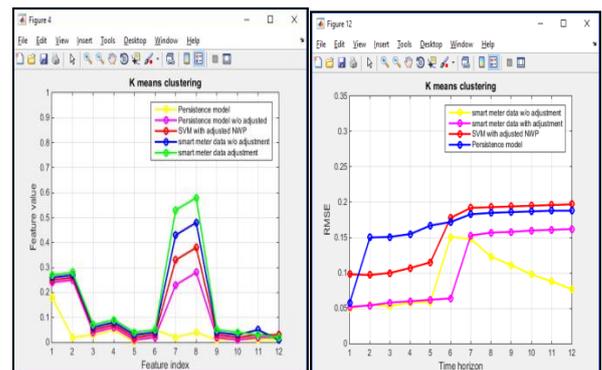


Fig.6(d)(e):. Extracted Feature values and mean square error from the dataset

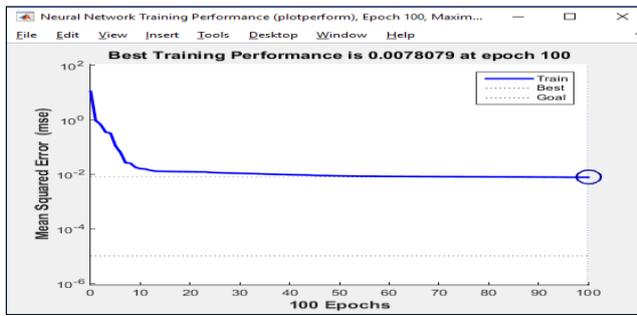


Fig.7(a): Performance achieved by training the dataset in Neural network

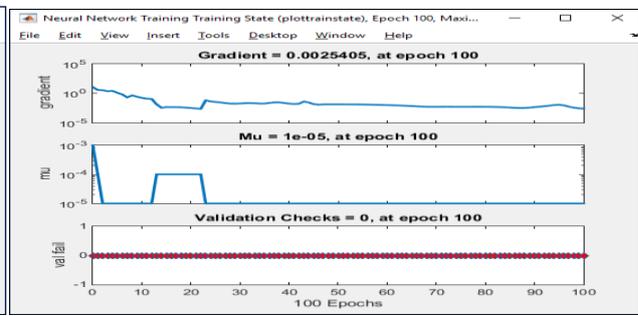


Fig.7(b): Training states required to completely analyse the dataset

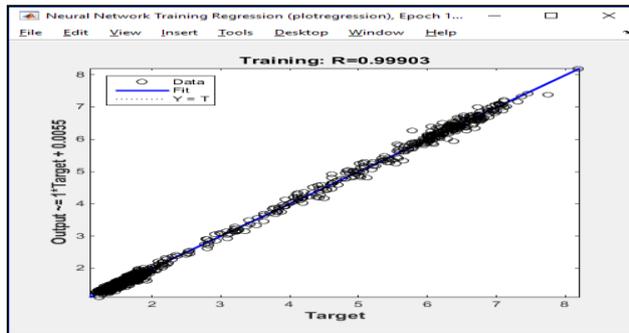


Fig.7(c): Prediction values made from the given input dataset that will follow the similar pattern in future.



Fig.8(a)(b): Mobile App created for having a check over the power consumption made by individual users

The Application notifies the total units consumed by the individual and the total bill charged for the consumption with reminder to pay bills time-to-time. This can be helpful as the individual can have a control over his consumption. It also gives an alert message if in-case the maximum limit of units have been consumed per individual well in advance. The App also supports online complaint registration by the user if he/she faces any problem with the meter.

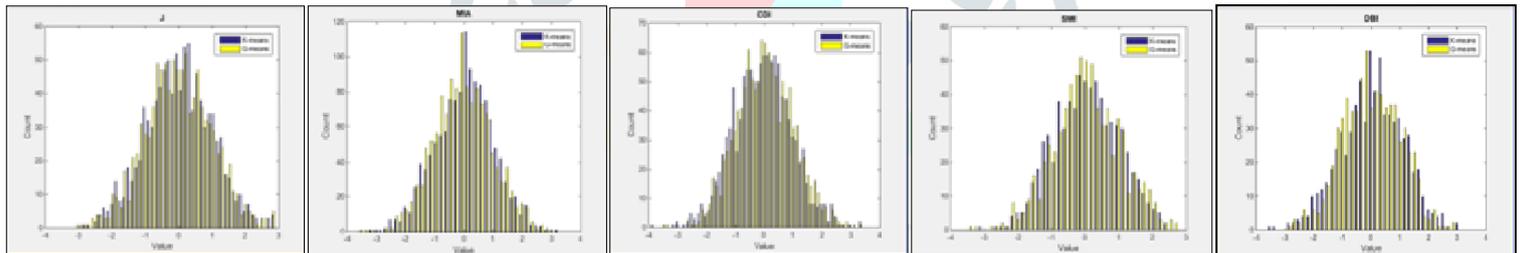


Fig.9: Histograms estimating the adequacy measures (cluster quality) for the g-means and k-means algorithm. The y-axis of a bar represents the number of cases where the quality indicator amounted to the x-axis.

Both algorithm shows the similar results, independent of the features used. Still, the prior assumptions made by the respective algorithms varies. The k-means algorithm assumes that data points in each cluster are spherically distributed. More generally, the g-means algorithm assumes a multi-dimensional Gaussian distribution.

| Date | M | L | A | S |
|-----------------------|------|------|-----|---|
| May 3, 2017, 1:20 am | 100 | 100 | 20 | 1 |
| May 3, 2017, 1:44 am | 0.00 | 0.00 | 000 | 1 |
| May 3, 2017, 2:01 am | 0.00 | 0.00 | 000 | 1 |
| May 3, 2017, 2:04 am | 0.00 | 0.00 | 000 | 1 |
| May 3, 2017, 2:07 am | 0.00 | 0.00 | 000 | 1 |
| May 3, 2017, 2:09 am | 0.00 | 0.00 | 000 | 1 |
| May 15, 2017, 2:56 pm | 100 | 100 | 20 | 1 |
| May 15, 2017, 2:57 pm | 100 | 100 | 20 | 1 |
| May 15, 2017, 2:58 pm | 200 | 200 | 40 | 1 |
| May 15, 2017, 2:59 pm | 0.00 | 0.00 | 02 | 1 |
| May 15, 2017, 3:05 pm | 0.00 | 0.00 | 000 | 1 |
| May 15, 2017, 3:09 pm | 0.01 | 0.01 | 000 | 1 |
| May 15, 2017, 3:11 pm | 0.02 | 0.01 | 10 | 1 |
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| May 15, 2017, 4:09 pm | 0.00 | 0.00 | 000 | 1 |
| May 15, 2017, 4:11 pm | 0.01 | 0.00 | 000 | 1 |
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Fig.10: Power readings that are updated periodically at the server side database through IoT

Server database at the utility will be loaded from time to time with the smart meter data measured at the consumer's residence through IoT. By this the utility can have a control over the users meter for auto connect/resume of electricity.

XII. CONCLUSION

Energy meters are gradually being replaced by more sophisticated and accurate digital and electronic meters. A high percentage of electricity revenue is lost to power theft, incorrect meter reading and billing. This is reduced by the use of smart meters and Internet-of-Things as a communication medium. The proposal is to perform the clustering in a space of lower dimensionality by transforming the time series data using fast wavelet transformation. In addition, the load forecasting and prediction models prove to be very efficient for the power management. This analysis of power consumption of individual customers can be used to provide feedback on, e.g., energy consumption, tariffs selection, and load forecasting.

XIII. FUTURE SCOPE

Future work comprises implementing the proposed method into demand response(DR) applications, e.g., improved load forecasting, Identify and predict flexibility in power consumption, to examine the potential of DR and eventually exploit it, automatically learn flexibility, from minimally intrusive measurement data, decreasing or even eliminating the need for manual user input. Apart from these improvements, a Home-Area-Network integrated with smart meter can be developed to monitor load analysis of each appliance at server. An interesting suggestion is an individual user can make adjustment of the meter maximum daily energy consumption (the costs), above which an alarm would be signaled.

REFERENCES

- [1] Praveen Vadda, Sreerama Murthy Seelam, "Smart Metering for SmartElectricity Consumption", School of Computing, Blekinge Institute of Technology, 37179 Karlskrona, Sweden May 2013.
- [2] Shikha Rastogi ,Manisha Sharma, Pratibha Varshney, "Internet of things based smart electricity meters" International Journal of Computer Applications (0975 – 8887) ,Vol.133,No.8, pp.13-16, January 2016.
- [3] Alberto Sendin , Ivan Peña and Pablo Angueira "Strategies for power line communications smart metering network deployment" Energies , Vol.7, pp. 2377-2420, April 2014.
- [4] Mohamed Azeem Hafeez , Vinay Birmhan, "Implementation of power line communication for energy measurement" , International Journal Of Engineering Sciences & Research Technology (IJESRT), Vol.3, No.11, pp292-295, November, 2014.
- [5] EEI-AEIC-UTC White Paper "Smart Meters and Smart Meter Systems: A Metering Industry Perspective", A Joint Project of the EEI and AEIC, March 2011.
- [6] A. Antoniadis, X. Brossat, J. Cugliari, and J.-M. Poggi, "Clustering functional data using wavelets," Int. J. Wavelets Multiresolution Inf. Process., vol. 11, no. 1, pp. 1–30, Jan. 2013.
- [7] B. Stephen, A. Mutanen, S. Galloway, G. Burt, and P. Jarventausta, "Enhanced load profiling for residential network customers", IEEE Trans. Power Delivery, vol. 29, no. 1, pp. 88–96, Feb. 2014.
- [8] Duplex, J.; Gosswiller, S.; Fagnoni, S.,(2013), "A better knowledge of electricity consumption for residential customers through the Linky smart meter", In Proceedings of the 22nd International Conference and Exhibition on Electricity Distribution (CIRED), Stockholm, Sweden, 10–13 June 2013; pp. 1–4.
- [9] Marek Pawlowski, Piotr Borkowski, Bartosz Balsam, "Model of smart electricity meter",Lodz University of Technology, Department of Electrical Apparatus, pp. 239-242, 2015.
- [10]G. Tsekouras, N. Hatziargyriou, and E. Dyalynas, "Two-stage pattern recognition of load curves for classification of electricity customers," IEEE Trans. Power Syst., vol. 22, no. 3, pp. 1120–28, Aug. 2007.
- [11]Dhiraj S. Bhojane, Saurabh R. Chaudhari, Eshant G. Rajgure, Prakash D. More, "Power line communication" ,International Journal of Engineering Research and Applications(ISSN:2248-9622),Vol. 2,No.1,pp.747-753, February 2012.
- [12]H.S. Hippert, C.E. Pedreira, R.C. Souza, "Neural Networks for Short-Term Load Forecasting: A Review and Evaluation," *IEEE Trans. on Power Systems*, vol. 16, pp. 44-55, 2001.
- [13]T. Zhang, G. Zhang, J. Lu, X. Feng, and W. Yang, "A new index and classification approach for load pattern analysis of large electricity customers," IEEE Trans. Power Systems, vol. 27, no. 1, pp. 153–160, Feb. 2012.