

# Residential Customer Energy Behavioural Demand Information Provider using GSM Technology

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**ABSTRACT:** The main goal of this research is to discover the structure of home appliances usage patterns, hence providing more intelligence in smart metering systems by taking into account the usage of selected home appliances and the time of their usage. In particular, we present and apply a set of unsupervised machine learning techniques to reveal specific usage patterns observed at an individual household. The work delivers the solutions applicable in smart metering systems that might: (1) contribute to higher energy awareness; (2) support accurate usage forecasting; and (3) provide the input for demand response systems in homes with timely energy saving recommendations for users. The results provided in this paper show that determining household characteristics from smart meter data is feasible and allows for quickly grasping general trends in data.

**KEYWORDS:** data mining; users behaviors; smart metering; smart home; energy usage patterns

## I. INTRODUCTION

Smart metering systems are key components for creating environmental sustainability by managing energy at homes. They are supposed to play an important role in reducing overall energy consumption and increasing energy awareness of the users through being better informed about consumption patterns. Smart meter data is being analysed through publicly available data sets such as the Irish smart meter trial and other research projects. Clustering customers based on attributes derived from smart meter data creates better understanding of the different types of energy behavioural groups. The focus of this paper is to derive and cluster suitable attributes from smart meter data which can assist a DNO with two main applications for better LV network modelling and management.

The primary application that motivates our approach is to help a DNO identify suitable customers for energy management solutions such as demand-side response (DSR) and through storage devices. These applications have already been considered recently. By choosing the correct attributes, a DNO can use the clustering to identify suitable customer groups for demand reduction solutions and hence, help to reduce network demand and volatility. For example, customers with heavy but regular demand in the evening time period could be ideal candidates for peak demand reduction through storage devices, whereas those with irregular demand may be more suitable for DSR.

The secondary application is for identifying links between energy behavioural usage and publically available information. Such links can be used to improve modelling of residential customer demand and reduce necessary monitoring on the LV network. However, besides these two, the methodology can also be used for further applications of smart meter-based. Choosing the correct attributes is potentially the most important aspect of a successful clustering. This is particularly challenging when considering extremely volatile household-level demand which is much less regular than higher voltage demands [6]. The number of attributes should be optimized to: ensure the data distribution

over parameter space is dense, reduce computational costs, and ensure the results can be easily interpreted. In addition, if the number of attributes is not optimized then the clustering is less likely to be representative and fit for purpose. A main contribution of this paper is a detailed analysis of a large amount of domestic smart meter data, especially with

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regard to better understanding of the peak demands and sources of variability. This helps us to identify and minimize the important attributes to be used in the clustering. In addition, we discover four key time periods within which data should be analysed since they describe the most frequent largest demand. The possible means that can support energy and, in general, resource conservation at individual homes have been the object of the studies in social sciences and in engineering sciences since the 1970s and are still conducted nowadays [3]. It has been identified that the provision of feedback about energy usage is one of the most effective strategies for conservation [3,6].

The other strategies include the provision of information about energy conservation, goal setting to induce energy efficiency and conservation actions, and the reward of savings in monetary terms. Recent years, with the development of smart metering solutions, have seen an increase in the number of tools that individual users can employ to monitor their energy consumption. Most of the tools simply provide access to raw usage data including, for instance, readouts of the watt hours consumed by a household or by a particular home appliance, and calculate the estimated costs. Previous researches have shown that users seek solutions that can provide greater insight into energy usage and its impact as they desire more real-time information to help them save money, and keep the homes comfortable and environmentally friendly [1-3].

## II. PROPOSED METHOD - BLOCK DIAGRAM

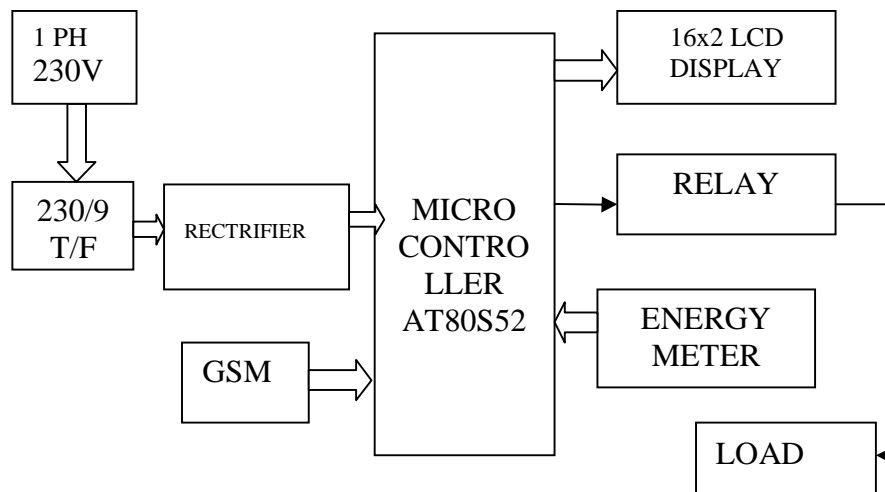


Fig 1 Block Diagram

## METHODOLOGY FOLLOWED

Active energy consumption (kWh) Reactive energy consumption (kvarh) Maximum Demand Traditionally, utility companies have concentrated their energy saving efforts on two items: Reduction of Kilowatt Hour consumption Improving the electrical system's Power Factor There is a third item to consider when reducing the amount of the electric company bill, proper kW Demand management which allows: The reduction of the contracted power Adjusting to the new kW limit Avoiding kW Demand limit penalties. Active energy consumption (kWh) Reactive energy consumption (kvarh) Maximum Demand Traditionally, utility companies have concentrated their energy saving efforts on two items: Reduction of Kilowatt Hour consumption Improving the electrical system's Power Factor There is a third item to consider when reducing the amount of the electric company bill, proper kW Demand management which allows: The reduction of the contracted power Adjusting to the new kW limit Avoiding kW Demand limit penalties

The starting point for the usage patterns detection, based on the sequential association rules, was to determine the transaction matrix. Each transaction has a time stamp indicating the occurrence of the elements in the specified sequence. In this case, we assume that a single sequence is the whole day, therefore, the tag sequence is the particular

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date. The time stamp is the hour at which specific devices were turned ON. Created transaction table takes into account only the binary information (the appliance was turned ON or not), but does not include the number of switch ON states in a given hour. In the analysed period, there are theoretically  $24 \times 44 = 1056$  transactions (the number of hours multiplied by the number of days), whereas the used SPADE algorithm (Sequential Pattern Discovery using Equivalence classes [3]) does not include empty transaction (hours, in which none of the tested devices was turned ON); therefore, the final transaction table contains only 319 transactions. Given the rules with the support of more than 0.1, the minimum time difference between successive elements in the sequence of 1 and a maximum time difference between successive elements in the sequence of 1, the following behaviour patterns can be observed: with the support equal to 0.1 and with the confidence of 100%, if in a certain hour the washing machine operated, in the next hour the tumble dryer and kettle operated; with the support equal to 0.1 and with the confidence of 100%, if in a certain hour the washing machine operated, in the next hour the washing machine and kettle operated, and in the next hour the washing machine also operated, so did the tumble dryer and kettle; rule No. 4 with the support equal to 0.15, and with the confidence of 75% shows that the occurrence in a sequence of such devices as kettle, dish washer and washing machine influences the occurrence in a sequence of such appliances as tumble dryer and kettle. With the support equal to 0.1 and with the confidence of 66%, if in a certain hour the kettle operated, in the next hour the washing machine was turned ON, then in the next hour the washing machine and microwave were in operation. All these observed sequential rules have lifted greater than one, which means that the occurrence of the elements in the left side of the rules influence the occurrence of the elements contained on the right side of the sequential rule.

It is a device designed to meet the need of industries conscious of the value of load management Alarm is sounded when demand approaches a preset value. If corrective action is not taken, the controller switches off non-essential loads in a logical sequence. This sequence is predetermined by the user and is programmed jointly by the user and the supplier of the device.

### III. CIRCUIT DIAGRAM

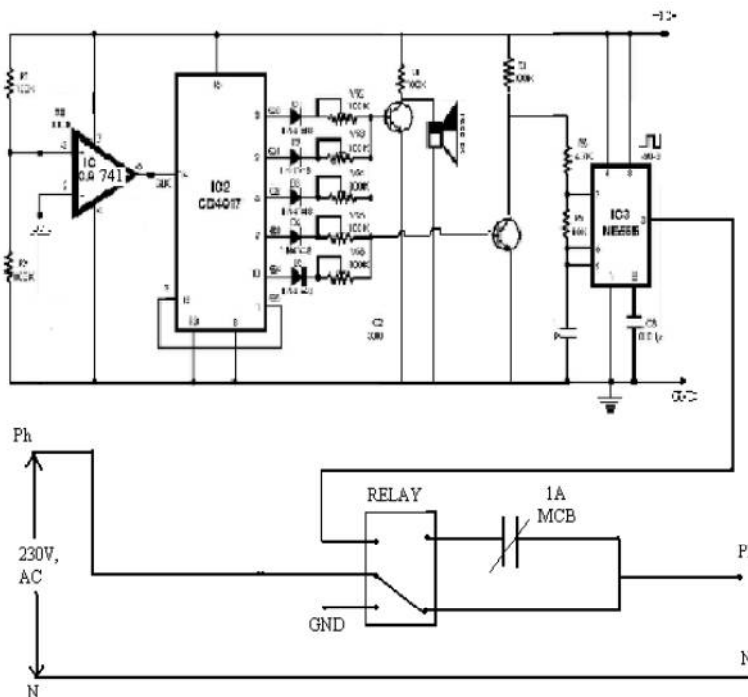


Fig 2 Circuit Diagram

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## CIRCUIT DIAGRAM EXPLANATION

The 555 monolithic timing circuits is a highly stable controller capable of producing accurate time delays, or oscillation. In the time delay mode of operation, the time is precisely controlled by one external resistor and capacitor. For a stable operation as an oscillator, the free running frequency and the duty cycle are both accurately controlled with two external resistors and one capacitor. The circuit may be triggered and reset on falling waveforms, and the output structure can source or sink up to 200 mA.

pair of points is close in some sense to the dissimilarity between the points. All methods must find the coordinates of the points and the dimension of the space,  $n$ . Two basic types of MDS are metric and nonmetric MDS. Metric MDS assumes that the data are quantitative and metric MDS procedures assume a functional relationship between the inter point distances and the given dissimilarities. Nonmetric MDS assumes that the data are qualitative having perhaps ordinal significance and nonmetric MDS procedures produce configurations that attempt to maintain the rank order of the dissimilarities. In our study we used one form of metric MDS, namely classical scaling. In general, given a set of  $n$  points in  $p$ -dimensional space,  $x_1, \dots, x_n$ , it is straightforward to calculate the distance between each pair of points. Classical scaling (or principal coordinates analysis) is concerned with the converse problem to determine the coordinates of a set of points in a dimension  $n$  [8]. Classical scaling is one particular form of metric MDS in which an objective function measuring the discrepancy between the given dissimilarities,  $\delta_{ij}$ , and the derived distances in  $n$ ,  $d_{ij}$ , is optimized. The derived distances depend possible to calculate on the coordinates of the samples that we wish to find. There are many forms that the objective function may take. To find the minimum of the stress function, most implementations of MDS algorithms use standard gradient methods [2]. The purpose of this computational experiment is to discover similar profile, in the same way as in the previous case. As it was mentioned, the partitioning method divides the data into  $C$  disjoint clusters, so that objects of the same cluster are close to each other and objects of different clusters are dissimilar. The output of a partitioning method is simply a list of clusters and their objects, which may be hard to interpret. Therefore, it would be useful to have a graphical display which describes the objects with their interrelations, and showing, at the same time, the clusters. Such a display was constructed using so-called CLUSPLOT [3]. For this purpose we have used the  $k$ -means algorithm, but of course also other clustering methods can be applied. For higher-dimensional data sets a dimension reduction technique before constructing the plot was applied. The MDS method yields components such that the first component explains as much variability as possible, the second component explains as much of the remaining variability as possible. The percentage of point variability explained by these two components (relative to all components) is listed below the plot. Then, CLUSPLOT uses the resulting partition, as well as the original data. The ellipses are based on the average and the covariance matrix of each cluster, and their size is such that they contain all the points of their cluster.

## IV HARDWARE

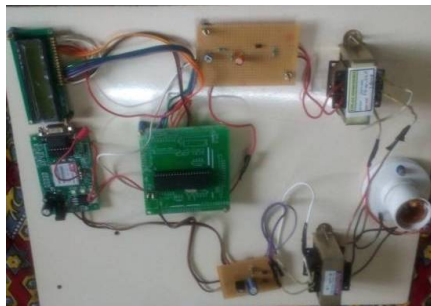


Fig 3 Hardware

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## V. RESULTS AND DISCUSSION

S.No	Condition	Status	Message
1	30 UNITS CROSSED	ALARM 1	SLAP RATE 1 COST RS 30
2	50 UNITS CROSSED	ALARM 2	SLAP RATE 2 COST RS 150
3	100 UNITS CROSSED	ALARM 3	SLAP RATE 3 COST RS 200

**Table 1 Results**

The Consumed Energy is easily monitored by the above system, When the consumed energy unit is below or equal to **30 units** the **alarm 1** is alert the consumer and sent the message as “**SLAP RATE 1 COST Rs 30** “.If the consumed value moves above then **30** like **50 or 100 units** the corresponding alarm alert the consumer and sent the message has been shown in the above table. By using the proposed system the consumer can easily identified the consumed units and slap rate and also the system useful for reducing the unnecessary usage of electrical energy.

### ADVANTAGES

- High-tension consumers have to pay a maximum demand charge in addition to the usual charge for the number of units consumed
- This charge is usually based on the highest amount of power used during some period during the metering month.
- The maximum demand charge often represents a large proportion of the total bill and may be based on only one isolated 30 minute episode of high power use.
- Considerable savings can be realized by monitoring power use and turning off or reducing non-essential loads during such periods of high power use.
- It is a device designed to meet the need of industries conscious of the value of load management Alarm is sounded when demand approaches a preset value.
- If corrective action is not taken, the controller switches off non-essential loads in a logical sequence.
- This sequence is predetermined by the user and is programmed jointly by the user and the supplier of the device.

### FEATURES

- Turn-off time less than 2 ms
- Max. Operating frequency greater than 500 kHz
- Timing from microseconds to hours
- Operates in stable and monostable modes
- High output current
- Adjustable duty cycle
- TTL compatible
- Temperature stability of 0.005% per °C

### APPLICATIONS

- Precision timing
- Pulse generation
- Sequential timing
- Time delay generation
- Pulse width modulation

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## VI. CONCLUSION

The proposed set of diversified data mining algorithms provides, in our opinion, the best way to illustrate individual patterns of energy consumption. It shows that revealing household characteristics from smart meter data is feasible and offers appealing visualization of general patterns in data. We need to keep in mind that those particular techniques represent slightly different approaches to data analysis, thus they cannot be compared directly, since their evaluation may be, to a large extent, subjective and may depend on user preferences. For future research, we see the following direction. Since the results are promising and visually appealing, we plan to design a larger experiment for a dozen or more households. Additionally, we aim to explore algorithmic approaches for mining usage patterns and utilize them for the purpose of energy consumption forecasting and the development of unique, individualized energy management strategies. Additionally, since the electricity consumption of households varies over time based on the actions of individual electrical appliances operated by the members, we would like to propose the optimal structure of the data set, which takes into account the variability associated with the switch ON states of individual devices to support their accurate recognition. In future studies, special attention will also be focused on the design of algorithms that in real time will be able to identify working states of the electrical appliances in the household. In the end, it is worth mentioning there are high expectations for combination of research on forecasting systems utilizing non-intrusive appliance recognition and user pattern behaviour with multi-agent systems

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## BIOGRAPHY



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