Developing a framework for using electricity consumption data to drive energy efficiency in the residential sector

Closure Report
30 May 2017

Indian Institute of Science, Bangalore

In partnership with

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Project sponsored by

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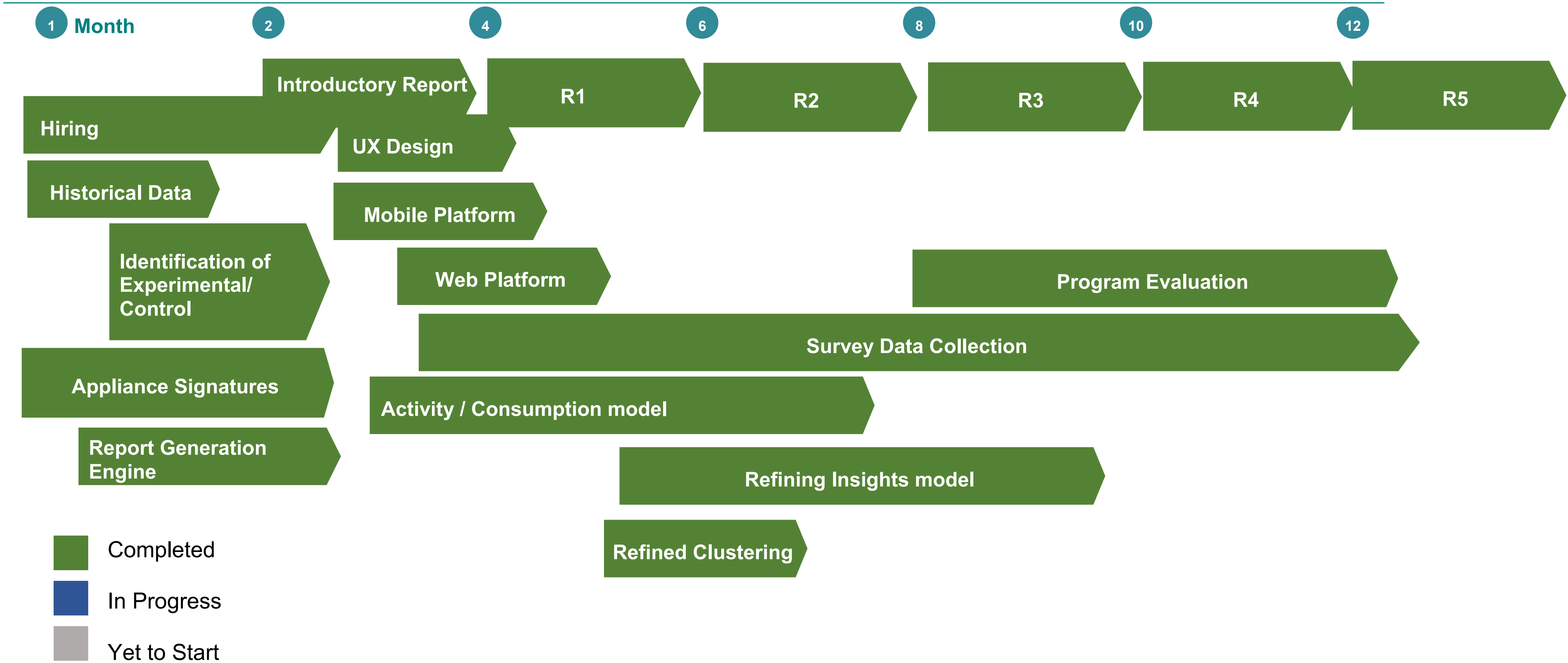
Programme timelines



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1. Overview

Even though there is a pressing need for awareness of energy consumption, most consumers spend very little time on their monthly or bimonthly energy bill, or on pondering over their energy consumption. Only 5% have some recollection of their consumption for the previous month. Close to a third of the respondents of a recent survey revealed that they were not aware of energy efficient alternatives while making a purchase. Over a fifth of them did not purchase efficient appliances even though they were aware of alternatives [1]. While consumers might realise the importance of conservation, most have very little knowledge of where they stand on the consumption scale.

1.1. Motivation

Significant savings in energy consumption can be achieved by addressing energy efficiency within the low-tension (LT) segment. For example, considering the pan-India figure of 32% consumption in the low-tension segment, improving room AC efficiency from business-as-usual to the best available technology can offset the requirement of 120 new 500 MW coal fired power plant by 2030 [2].

Distortion in pricing, difficulty in price-correction, and fragmentation of the market have made implementation of energy efficiency programmes in the low-tension segment less popular in India when compared with the high-tension (HT) segment. Our objective in this project was to use behavioural science to drive energy efficiency in this segment.

1.2. KSEB

Over the last five years, electricity consumption in Kerala has grown by about 33%. This observation is based on the data of past five years taken from the Annual Revenue Requirement documents of Kerala State Electricity Board [3]. Extrapolating the growth rates, we predict that the net consumption in the state will grow by 80% over the next decade. Close to 30% of the energy demand is currently met by hydel resources; however, the Forest Conservation Act of 1980 has made hydel capacity addition difficult. Most of the future requirements of the state will therefore have to be procured from outside. Consequently, the embedded cost of power, which has increased by 31% over the last five years [3], is likely to increase further. This will put additional pressure on the annual revenue requirement for the state.

The residential segment in Kerala (which is one major component of the LT consumers) constitutes close to 51% of the net consumption, and is likely to remain close to the same figure in the next decade. The commercial segment (another component of the LT consumers) is 13% of the net consumption and is expected to rise to 20% of the net consumption over the next decade. Overall, the LT consumption is today at 70% of the net consumption (as against 32% pan-India) and is expected to constitute 75% of the net consumption over the next decade. These points, taken from [3], are summarised in Figure *1*. They make Kerala a good choice for our behavioural science study in the LT consumer segment.

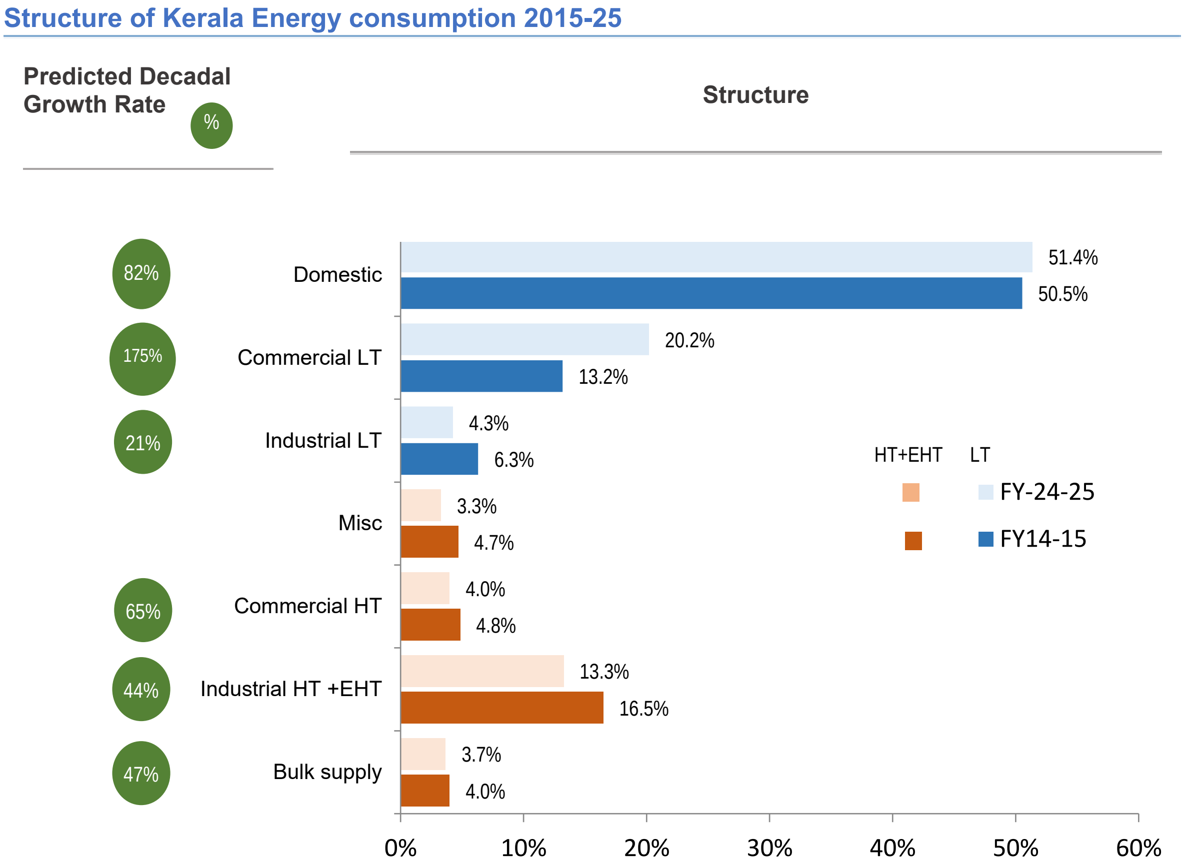


***Figure 1:** Extending the observed consumption growth rates from 2010-11 to 2014-15 we find that the domestic segment will continue to account for the bulk of the consumption. Commercial LT which increased at an annual compounded rate of 11% in the past five years will continue its rapid increase. (The FY24-25 predictions total to 100.2% due to rounding to one place after the decimal point.)*

1.3. Structuring the Programme

Over the past five years the management information systems (MIS) department in KSEB (*Vaidyutha bhavan, Thiruvananthapuram*) had been linking over 600 section offices to a centralized server, which would host the data for over 66 lakh consumers of Kerala. This project group had, at that juncture, approached KSEB with an intent to demonstrate the application of behavioural science for driving energy conservation. Fortunately, KSEB was also looking at driving applications using the aggregated data stored in their servers. It was decided that a pilot programme could be implemented in the Aluva Division of KSEB.

Aluva is to the north of Ernakulam (40 minutes by road). It has 11 electrical sections. Residential consumers dominate in terms of net consumption. A typical home (e.g. Figure *2*) has two storeys, and often has elderly residents. While not entirely urban, some parts of Aluva, especially the north-western regions, have more spread out dwellings. The southern parts towards the border of Ernakulam as well as the regions lying on the Ernakulam – Kochi Airport road have comparatively higher population density.

Figure 2: *A typical house in Aluva*

Of the 11 sections in the Aluva Division, we had historical data for about 1 lakh consumers (households). The period 2013-14 contained the maximum information. KSEB follows a bimonthly billing system. Meter reading staff are allocated two areas, one for data collection during the even months and the other for collection during the odd months. They visit homes based on their billing day as per a pre-allocated walk order. From our analysis of the data, about 72% of the LT revenues comes from three sections: Kalamassery, Aluva Town, Aluva West in Aluva circle (see Figure *3*); close to 50% of consumers reside within these (see Figure *4*). The average bimonthly bill in these sections is Rs. 447/-, while in the rest of the dataset, the average is Rs. 317/-. Since our goal was to cover about 50,000 households (including experimental and control households), we decided to implement the pilot programme covering consumers of these three sections.

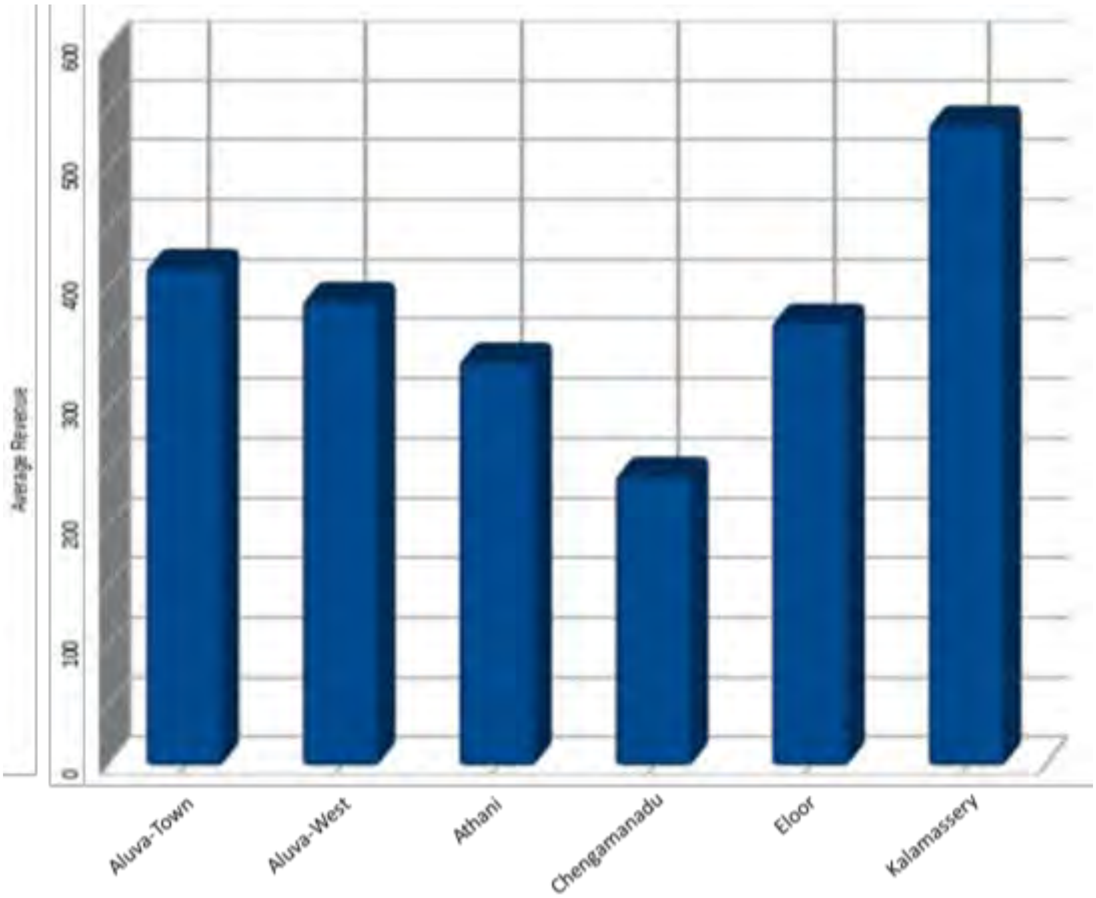


Figure 3: Distribution of average bimonthly bill amounts in Rupees in the different regions of Aluva.

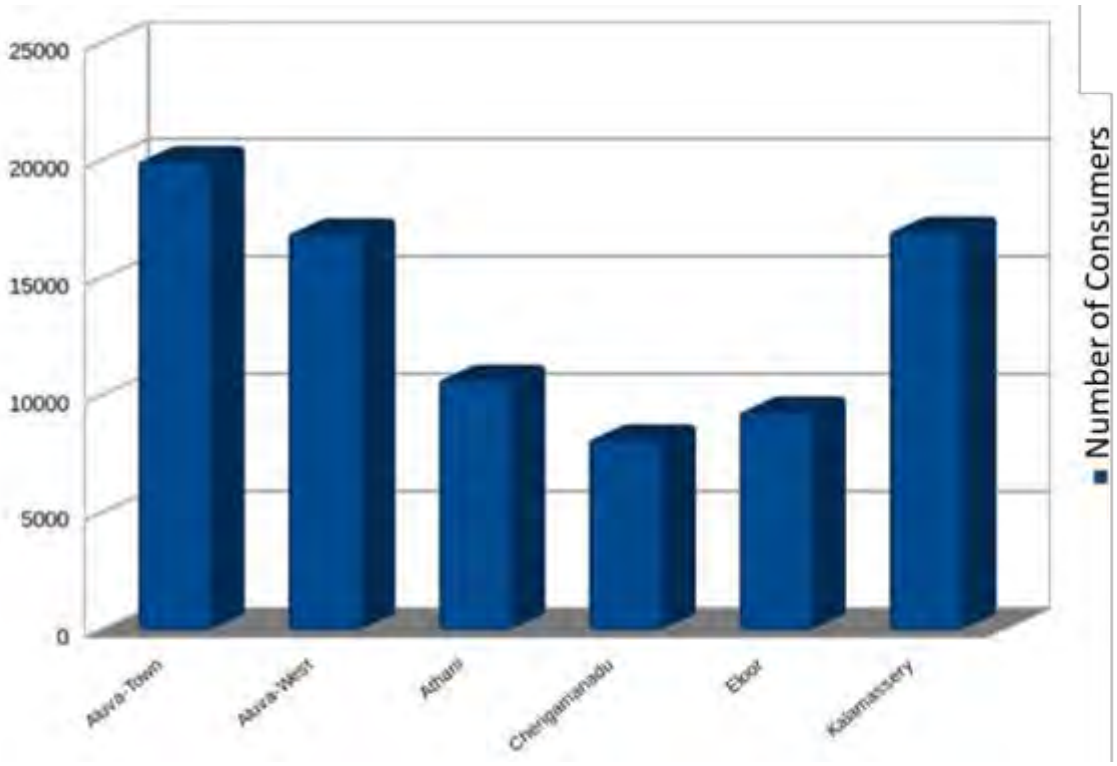


Figure 4: Distribution of population in the Aluva region.

2. Programme

The programme was structured to cover a period of a year to assess its impact through an entire annual weather cycle. Consumer meta-data and historical consumption were shared by KSEB two months prior to the starting of the programme. Consumers were to be given a feedback along with their energy bill. The information would also be made available in an electronic format to those registering on the platform. We planned to set up the programme as a randomized control trial and assess the efficacy of the programme by comparing consumptions of experimental households (those that received the intervention and energy report) to consumptions of control households (those that did not receive an intervention and energy report).

2.1. Overview of Consumption pattern in Aluva

The 49,639 consumer records belonging to Aluva Town, Aluva West, and Kalamassery were analysed for identifying survey participants. The average consumption varied in 2016 from a peak of 144 units during March to a minimum of 118 units in June. All the three sections had more or less similar consumption patterns (see Figure 5).

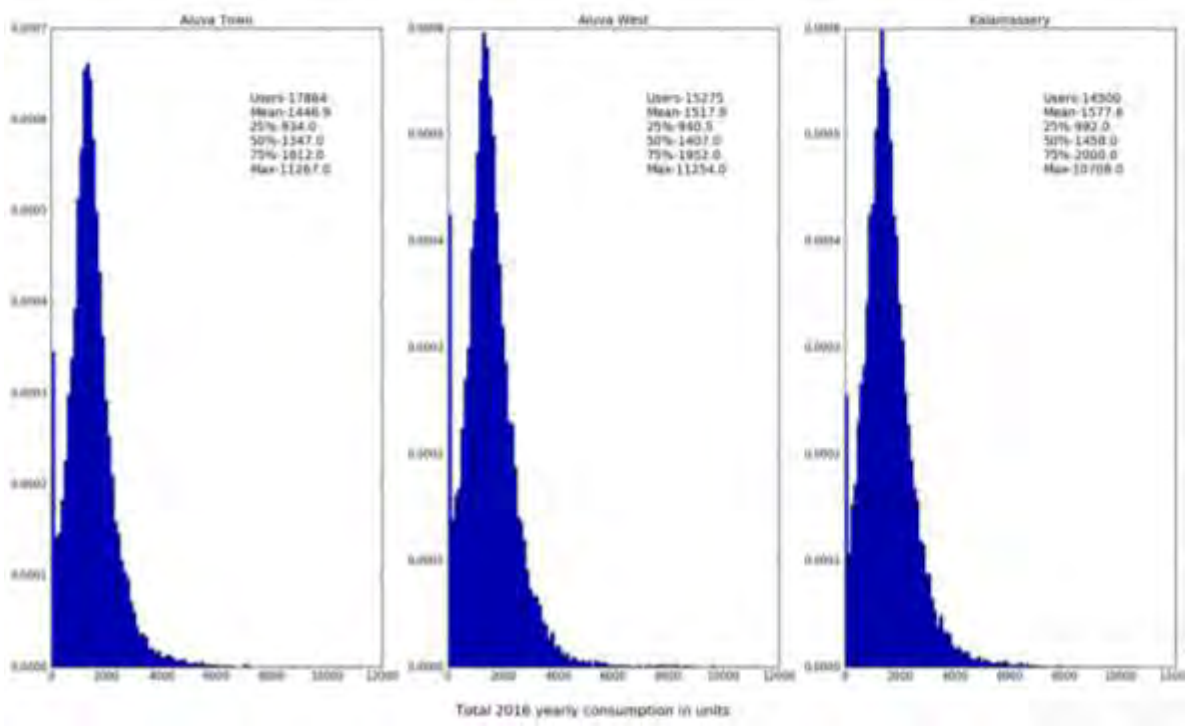


Figure 5: *Aluva Town, Aluva West and Kalamassery sections have similar consumption pattern. Kalamassery has the highest consumption.*

Kalamassery had the highest annual consumption per household at 1,578 units (for the year 2016) followed by Aluva West (1,518 units) and Aluva Town (1,447 units).

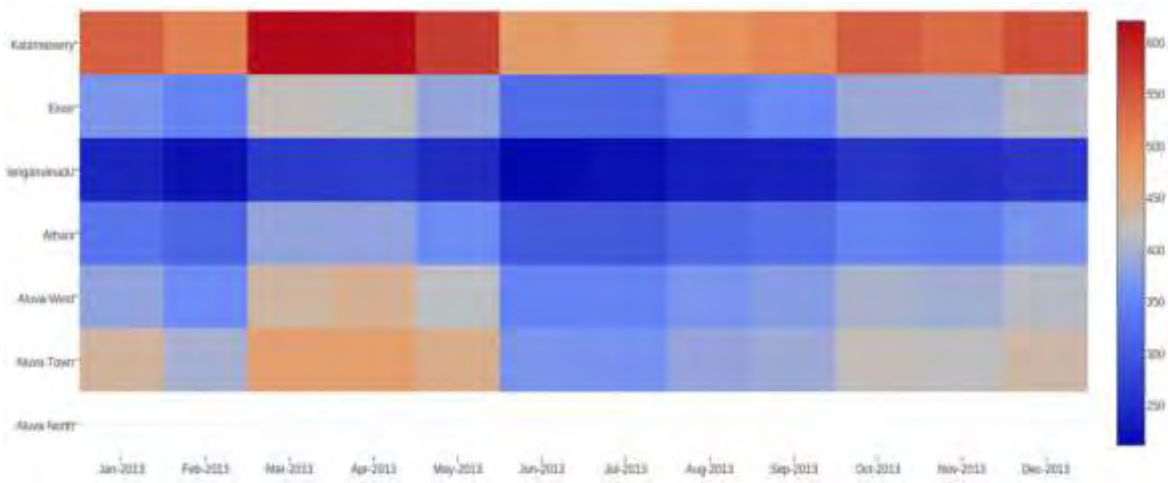


Figure 6: *A heat map showing variation of electricity consumption, in terms of average bill amount in Rupees, across time in various regions of Aluva.*

Data preprocessing: Since the consumers were given bimonthly bills with staggered start dates, we assumed constant usage across the billing period to arrive at calendar-synchronized monthly consumption estimates. The consumer bill amount data was available for about 36 months while the actual consumption in kWh was available only for 16 months. We therefore proceeded with clustering based on the 36 months bill amount data for the period prior to the start of our programme.

The calendar-month-aligned estimates were vectored into a 36-component vector and were supplied to a K-means clustering algorithm, with the K parameter denoting the number of clusters. This was done to identify groups of similar consumers. Comparison information would subsequently be supplied to consumers based on groupings arising out of this clustering mechanism. We also intended to limit the number of cluster within fifty as higher clusters will make the administration of the project difficult. A scree plot of the mean square error vs the number of cluster showed that error declined rapidly within this range. A hierarchical clustering approach was implemented over the dataset using K-means clustering algorithm. Clusters having higher population were identified and subsequently broken down into sub clusters. Similarly, cluster having very few members were merged into the nearest cluster. This resulted in a total of 29 clusters.

We found that most clusters could be identified as *bands of curves*, when their monthly consumptions were plotted across time, but a few clusters were identified based on their actual *pattern of usage*. For example, in Figure 7, clusters 23 and 28 are clusters with significant increased and patterned usage from June to August, the difference between these two clusters being the amount of usage. The faint lines in the figure below are consumption patterns of randomly chosen consumers within the cluster, and the solid lines are the cluster means plotted across time.

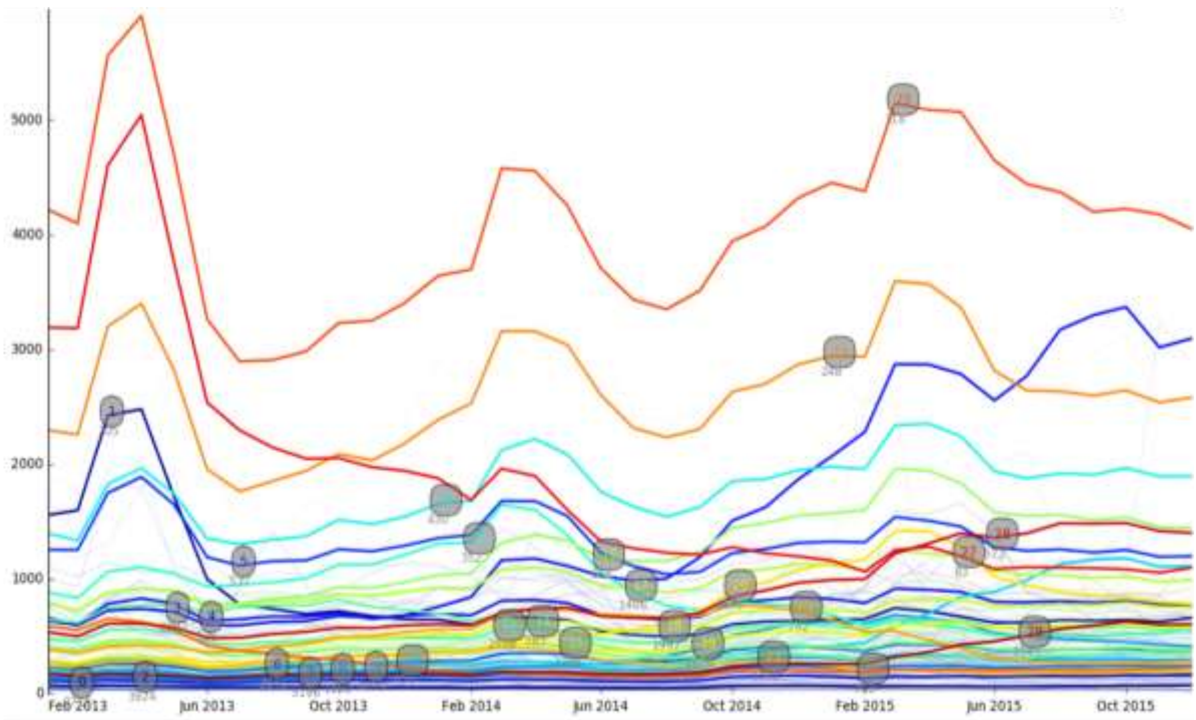


Figure 7: *Tendency graph. Variation of consumption in different clusters across 36 months.*

2.2. Setting up a Randomized Control Trial

The consumer metadata showed that most of the records of consumer addresses were incomplete. Address data was available for only 20% of the consumers. Our initial plan, to deliver the reports through the postal/courier service, could therefore not be executed.

KSEB meter reading is done every alternate month by meter readers. Most of these personnel are contract employees. After receiving guidance from KSEB, we decided to take their help in delivering the reports. Consequently, the selection of the control and experimental households could not be fully randomized. Despite this constraint, some randomization was done as described below.

The meter readers visited a set of houses on a particular day as per an assigned sequence (walk order). On a particular day, they visit houses which are in general close to each other. As broached above, selection of control and experimental households had to be done in accordance with the physical constraints imposed by the logistics employed by the meter reading staff.

We decided to label consumers whose bill generation dates fall on alternate days as either control or experimental consumers. Thus, all even bill-generation-date consumers of Aluva Town and Kalamassery were labelled as experimental consumers who would receive our energy audit reports. On the other hand, all odd bill-generation-date consumers of Aluva West were labelled as experimental consumers.

For the randomized control trial, it was necessary that both the experimental and the control group were similar to each other in their consumption patterns. The histograms of consumptions across these two groups, plotted in Figure *8* below, confirms the broad similarity between the two groups.

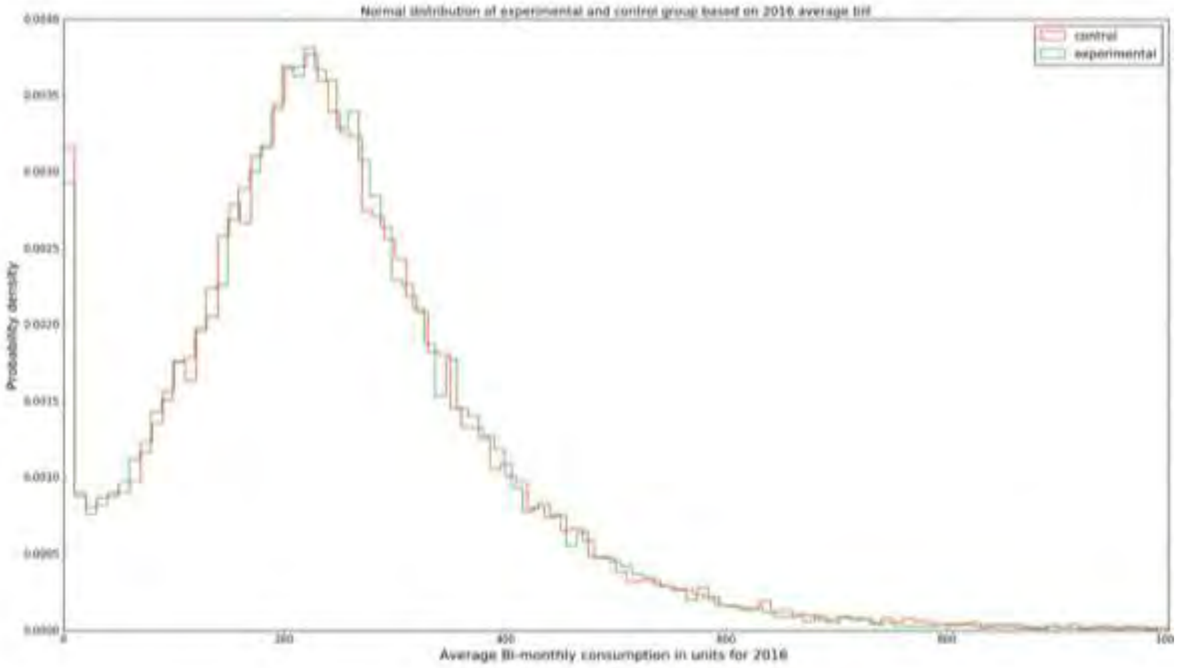


Figure 8: *The empirical distributions of the average bimonthly bill for experimental and control consumers show a similar trend.*

2.3. Scheduling of the Programme

The distribution of reports was staggered across the three sections. The first report was distributed in Aluva Town on the 20th of April 2016, in Kalamassery on the 24th of April 2016, and in Aluva West on the 1st of May 2016.

Reliance on the meter readers for the logistics meant that our reports had to be published before they went on their rounds for distributing the bill. All the reports were generated using the last billing cycle data and were distributed in the subsequent billing cycle. The information provided to the user had a latency of one billing cycle.

Through the course of the programme, impact was monitored but only to update the computational tools for automated generation of the reports.

KSEB delivered the billing data to us in a batch on the 2nd of every month. Our energy audit reports (please refer to the next section for details) were generated and printed by the 15th of every month and were dispatched for distribution in the subsequent month to the corresponding section offices. The reports started from the introductory reports (R0) to the final reports (R5). The reports were progressively more complex, with reporting features added as and when our tools and algorithms matured. All reports were two pages long.

Alongside report generation, work was carried on the electronic platform to allow consumers to access their reports online. Users had to register with the login information made available in the hard copy reports. This and subsequent reports could all be accessed online even as the hard copy reports reached the consumers. The electronic platform was released along with the R0 report and additional functionalities were added in the subsequent months.

The process of data collection was initiated in June 2016. We reached out to about ten percent of the households (about 5000 out of 50,000) and were successful in getting a response from about 3200 households. The clusters that were identified using the 36 month billing data were of different population densities. The sampling of households for surveying had to respect this nonuniform population density. Further, in order to ensure that the control group was unaware of the programme (to the extent possible), the surveys were restricted to the experimental group. A random sampling technique, in proportion to the nonuniform densities but with a guaranteed minimum representation from each cluster, was employed to identify the 5000 households. These were then indicated to the meter readers through a mobile application for conducting the survey.

We relied on a bottom up model (*to be described in a later section*) to construct most of the insights driving the functionality of the programme. The construction of these models depended on the data being collected from the field. From the initial crude model which was made available by the second billing cycle (R1), we progressively fine-tuned our approach using the data we collected from the field.

2.4. User Experience

The programme was designed keeping the end user's "user experience" in mind. The reports were to be designed to appeal to all kinds of consumers, age groups and gender. We used a bilingual format, English and Malayalam, in all our communications to ensure that the information is understood by all consumers. All texts, interventions and labels were produced in both languages. Most of the communication was pictographic (e.g. Figure *9*). We used characterizations to help people relate readily with the information provided. Technical text was worded and suitably illustrated to enable quick information transfer.

Figure 9: *Illustration of an intervention. All interventions were conveyed by using some character to produce a story.*

The reports and the electronic platform were tailored to create a personalised user experience. Personalisation, i.e. adapting the information to be sent to a consumer, was achieved largely through clustering which grouped similar consumers together. We now highlight our approach.

Social comparison: To ensure greater engagement with the users, we felt that social comparison would be a more effective tool rather than a mere indication of savings (or increase) in consumption month on month. Social comparison provides us with a powerful means to nudge consumers towards reduced consumption by showing them as being progressive within their community. The community itself is a hypothetical one obtained via our clustering scheme. For each billing cycle, each consumer was informed on whether his usage was efficient, average, or high, within the cluster. An example of picture that summarized this information is given in Figure *10*.

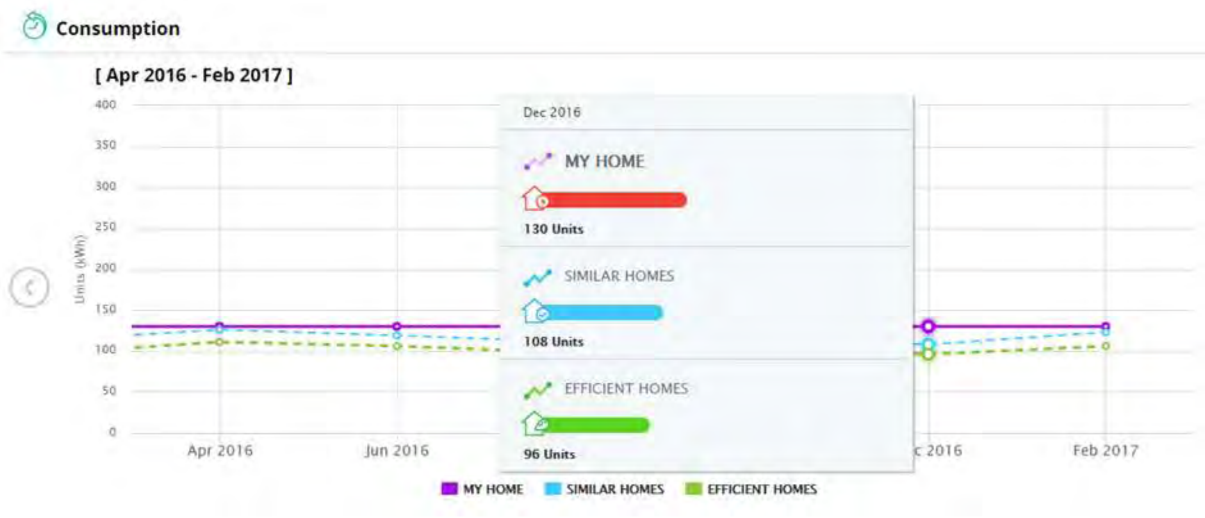


Figure 10: *Social Comparison - Comparison of consumers to other similar consumers.*

Gamification: In order to better appeal to the consumer, we also attempted to gamify the interaction by linking a tree whose growth was reflective of the energy conservation steps taken by the consumer, as deduced from the reduced or increased consumption or bill amount. This was picturised as an arrow (indicating the trend) and a number (indicating the current level).

Gamifying

Figure 11: *Gamification by indicating growth of 'coccinea flower'.*

To personalise the energy efficiency interventions to specific consumers, interventions were introduced through their effect on a character, the 'coccinea flower', which is a common flowering plant in Kerala. It was hoped that users could relate to the impact of their interventions on the growth of this flower.

The interaction was gamified by showing various stages of growth of the plant based on the consumer's usage reduction.

3. Components of the Programme

3.1. Report Generation

The first report (R0) was an introductory one. It did not have any contextualized information or intervention. The purpose of this report was to introduce the platform to the consumers and set their expectations. Report R0 contained consumer information, a comparison statement of a home's consumption to similar homes in a neighborhood. The rear side of the report provided an explanation about the programme, explained the elements of the report and introduced the stakeholders among others. The report also provided each consumer with a pass key to log into the electronic platform. (*Please refer to Annexure II.*)

The gamification using the plant was also introduced in R0. A historical consumption chart provided the consumption trend over the past twelve months.

Interventions were supplied from a subsequent billing cycle in the R1 report. However, at that stage, the algorithms were yet to be tuned. Generic interventions were assigned based on heuristic rules. From the third cycle, these interventions were tuned through machine learning approaches based on survey data and historical consumption data. (*Please refer to Section 4*).

All reports were grouped by section/month/day/walk in that order and were dispatched to the corresponding section offices for delivery by the 15^{th} of every month. For a few consumers who registered on the e-platform, an e-report (pdf document) was sent to their email address.

3.2. Consumer Platform

A basic version of the electronic platform[1] (see Figure *12*) was released along with R0 report. The web platform allows the consumer to view the information given in the paper reports on the web. The subsequent release, during the second billing cycle, allowed the consumer to view the suggested interventions. An e-survey form was also provided to allow consumers to upload details such as their building type, family size, ownership of appliances, consumption patterns, etc., many of which were components of our physical survey.

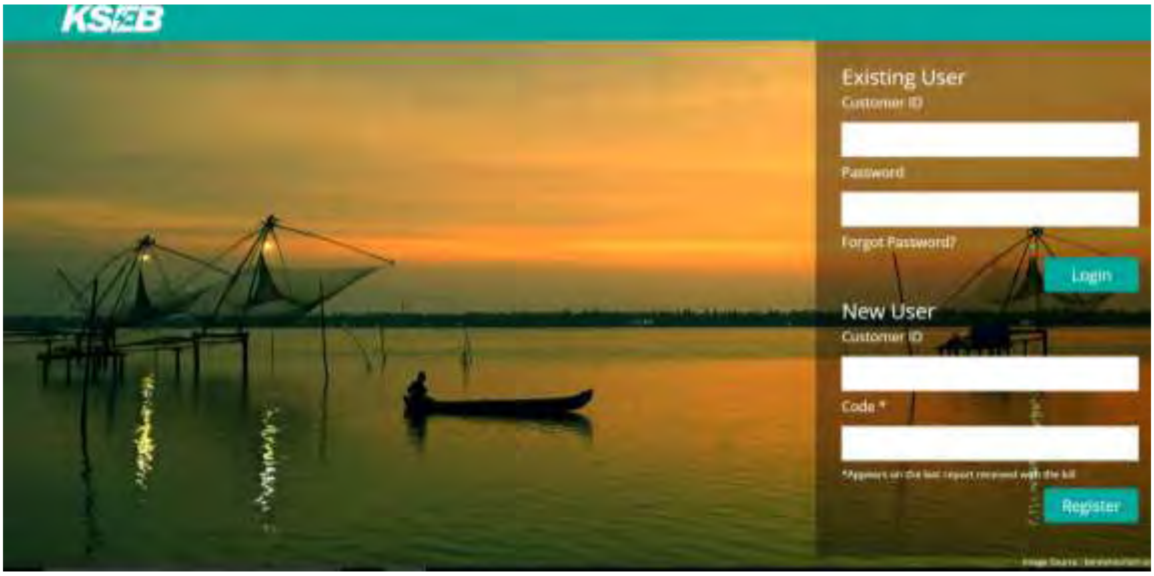


Figure 12: *Electronic Platform: Apart from reproducing the information contained in the report, the consumer could also find historical consumption data and could enter data onto the platform (similar to the survey being administered).*

[1] The platform can be accessed at http://kseb.clytics.com/ Credentials consumer2@gmail.com Password: pwd2. The platform will be active till June 30th 2016

We were hoping to get about 2% of the experimental group users registered (approximately five hundred). However, Aluva has comparatively lower internet penetration. The average age of the consumers is also in the higher 50's. Further, our resource limitations did not allow us to advertise this e-platform in an aggressive fashion. These factors perhaps limited the penetration of the internet platform to about a hundred.

3.3. Survey

The bottom up modelling framework required us to collect information regarding the dwelling type and size, occupancy, type of appliances, and usage patterns. This information had to be collected from representative samples of the experimental group within Aluva.

We developed a mobile application to administer the survey. This allowed us to administer different questionnaires suited to various categories of users so that some of their inputs could be validated in real-time. The mobile application was necessary because it allowed us to capture additional information such as location and the duration of the survey which were used to validate the authenticity of the survey record. A mechanism was also created to capture the location of a household from the GPS tag of the device. However, network connectivity was poor in the regions of deployment. More than 50% of the locations were not GPS tagged. We therefore could not exploit this information.

Figure 13: *Survey Data Collection: Sujith Kumar, a meter reader in Aluva West, interviews a consumer on 3rd June 2016 and enters the received information into his tablet. He conducted 4 to 8 interviews in a day after being trained, a week earlier, on how to administer them.*

3.3.1. Consumer Survey

- The survey sought information about the following: (i) building type (flat or bungalow), size (for example, 1BHK, 2BHK), ventilation, etc.; (ii) family information classified by age, occupancy during various times of a day; (iii) appliance information such as the type of lamp(s) used in the drawing room, nominal AC settings, etc. A total of 5060 homes were approached to gather such information.
- Survey manifest, the list of individuals to be surveyed within a day by a particular surveyor, was created ensuring all clusters received a weightage in accordance to the population proportion in the entire dataset (all experimental and control households). The survey application was able to handle situations such as a consumer not being present at home and could re-populate the manifest with a similar replacement.
- About a third of the consumers intended to be surveyed were either not present at home or declined to participate.

Figure 14: *Survey Data Collection: Interview being carried out in Kalamassery. The survey covered a broad spectrum of locations and consumers from different socio-economic categories.*

3.3.2. Real-time Data

The consumer survey provided information about the unit type and ownership, the different classes of appliances present in the home, their wattages, etc. The precise usage of appliances is difficult to assess based merely on response to surveys because an interview to gather *a daily diary* of consumption would be rather lengthy. Besides, we would only get the consumer's own (and possibly distorted) perspective of his usage. In the absence of such information, we decided to instrument a few homes with a smart meter and an in-house designed data logger to capture the consumption data every second for the duration of a month. We developed some algorithms for effective inference of appliance usage, which we describe in the next section.

Figure 15: *Data logger: Smart meter and data logger being fixed in a 1BHK home in Kalamassery, South Aluva. The unit measured the consumption every second and logged the parameters into a memory device. The unit along with the data was extracted after a month. The extracted data was subsequently analysed while the unit was attached in another home.*

4. Algorithms

This project involved creating a framework for modelling energy consumption by combining weather data [4], appliance ownership, readily available appliance specifications [5] as well as information from the survey carried out by us. Our survey data included building information, appliance ownership, etc. We also used real-time data captured by us in 35 households.

4.1. Predicting Appliances Ownership with Bill and Survey Data

Residential energy consumption is driven by the appliances owned and used by consumers. But in non-metro centres, apart from energy bill data, there is little or no information available about the consumer. Such information would enable the utility provider to better plan for procurement or capacity building. A case can thus be made for studying inference techniques to gather as much information as possible from the monthly energy bills and basic profile information maintained by the utility provider.

The information collected in surveys was used to come up with appliance ownership information for each cluster of population, and was thus used to provide contextual insights for intervention and disaggregated energy consumption.

Total energy usage in a residential building is based upon a combination of the building envelope's thermal performance, installed equipment and appliances, occupancy patterns and behaviours. The actual energy consumption information from an energy bill cannot be easily disaggregated. It could depend on specific factors such as building construction components alone, or occupants' behaviour alone, etc. [6]. In our survey, we found that in any neighbourhood, buildings are generally of similar type and material, though they might vary in size. Given very little variance in building types and material, we assumed that households in the same neighbourhood (i.e. same section-area-day combination in our case) with similar energy bill history/pattern have similar thermal performance. In addition, we also assumed that they have higher probability of owning similar appliances. Energy consumption of an appliance depends upon various factors like its type, size, age, energy-efficiency, etc., but we have ignored this variation in this study to reduce complexity.

A *k*-nearest neighbour (kNN) classifier, a simple and effective instance-based learning technique, was used to classify all users into one of the category of surveyed users based on the features that describe the user energy consumption. A feature vector represents a user as an abstract vector, distances from which are then used to identify nearest neighbours. Only locality (section-area-day) and bi-monthly bill information (calendar-synchronised for the last 20 months) were available for all users. Hence, the feature vector was created using only these data components.

Distances based on heterogeneous data were mostly computed after calculating distances or dissimilarity matrices for each set of homogeneous variables and then taking weighted linear combination of such matrices.

For the categorical feature vector (locality), distances calculated for the continuous and categorical data were then linearly added with appropriate weights to calculate the distance between any un-surveyed user and surveyed users. With the appliance ownership information of k closest surveyed-users, where the value of k is chosen through cross-validation, user's appliances ownership was predicted.

Distance between any two users i and j is given by

$$d_{ij} = \frac{w_1 d_{ij}^1 + w_2 d_{ij}^2}{w_1 + w_2}.$$

The weights w_1 and w_2 are fine-tuned to get best appliance ownership accuracy. In order to compute the distances d_{ij}^1 and d_{ij}^2, which correspond to monthly bill and location respectively, following two methods were evaluated to identify a suitable distance measure:

1. *Location distance using overlap:* The conventional similarity measure for categorical data is binary values, where each bit indicates the presence or absence of a possible attribute. The similarity between two objects is determined by the similarity between corresponding binary vectors. Distances are computed after mean-normalization of values for each attribute. In this method, d_{ij}^1 and d_{ij}^2 are computed as the Euclidean distances between features for two users.
2. *Location distance metric:* One location might be similar or different from some other location. Following steps were taken to come-up with supervised similarity measures for location (d_{ij}^2):
    a. The feature set of each location was created using bill data distribution of the users in that location.
    b. For every location 25, 50, 75 percentiles and average monthly bill amount of the related users were calculated for all the 20 months from available bill data.
    c. Euclidean distance was calculated between locations to generate a location distance matrix.

    An element x_{ij} of this matrix represents the location distance between users i and j. So, in this method, d_{ij}^1 was taken to be Euclidean distance and $d_{ij}^2 = x_{ij}$.

Ownership of an appliance for a user is a binary classification where a user either owns (1) or does not own (0) the appliance. Prediction of ownership of an appliance for a user is done by taking weighted average of ownership of the same appliance for its k nearest neighbours. The weights corresponding to a neighbour are inversely proportional to their distance from the user of interest.

The accuracy of prediction of ownership of different appliances is listed in Table *1*.

Table 1: *Accuracy of prediction of appliances using different approaches*

Appliance	Ownership of appliance within the population	Accuracy of appliance prediction methods		
		Random Assignment	Location overlap	Location Similarity Measure
Television (TV)	93.05%	88.86%	94.11%	93.84%
Refrigerator	86.31%	77.76%	88.92%	88.15%
Pump	82.82%	72.73%	89.22%	83.46%
Iron	59.35%	52.01%	79.43%	62.46%
Washing Machine	53.32%	50.34%	67.82%	66.12%
Induction Stove	16.69%	71.95%	87.72%	83.16%
Air Conditioner	9.55%	85.48%	91.78%	90.68%

The values in *Table 1* suggest that the use of kNN with bill and location data offers better prediction of ownership of appliances. However, the usage of similarity measure in the location data, contrary to our expectation, did not offer a comparatively better prediction.

4.2. Activity Modelling

Residential energy consumption has a strong correlation with building occupancy. In India, the field of activity modelling is quite novel and there are only limited time use surveys (TUS) datasets available. The latest dataset was published by Ministry of Statistics and Programme Implementation (MOSPI) in 1998 by taking daily diaries of approximately 30,000 users.

The survey administered by us captures information regarding unit occupancy during the first three quarters of the day. For the last quarter (night), we assumed that everyone is present. (We have tried to limit the number of questions to ensure that the interview is less intrusive to the consumer.) Besides this we have also obtained electricity power consumption signatures from a few homes to allow us to determine crude occupancy patterns for a few homes.

We also studied the transition patterns between activities in publicly available datasets (TUS – United States, United Kingdom) to look at the pattern of transitions from one activity to another. We used the surveys and our own judgment (when needed) to tweak activity transition probabilities to suit the Indian context.

The activity transitions (the probability to change the state at a certain instance of time, such as from studying to eating at 8:00 PM) are estimated based on (i) the data from the survey administered by us, (ii) similar time use survey carried out in other places and (iii) a fuzzy logic based approach that used responses from a few example households (individuals who led a similar lifestyle).

This activity transition model further considers gender composition, occupation, number of family members, ages, etc. within a household. Once the transition probabilities are obtained, a Markov chain for the activities of an individual is simulated for over a period of two months, with a one hour temporal resolution. This framework for individuals is integrated to obtain the activity profile of a family. Each family member’s activity state as well as transitions is influenced by activities of other individuals within the family.

4.3. Estimating Behavioral Patterns in Real-time Energy Data

Non-intrusive load monitoring (NILM) deals with the estimation of individual appliance usages from observations of aggregate power consumption. Prior algorithms assume availability of data sampled at high sampling rates from, as of now, expensive smart meters. We have explored the feasibility of NILM using data sampled at lower sampling rates. There are three motivations for doing this: we want a single smart meter device connected into the mains, a cheap smart meter, and data compression right at the source point.

For modelling the consumption, we worked on behavioural activity models along with an energy consumption model. A few select households were instrumented with an aim of gathering consumption data. The aim was to analyse energy consumption by appliances along with an inference of the underlying activity.

Our methodology involved a series of steps – data processing, event detection and feature extraction; learning of essential feature parameters; and inference of appliance states. We followed the plan shown in Figure 16 with an aim to achieve disaggregation.

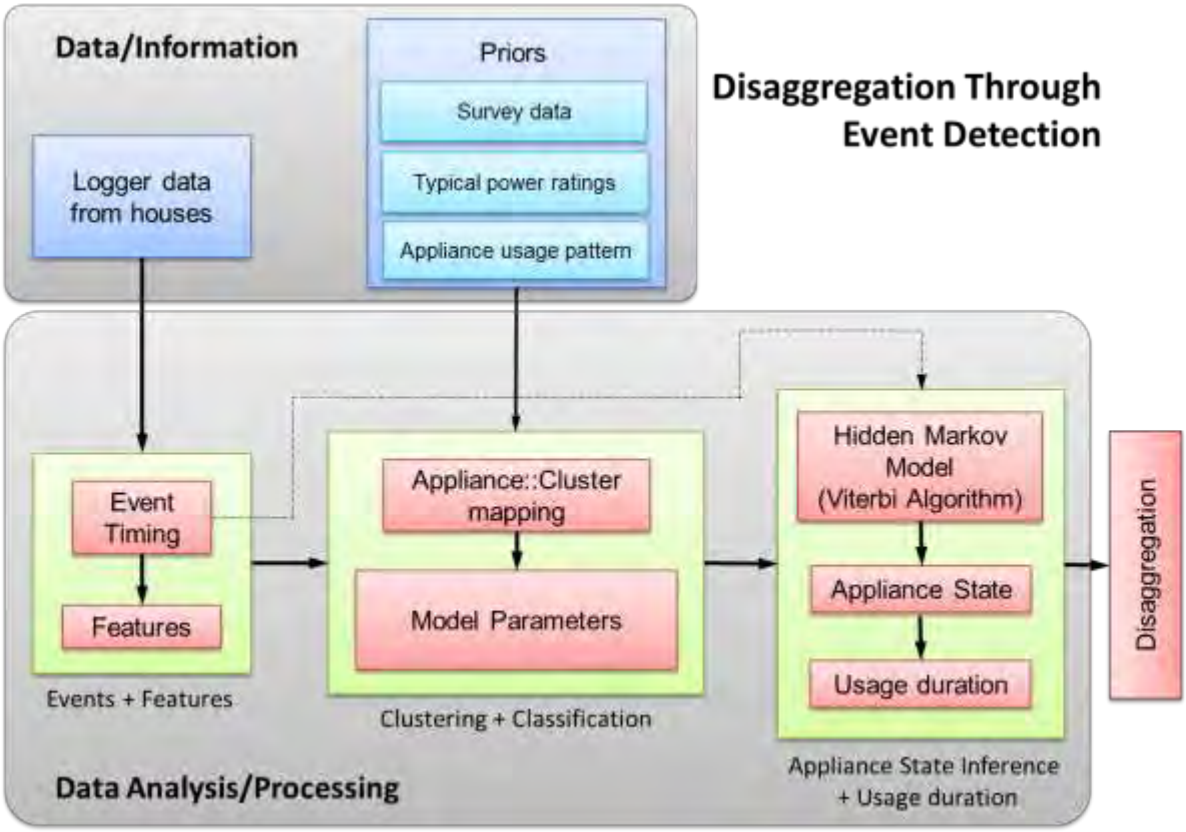


Figure 16: *Disaggregation architecture through event detection.*

Event

An event has occurred when an electrical appliance is turned on or off. Any event appears as a rise or a fall in level in the power consumption waveform. Also, every class of device has characteristic features of its own. Identification of these features leads to the identification of appliance which, in turn enables identification of the usage duration. The algorithm has the following steps.

We first pre-process a component of the signal, which is active power, to suppress spikes and irregularities. We then use the first and second differences to detect changes in the power level. Epochs with significant changes are marked as events, and this constitutes the event detection step. Our event detection algorithm offers robust performance in terms of both precision and recall values when compared with competing algorithms operating at a much higher sampling rate.

For extracting features corresponding to each event, where change in active and reactive power levels (ΔP and ΔQ respectively) are our features of interest, we use a clustering based approach [7]. This approach utilizes the shifts in clusters on the (P,Q)–plane associated with the occurrence of events.

For learning the feature parameters, we assume that the feature vectors corresponding to every appliance form a cluster over the $(\Delta P,\Delta Q)$–plane. A hierarchical approach, though currently executed with some manual supervision, gives better performance than a vanilla k-means clustering. We then proceed to compute the mean and variance for each of the clusters to learn the noise parameters associated with an appliance. For the sake of simplicity, we assume points in each cluster to be Gaussian distributed with mean as the cluster centres and independent noise components.

The mean and variance value of each appliance's load is then used to create a hidden Markov model for net instantaneous consumption. A Viterbi algorithm then performs maximum-likelihood sequence detection under the constraint that there is an alternation of states, from ON to OFF to ON and so on, for simple devices. We also force other reasonable constraints over state transitions that limit switching of appliances to at the most two per event epoch. This setup is capable of handling false alarms and missed detection to an extent.

4.3.1. Preprocessing

The implementation of event detection requires pre-processing of the signal to suppress spikes and other irregularities in the waveform. This step is helpful because the original waveform is observed to contain fluctuations and occasional surges of small duration. These could result from the supplied power itself or due to operation of different appliances (see Figure *17*). Once pre-processing is done the waveform essentially appears as a sequence of step rise/fall in the power level (see Figure *18*). It is easy to detect events with low false alarms on this kind of waveform.

It must be noted that while pre-processing helps event detection when the changes persist (more than 5 seconds), it is less effective in cases where there is a surge or a drop-in power level for a small duration (~5 seconds). Those small duration events tend to get suppressed.

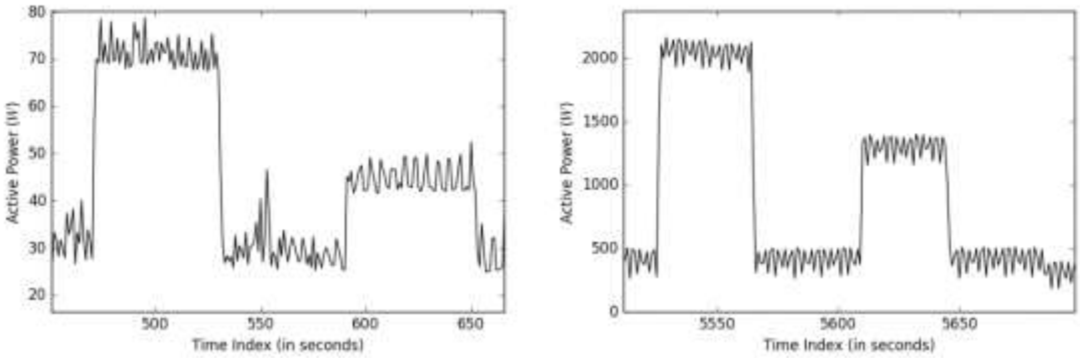


Figure 17: *A typical waveform contains a lot of fluctuations. The figure on the right corresponds to a situation where some appliances are turned ON/OFF while a washing machine runs in the background.*

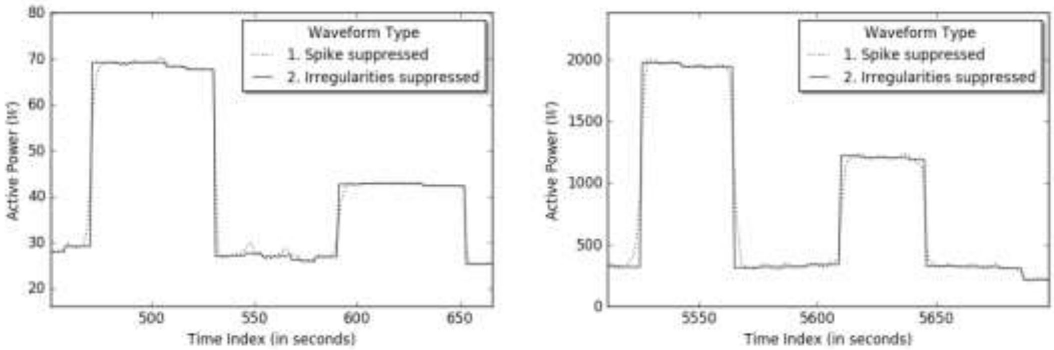


Figure 18: *Result of pre-processing on the sample waveforms presented in Figure 17.*

4.3.2. Event detection

Our event detection approach detects a level change using finite first and second order forward differences. It assumes that, at the low sampling rate of ~1Hz, events appear as step changes in power levels. The central idea is that whenever there is a step change, we should be able to observe a high magnitude of the corresponding derivative (first difference) and change in the sign of second derivative (second difference) due to the sigmoidal nature of the active power samples. Using this approach, it is possible to detect events separated in time by more than six seconds. If the separation is any lesser, as already alluded to earlier, those events may be detected as a single event. The performance of the event detection algorithm depends upon the threshold value used for declaring a change in active power ΔP and upon the moving average window size W used for smoothing. Our observation is that it is difficult to detect level changes less than 12.5 Watts. Also, if there is an appliance like a washing machine running in the background, there is a possibility of false alarms (false positives).

The performance of the event detection procedure for the standard BLUED dataset [8] is summarised in Table *2*. As seen in the table, the performance our event detection procedure is inferior to other procedures for Phase A in BLUED dataset. However, for the more challenging Phase B in the same dataset, our procedure performs much better. It is to be noted that our procedure detects events at the lower sampling rate data (1Hz) as compared to the other approaches which operate on data sampled at a much higher sampling rate (60Hz).

Table 2: *Performance of event detection procedure*

Approach		Our Method		BLUED [8]	Barsim et al. [7], [9]
Sampling Rate		1Hz		60Hz	60Hz
		Robust Values	Phase A Optimized		
Phase A	Recall	86.01%	88.55%	98.16%	98.41%
	Precision	97.36%	96.76%	97.94%	99.43%
	F-measure	0.913	0.925	0.980	0.989
Phase B	Recall	83.48%	88.83%	70.40%	70.48%
	Precision	89.83%	68.39%	87.29%	88.97%
	F-measure	0.865	0.773	0.779	0.787

4.3.3. Feature Extraction

The event detector identifies the epochs of significance where a state change has been detected. In order to extract the features to be used for the identification of appliances associated with the event, we use an approach inspired by [9]. The features of interest for an event are taken to be the changes in active and reactive powers, ΔP and ΔQ respectively, that result either from switching ON/OFF of an appliance(s), or from a change in state in case of a multistate appliance. Features for different classes of appliances should form different clusters on the $(\Delta P, \Delta Q)$ – plane because each class of appliance offers a different load in terms of impedance and hence consumes a certain complex power. Even in case of a multistate appliance like refrigerator, a cluster would appear for each multistate if data has been collected for sufficiently long duration. In principle, one could treat each of these clusters as a separate appliance. For each appliance, we model the $(\Delta P, \Delta Q)$ as a random variable with the Gaussian distribution. We then learn the mean and variance for the $(\Delta P, \Delta Q)$ of this appliance.

For the data collected by us in the uncontrolled environment in some Aluva households as part of our field trials, we did not know the appliance associated with $(\Delta P, \Delta Q)$ for any event. On these features, we use a clustering algorithm to group events into various categories (clusters), with each one to be treated as a different appliance state. We use a variation of k-means clustering on the $(\Delta P, \Delta Q)$ feature vectors associated with each event. We roughly cluster events by using a small value of k and then look deeper into each cluster to see if further clustering could be done within it. This hierarchical approach was found to yield better clusters as compared to using a larger value of k right at the beginning. If a cluster appears to have been wrongly split into multiple parts, those parts are manually grouped together as one. Once clustering is completed, mean and variance for each cluster are estimated and are taken to be the learnt model parameters for the hidden Markov model (HMM) based maximum likelihood sequence detection.

Results of the clustering procedure for one of the instrumented Kerala households are shown, at different zoom levels, in the scatter plots in Figure *19*.

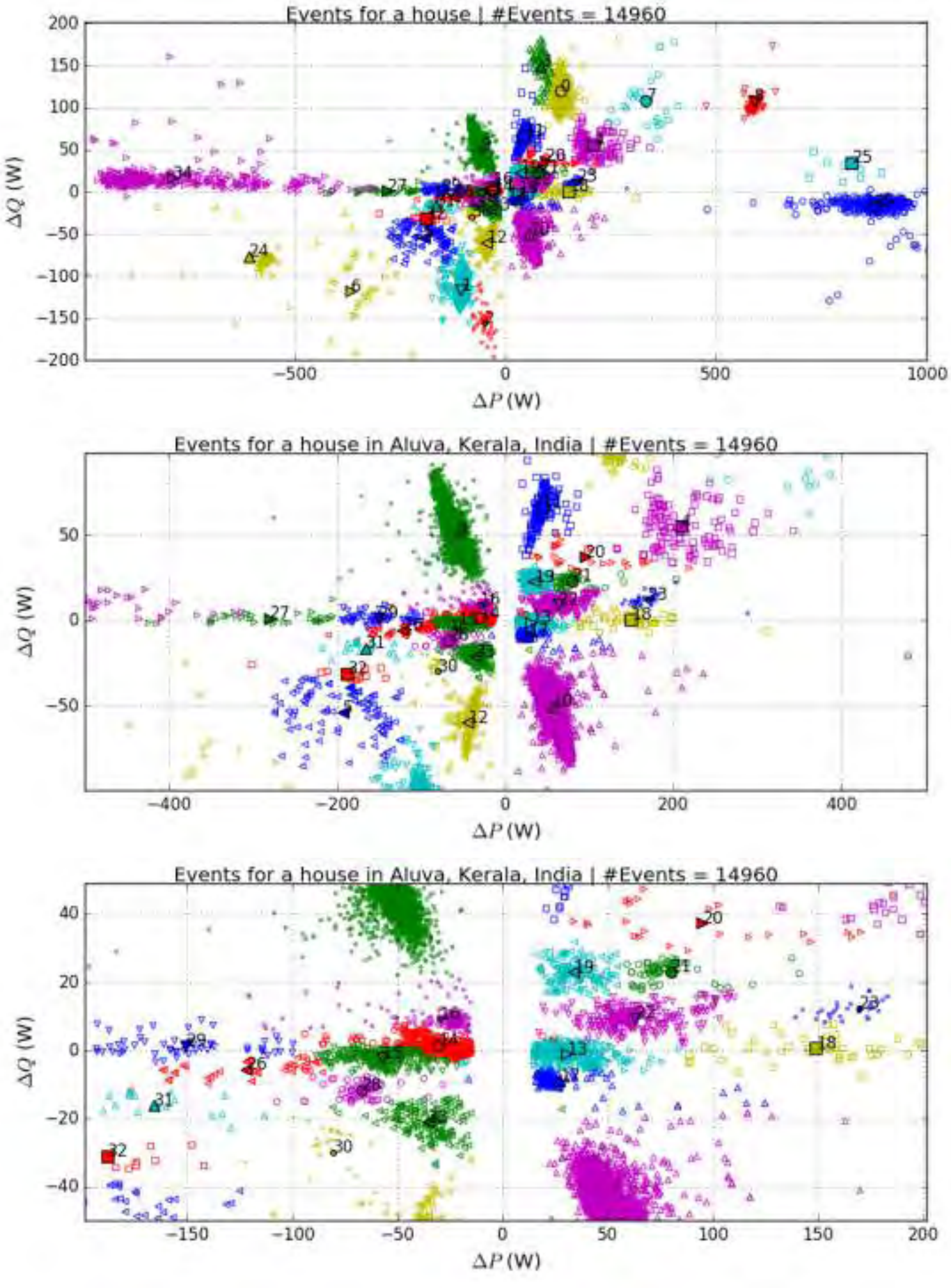


Figure 19: *Results of hierarchical k-means clustering in a Kerala household. The numbers on the clusters indicate the cluster indices.*

4.3.4. HMM based approach

To improve upon the clustering results which so far did not take into account the ON/OFF state-matching, we model the states of the system and the total consumption observations using a hidden Markov model and deploy the Viterbi algorithm for a maximum-likelihood sequence detection of appliance states. Our final goal is to use this inference for disaggregation. In a low sampling rate setting we also have to deal with compound events (two or more appliances changing state within the duration of sampling). We extend the

HMM approach by allowing more than one appliance to change state in a one second window.

Following simplifying assumptions have been made while modeling the system using a Hidden Markov Model (HMM):

- At most two appliances are turned ON/OFF at a time, i.e., each event shall correspond to a change of appliance state for at most two appliances.
- No appliance(s) can have multiple states. They can have exactly two states (ON /OFF) corresponding to 1/0 respectively. This is clearly a simplifying assumption. The approach can be extended to appliances with multiple states under certain constraints. Or each such state change can be viewed as a compound event of a switch off followed immediately by a switch on to the new state.
- Each appliance has a Gaussian distributed power demand given by $N(\mu_i, \sigma_i)$ where μ_i and σ_i are, respectively, the mean and the standard deviation of the i^{th} appliance.
- The distribution (modelled as a Gaussian) of the changes in the active and reactive powers for switching an appliance from 0 → 1 and from 1 → 0 are identical except for a sign change.

We use the traditional Viterbi algorithm that considers the transition probabilities of a time-homogeneous Markov chain, emission probabilities and initial probabilities. It is possible to accommodate multistate appliances, such as the refrigerator, by taking each possible state to be a separate virtual appliance. For such an appliance, OFF → multistate 1 → multi-state 2 → OFF, can be interpreted as, for example, OFF → virtual appliance 1 ON → virtual appliance 1 OFF and virtual appliance 2 ON → virtual appliance 2 turned OFF.

We can also exploit time-of-use information by using a time-varying transition matrix. For example, change in aggregate power consumption at night (sleeping hours) is more likely due to a refrigerator than other appliances with similar characteristics. A morning sequence of resistive loads is more likely to be a toaster or a water heater and less likely to be an electric iron. Dependency of activities, appliance usage and hence number of events, on the time of day can be seen in Figure *20*.

We tested our hidden Markov model on the labeled BLUED dataset. For simplicity, we assigned time independent transition probabilities according to the probability of an event corresponding to an appliance, based on their frequency distribution. For a suitable value of the model parameter of standard deviation, we could infer 89% of the appliance labels correctly, which is an encouraging result.

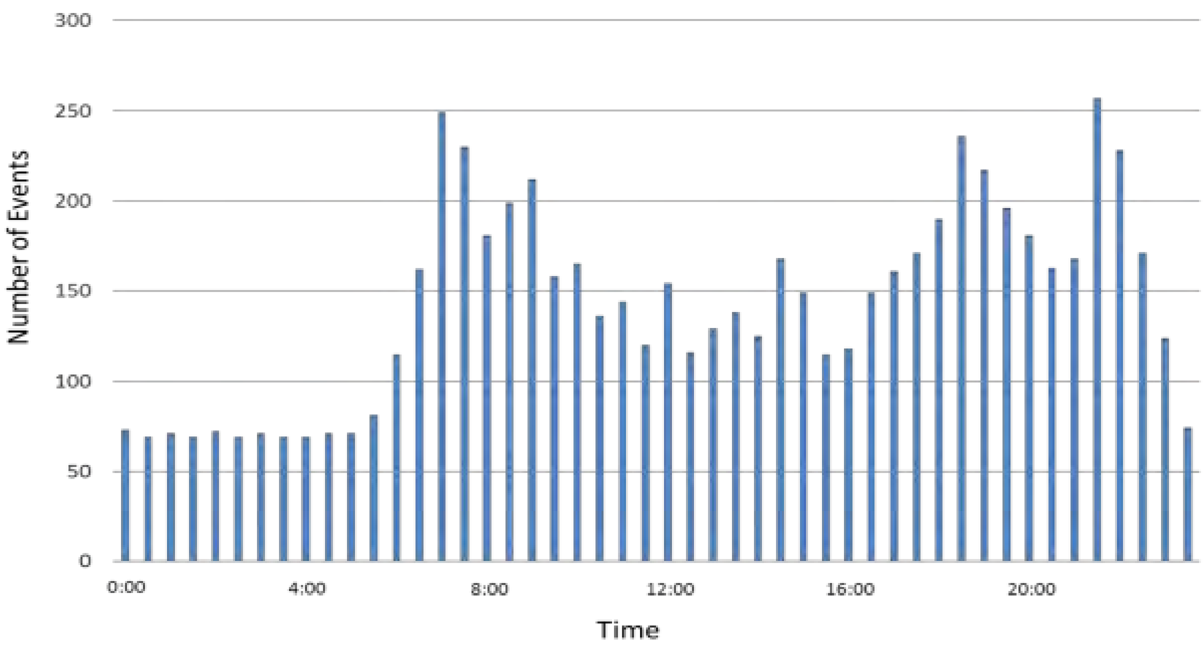


Figure 20: *The number of events is less during night time, increases during the day and peaks at certain times of the day. The histogram corresponds to events detected from a month of data.*

4.4. Bottom up engineering model to disaggregate consumption

Disaggregation information, or the break-up of the consumer's bill into individual appliances' consumptions (or a looser categorisation thereof), may drive consumer behaviour towards saving electricity, as noted by several other researchers. Apart from raising consciousness among users about their electricity consumption patterns, the energy audit report also provides an opportunity to suggest interventions; an alternative or suggestion to help bring down unnecessary electricity wastage.

From the point of view of the electricity provider, this can be used as a method to predict electricity demands and characterize loads at various points in time.

Instead of trying to find a way to break-down the total consumption into individual appliance usages, the bottom-up modelling tries to disaggregate using a model constructed out of parameters deduced from surveys and other public data. The method requires domain knowledge of behavioural patterns, building thermal behaviour, and occupancy to make accurate predictions. The method was suitable to disaggregate consumption in our scenario since it is constructed out of parameters which could be assessed from the surveys and could be further tuned to the actual observations from the instrumented households.

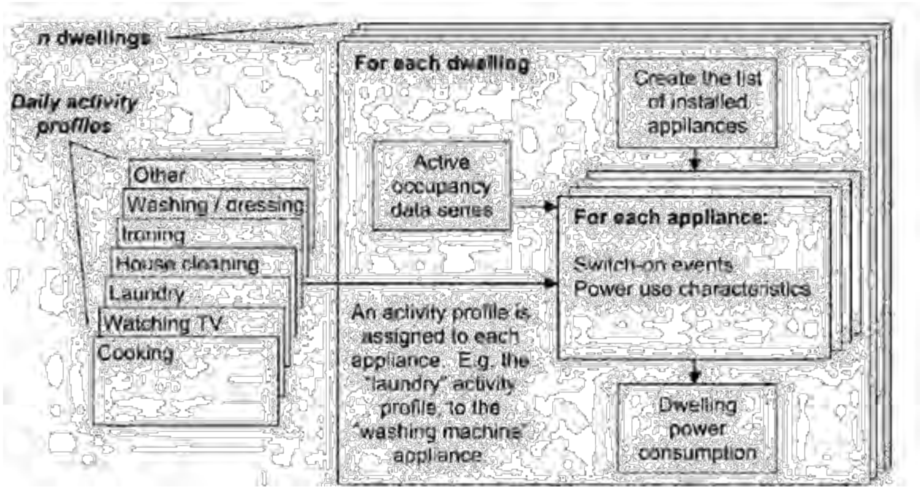


Figure 21: *Bottom up energy demand model: Activity profiles coupled with appliance usage patterns dictates the energy consumption in a household.*

4.4.1. Simulating Consumption of Appliances

The consumption of electricity by an appliance is perhaps the outcome of a behavioral pattern governing its usage. The behavioral pattern is influenced by the environment – the size of the home, temperature, etc. The physical parameters of an appliance can be easily determined from surveys and public data available. The behavioral data on the other hand is more difficult to determine (see Sections 4.1 and 4.2 above).

Our simulation model instantiated different electrical appliances, household members, and their interaction with the appliances. This was then simulated for multiple months, allowing us to fit the model to the observed parameters of actual consumption. This regression step allowed us to tune behavioral parameters such as the temperature threshold for taking the decision to switch on a ceiling fan at a household. Similarly, the simulation was repeated for multiple households, and was regressed to learn parameters which are similar for a range of households such as the wattage of a 21 inch CRT television. Integrating both these approaches we were able to construct a bottom-up model of the household. The tables below outline the approach followed for two major categories of appliances.

Steps to simulate the consumption of an appliance class, e.g. fan, and lighting

a. Simulating the consumption of ceiling fan

Step-1 Instantiate instances of a ceiling fan
Working from the estimated unit type and size, we instantiate the number of fans in various parts of the house.

Step-2 Estimate parameters determining consumption
The consumption of ceiling fan is strongly correlated with the occupancy and the temperature threshold for switching on the fan which is specific to the house. We assume fans to be used only when the temperature crosses this particular threshold, and occupants are present in the room. The parameters are estimated out of the survey which was administered via questions like "Did you keep the fan ON yesterday?"

Step-3 Simulate consumption
We finally estimate the consumption by combining these parameters with the actual observed temperatures in the target region.

b. Simulating the consumption for Lighting

Step-1 Instantiate instances of Lights
Working from the size of the unit, we instantiate different room types in our simulation viz.: bedroom, bathroom for the unit. We allocate different activities for different locations and use the lumen intensity required for different activities to determine the overall lumen requirement in a particular room

Step-2 Estimate parameters determining consumption
Calculating the usage of the lights takes into account the user's tendency to use lighting in the daytime as well as the occupancy information captured by the survey.

Step-3 Simulate consumption
We finally estimate the consumption by combining these parameters with the calculated lumen intensity (diurnal patterns) and the estimated occupancy (lights are used only when someone is present) to simulate the consumption due to lighting.

4.4.2. Combining Individual Predictions

The simulation gives us an estimated pattern of consumption. While this would agree with the overall trend in consumption for a particular consumer over a typical billing cycle, it may differ for a given billing cycle in which the consumer has left his home for a vacation. It may also differ if the consumer hosts a guest for the month.

Some appliances tend to be used even if there is no one present in the home. For instance, a fridge may be left on if the family leaves home for a short two-day vacation while most of the other appliances have been turned off. We account for this behaviour by setting weights for different appliances and by trying to fit the computed value of total consumption to its actual value.

4.5. Tuning Interventions to consumers

Personalizing information was viewed as being crucial to the success of the program. But this poses challenges. A consumer who does not possess an AC should not get a report advising on how to maintain an AC. Similarly, someone living in a second-floor apartment should not get an advice to plant shady trees in his garden. The framework should include a recommender which is able to tune interventions based on the observed pattern of a said household when compared to another similar household (The process of estimation of such parameters has been discussed in detail in Section 4.1).

The performance of the recommending system could be taken to be the objective of the programme itself, i.e., reduction in consumption of a said consumer as against other similar consumers.

At the start of the programme there was insufficient information to run the recommender since effectiveness of the interventions presented to them was unclear. To cold start the system we used experts as proxies for the consumers. Experts were assigned the task of rating the interventions, for different characteristic features as supplied by the consumers in the surveys. The coefficients related to these ratings were then supplied to the recommender system and it was allowed to make its predictions for the surveyed consumers.

Processes similar to predicting appliances ownership (refer to Section 4.1) were used to predict intervention ratings for the whole population.

The recommender was further constrained to have a seasonal variation in its advice. For example, the advice for AC maintenance is offered only in the early summer when a user is more likely to maintain it instead of winter when it is not used.

Our resource limitations and commitments have prevented us from integrating this feature in our current platform. In an integrated platform, performance of the recommender will be evaluated after every billing cycle for a said consumer with his specific characteristic features.

5. Evaluation

5.1. Randomized control trial results

The impact of behavioural programmes in other parts of the world has been between 0 to 5% [10]. To assess the impact of our programme, we use the raw bi-monthly bill data.

The first report was initiated towards the end of April 2016. On account of the bimonthly billing cycle, the impact of that report would have become apparent from 1st of July 2016 onwards. The period prior to 1st of July 2016 is referred to as the pre-programme period. The period afterwards is referred to as the post programme period. The energy consumption data was made available by KSEB from January 2015.

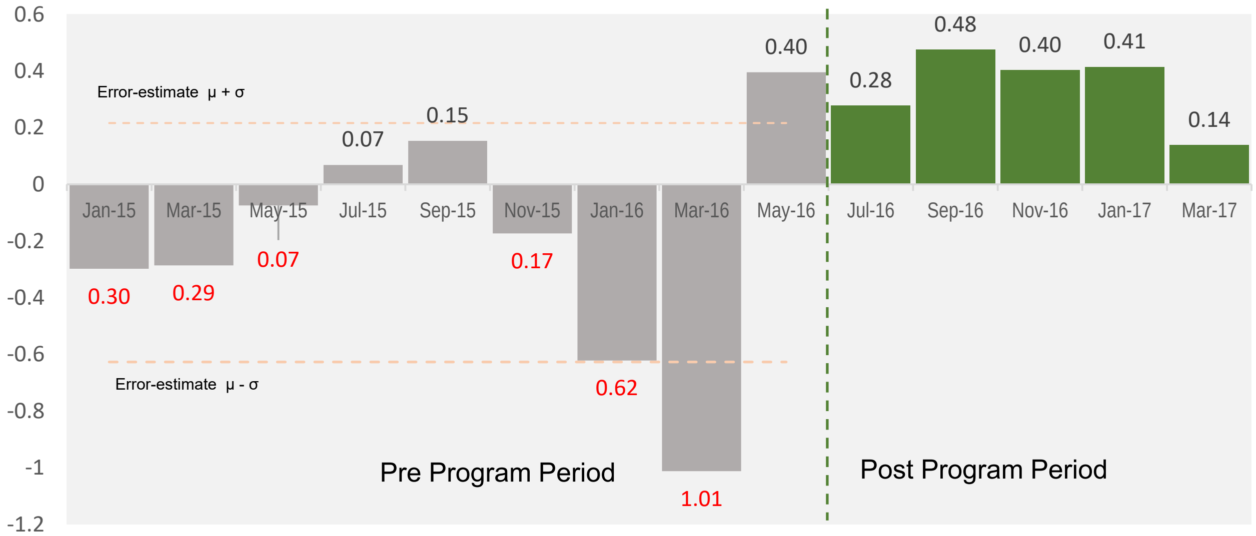
About 10% of the consumers have zero consumption (0 kWh) for any one billing cycle during the observation period (Jan 2015 to Feb 2017). Such cases can arise when the consumers are not present at home. It is also likely that some of these consumers have been introduced into the '*walk order*' during the observation period, resulting in zero consumption records for some of the months. Other scenarios include faulty meters. For those with faulty meters, the bill is reconciled in a subsequent billing period. Such cases can impact the assessment of the programme. Hence, we leave out such consumers from consideration in both experimental and control groups.

Logistical constraints such as walk orders and the absence of address information have resulted in the histograms of average consumption data to differ slightly for the experimental and control groups. To ensure comparison of identical sets, we grouped consumers by their average bill amounts and further selected an equal number of random users from both the groups. The details are given in Figure *22*.

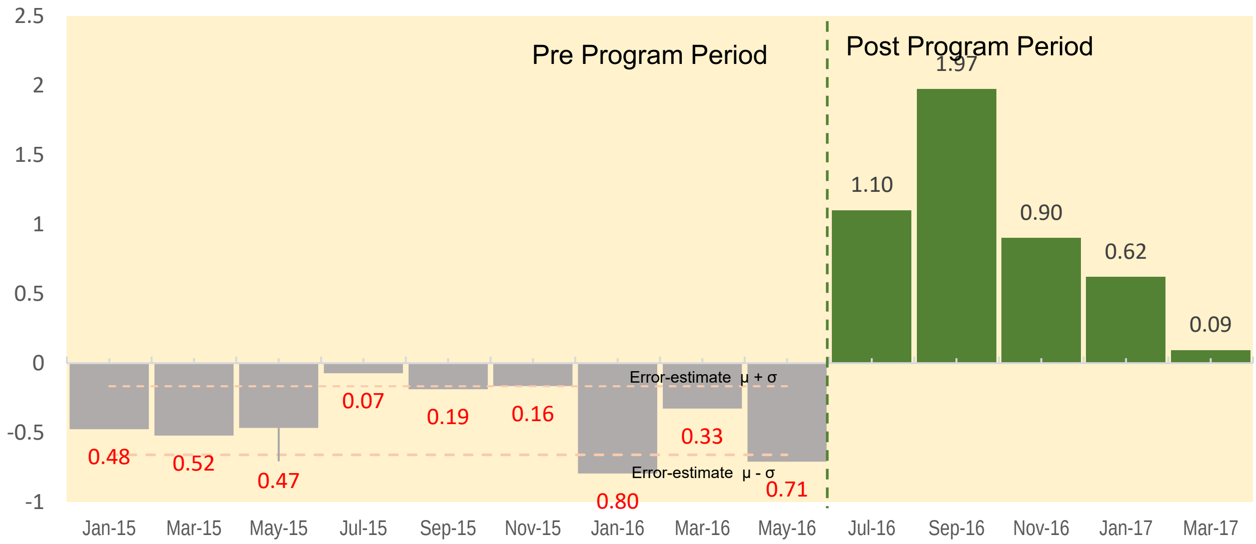
In Figure *22*, we provide the difference (in percentage of experimental group's usage) between the control and the experimental groups' consumptions. The control group generally consumed less than the experimental group in the pre-programme period. But during the programme period, the difference turns positive, or the experimental group reduced their consumption. The reduction in consumption is more pronounced for those beyond the 40 percentile point. The bars indicate one standard deviation of uncertainty, also estimated from the samples.

Pre-& Post Program Period

Randomized Control Results [% difference between Control and Experimental]



Randomized Control Results 40-60 Percentile [% difference between Control and Experimental]



Randomized Control Results 80-100 Percentile [% difference between Control and Experimental]

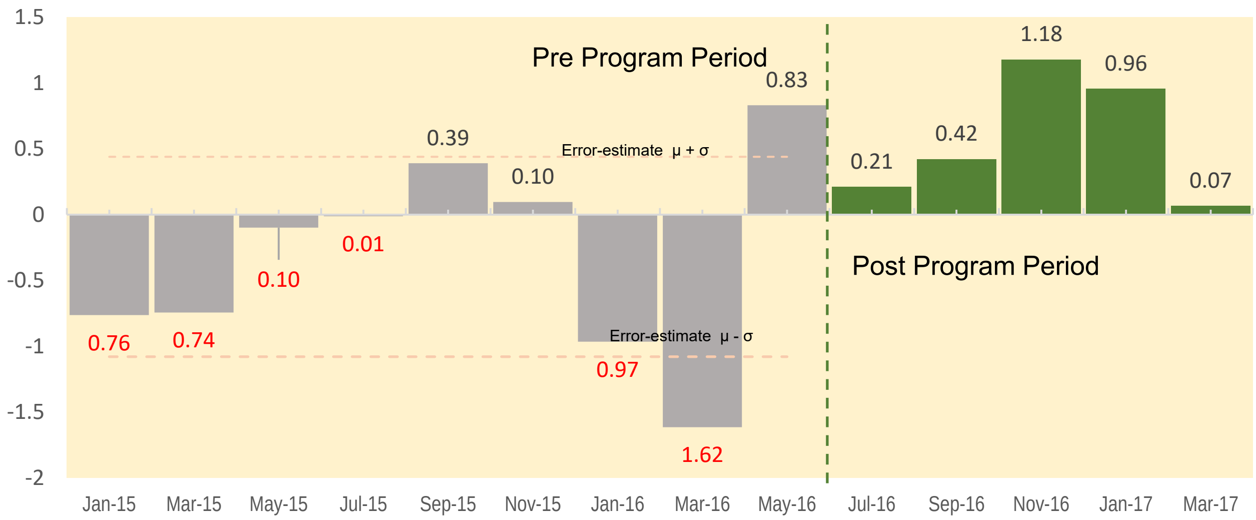


***Figure 22:** Pre- and post-programme Period: The impact of the pilot program has resulted in an overall 0.7% reduction in the energy consumption. The impact is higher in the higher percentile consumers as compared to consumer in the low percentile. From 40 percentiles, (with a bimonthly consumption of 214 units) the impact is significantly higher.*

5.1. Qualitative Assessment

Near the end of the project duration, three of us visited a few homes in Aluva Town (3 households) and Aluva West (4 households) to make an on-field qualitative assessment of the impact of our programme. All the homes visited were independent houses of varying sizes. We visited these homes with the corresponding meter readers.

Programme information recall:

(i.) In the Aluva Town area, all were aware of the reports, and indeed, were even able to retrieve the reports we had sent them, and had them in their hands during the interview. This was gratifying to see. In the more rural Aluva West area, only one of the four was aware of the programme and the reports, and none were able to retrieve the reports.

(ii.) All of them knew roughly, their electricity bill amounts.

(iii.) One of the households in Aluva Town belonged to a former KSEB employee. Except for this resident, the others that knew of the reports had paid only cursory attention to the reports and suggested interventions.

(iv.) The former KSEB employee was the only one who was aware of her usage level ranking in comparison to others in the cluster.

Action taken: The former KSEB employee took proactive measures to minimize her household's consumption. She had a significantly lower bimonthly bill. She however did not recollect the interventions we suggested in the reports. One of the residents in Aluva West had an unusually high consumption and had it investigated by KSEB itself. He figured it to be an issue with one of his inverters, and is investigating this further. Another household in Aluva West changed all his incandescent lamps to CFLs during the programme period. But this might have been due to KSEB's own advertisement effort.

Programme approval: One of the residents remarked that he was positively surprised that KSEB was making such consumer engagement efforts. The former KSEB employee appreciated the reports. All indicated that disaggregation and comparison would be very useful information to have. Most said that, after the interview, they plan to pay a little more attention to future reports, since they now knew what it contained and the effort that went into generating them.

Interaction with the meter readers: The two meter readers were very cooperative to help with the introductions and the interviews. It appeared that they too were eager to see to what extent the reports had an effect on the consumers. We however did not get any feedback from them on how this could have been implemented better. It appeared that they were more focused on executing the tasks rather than on questioning the utility of the programme, increasing the efficacy of tasks assigned to them, and in suggesting better methods to meet the goals of the programme.

Assessment: All in all, we felt that the programme perhaps could have been a little more effective if we had advertised it a bit more. Our efforts in this would have been better directed if we had a social scientist on board who could have helped us with better methods

Figure 23: *A photograph with one of the consumers (second and third from right) at Aluva West after conducting programme assessment survey. From left to right, Viney Kumar (Clytics), Rajesh Sundaresan (IISc Bangalore), Abdul Salim and his spouse, Pradeep (meter reader).*

to increase awareness, and to capture and retain attention. Perhaps this is something that could be suggested to other investigators involved in similar deployments.

5.2. Impact Assessment Survey

Towards the end of the programme we carried out a programme assessment survey. It used the existing infrastructure we had developed for the original programme. The assessment was carried out during the month of March on consumers who received the reports.

The assessment evaluated the responses in two dimensions: programme approval and action taken. We have listed the questions posed to the consumers and a summary of their corresponding answers.

5.2.1. Programme approval

This section attempted to assess the approval and participation of the respondents in the programme.

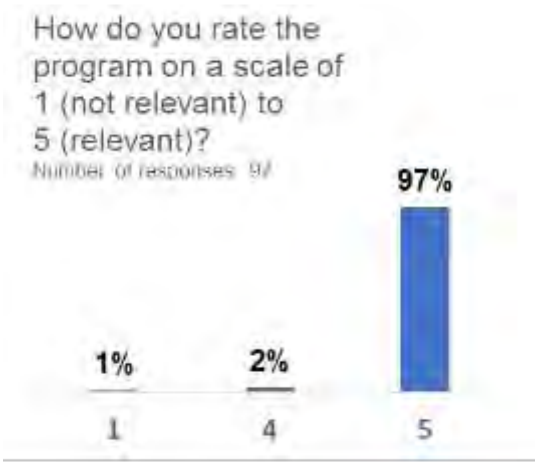


Figure 24: *Programme approval.*

Q1. What is your rating of the programme for the reports received over the last eight months, on a scale of 1 (not relevant to me) to 5 (quite relevant)?

Summary: Most of the consumers have given a high rating to the home energy audit report.

Q2. Would you use an internet portal giving similar information?

Summary: Majority of the consumers responded stating they would not use an internet portal for accessing this information.

5.2.2. Programme action

This section attempted to assess action taken by the consumers on receiving the reports.

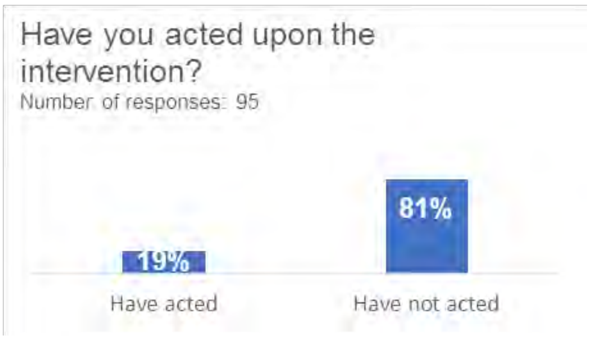


Figure 25: *Programme action.*

Q. Have you undertaken any step over the last few months based on the recommendations in the reports: Yes | No?

Summary: A fifth of the surveyed consumers stated that they acted upon the interventions presented in the home energy audit report.

6. Learning and Recommendation

- The overall impact of the programme was computed to be around 1% reduction in consumption. This is above the threshold of noise in the data. Similar programmes elsewhere [11] have reported an impact between 1-5%. The pilot has resulted in a reduction in consumption of the control group by 2,69,325 units of energy, which has a net value of Rs 14 Lakh at the levelised cost of Rs. 5.26 per unit of energy. If the programme was extended to entire Kerala comprising over one crore LT domestic connection with a projected consumption of 11106 million units [12], the financial impact will be to the tune of Rs. 41 Crores. The average cost of supply for the FY 2017-18 is projected as Rs. 5.26 while the average sale to the LT Domestic segment is projected as Rs. 3.76. A revenue gap of Rs. 1.50 exists in the LT Domestic segment in Kerala.

Implementation of this programme throughout Kerala will reduce subsidy by Rs 12 Crore.

- About 10% of the cost of the programme was consumed in setting up and executing the delivery logistics. We anticipate this will turn out as the major component if this programme were to be scaled over an even larger consumer base. We would recommend that other similar programmes consider using the electronic medium as the primary mode of communication. Electronic communication imposes a constraint that users must '*opt-in*' by registering into the platform rather than '*opt-out*' as in this programme. However electronic communication medium will be much easier to administer and integrate.

- We had a latency of one billing cycle imposed due to the logistical constraints in this programme. This was due to the bimonthly billing cycle, and the use of meter readers to deliver reports as per their walk order. Users are more likely to act upon information when the reference period is comparatively recent. We anticipate that the results of this programme and similar programmes can improve if the latency is reduced to one billing cycle. Corrupted records, dated information and absence of full consumer information restricts delivery of reports to the consumer as soon as it is generated (as in our project in Kerala). Electronic means of communication on the other hand will be more effective because shorter latency.

- Based on our experience, we feel that the target audience of such programmes should be selected carefully. The impact of this programme was marginal for consumers whose monthly consumption falls below 100 units in a month. While it was above 2% for those with a consumption over 100 units a month.

- The key to driving conservation within the LT consumer segment is engagement. Convenience of accessing services is one of the foundations of building consumer engagement. The participation of consumers in the platform and home energy audit reports can increase if other services such as billing and complaints are integrated into the existing platform. The home energy audit reports in this programme did not present bill information (on account of the latency and the elaborate nature of approval required for operation). We anticipate that a consumer engagement platform will improve the outcomes of some of the other workflows employed by utilities in bill management and complaint handling. Consumer interactions can be tuned (using some of the approaches outlined above) to ensure on-time payment, and to reduce the receivable burden of a utility.

- Sharing of energy data can be a vehicle for driving new applications and products. This programme makes a convincing case for creating seamless infrastructure for authenticating and sharing energy data. This will enable third party applications: ranging from energy audits (such as this programme) to product finance for efficient products to be built upon such information, and to create additional value for end consumers. The Green Button [12] initiative of US has been built along the same lines and has been operating since 2012. This initiative has allowed consumers to download and control the sharing of their energy data.

- Any such programme should include a social scientist as part of the team to come up means to increase awareness, and to scrutinize survey questions and energy audit reports.

In the subsequent subsections, we discuss a possible roadmap and suggest some additional functionalities which could be built into the platform in case of similar implementation with other Indian utilities.

6.1. Roadmap

The operating environment of utilities will change over the next five years. This will be accentuated by three major factors.

First, revenue shortfall will continue to exercise its pressure on Aggregate Technical and Commercial (AT&C) losses in utilities. AT&C losses reduced from 26.35% in 2010-11 to 24.35% in 2014-15 [2]. However significant potential exists wherein AT&C losses in some of the progressive Indian utilities can be reduced to below 10%.

Second, the end consumer of a utility is changing. A digitally aware consumer will want better and faster service from his utility. He would have similar expectations on a utility as he does on some of the e-commerce providers. He would need faster information, better reliability, and perhaps would be willing to pay a differential rate for differential services.

Finally, power generation is likely to become more and more distributed, changing from centralised power plants towards distributed renewables. The role of the utility provider will

	Current Capability	Future Capability
Operations	• React to failures • Commercial losses	• Predict potential asset failure • Revenue assurance
Customer Experience	• Payment kiosks • Call centre dial in • Broad 6 -8 categorisations of consumer	• Multi-platform payments • Self-service billing • Proactive communication • Each consumer is different
Products	• Power	• Infrastructure to support distributed generation • Efficient product market place • Financial product linked to energy bill

then change from one that offers energy to one that facilitates exchange between producers and consumers, similar to a financial exchange, absorbing some of the fluctuations and ensuring that both the sides continue to remain protected.

[2] As per provisional figures released by CEA in Jan 2017 http://www.cea.nic.in/reports/monthly/executivesummary/2017/exe_summary-01.pdf

A utility has to be responsive to the above transformations. Reducing commercial losses, for example, would need the utility to understand anomalous behavior in such exchanges (technological or behavioral) and fix them to ensure smooth operation. Similarly, in order to

Kick-off

- Digitized records
- Centralized repositories
- E-accounts for consumers

Growth

- Consumer engagement platform
- Call centre integration – online complaints filing and resolution
- Social network integration – raising helpdesk tickets, consumer insights
- Revenue assurance, theft analytics

Innovate

- Marketplace for efficient product and services
- Consumer self-billing
- Personalized product bundling
- Demand Response
- Stream line distribution network
- Active communication

extend its offerings to a digitally aware consumer the utility should be able to understand consumers' characteristics and adapt its products to provide greatest value to the consumers. With a consumer base of over a million, technology and data are the only pathways for being responsive. Utilities are at various stages in this transformation, some have recently finished digitizing all consumer records while others have gone ahead to integrate revenue assurance and theft analytics into workflow. Broadly the transformation can be grouped into three major phases. The first phase is digitisation which creates the foundation over which other services can be based. Most Indian utilities are in the process of doing this in some form or the other. The second phase is to integrate digitisation into core-operational processes from handling complaints to consumer engagement. The third phase involves innovation to provide an efficient market place, personalization, demand response tuning, and active communication. In the subsequent sections we briefly mention some approaches for these functionalities.

6.2. Market place for efficient products and services

The recommendation and clustering framework developed by us (as explained in section 4.5) can be extended to create a market place of efficient products and services. These services can be offered by utility providers to their consumers. Such a market place will curate data from multiple sources (such as those implemented in this programme) and serve personalized recommendations/offers to end consumers enabling greater adoption of efficient appliances.

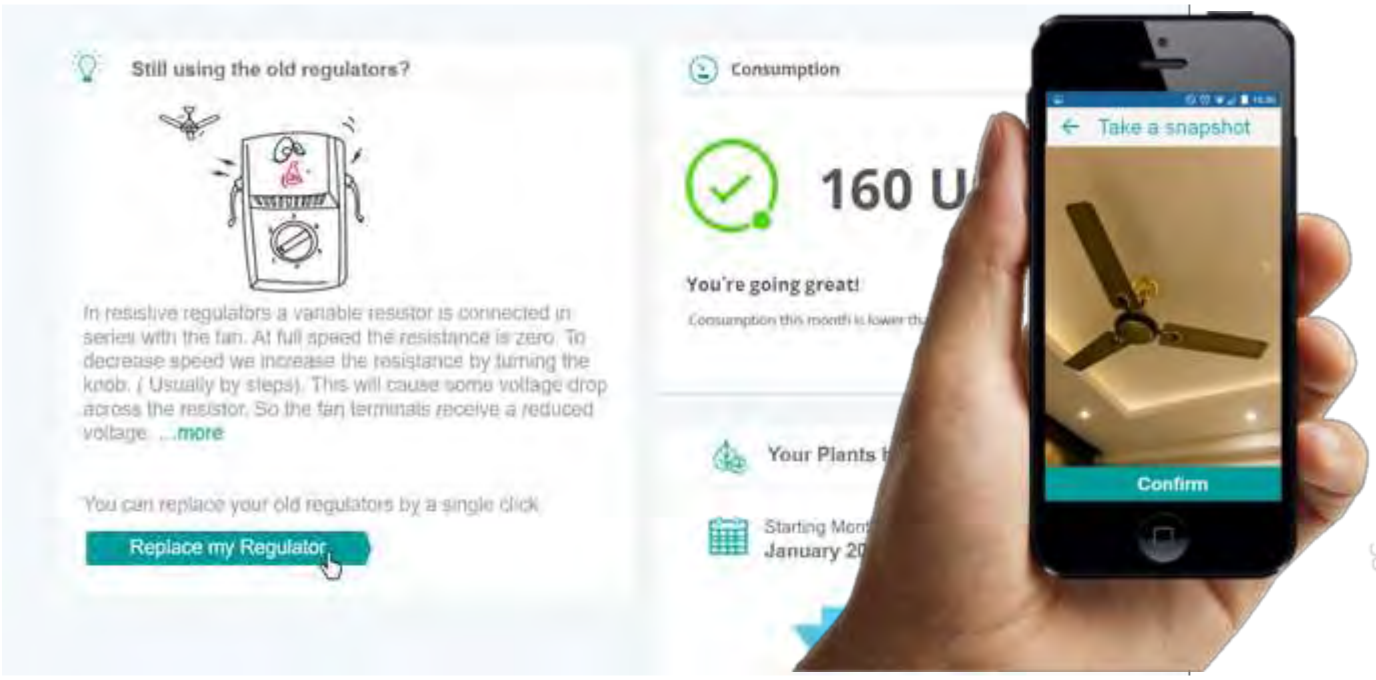


Figure 26: *A sample recommendation.*

6.3. Updating Records for Optimization

Legacy records (often dating back to 1980) constitute more than three quarters of consumer data for most utilities. Incomplete records make energy accounting and network rationalisation difficult in the absence of address data. For the near future, an engagement platform will allow the utility to tap valuable consumer data. Sparsity in the meta-data can be filled using statistical techniques, allowing energy utility to make network optimization with higher confidence.

7. Acknowledgement

The successful completion of this programme would not have been possible without help, co-operation and guidance of many key personnel. We are thankful to everyone who helped us directly or indirectly in executing this programme.

We would like to express our sincere gratitude to KSEB (Kerala State Electricity Board) especially to Mr Shiva Shankaran (Ex MD KSEB) for allowing us to implement the pilot in Aluva. We want to offer our special thanks to Mrs. Veena Devi (EE, Aluva) and Mr. Jose Oomen KP (AE, Aluva) for coordination of the operations of the project along with their field staff and getting everyone on board for executing the logistics of the project on ground. We also acknowledge the help we received from the Department of Renewable Energy and Energy Savings (REES). Mr Suku (Chief Engineer REES) facilitated our smooth interaction among multiple departments of KSEB. Mr Bipin Shankar (Dy CE REES) spent substantial time reviewing the format of our reports to ensure they would be easy to understand. We are also grateful to the IT department staff Mr Khesava Das, Mr Sathyarajan (EE, MIS) and Mr Suresh for making arrangements to share the data. Most importantly, this programme would not have been possible without the efforts of the meter readers who took additional burden of distributing the reports and collecting the survey data from the consumers.

We are grateful to the respondents of the survey who took time to patiently answer our survey questions. We also acknowledge the role played by our printing staff who ensured that over 25,000 consumers receive correct set of personalised reports on time.

Finally, we would also like to thank the funding agencies, Shakti Sustainable Energy Foundation and the Robert Bosch Centre for Cyber-Physical Systems for their support throughout the project

8. Project Staff

Indian Institute of Science

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Dr. Rajesh Sundaresan received the B.Tech. degree in electronics and communication from the Indian Institute of Technology Madras, the M.A. and Ph.D. degrees in electrical engineering from Princeton University in 1996 and 1999, respectively. From 1999 to 2005, he worked at Qualcomm Inc. on the design of communication algorithms for wireless modems. Since 2005, he has been with the Department of Electrical Communication Engineering, Indian Institute of Science (IISc), Bangalore His interests are in the areas of communication networks and information theory.

Shayan Garani Srinivasa

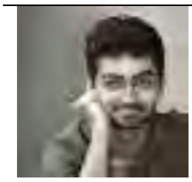
Dr. Shayan Garani Srinivasa received his Ph.D. in Electrical and Computer Engineering from Georgia Institute of Technology - Atlanta, M.S. from the University of Florida - Gainesville and B.E. from Mysore University. He has held senior engineering positions within Broadcom Corporation, ST Microelectronics and Western Digital. His research interests include broad areas of applied mathematics, physical modelling, coding, signal processing and VLSI systems architecture for novel magnetic/optical recording channels, quantum information processing, neural nets and math modelling of complex systems.

Priti Bharadwaj

Priti worked as a Project Assistant at IISc. She completed her B. Tech. from IIT Kanpur and holds 7 years of experience in web-application domain and in various capacities with an IT major. In this project she developed paper reports, survey application and web-platforms. She also worked on different analysis algorithms for intervention recommendation.

Tarun Khandelwal

Tarun is working as a Junior Research Fellow at IISc. He completed M. Tech., VLSI Design from VNIT, Nagpur. He worked on pre-processing of power waveform, event detection, feature extraction, clustering of features, extraction of cluster properties, and partly on appliance inference using Hidden Markov Model.



Nakul Saxena

Nakul is a User Experience designer. A graduate of NID he had worked on similar projects earlier. He was responsible for creating the prototypes for the reports and the web applications which were subsequently deployed.

Harshavardhan Ramanna

Harsh worked as a Project Assistant at IISc. He did his B. Tech., Electrical, Electronics and Communications Engineering from NIT, Surathkal. He worked on non-linear regression models and bottom up models for disaggregation of total energy consumption.

Divyansh Khanna

Divyansh worked as a Project Assistant at IISc. He did his B. E,, Computer Science from BITS Pilani, Goa. He worked on models to map household activity to appliance usage and Hidden Markov Model for consumption patterns.

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Karan worked as a Project Assistant at IISc. He did his B. Tech., Mechanical Engineering from IIT, Guwahati. He worked on models to map household activity to appliance usage and Hidden Markov Model for ML sequence detection.

Shahid Mehraj

Shahid did his B. Tech in ECE from NIT, Srinagar in 2008. He obtained his Masters and PhD from IISc in 2017. He worked on pre-processing the data and initial regression of the dataset.

clytics

Shuvashish Chatterjee

Shuvashish Chatterjee is a mechanical engineer and an MBA from ISB Hyderabad. At clytics he takes care of operations.

Viney Kaushik

Viney Kumar did his B.Tech from NIT Hamirpur and M.Tech from IISc Bangalore. He has started his engineering career from BARC, Bombay. He has also worked with Department of Atomic Energy at Nuclear Power Corporation of India Ltd. At clytics he takes care of product development and analytics.

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[14] *KERC Tariff Order Order No. 1007/F&T/2016/KSERC dated 17th April 2017.*

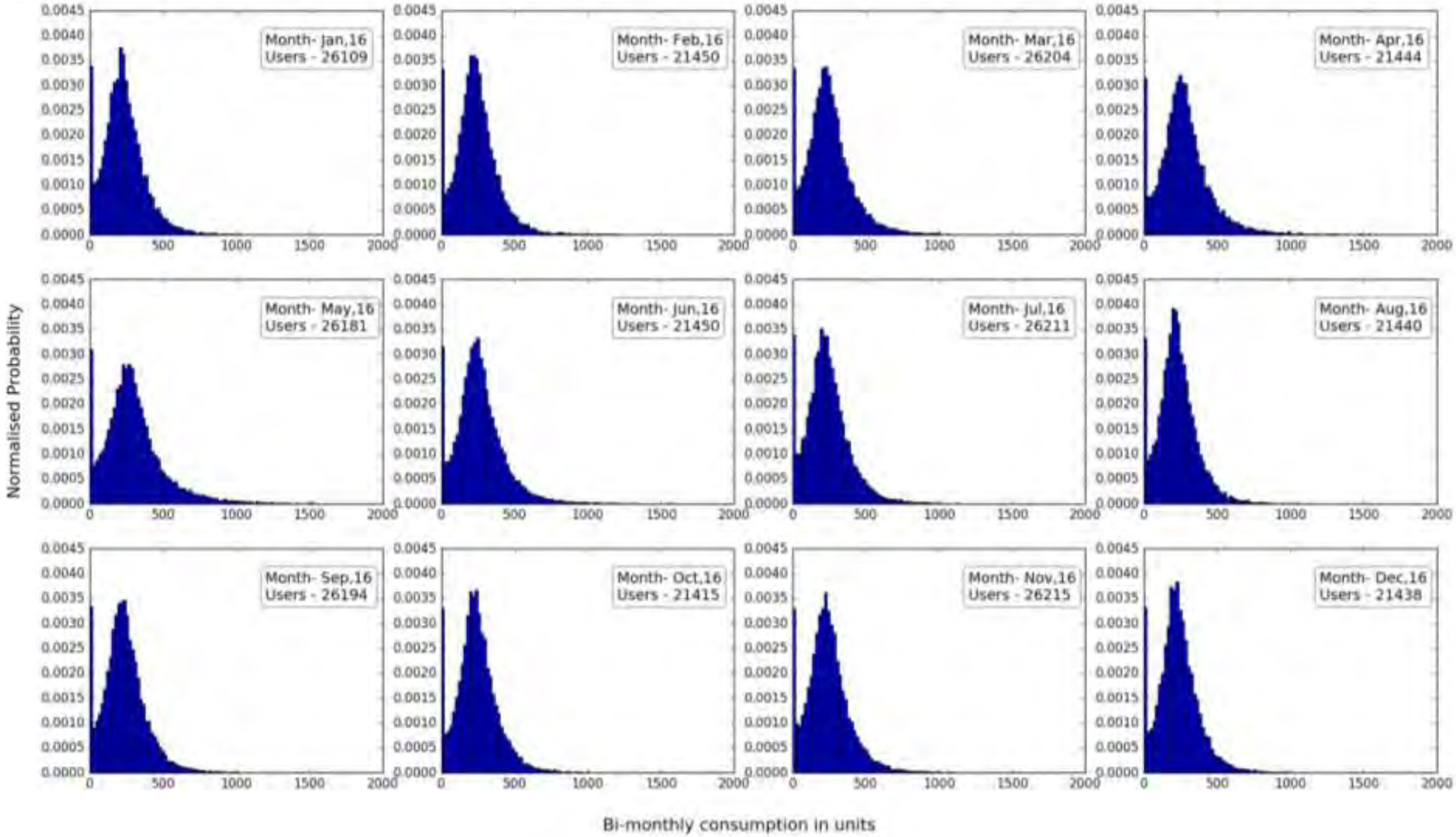


Figure 27: *Plot of consumption in Aluva West, Aluva Town, and Kalamassery across 2016-17. Each subplot represents the normalized histogram of consumption for consumers whose bills were generated in the respective period. For summer months, April and May, the consumption increases (histogram flattens) across the sections while for December it reduces (sharper peak)*

Annexure II

Reports R0 through R5 were delivered to the consumers. From R3 onwards there was no change in the appearance of the reports. However, the information contained in these reports was computed using algorithms which were more sophisticated. Sample R0, R1, R2 and R3 reports can be found on the following pages:

Kerala State Electricty Board
Aluva Town

Area Code
A04-18-23

Report for
Feb 2016 - Mar 2016*

*Reflects the consumption of the previous billing cycle
*കഴിഞ്ഞ ബില്ലിംഗ് കാലയളവിലെ വൈദ്യുതി ഉപഭോഗത്തെ സൂചിപ്പിക്കുന്നു

Consumer ID ഉപഭോക്താവിന്റെ ഐഡി

[redacted]

Address not available

Introducing your personalised home energy report!
നിങ്ങളുടെ വ്യക്തിഗത ഭവനഊർജ്ജ റിപ്പോർട്ടിലേക്ക് സ്വാഗതം!

-Fold Here-

About This Programme ഈ പരിപാടിയെ കുറിച്ച്

You are holding your first personalised home energy report. This programme is made available in select households in Aluva Town. Along with your energy bill you will receive a personalised report on your previous billing cycle's consumption. The objective of the programme is to provide contextual information to you so that you have more control over your consumption. Your participation in the programme will contribute to meeting the overall energy conservation targets of Aluva Town.

ഇത് നിങ്ങളുടെ ആദ്യത്തെ ഭവന ഊർജ്ജ സംരക്ഷണ റിപ്പോർട്ടാണ് . ഈ പദ്ധതി ആലുവയിലെ തിരഞ്ഞെടുക്കപ്പെട്ട വീടുകളിൽ ലഭ്യമാക്കപ്പെട്ടിരിക്കുന്നു. വൈദ്യുതി ഉപഭോഗ ബില്ലുകൾക്കൊപ്പം, താങ്കളുടെ ഏറ്റവും ഒടുവിലത്തെ ഉപഭോഗമനുസരിച്ചുള്ള വ്യക്തിഗത റിപ്പോർട്ടും താങ്കൾക്ക് ലഭിക്കുന്നതാണ്. നിങ്ങളുടെ ചുറ്റുപാടുകൾക്കനുസൃതമായി വൈദ്യുതി ഉപഭോഗം നിയന്ത്രിക്കാൻ ഉതകുന്ന വിവരങ്ങൾ നല്കുക എന്നതാണ് ഈ പദ്ധതിയുടെ ലക്ഷ്യം. ഈ പദ്ധതിയിൽ ഉള്ള നിങ്ങളുടെ പങ്കാളിത്തം നിങ്ങളുടെ പട്ടണത്തിലെ ആകെ മൊത്തമുള്ള ഊർജ്ജ സംരക്ഷണത്തിന് സഹായകമാകും.

Get Personalised Tips
വ്യക്തിഗത നുറുങ്ങുകൾ നേടുക

We compare your consumption with those of similar homes in your neighbourhood to find opportunities for you to save energy. It will be presented to you in subsequent reports.

നിങ്ങളുടെ വൈദ്യുതി ഉപഭോഗത്തെ ചുറ്റുവട്ടത്തുള്ള സമാനവീടുകളിലേതുമായി താരതമ്യം ചെയ്യുന്നു. കണ്ടെത്തലുകൾ തുടർ റിപ്പോർട്ടുകളിൽ നിങ്ങൾക്ക് ലഭ്യമാകുന്നു.

Access e-Reports
ഇ-റിപ്പോർട്ടുകൾ

You can also access this information electronically by logging into our website (please turn overleaf).

ഈ വിവരം ഞങ്ങളുടെ വെബ്സൈറ്റിൽ ലോഗിൻ ചെയ്യുന്നതിലൂടെയും നിങ്ങൾക്ക് ലഭിക്കുന്നതാണ് (മറുപുറം നോക്കു).

Powered by **clytics .**

Comparison for താരതമ്യം

Feb 2016 - Mar 2016

Your consumption was average. Some of the efficient homes have used 7% less energy.

താങ്കളുടെ ഉപഭോഗം ശരാശരിയാണ്. ഉപഭോഗക്ഷമതയുള്ള വീടുകൾ 7 % വൈദ്യുതി കുറവാണ് ഉപയോഗിച്ചിട്ടുള്ളത്.

YOUR HOME ഈ വീട്

You have consumed 230 units in the last billing period: 23 Jan 2016 – 21 Mar 2016.
Are you curious to find out how you can save energy? The subsequent reports will include personalised measures to lower your consumption.
നിങ്ങൾ കഴിഞ്ഞ ബില്ലിംഗ് കാലയളവിൽ 230 units ഉപയോഗിച്ചു : 23 Jan 2016 – 21 Mar 2016.
വൈദ്യുതി എങ്ങനെയാണ് ലാഭിക്കേണ്ടത് എന്നറിയാൻ ആകാംക്ഷയുണ്ടോ? വൈദ്യുതി ഉപഭോഗം കുറക്കാനുള്ള മാർഗങ്ങൾ തുടർ റിപ്പോർട്ടുകളിൽ ഞങ്ങൾ ഉൾപ്പെടുത്തുന്നതാണ്.

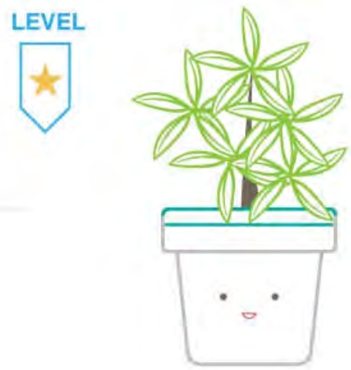
SIMILAR HOMES സമാന വീടുകൾ

What are similar homes? These homes have a consumption pattern similar to your home. Similar homes consumed on an average 226 units in the last period.
സമാനമായ വീടുകൾ ഏതൊക്കെ ആണ്?സമാനമായ ഉപഭോഗ രീതിയുള്ള താങ്കളുടെ സമീപത്തുള്ള മറ്റ് ഗൃഹങ്ങളാണവ. സമാന വീടുകൾ കഴിഞ്ഞ കാലയളവിൽ 226 units കുറവ് വൈദ്യുതി ഉപയോഗിച്ചിരിക്കുന്നു.

EFFICIENT HOMES കാര്യക്ഷമമായ വീടുകൾ

What are efficient homes? These homes consume less (they are in the top three-eights) among homes similar to yours. Efficient homes in your locality used less than 215 units in the last billing period.
ക്ഷമതയുള്ള വീടുകൾ ഏതൊക്കെ ആണ്?സമാനവീടുകളിൽ ഏറ്റവും കുറഞ്ഞ ഉപഭോഗമുള്ളവയാണ് ക്ഷമതയുള്ള വീടുകൾ. ക്ഷമതയുള്ള വീടുകൾ കഴിഞ്ഞ കാലയളവിൽ 215 units കുറവ് വൈദ്യുതി ഉപയോഗിച്ചിരിക്കുന്നു.

Save energy to grow the plant!
ഊർജ്ജം സംരക്ഷിക്കു, ചെടിയെ വളർത്തു!



In every home energy report that you will receive subsequently, the plant will give personalised energy saving tips. The more energy you save compared to others, the faster your plant will grow. The level banner will represent the current stage of your plant.

തുടർന്നങ്ങോട്ട് നിങ്ങൾക്ക് ലഭിക്കുന്ന ഭവന ഊർജ്ജസംരക്ഷണ റിപ്പോർട്ടുകളിൽ, ചെടി നിങ്ങൾക്ക് വൈദ്യുതി ലാഭിക്കാനുള്ള നുറുങ്ങുകൾ പകർന്ന് തരും. ഈ നുറുങ്ങുകൾ പിന്തുടർന്നാൽ നിങ്ങൾക്ക് ഊർജ്ജം സംരക്ഷിക്കാനാവും. നിങ്ങൾ എത്രത്തോളം വൈദ്യുതി ലാഭിക്കുന്നുവോ, അത്രത്തോളം വേഗത്തിൽ ചെടി വളരും. നിങ്ങൾ ഈ ചെടിയെ പരിപാലിക്കു. ഇവിടെ കാണിക്കുന്ന നിരപ്പ് സൂചിക ചെടിയുടെ നിലവിലുള്ള ആരോഗ്യസ്ഥിതിയെ പ്രതിനിധീകരിക്കുന്നു. ഉയർന്ന നിരപ്പ് ചെടിയുടെ നല്ല ആരോഗ്യസ്ഥിതിയെ കുറിക്കുന്നു.

Log on to	Code
www.kseb.clytics.com Register on the website to receive your reports online and save paper. Use the code on the right-hand side for registering.	**169489** Use this code along with your consumer ID while creating your account online.

Powered by **clytics**.

Kerala State Electricity Board
Aluva West

Area Code
A01-1-30

Report for
April 2016 - May 2016*

*Reflects the consumption of the previous billing cycle
*കഴിഞ്ഞ ബില്ലിംഗ് കാലയളവിലെ വൈദ്യുതി ഉപഭോഗത്തെ സൂചിപ്പിക്കുന്നു

Consumer ID **ഉപഭോക്താവിന്റെ ഐഡി**

[redacted]

Address not available

Introducing your personalised home energy report!
നിങ്ങളുടെ വ്യക്തിഗത ഭവനഊർജ്ജ റിപ്പോർട്ടിലേക്ക് സ്വാഗതം!

Save energy to grow the plant! ഊർജ്ജം സംരക്ഷിക്കൂ, ചെടിയെ വളർത്തൂ!

Your plant is currently at level 12.
The more energy you save compared to others, the faster your plant will grow.
Please turn overleaf to find out how you can save energy.

നിങ്ങളുടെ ചെടി ഇപ്പോൾ വളർച്ചയുടെ 12 ആം ഘട്ടത്തിലാണ്.
നിങ്ങൾ മറ്റുള്ളവരെ അപേക്ഷിച്ച് എത്രത്തോളം വൈദ്യുതി ലാഭിക്കുന്നുവോ, അത്രത്തോളം വേഗത്തിൽ ചെടി വളരും.
വൈദ്യുതി ലാഭിക്കാനുള്ള നുറുങ്ങുകൾ ലഭിക്കാൻ മറുപുറം കാണുക.

Comparison for താരതമ്യം April 2016 - May 2016

Your consumption was amongst the efficient homes. You have used 85 units less energy than similar homes.

വളരെ ക്ഷമതയുള്ള വീടുകളിൽ ഒന്നാണ് താങ്കളുടെത്. സമാനമായ മറ്റു വീടുകളിലേതിനേക്കാൾ 85 units കുറച്ചു വൈദ്യുതിയേ താങ്കൾ ഉപയോഗിച്ചിട്ടുള്ളു.

You have consumed 40 units in the last billing period: 01 Mar 2016 – 02 May 2016.
നിങ്ങൾ കഴിഞ്ഞ ബില്ലിംഗ് കാലയളവിൽ 40 units ഉപയോഗിച്ചു : 01 Mar 2016 – 02 May 2016.

What are similar homes?
These homes have a consumption pattern similar to your home.
സമാനമായ വീടുകൾ ഏതൊക്കെ ആണ്?സമാനമായ ഉപഭോഗ രീതിയുള്ള താങ്കളുടെ സമീപത്തുള്ള മറ്റു ഗൃഹങ്ങളാണവ.

What are efficient homes?
These homes consume less energy among homes similar to yours.
ക്ഷമതയുള്ള വീടുകൾ ഏതൊക്കെ ആണ്?സമാനവീടുകളിൽ ഏറ്റവും കുറഞ്ഞ ഉപഭോഗമുള്ളവയാണ് ക്ഷമതയുള്ള വീടുകൾ.

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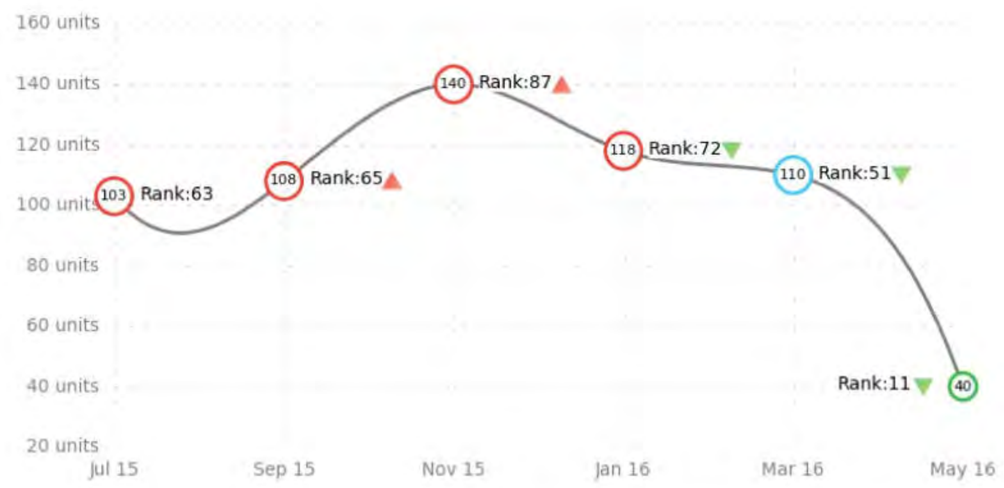
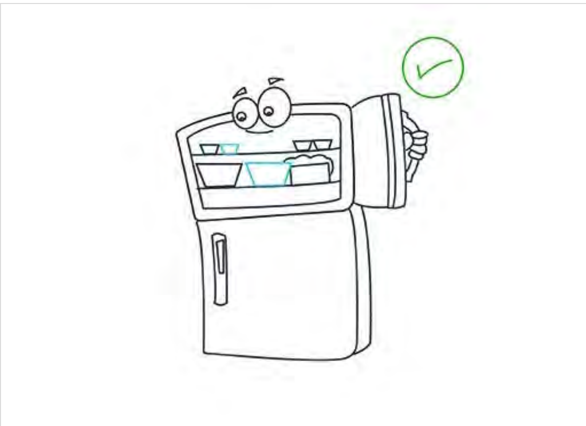
Consumption History കഴിഞ്ഞ കാലയളവിലെ ഉപഭോഗം

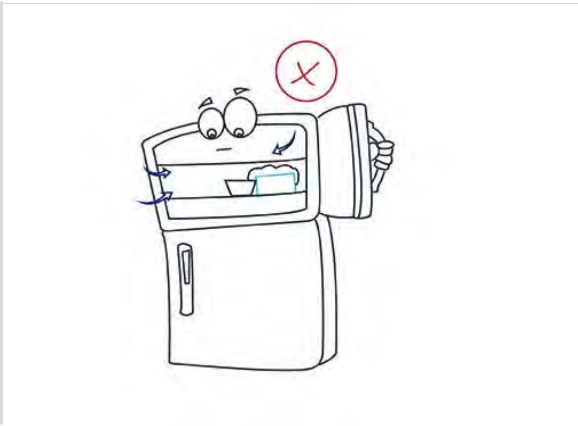
What was your electicity consumption in the last 12 months?
താങ്കളുടെ വീടിന്റെ കഴിഞ്ഞ 12 മാസത്തെ വൈദ്യുതി ഉപഭോഗം എത്രയാണ് ?



Rank indicates how your consumption compared with other 100 similar homes.
സമാനമായ 100 വീടുകളെ അപേക്ഷിച്ച് താങ്കളുടെ വൈദ്യുതി ഉപഭോഗം എത്രയെന്ന 'റാങ്ക്' സൂചിപ്പിക്കുന്നു.

Do you know: A full freezer is better than a partially filled
നിങ്ങൾക്കറിയാമോ: ഫ്രീസർ മുഴുവനായി നിറഞ്ഞിരിക്കുന്നതാണ് പകുതി നിറഞ്ഞിരിക്കുന്നതിനേക്കാൾ നല്ലത് ?





A non-empty freezer would increase efficiency slightly because there would be less air that changes when the door opens.
ഓരോ തവണ ഫ്രിഡ്ജ് തുറന്നടക്കുമ്പോഴും കുറച്ച് ചൂട് വായു ഫ്രീസറിൽ തങ്ങുന്നു. ഈ വായുവിനെ തണുപ്പിക്കാൻ കൂടുതൽ ഊർജം ആവശ്യമായി വരും.

A filled freezer contains less air that can exchange, so there's less warmer air inside to cool down when you finally close the door.
നിറഞ്ഞിരിക്കുന്ന ഫ്രീസർ അകത്തു തങ്ങിനില്ക്കുന്ന ചൂട് വായുവിന്റെ അളവ് കുറയ്ക്കും.

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റിപ്പോർട്ടുകൾ ഓൺലൈനിൽ ലഭിക്കാൻ വെബ്സൈറ്റിൽ റജിസ്റ്റർ ചെയ്യൂ.

Code കോഡ്
262182
Use this code along with your consumer ID while creating your account online.
ഈ കോഡും ഉപഭോക്താവിന്റെ ഐഡിയും ഉപയോഗിച്ച് ഓൺലൈൻ അക്കൗണ്ട് ഉണ്ടാക്കൂ.

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Kerala State Electricity Board
Aluva Town

Area Code
A01-18-5

Report for
June 2016 - July 2016*

*Reflects the consumption of the previous billing cycle
*കഴിഞ്ഞ ബില്ലിംഗ് കാലയളവിലെ വൈദ്യുതി ഉപഭോഗത്തെ സൂചിപ്പിക്കുന്നു

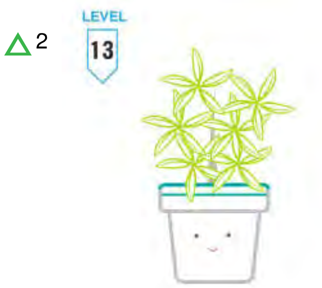
Consumer ID ഉപഭോക്താവിന്റെ ഐഡി

[redacted]

Address not available

Presenting your personalised home energy report!
നിങ്ങളുടെ വ്യക്തിഗത ഭവനഊർജ്ജ റിപ്പോർട്ടിലേക്ക് സ്വാഗതം!

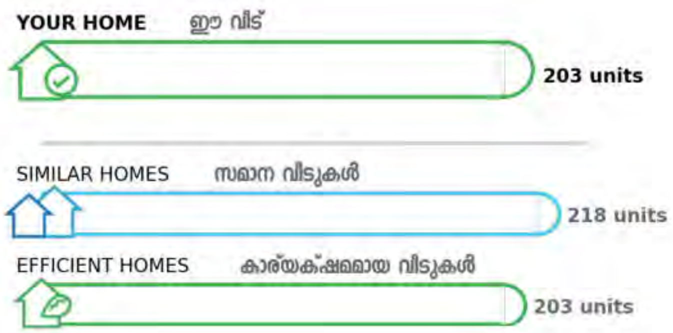
Save energy to grow the plant! ഊർജ്ജം സംരക്ഷിക്കു, ചെടിയെ വളർത്തു!



Your plant is currently at level 13. Congratulation! Your plant has grown up 2 places.
The more energy you save compared to others, the faster your plant will grow.
Please turn overleaf to find out how you can save energy.

നിങ്ങളുടെ ചെടി ഇപ്പോൾ വളർച്ചയുടെ 13 ആം ഘട്ടത്തിലാണ്. അഭിനന്ദനങ്ങൾ, നിങ്ങളുടെ ചെടി 2 ലെവൽ കൂടുതൽ വളർന്നിരിക്കുന്നു.
നിങ്ങൾ മറ്റുള്ളവരെ അപേക്ഷിച്ച് എത്രത്തോളം വൈദ്യുതി ലാഭിക്കുന്നുവോ, അത്രത്തോളം വേഗത്തിൽ ചെടി വളരും. വൈദ്യുതി ലാഭിക്കാനുള്ള നുറുങ്ങുകൾ ലഭിക്കാൻ മറുപുറം കാണുക.

Comparison for താരതമ്യം June 2016 - July 2016



Your consumption was amongst the efficient homes. You have used 15 units less energy than similar homes.

വളരെ ക്ഷമതയുള്ള വീടുകളിൽ ഒന്നാണ് താങ്കളുടെത്. സമാനമായ മറ്റ് വീടുകളിലേതിനേക്കാൾ 15 units കുറച്ചു വൈദ്യുതിയേ താങ്കൾ ഉപയോഗിച്ചിട്ടുള്ളു.

You have consumed 203 units in the last billing period: 23 May 2016 – 23 Jul 2016.
നിങ്ങൾ കഴിഞ്ഞ ബില്ലിംഗ് കാലയളവിൽ 203 units ഉപയോഗിച്ചു : 23 May 2016 – 23 Jul 2016.

What are similar homes?
These homes have a consumption pattern similar to your home.
സമാനമായ വീടുകൾ ഏതൊക്കെ ആണ്?സമാനമായ ഉപഭോഗ രീതിയുള്ള താങ്കളുടെ സമീപത്തുള്ള മറ്റു ഗൃഹങ്ങളാണവ.

What are efficient homes?
These homes consume less energy among homes similar to yours.
ക്ഷമതയുള്ള വീടുകൾ ഏതൊക്കെ ആണ്?സമാനവീടുകളിൽ ഏറ്റവും കുറഞ്ഞ ഉപഭോഗമുള്ളവയാണ് ക്ഷമതയുള്ള വീടുകൾ.

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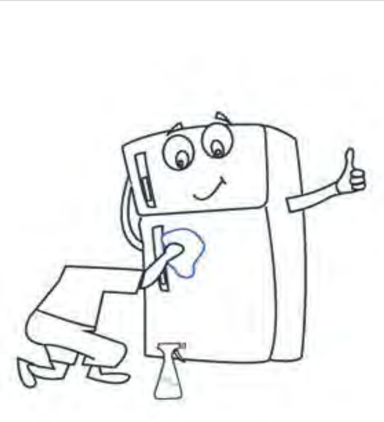
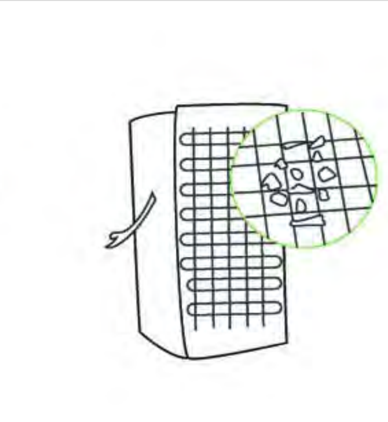
Consumption Ranking History കഴിഞ്ഞ കാലയളവിലെ ഉപഭോഗം

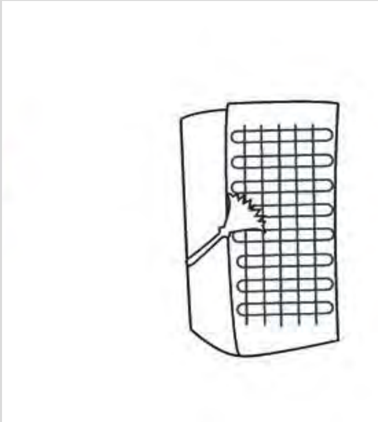
How has your rank changed in the last 12 months?
കഴിഞ്ഞ 12 മാസത്തെ താങ്കളുടെ വീടിന്റെ റാങ്കിങ് എത്രയാണ് ?

Rank indicates how your consumption compared with other 100 similar homes.
സമാനമായ 100 വീടുകളെ അപേക്ഷിച്ച് താങ്കളുടെ വൈദ്യുതി ഉപഭോഗം എത്രയെന്ന 'റാങ്ക്' സൂചിപ്പിക്കുന്നു.

Do you clean your fridge often?
നിങ്ങളുടെ ഫ്രിഡ്ജിന്റെ പൊടി തട്ടുക







Dust your fridge the next time you dust your house.
വീടിന്റെ പൊടി തട്ടുമ്പോൾ ഫ്രിഡ്ജിന്റെയും പൊടി തട്ടുക.

Check the coils behind the refrigerator
ഫ്രിഡ്ജിനു പിന്നിലെ കോയിലുകൾ പരിശോധിക്കുക

and use vacuums or dusters to clean it off and keep costs down.
അത് വാക്വം ക്ലീനറോ ഡസ്റ്ററുകളോ ഉപയോഗിച്ച് വൃത്തിയാക്കുകയും ചെലവ് കുറയ്ക്കുകയും ചെയ്യുക

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Kerala State Electricity Board
Aluva Town

Area Code
A01-18-34

Report for
August 2016 - Sep 2016*

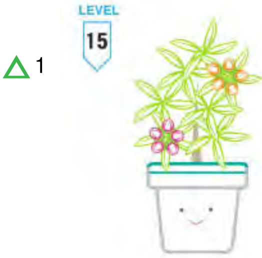
*Reflects the consumption of the previous billing cycle
*കഴിഞ്ഞ ബില്ലിംഗ് കാലയളവിലെ വൈദ്യുതി ഉപഭോഗത്തെ സൂചിപ്പിക്കുന്നു

Consumer ID ഉപഭോക്താവിന്റെ ഐഡി

[redacted]

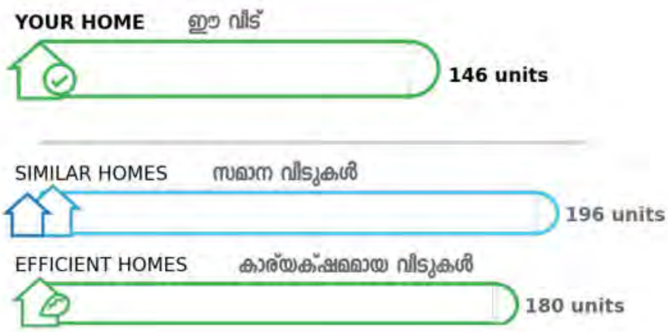
Address not available

Save energy to grow the plant!
ഊർജ്ജം സംരക്ഷിക്കൂ, ചെടിയെ വളർത്തൂ!



Your plant is currently at level 15. Congratulation! Your plant has grown up 1 place.
നിങ്ങളുടെ ചെടി ഇപ്പോൾ വളർച്ചയുടെ 15 ആം ഘട്ടത്തിലാണ്. അഭിനന്ദനങ്ങൾ, നിങ്ങളുടെ ചെടി 1 ലെവൽ കൂടുതൽ വളർന്നിരിക്കുന്നു.

Comparison for താരതമ്യം August 2016 - Sep 2016



Your consumption was amongst the efficient homes. You have used 50 units less energy than similar homes.

വളരെ ക്ഷമതയുള്ള വീടുകളിൽ ഒന്നാണ് താങ്കളുടെത്. സമാനമായ മറ്റ വീടുകളിലേതിനേക്കാൾ 50 units കുറച്ച വൈദ്യുതിയേ താങ്കൾ ഉപയോഗിച്ചിട്ടുള്ളൂ.

You have consumed 146 units in the last billing period: 23 Jul 2016 – 24 Sep 2016.
നിങ്ങൾ കഴിഞ്ഞ ബില്ലിംഗ് കാലയളവിൽ 146 units ഉപയോഗിച്ചു : 23 Jul 2016 – 24 Sep 2016.

What are similar homes?
These homes have a consumption pattern similar to your home.
സമാനമായ വീടുകൾ ഏതൊക്കെ ആണ്?സമാനമായ ഉപഭോഗ രീതിയുള്ള താങ്കളുടെ സമീപത്തുള്ള മറ്റ ഗൃഹങ്ങളാണവ.

What are efficient homes?
These homes consume less energy among homes similar to yours.
ക്ഷമതയുള്ള വീടുകൾ ഏതൊക്കെ ആണ്?സമാനവീടുകളിൽ ഏറ്റവും കറഞ്ഞ ഉപഭോഗമുള്ളവയാണ് ക്ഷമതയുള്ള വീടുകൾ.

How have you consumed energy in the last billing period ?
നിങ്ങൾ കഴിഞ്ഞ ബില്ലിങ്ങ് കാലയളവിൽ ഊർജ്ജം ഏതു രീതിയിൽ ഉപയോഗിച്ചു?

51 %	Cooling തണുപ്പിക്കുന്നതിന്	74 units
33 %	Lighting ലൈറ്റിംഗ്	48 units
9 %	Kitchen അടുക്കള	13 units
7 %	Others മറ്റുള്ളവ	10 units

The table on the left gives the pattern of consumption in homes similar to you, across major categories. Kitchen for instance comprises the consumption of fridge, induction stove, mixer grinder, etc.

ഇടതുവശത്തെ പട്ടികയിൽ, നിങ്ങളുടെ സമാനമായ വീടുകളിലെ ഉപഭോഗ രീതി നൽകിയിരിക്കുന്നു.
ഉദാഹരണത്തിന് , അടുക്കളയിൽ ഫ്രിഡ്ജ് , ഇൻഡക്ഷൻ സ്റ്റൌ, മിക്സർ ഗ്രൈൻഡർ എന്നിവയുടെ ഊർജ്ജ ഉപഭോഗം ഉൾപ്പെടുന്നു.

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Consumption Ranking History കഴിഞ്ഞ കാലയളവിലെ ഉപഭോഗം

How has your rank changed in the last 12 months?
കഴിഞ്ഞ 12 മാസത്തെ താങ്കളുടെ വീടിന്റെ റാങ്കിങ് എത്രയാണ് ?

Rank indicates how your consumption compared with other 100 similar homes.
സമാനമായ 100 വീടുകളെ അപേക്ഷിച്ച് താങ്കളുടെ വൈദ്യുതി ഉപഭോഗം എത്രയെന്ന 'റാങ്ക്' സൂചിപ്പിക്കുന്നു.

Exterior Finish: Install a reflective coating
പുറത്തെ ഫിനിഷിങ്: ഒരു റിഫ്ലക്ടീവ് കോട്ടിങ് നൽകുക

80% to 95% of heat gain during summer is transferred through the walls and ceiling of the building by way of conduction and radiation.
വേനൽക്കാലത്തെ 89%-95% ചൂടും ചാലനവും വികിരണവും വഴി കെട്ടിടത്തിന്റെ ചുവരുകളിലൂടെയും മച്ചിലൂടെയുമാണ് കടന്നു വരുന്നത്.

Install a reflective coating on your roofs and walls, which reduces temperature up to 5 C
നിങ്ങളുടെ മേൽക്കൂര, ചുവരുകൾ എന്നിവയിൽ ഒരു റിഫ്ലക്ടീവ് കോട്ടിങ് നൽകുക, ഇത് ചൂട് 5 സെല്ഷ്യസ് വരെ കുറയ്ക്കുന്നു.

What's more cooler walls, contract and expand less, so there are fewer cracks in your masonary
മാത്രമല്ല, തണുപ്പുള്ള ചുവരുകൾ വളരെ കുറച്ചു മാത്രം വികസിക്കുകയും സങ്കോചിക്കുകയും ചെയ്യുന്നതിനാൽ കെട്ടിടത്തിൽ വിള്ളലുകളും കുറവായിരിക്കും.

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റിപ്പോർട്ടുകൾ ഓൺലൈനിൽ ലഭിക്കാൻ വെബ്സൈറ്റിൽ റജിസ്റ്റർ ചെയ്യൂ.

Code കോഡ്

270310

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ഈ കോഡും ഉപഭോക്താവിന്റെ ഐഡിയും ഉപയോഗിച്ച് ഓൺലൈൻ അക്കൗണ്ട് ഉണ്ടാക്കു.

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Kerala State Electricity Board
Kalamassery

Area Code
A02-4-24

Report for
Oct 2016 - Nov 2016*

*Reflects the consumption of the previous billing cycle
*കഴിഞ്ഞ ബില്ലിംഗ് കാലയളവിലെ വൈദ്യുതി ഉപഭോഗത്തെ സൂചിപ്പിക്കുന്നു

Consumer ID ഉപഭോക്താവിന്റെ ഐഡി

[redacted]

[redacted]

Save energy to grow the plant!
ഊർജ്ജം സംരക്ഷിക്കൂ, ചെടിയെ വളർത്തൂ!

Your plant is currently at level 13. Congratulation! Your plant has grown up 1 place.
നിങ്ങളുടെ ചെടി ഇപ്പോൾ വളർച്ചയുടെ 13 ആം ഘട്ടത്തിലാണ്. അഭിനന്ദനങ്ങൾ, നിങ്ങളുടെ ചെടി 1 ലെവൽ കൂടുതൽ വളർന്നിരിക്കുന്നു.

Comparison for താരതമ്യം Oct 2016 - Nov 2016

Your consumption was higher than average. You have used around 18% more energy than similar homes.

താങ്കളുടെ ഉപഭോഗം സമാന വീടുകളിലേതിനേക്കാൾ കൂടുതലാണ്. താങ്കൾ സമാന വീടുകളിലേതിനേക്കാൾ 18 % കൂടുതൽ വൈദ്യുതി ഉപയോഗിച്ചു.

You have consumed 266 units in the last billing period: 03 Sep 2016 – 04 Nov 2016.
നിങ്ങൾ കഴിഞ്ഞ ബില്ലിംഗ് കാലയളവിൽ 266 units ഉപയോഗിച്ചു : 03 Sep 2016 – 04 Nov 2016.

What are similar homes?
These homes have a consumption pattern similar to your home.
സമാനമായ വീടുകൾ ഏതൊക്കെ ആണ്?സമാനമായ ഉപഭോഗ രീതിയുള്ള താങ്കളുടെ സമീപത്തുള്ള മറ്റു ഗൃഹങ്ങളാണവ.

What are efficient homes?
These homes consume less energy among homes similar to yours.
ക്ഷമതയുള്ള വീടുകൾ ഏതൊക്കെ ആണ്?സമാനവീടുകളിൽ ഏറ്റവും കുറഞ്ഞ ഉപഭോഗമുള്ളവയാണ് ക്ഷമതയുള്ള വീടുകൾ.

How have you consumed energy in the last billing period ?
നിങ്ങൾ കഴിഞ്ഞ ബില്ലിങ് കാലയളവിൽ ഊർജ്ജം ഏതു രീതിയിൽ ഉപയോഗിച്ചു?

53 %	Cooling തണുപ്പിക്കുന്നതിന്	140 units
22 %	Kitchen അടുക്കള	58 units
17 %	Lighting ലൈറ്റിംഗ്	45 units
8 %	Others മറ്റുള്ളവ	21 units

The table on the left gives the pattern of consumption in homes similar to you, across major categories. Kitchen for instance comprises the consumption of fridge, induction stove, mixer grinder, etc.

ഇടതുവശത്തെ പട്ടികയിൽ, നിങ്ങളുടെ സമാനമായ വീടുകളിലെ ഉപഭോഗ രീതി നൽകിയിരിക്കുന്നു. ഉദാഹരണത്തിന് , അടുക്കളയിൽ ഫ്രിഡ്ജ് , ഇൻഡക്ഷൻ സ്റ്റൌ, മിക്സർ ഗ്രൈൻഡർ എന്നിവയുടെ ഊർജ്ജ ഉപഭോഗം ഉൾപ്പെടുന്നു.

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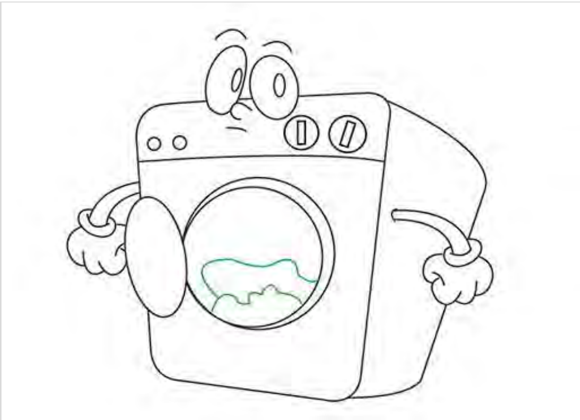
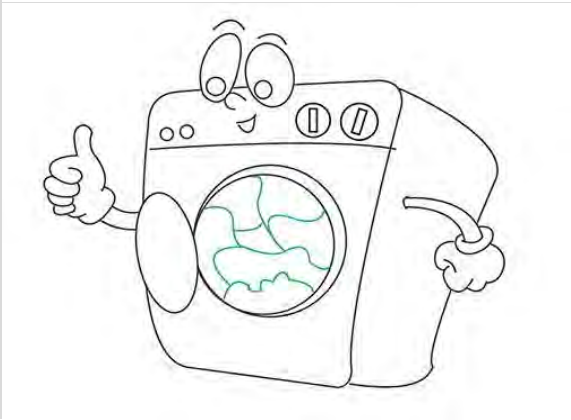
Consumption Ranking History കഴിഞ്ഞ കാലയളവിലെ ഉപഭോഗം

How has your rank changed in the last 12 months?
കഴിഞ്ഞ 12 മാസത്തെ താങ്കളുടെ വീടിന്റെ റാങ്കിങ് എത്രയാണ് ?

Rank indicates how your consumption compared with other 100 similar homes.
സമാനമായ 100 വീടുകളെ അപേക്ഷിച്ച് താങ്കളുടെ വൈദ്യുതി ഉപഭോഗം എത്രയെന്ന 'റാങ്ക് ' സൂചിപ്പിക്കുന്നു.

A full load is same as a half load when it comes to washing
അലക്കുമ്പോൾ ഫുൾ ലോഡും ഹാഫ് ലോഡും ഒരു പോലെയാണ്





Wash full loads of clothes when possible. The energy used is same even if you partially load the washing machine.

പറ്റുമെങ്കിൽ എപ്പോഴും ഫുൾ ലോഡിൽ അലക്കുക. നിങ്ങൾ മെഷീൻ ഫുൾ ലോഡ് ചെയ്താലും ഭാഗികമായി ലോഡ് ചെയ്താലും ഉപയോഗിക്കുന്ന കറന്റ് ഒന്നാണ്.

If you have a load sensor in the washing machine it will help you to determine the appropriate lot.If smaller load is absolutely necessary do remember to use less water.

മെഷീനിൽ ഒരു ലോഡ് സെൻസർ ഉണ്ടെങ്കിൽ ഉചിതമായ ലോഡ് കണ്ടെത്താൻ ഇത് സഹായിക്കും. കുറഞ്ഞ ലോഡ് അലക്കിയേ പറ്റൂ എങ്കിൽ വെള്ളവും കുറച്ച് മാത്രം ഉപയോഗിക്കുക.

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റിപ്പോർട്ടുകൾ ഓൺലൈനിൽ ലഭിക്കാൻ വെബ്സൈറ്റിൽ റജിസ്റ്റർ ചെയ്യൂ.

Code കോഡ്

854042

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ഈ കോഡും ഉപഭോക്താവിന്റെ ഐഡിയും ഉപയോഗിച്ച് ഓൺലൈൻ അക്കൗണ്ട് ഉണ്ടാക്കൂ.

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Kerala State Electricity Board
Kalamassery

Area Code
A02-2-78

Report for
Dec 2016 - Jan2017*

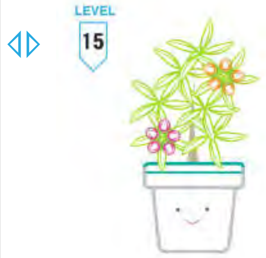
*Reflects the consumption of the previous billing cycle
*കഴിഞ്ഞ ബില്ലിംഗ് കാലയളവിലെ വൈദ്യുതി ഉപഭോഗത്തെ സൂചിപ്പിക്കുന്നു

Consumer ID ഉപഭോക്താവിന്റെ ഐഡി

[redacted]

Address not available

Save energy to grow the plant!
ഊർജ്ജം സംരക്ഷിക്കു, ചെടിയെ വളർത്തു!



Your plant is currently at level 15. Your plant is at the same level as the last month.
നിങ്ങളുടെ ചെടി ഇപ്പോൾ വളർച്ചയുടെ 15 ആം ഘട്ടത്തിലാണ്. നിങ്ങളുടെ ചെടി കഴിഞ്ഞ മാസത്തെ അതേ അവസ്ഥയിലാണ്.

Comparison for താരതമ്യം Dec 2016 - Jan2017

Your consumption was average. Some of the efficient homes have used 18% less energy.

താങ്കളുടെ ഉപഭോഗം ശരാശരിയാണ്. ഉപഭോഗക്ഷമതയുള്ള വീടുകൾ 18 % വൈദ്യുതി കുറവാണ് ഉപയോഗിച്ചിട്ടുള്ളത്.

You have consumed 170 units in the last billing period: 02 Nov 2016 – 04 Jan 2017.
നിങ്ങൾ കഴിഞ്ഞ ബില്ലിംഗ് കാലയളവിൽ 170 units ഉപയോഗിച്ചു : 02 Nov 2016 – 04 Jan 2017.

What are similar homes?
These homes have a consumption pattern similar to your home.
സമാനമായ വീട്ടുകൾ ഏതൊക്കെ ആണ്?സമാനമായ ഉപഭോഗ രീതിയുള്ള താങ്കളുടെ സമീപത്തുള്ള മറ്റു ഗൃഹങ്ങളാണവ.

What are efficient homes?
These homes consume less energy among homes similar to yours.
ക്ഷമതയുള്ള വീടുകൾ ഏതൊക്കെ ആണ്?സമാനവീടുകളിൽ ഏറ്റവും കുറഞ്ഞ ഉപഭോഗമുള്ളവയാണ് ക്ഷമതയുള്ള വീടുകൾ.

How have you consumed energy in the last billing period ?
നിങ്ങൾ കഴിഞ്ഞ ബില്ലിങ്ങ് കാലയളവിൽ ഊർജ്ജം ഏതു രീതിയിൽ ഉപയോഗിച്ചു?

50 %	Kitchen അടുക്കള	85 units
32 %	Cooling തണുപ്പിക്കുന്നതിന്	54 units
14 %	Lighting ലൈറ്റിംഗ്	23 units
4 %	Others മറ്റുള്ളവ	6 units

The table on the left gives the pattern of consumption in homes similar to you, across major categories. Kitchen for instance comprises the consumption of fridge, induction stove, mixer grinder, etc.

ഇടതുവശത്തെ പട്ടികയിൽ, നിങ്ങളുടെ സമാനമായ വീടുകളിലെ ഉപഭോഗ രീതി നൽകിയിരിക്കുന്നു.
ഉദാഹരണത്തിന് , അടുക്കളയിൽ ഫ്രിഡ്ജ് , ഇൻഡക്ഷൻ സ്റ്റൌ, മിക്സർ ഗ്രൈൻഡർ എന്നിവയുടെ ഊർജ്ജ ഉപഭോഗം ഉൾപ്പെടുന്നു.

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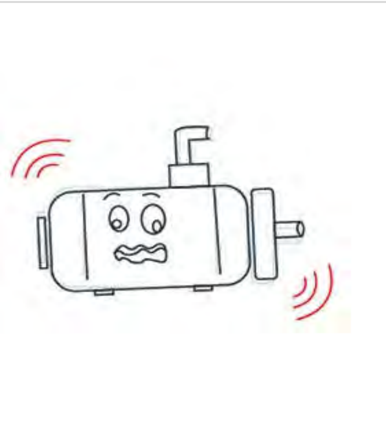
Consumption Ranking History കഴിഞ്ഞ കാലയളവിലെ ഉപഭോഗം

How has your rank changed in the last 12 months?
കഴിഞ്ഞ 12 മാസത്തെ താങ്കളുടെ വീടിന്റെ റാങ്കിങ് എത്രയാണ് ?

Rank indicates how your consumption compared with other 100 similar homes.
സമാനമായ 100 വീട്ടുകളെ അപേക്ഷിച്ച് താങ്കളുടെ വൈദ്യുതി ഉപഭോഗം എത്രയെന്നു 'റാങ്ക് ' സൂചിപ്പിക്കുന്നു.

When was the last time you got your pump serviced?
പമ്പ് സർവീസ് ചെയ്യുക



Is there any unusual noise, vibrations or high temperatures observed while you operate your pump?
നിങ്ങൾ പമ്പ് പ്രവർത്തിപ്പിക്കുമ്പോൾ അസാധാരണമായ ശബ്ദമോ കമ്പനങ്ങളോ ചൂടോ ശ്രദ്ധയിൽ പെട്ടിട്ടുണ്ടോ?

It is recommended that you undertake annual maintenance of your pumps.
നിങ്ങളുടെ പമ്പുകൾ വർഷം തോറും കേടുപാടുകൾ തീർക്കേണ്ടതുണ്ട്.

It saves you an unplanned downtime. You save money on energy costs as well.
മുൻ കൂട്ടി കാണാത്ത വിധം അവ കേടാകുന്നത് ഇതിലൂടെ തടയാം. നിങ്ങളുടെ കറന്റ് ചാർജും ലാഭിക്കാം.

Log on to ലോഗ് ഇൻ	Code കോഡ്
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