EnerPlan: Smart Energy Management Planning for Home Users

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Abstract. The impending energy crisis has driven up the cost of electricity at an exponential rate. Managing electric consumption thus has become a very crucial task especially for home consumers. In this paper we present EnerPlan, a non-intrusive method to aid consumers to reduce their energy cost by advising them a consumption plan for their devices. Our system builds consumer classes based on regional statistical data. Using these classes a target consumer's device load and distribution is inferred and this inferred data is used to construct a device usage plan which when followed can reduce the electric bill of the user. We use expert-based and auto-generated fuzzy rules to construct our system. Results of the two different methods are presented and compared. Our results demonstrate that the data prepared using the proposed approach can be used to save electricity. The users can reduce their electricity bills by following the plans made by EnerPlan.

1 Introduction

Only few years ago, the push for utility providers was to increase their distribution networks to provide electricity to as many people as possible. But the continuous increase in electricity demand and the shrinking resources of energy has provided a new scenario where we are seeing scarcity of electricity in the existing setup. It is argued that the current usage of electricity is not optimal and various ways to conserve energy exist through which the same resources can be extended to provide energy to more people [10],[5]. So much so that it has been shown that only by providing the consumption of energy in real time has resulted in savings of up to 20% [4]. If more support is provided for user in planning their consumption then surely more savings can be achieved.

On the other hand it has been shown that peer competition based systems are also very effective in energy conservation. Abrahamse and colleagues present various energy conservation measures taken by various researchers and utilities [1]. For instance Alcot presents the results of OPOWER in which reports of consumption of the household and that of neighbors was mailed to participant [2]. Statistically significant savings were observed across the board during this study.

But planning to conserve energy or to have realistic targets for each device to achieve savings is not an easy task. This has been shown by Kim and

Shcherbakova [7] where they have described user fatigue and lack of relevant knowledge as the most important factors in the failure of demand side management. The issue is for user to know where and how much can she save. There are various scheduling algorithms proposed to plan consumption of energy for reducing cost. However, the schedulers proposed do not consider the socio-economic aspect of the consumption. But, as has been shown by Dhalquist and colleagues, socio-economic factors greatly impact the residential consumption habits [15]. Thus a successful scheduler must consider these factors to be acceptable by the users.

In this paper we provide peer-support inspired solution which builds device consumption patterns based on the socio-economic groupings in a society and for energy conscious consumer, provide the range of consumption within their peer to inspire conservation. Our philosophy is that a person is more likely to draw inspiration from a person in a similar situation. If a person in specific socio-economic group is provided the information of how her peers are consuming then she is more likely to follow suit. It will be even more beneficial if this information is provided at the granularity of a device, for instance a user is informed how much HVAC is used by her peers. This provides a concrete target for the consumer for each device to conserve energy. To achieve this goal our system goes through the following three step process.

- Simulate social patterns to construct different classes of users.
- Generate user preference, usage and consumptions of different devices for each class.
- Provide information of peer bounds to consumers.

The architecture of these steps are shown in figure 1. The statistical basis for the simulation and data generation are discussed in section 2.

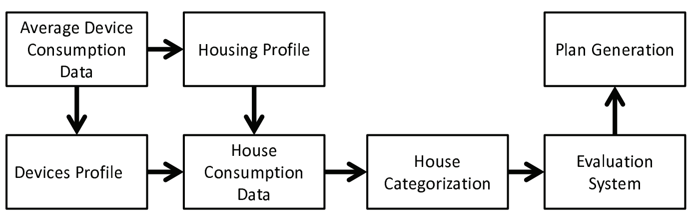


Fig. 1. EnerPlan Application Architecture

Through this way we create consumption bounds for peers for each device. That is, for each user we provide a general bound of usage of devices for people who belong to similar socio-economic background. When a user wishes to conserve energy using our technique, we evaluate her consumption habits through her bill. We then provide her a comparison with her peers on device per device basis. By knowing what other people in her socio-economic group consume she now has a good idea of where she is over-spending and how much she can possibly save if she wants to conserve energy and thereby reduce her bill.

We evaluated our system using expert-based and auto-generated fuzzy inference systems. The results show that in absence of experts the auto-generated systems can be used to get the most appropriate plan if optimized as proposed here.

The paper is organized as follows: Section 2 discusses the classification of houses and the process to assemble the devices in a house. The process of generating plans through fuzzy inference system is discussed in section 3. Results and discussion on the results is provided in section 4. Section 5 concludes the paper and presents the future directions.

2 Data Acquisition

We have developed a system to assist a consumer to conserve as much electricity as possible. We provide this assistance by providing device consumption ranges for her socio-economic peers. To build this assistance system we require a simulation model of the different socio-economic group and then infer the devices and their consumption for each group. In this section we discuss how we build the population classes and the process to identify the device distribution and its consumption.

2.1 Simulating Socio-economic classifications

We divided our population in four categories. This division is based on the statistical data available for city of Roseville, California, USA. The major discriminating feature is the number of rooms in a house and the income levels. Since exact data of number of devices present in the house is not available, we use the penetration rates in conjunction with size of house, number of occupants and the income distribution to construct a sample representative house population for our plan construction.

2.2 Construction of Device Consumption Model

The second task of data acquisition is to model consumption of device for each class. Based on the device distribution in the simulation house population, we constructed average monthly consumption for devices using the online published data by city of Roseville [1]. Table 1 Shows the consumption records from city of Roseville for the consumption in hours, watts and dollar amount for each appliance type in the city of Roseville. The simulation model was verified by comparing the average bill for different classes against the published data by U.S. department of energy [2].

[1] http://www.roseville.ca.us/civica/filebank/blobdload.asp?BlobID=7086
[2] http://www.eia.gov/electricity/sales_revenue_price/html/table5_a.html

Appliance	Watts	Average hour use per month	KWh used per month	Average cost per month
Air Conditioner (Window Unit)	1,100	90	99	$22
Fan Ceiling	80	50	12	$3
Iron	1,000	6	6	$6
Refrigerator/Freezer	2,000	24	48	$11
TV	156	180	28	$6
Computer	65	192	47	$10
Dishwasher	1,200	25	30	$7
Microwave Oven	1,400	15	21	$5
Indoor Grow Light	600	360	216	$48
Clothes Dryer - Electric	4,600	20	92	$20
Electric Wall Heater	1,500	150	225	$50
Clothes Washer Standard	250	10	42	$9

Table 1. Average consumption of devices on monthly basis for the city of Roseville, Califorina, USA

3 Planning through Fuzzy Inference Systems (FIS)

We have evaluated the categorization of the households using Fuzzy Inference Systems (FIS). FIS are useful in modeling systems with uncertainty and complexity. An FIS has a set of fuzzy rules and an inference mechanism where more than one rules can be triggered at one time instance [11]. Rule in a FIS have fuzzy inputs as antecedents and fuzzy output as consequent. A typical conjunctive rule in a FIS looks like as follows:

$$IF\ input1\ is\ Low\ AND\ input2\ is\ High\ THEN\ output\ is\ Medium \tag{1}$$

where Low, $Medium$, $High$ are examples of linguistic labels used for input and output variables. We have generated different Sugeno type FIS [14] to generate electricity consumption plans, one Mamdani [9] type FIS since it is more intuitive and easy to understand. The Sugeno-type FIS have been optimized using Adaptive-Network-Based Fuzzy Inference System (ANFIS) [12]. The complete process of FIS development is depicted in figure 2.

Rules in the fuzzy inference systems have been developed using two methods: through expert as well as through auto-rule generation. The expert-based rules have been conjunctive with multiple antecedents. The antecedents are linguistic labels for the input parameters rooms, usage, and season.

3.1 Expert-based FIS

First step to develop the FIS is to analyze the inputs and design membership functions for each input. The second step is to apply t-norm operator [11] to calculate the final output. These steps are carried out for both the Mamdani and the Sugeno models. Difference between these two systems is the type of

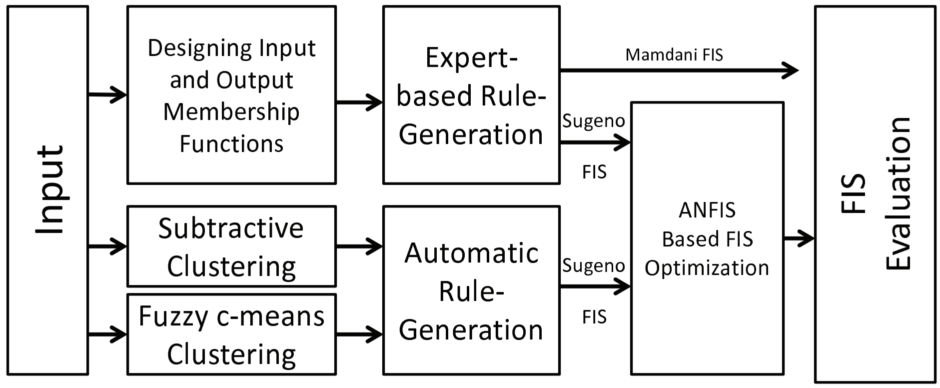


Fig. 2. Complete FIS development process

output function. The output function for a Mamdani FIS is also fuzzy whereas the output function y for Sugeno FIS can be linear as well as constant as follows:

$$y \;=\; \sum_{i=1}^{k} \alpha_i x_i + \beta_i \tag{2}$$

where k is total number of antecedents (input parameters), α_i and β_i are coefficients which can be different for each parameter x_i. Values of α_i and β_i can be modified in order to optimize the FIS performance.

3.2 Auto-Generated FIS

Automatic fuzzy rules have been generated using two cluster analysis methods namely subtractive clustering [13], and fuzzy c-means clustering [3]. Afterwards Sugeno-type inference systems have been developed for all methods.

Subtractive Clustering (SC) based methods requires the cluster *radii*. Two parameters are determined using the cluster *radii*; the number of rules generated and the number of membership functions for each input. The input parameters remain in same cluster as long as their distance from each other is less than the specified radius. The data points at a distance less than *radii* are removed. After this removal the next most probable cluster center is identified and the same process of removing data points is repeated. Once the clusters have been identified, the number of clusters corresponds to the number of membership functions for each input and the total number of rules to be extracted. The input functions are Gaussian and the output function is linear in this case.

The number of rules to be generated and the number of membership functions for each input are determined differently in the first two methods. In the first method these values are explicitly specified whereas in the second method subtractive clustering determines the values for these parameters. Our third method employs Fuzzy c-means Clustering (FC) to determine these two values. The type of membership functions for this method is kept Gaussian and the the output is linear.

3.3 ANFIS for FIS Optimization

Adaptive-Network-Based Fuzzy Inference System [12] has been used to determine the optimal membership function parameters i.e. what should be range for a certain membership function. A Sugeno-type FIS is sent as input to ANFIS alongwith training data and ANFIS uses neural networks to find the best parameters for the membership functions using least squares and back-propagation gradient descent methods [6] simultaneously. This optimized FIS is then evaluated using test data.

3.4 Evaluation Parameters

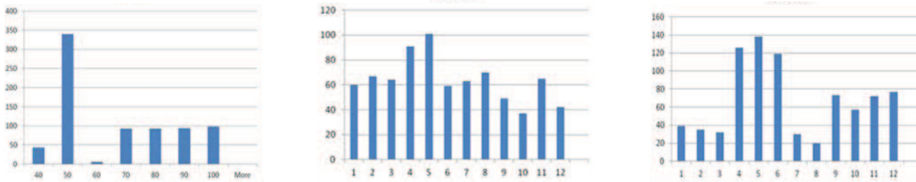
The evaluation parameters used for comparing the models are *Accuracy*, *Precision*, *Recall* and False Positive Rate (*FP Rate*). Our data has multiple classes therefore Precision, Recall and False Positive Rate are separately calculated for each class and their average values are reported. All these measures can be derived from a confusion matrix.

4 Results and Discussion

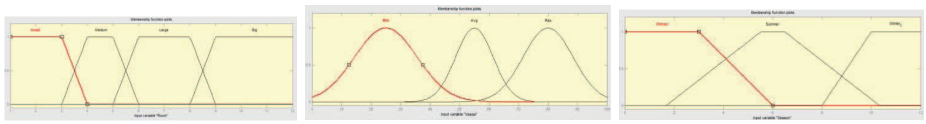
We have used two types of membership functions to generate Mamdani and Sugeno type FIS: Trapezoidal and Gaussian. These FIS have been generated by observing the distribution of input parameters as shown in figure 3. Since there are 16 types of plans, there are 16 bell shaped membership functions for the output variable *Plan* in case of Mamdani FIS. In case of Sugeno FIS the output function has 16 constant values. Since there are 16 classes, the figure shows 16 membership functions for each FIS. Using the expert knowledge 48 rules have been generated and performance of the two FIS have been recorded. The Sugeno FIS has been further optimized using ANFIS.

In order to demonstrate the planning task in absence of experts, we have generated automatic fuzzy rules using three methods. The input membership functions for the three methods are shown in figure 4. Parameter of membership functions for these FIS are then optimized through ANFIS with the parameter settings given in table 2. The shape of the input membership functions after optimization is also given in figure 4.

The randomly generated data for 2000 houses has been divided into training and test sets with 50% houses in each set. The FIS have been generated using training data and tested using test data. Further noise was added to data to make the data realistic. The data with noise includes houses with large number of rooms but a small number of appliances, small number of rooms with large number of appliances and houses with strange usage patterns in different seasons.

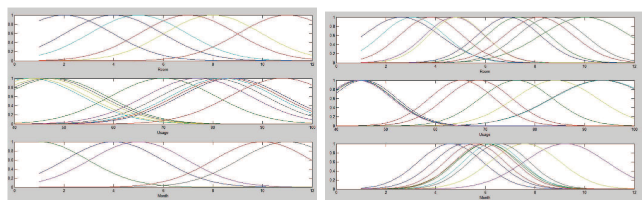


(a) rooms (b) usage (c) season

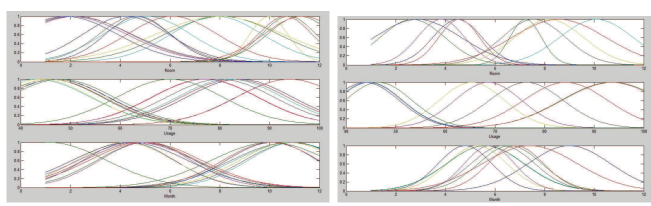


(d) rooms (e) usage (f) season

Fig. 3. Frequency distribution and corresponding membership functions for all input variables



(a) SC (b) FC



(c) SC (d) FC

Fig. 4. Shape of membership functions for all input to auto-generated FIS before and after ANFIS based optimization. Inputs are rooms, usage, season in each sub-figure. (a) to (c) before ANFIS, (d) to (f) after ANFIS

Rule Generation	Epoch	Nodes	Total Parameters	Linear Parameters	Nonlinear Parameters	Training Data Pairs	Fuzzy Rules
Expert-based	100	74	24	1536	34	58	24
SC	100	142	68	1536	102	170	17
FC	100	86	40	1536	60	100	10

Table 2. ANFIS Parameter Settings for the Expert-based and Auto-Generated Rules

Models	Accuracy	Recall	FP Rate	Precision
Expert-based Mamdani	0.79	0.785	0.014	0.843
Expert-based Sugeno	0.78	0.779	0.015	0.784
Sugeno with ANFIS	0.99 ↑	0.991 ↑	0.001	0.991 ↑
SC	0.37	0.372	0.036	0.361
SC with ANFIS	0.46 ↑	0.462 ↑	0.031	0.427 ↑
FC	0.25	0.254	0.053	0.228
FC with ANFIS	0.41 ↑	0.409 ↑	0.033	0.416 ↑

Table 3. Comparison of all FIS

This data has been used to develop and test the best performing FIS. Test results for all the FIS are reported in table 3.

The results show that before the optimization, the expert based FIS performed significantly better than the auto-generated FIS. But it is difficult to have an expert to develop fuzzy rules. In such a case auto-generated FIS are a good option. But the poor results from all the auto-generated FIS here show that they may not become the first choice for planning. But the ↑ arrows in the table demonstrate that the performance of expert-based as well as auto-generated FIS can be enhanced using ANFIS based optimization. Hence the auto-generated FIS are an obvious choice in absence of experts. The boost in performance of the expert-based FIS after optimization is encouraging. This way the parameters of the membership functions can be readjusted if an expert has chosen incorrect parameter values.

The optimization has always improved the values for all the evaluation parameters. In case of *Accuracy*, *Recall*, and *Precision* the values have always increased and the $FPRate$ has always decreased.

5 Conclusions and Future Works

This paper has presented EnerPlan as a technique to manage the electricity consumption for home users. The proposed technique provides device consumption ranges to the home users with respect to their home size and the season. We have used real device consumption data to simulate four classes of households. This simulated data is then used to provide energy consumption plans. These have been generated using fuzzy inference systems (FIS). The fuzzy inference systems have been generated with the help of experts as well as through auto-rule generation. Both types of the FIS have been optimized using neural networks in order to obtain the accurate plans. The expert based FIS have performed better than the auto-generated FIS but unavailability of an expert is always a problem. The auto-generated FIS are the alternative solution but the three methods discussed in this paper do not perform better than the expert based FIS. However, optimizing the auto-generated FIS has resulted in performance gain for all the optimizable FIS.

Our proposed technique is part of home energy management (HEM) infrastructure proposed for the future smart grids. We intend to integrate our technology with our home grown PCAT solution [8]. PCAT is capable of integrating with home area network to visualize and energy consumption. With addition of this technology our tool will provide all the features except for social media. Currently our tool is a stand alone application downloadable from URL.

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