Electrical Power and Energy Systems 100 (2018) 508–516

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

journal homepage: www.elsevier.com/locate/ijepes

# Probabilistic baseline estimation based on load patterns for better residential customer rewards

Yang Weng[a,*], Jiafan Yu[b], Ram Rajagopal[c]

[a] School of Electrical, Computer and Energy Engineering, Arizona State University, United States
[b] Department of Electrical Engineering, Stanford University, United States
[c] Civil and Environmental Engineering, Stanford University, United States

ARTICLE INFO

*Keywords:*
Demand response
Residential customers
Reward
Probabilistic baseline estimation
User behavior

ABSTRACT

Residential customers are increasingly participating in demand response program for both economic savings and environmental benefits. For example, baseline estimation-based rewarding mechanism is currently being deployed to encourage customer participation. However, the deterministic baseline estimation method good for commercial users was found to create erroneous rewards for residential consumers. This is due to larger uncertainty associated with residential customers and the inability of a deterministic approach to capturing such uncertainty. Different than the deterministic approach, we propose to conduct probabilistic baseline estimation and pay a customer over a period of time when the customer's predicted error decreases due to reward aggregation. To achieve this goal, we analyze 12,000 residential customers' data from PG&E and propose a Gaussian Process-based rewarding mechanism. Real data from PG&E and OhmConnect are used in validating the algorithm and showing fairer payment to residential customers. Finally, we provide a theoretical foundation that the proposed method is always better than the currently used industrial approaches.

## 1. Introduction

Federal Energy Regulatory Commission defines demand response (DR) as electric usage adjustments by the consumers from their normal consumption patterns [1]. Such adjustments are in response to (1) changes in the price of electricity over time, or (2) incentive payments designed to induce lower electricity consumption at usage peaks or when the system reliability is jeopardized [2].

Traditional DR programs are usually designed for large commercial customers, where a baseline is used for rewards. As the power usage of these customers is predictable, current baseline estimation methods for commercial users assume that the uncertainties can be ignored. So, a deterministic baseline evaluation is used for the electricity consumption estimation based on the no-DR period [3,4]. The difference between an estimated normal consumption and the actual usage is used to calculate the savings [5–7]. For example, deterministic methods such as simple load average and temperature-based linear regression have been used for commercial customers with satisfactory results [8–10]. DR program had a great success with large power consumption users. GreenTech Media reported in 2013 that 8.7 million dollars in revenue had been generated within seven months in the Pennsylvania, Jersey, Maryland (PJM) Power Pool by conducting demand response in system operation with mostly large customers.

While large customers currently create a significant portion of the revenue in the DR programs, the smaller residential consumers hold the key to potential growth in the DR customer number and the DR revenue. For example, there are 9.3 million customers participated in DR programs by March 2016 in U.S., but more than 90% of them are in the residential sector. In addition to making profits, DR at residential level is also becoming an attractive solution for the radically increased renewable energy to balance the local power flow. For these reasons, California Public Utilities Commission (CPUC) issued the Electric Rule 24, calling for the opening of direct participation of residential customers in DR programs. Now, consumers can call into bid for aggregated 15-min load reductions into Pacific Gas and Electric Company (PG&E)'s Intermittent Renewable Management Pilot Phase 2 program to earn payments directly from CAISO's Proxy Demand Resource product. These grid market calls can happen several times a week, compared to the relatively rare peak events that can trigger a traditional DR.

In response to this incentive, private companies like OhmConnect started to expand beyond utility-operated demand response for residential customers. As these consumers are reluctant to let aggregator companies have total control of their related assets [11], a baseline-based rewarding method for large customers was initially

* Corresponding author.
*E-mail address:* yang.weng@asu.edu (Y. Weng).

https://doi.org/10.1016/j.ijepes.2018.02.049
Received 15 August 2017; Received in revised form 11 December 2017; Accepted 27 February 2018
0142-0615/ 

indiscriminately applied to residential customers. However, high uncertainty in these consumers' load consumption makes the estimation error rate as high as 50% [12], leading to lots of complaints from participating consumers. Therefore, a new baseline estimation method and an accordingly reward mechanism are needed to keep the current consumers and attract new participants.

For improving the deterministic baseline estimation, [13] proposes to consider non-DR days preceding the DR event and choose the average load of the highest consumption days within those days for a baseline. Such a method is called HighXofY (used by New York Independent System Operator (NYISO)). [14,15] compare HighXofY, LowXofY, MidXofY in [13] with an exponential moving average (used by ISO New England) and regression methods with adjustments. An economic analysis of a hypothetical peak time rebate (PTR) program is carried out afterward. To improve accuracy, non-DR participants can be used in the control group [16–18]. However, it may be hard to uniquely define the best control group that properly captures user behavior of the treatment group (DR participants). To resolve this problem, [19] presents a clustering-based method, where customers are first divided into groups. Within each group, DR participants' baselines are estimated by non-DR participants' loads.

While there are some improvements, the drawback of deterministic methods lies in (1) their failure to utilize the historical data in capturing the dynamics of complex user behaviors [20,10], particularly important for small to medium consumers with more variability [21]; and (2) their unfair rewards which can have very different baseline estimation errors for different DR-participants. As large utility companies have started to make historical data available to approved third parties, e.g., the Green Button initiative in CA [22], we propose to (1) conduct machine learning of historical data to capture the residential consumer uncertainties and (2) reward customer at a similar baseline-estimation-error rate for fairness.

Specifically, our data analytics of a fairly large residential customer dataset shows properties of Gaussianity, so we propose to use Gaussian Process (GP) regression for machine learning [23,24]. This is because GP regression naturally provides the prediction of uncertainties inherent in the customer loads. It also has the flexibility of an adaptive component design according to customer behavior [23]. Based on probabilistic estimates, we further propose to reward consumers until most users' aggregated but averaged rewarding uncertainty decreases to a tolerable level, e.g., 5%. Finally, we prove that Gaussian process-based baselining method's mean estimate is equivalent or better than the estimates generated by currently used baseline estimation methods.

For simulation, we use an hourly PG&E dataset with 12,000 residential customers [12,25] and OhmConnect dataset with 425 users, where the demand response period occurs in the afternoon and evening of summer days. By using these dataset sets, the proposed method is compared with other state-of-the-art baseline estimation approaches. The results show that the probabilistic estimate not only has a mean estimate better than the currently used deterministic estimates, but also provides a new 95% confidence zone estimate, which covers true load values completely. Notably, we add a machine learning method-based on gradient boosting model, for comparison. Its worse performance indicates that our data analytics for machine learning modeling is necessary for estimation accuracy. If we further aggregate a user's estimates over days based on the mean and variance estimates, the rewarding error can reduce to 5%. This result aligns well with our theoretical expectation thus validates the correctness of the estimate. While we provide simulation results for all customers, we notice that different customers reach the 5% error tolerate threshold at a different speed. So, our suggestion of waiting until most of the consumers reach a threshold is practical to both the aggregators and the consumers.

The innovation comes from the following: (1) motivate the need of probabilistic baselining, (2) use load pattern to justify the Gaussian Process (GP) modeling for residential customers, and (3) use real dataset for design and validation. Comparing to [26], we use feature extraction to demonstrate why a Gaussian process is proper for modeling uncertainty. We show how to embed different covariance functions to the GP platform to model residential users power assumption pattern. Instead of a simple demonstration of aggregation in users, we also extensively simulate aggregations in the days for fairer payments. Different user types are also compared to understand user behavior and its impact on payments. Finally, computational time is analyzed for large-scale implementation.

The rest of this paper is organized as follows: Section 2 reviews current methods; Section 3 introduces the modeling and proves its superior property; Section 4 shows how to utilize a probabilistic estimate for rewards; Section 5 illustrates simulation results and Section 6 concludes this paper. In Table 1, we list all the notations that will be used in the paper sequentially.

**Table 1**
Table of Notations

| | | |
|---|---|---|
| $y_i$ | : | historcal load data |
| $t_i$ | : | historcal temperature data |
| $\boldsymbol{x}_i$ | : | a column vector containing time index $i$ and the temperature $t_i$ |
| $X$ | : | $\boldsymbol{x}_i$ at different time slots form the matrix |
| $y_i^*$ | : | probabilistic load estimate for the demand response period at time index $i$ |
| $\boldsymbol{y}$ | : | the joint probability distribution of the load data in a vector form during the no-DR period |
| $K(\cdot,\cdot)$ | : | the covariance matrix |
| $\boldsymbol{\mu}_{X^*}$ | : | the expectation for each row of $X^*$ |
| $m(X)$ | : | the expectation for each row of X |
| $I$ | : | the identity matrix |
| $Cov(\boldsymbol{y})$ | : | the covariance matrix of the variable vector $\boldsymbol{y}$ |
| $y_{1:N}$ | : | time series output data between time 1 and time $N$ |
| $y_{1:N-r}$ | : | time series output data between time 1 and time $N-r$ |
| $y_{r+1:N}$ | : | time series output data between time $N-r$ and time $N$ |
| $y'$ | : | the random variable that creates the empirical results of $y_{1:N-r}$ |
| $y''$ | : | the random variable that creates the empirical results of $y_{r+1:N}$ |
| $k(r) = k(\boldsymbol{x}_t,\boldsymbol{x}_{t+r})$ | : | the covariance matrix between two time series |
| $w_i$ | : | weighted coefficient with respect to index $i$ |
| $T$ | : | the number of covariance functions in consideration |
| $L_d$ | : | the actual load recorded by the smart meter |
| $L_{d,estimated}$ | : | the estimated load |
| $S_d$ | : | $L_{d,estimated}$ - $L_d$ |
| $P_\mu$ | : | The expected total reward |
| $P_{\mu,aggregate}$ | : | The expected and aggregated total reward |
| $E(\cdot)$ | : | expectation |
| $D$ | : | the total dates for the demand response events |
| $O(\cdot)$ | : | Computational complexity |
| $L(\cdot)$ | : | Log-likelihood |

## 2. Probabilistic baseline estimation for residential customers

For commercial customers, the consumption without DR signal is quite regular. Therefore, a deterministic baseline estimation shown in Fig. 1 is used to calculate the reward. Once the baseline estimate is found, the difference between the actual consumption and the baseline estimate can be used for reward calculation.

As residential customer level demand response is becoming more important, various schemes have been developed to evaluate responsive loads for ancillary services to grids [8].

(1) Simple Average: average loads in the past ten days.
(2) Selected Simple Average: an average of the highest (or median) three out of ten most recent days, e.g., HighXofY [13] or MedXofY.
(3) Weighted Average: weighted average over historical loads in the past ten days.
(4) Morning Usage Adjustment: methods above can also be