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An Investigation of the Accuracy of the Measurement of Load Reduction for Demand Response Programs offered to Residential Customers

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Abstract: In this paper, the evaluation of load reduction through customer baseline load calculation is investigated. Moreover, the impact of accuracy of this calculation on the peak time rebate program offered to residential customers is investigated. In a hypothetical case, this program is offered to residential customers and its economic performance is evaluated with respect to the customer baseline load accuracy performance. For the purpose of this analysis, two popular methods of High5of10 (commonly known as NYISO method) and regression, and their adjusted forms are selected to compute the customer baseline load. Then, this calculation is utilized to examine the performance of a hypothetical case of peak time rebate program offered to 300 residential customers collected by the Irish Commission for Energy Regulation smart metering trial dataset. Based on the results of the case study, this hypothetical utility pays over 50 percent of its revenue as a rebate just because of the inaccuracy of the customer baseline load calculation methods. This loss would increase if the aforementioned methods get adjusted for the morning consumption. In the end, it is discussed that peak time rebate programs can cause an unfair redistribution of the utility's revenue. Moreover, it is argued that such random distribution of rebates can cause a financial loss to the customers eventually.

Keywords: Demand Response (DR), Peak Time Rebate (PTR), Percent Accuracy Metrics, Percent Bias Metrics, Customer Baseline Load (CBL).

I. INTRODUCTION

The electricity markets are developing steadily over many years of restructuring and competition and as a result, many points of inefficiencies are detected and resolved on the supply side [1-3]. With the advance of new components in the power network such as solar cells and wind turbines the traditional one-way direction supply has changed. Plug-in electric vehicles (PHEVs) are being used in power grids in recent years [4]. They can be used as both energy consumers and suppliers.

However, due to overcoming conflicting interests of different stock-holders in the electricity market, the demand-side is still plagued with many inefficiencies [5]. Recent studies suggest that demand response (DR) programs can provide a reasonable response to such challenges. These programs can open up various possibilities to system operators as well as utilities in hopes of improving both economic and technical indices of their systems [6-7]. In [8] An Optimal security constrained Demand Response in Home Energy Management System is performed, using the Genetic Algorithm. Genetic algorithm can easily solve nonlinear constrained problems [9-10].

Although DR programs look highly promising in theory, a host of problems make them difficult to implement in practice. These problems root in diversity of customers, loads and heterogeneity in types of DR programs [11-13]. As a result, due to such complications, policy makers are concerned about the way load aggregators compensate customers financially. Utilities conventionally offer electricity at a flat rate. This flat rate reflects the average cost-of-service plus a premium that compensate the retailer for the risks associated with buying variable price electricity and selling it at a fixed rate. DR programs offer a different pricing structure in order to affect the customers' decision regarding their consumption. As one of the solutions to the abovementioned issues, decentralized methods for interconnection of the DRs have been developed. For example, in [14], Hamidi et al provided a thorough literature review on different control methods for DR interconnection and suggested a new decentralized method for controlling the DRs in all operation modes of smart grids. However, decentralized methods inherently are not able to find the global optimum points.

Many DR programs rely on customer baseline (CBL) to compensate customers financially for their load reduction. CBL is a counterfactual consumption level, i.e. the amount of electricity that customers would have consumed in the absence of DR event. CBL is also a basis to measure DR programs' performance. A well-designed baseline could benefit all stakeholders by aligning their incentives, actions and interests. However, authors in [15] show that, in practice, because of the complicated nature of forecasting and limited availability of the information about customers' future plans and other relevant parameters, designing such CBL is not an easy task [16].

An extensive review of CBL calculation methods has been presented by authors in [17]. Their paper examines empirically numerous methods used by utilities and ISOs within the US. For carrying out such task, they employ real data from several hundred commercial and industrial customers in California State, and in order to evaluate the performance of the methods, they utilize accuracy and bias metrics. These metrics are employed by this paper as well, and they are elaborated in the future sections.

Moreover, an industrial working group from California State tries to examine methods for CBL estimation in [18]. This study is part of the broader evaluation of California's 2004 DR programs, which targeted the industrial and commercial customers. The methods examined in this study are 3-day, 10-day and prior-day CBL calculation methods. According to the results, 10-Day CBL calculation method with same day adjustment is the most accurate approach.

In another attempt to evaluate CBL calculation methods, the authors in [18-19] evaluate the methods' performance on non-residential buildings in California. This work which is conducted in Lawrence Berkeley National Lab (LBNB) on sample data from 32 sites in California, and it employs a statistical analysis to evaluate the performance of different CBL calculation models for non-residential buildings participating in DR program with emphasis on the importance of weather effects. According to the results, applying the morning adjustment could significantly reduce the bias and improve the accuracy of all CBL models.

The effect of CBL accuracy on residential customers' decisions in DR programs are assessed by the authors in [20]. In their study, different CBL methods are compared and ranked based on their accuracy and biases. Moreover, the study explains how CBL will affect customers' decision and participation in a DR event and how it affects both customers and utility profit.

In this paper, two CBL calculation methods and their adjusted forms are evaluated on real data collected from residential customers. The details of the data will be described in the following sections. The accuracy and bias metrics are utilized to evaluate the performance of the CBL calculations, and they, also, would be elaborated in future. Moreover, an economic case is introduced to evaluate the economic performance of Peak Time Rebate (PTR) program. PTR program is selected as a prominent example of a DR program that relies heavily on CBL calculation methods for its efficient performance. PTR is one of the popular DR programs in electricity industry. This program is frequently employed by utilities for their industrial customers. The performance of this program strongly hinges on the performance of CBL. Although it is employed successfully for industrial customers, its performance for residential customers is untested. PTR program is extremely appealing from the policy point of view as it requires a minimal revision to status quo and could provide a huge positive impact if it works correctly. However, it is vulnerable to many implementation deficiencies. The author in [21] reviews some of these practical issues including opportunities for gaming and problems with CBL methods. Moreover, the authors in [22] studied behavioral aspects of customers' engagement in the PTR program. It is shown that the reward mechanism which PTR employs to incent the customers for load reduction is another source of inefficiency in this DR program.

In this work, the CBL for residential customers are studied whereas previous works in this area [17-20] and [24] focus on industrial and commercial customers. Industrial customers as opposed to residential customers have a high degree of predictability due to their pre-scheduled loads. In past, because utilities were interested in the aggregated loads of residential customers, a few studies have been done to analyze these customers in the individual level. However, since DR programs need to deal with the customers in the individual level, recently, researcher have shown interest to this topic. The authors in [25-26] have explored the CBL performances exclusively for the residential customers. Findings for industrial customers could not be generalized to residential customers, and CBL calculation methods must be revisited.

What distinguishes this paper from the previous studies is that in this paper, the authors go beyond analyzing accuracy and bias metrics of CBLs for residential customers and try to explain, first, what are the underlying mechanism of the error in CBL calculation methods, and second, how these metrics translate into financial losses for utility and customers. In order to carry out this analysis, an economic performance of a hypothetical case of PTR program offered to residential customers is assessed. This case employs a real data from 300 customers collected by Irish Commission for Energy Regulation (CER) smart metering trial dataset.

The rest of the paper is organized as follows. An overview of CBL calculation methods is provided in section II. Afterwards, in section III, first, the dataset is introduced, then, for the purpose of the error analysis, two metrics of accuracy and bias are introduced. Afterwards, the signal processing analysis by using DFT is performed on the dataset. The error metrics are then applied to baseline loads calculated for a dataset and the results are presented. In section IV, a case study for an economic analysis of PTR is introduced. The results of the case study as well as discussions are presented in section V. The paper then concludes in section VI.

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II. CBL CALCULATION

In this paper, two well-established methods of HighXofY and regression are selected for CBL calculation. Based on many works in the literature, these two methods are two of the best methods for calculating CBL for large industrial and residential customers. The algorithm and mathematical presentation of these methods are provided in [26].
In HighXofY methods, the subset of X days out of Y admissible days would be selected to calculate the CBL for the event day by using the average of these X days. However, the conditions on the event day are often different from the selected prior days. For this reason, X of Y baseline methods could be adjusted by the event day data. The same procedure can be followed for regression methods as well. The adjustment is defined by time frame of adjustment and it can be either multiplicative or additive. For the purpose of illustration, the concept of adjustment is shown through an example adjustment in Fig. 1.
In what follows, each of the aforementioned choice of adjustments will be elaborated.

$$b_i^{+}(d,t) = a^{+}(d,t) + b_i(d,t) \quad (1)$$

$$b_i^{\times}(d,t) = a^{\times}(d,t) + b_i(d,t) \quad (2)$$

Where:
$a^{+}(d,t)$: Additive adjustment
$a^{\times}(d,t)$ Multiplicative adjustment
$a^{+}(d,t)$ and $a^{\times}(d,t)$ can be calculated as follows:

$$a^{+}(d,t) = \frac{\sum_{i=t_1}^{t_2} (l(d,t-i) - b(d,t-i))}{t_2 - t_1} \quad (3)$$

$$a^{\times}(d,t) = \frac{\sum_{i=t_1}^{t_2} l(d,t-i)}{\sum_{i=t_1}^{t_2} b(d,t-i)} \quad (4)$$

Where:
t_1 The starting hour of the period used for adjustment
t_2 The last hour of the period used for adjustment
C A set of customers
T Timeslot division within a day
$l(d,t-i)$ Actual load of customer
$b(d,t-i)$ Predicted baseline of customer

As previously discussed, the difference between actual load and the estimated baseline in the adjustment time frame can be employed for adjustment purposes in two ways. Multiplicative adjustment uses the percentage change and applies it to the estimated baseline. On the other hand, the additive adjustment uses the absolute change. These adjustments are shown mathematically in (3) and (4). Time frame of adjustment is normally 2-4 hours before the start of the event. It is reported that the choice of multiplicative or additive adjustment does not change the outcome significantly [17], so in this work, the additive adjustment is used for adjusting CBL methods.

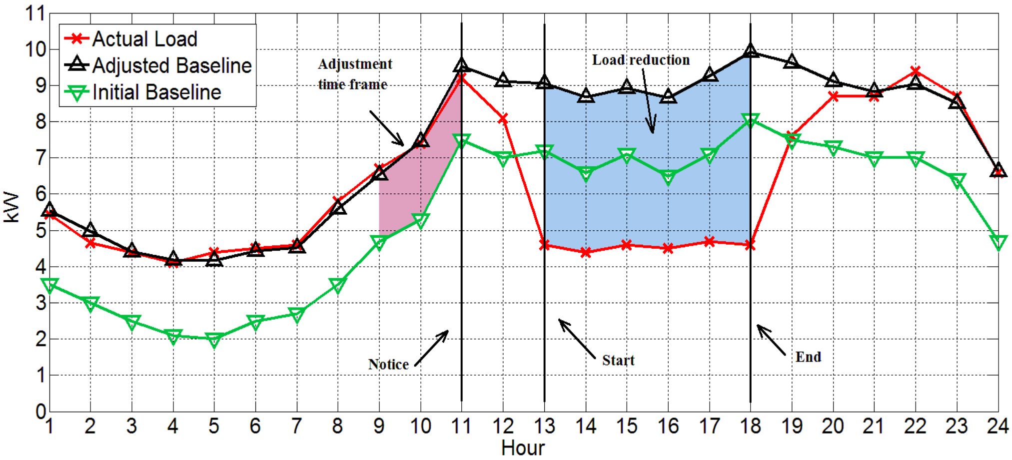

Fig. 1 Example baseline adjustment

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III.ERROR ANALYSIS

In this section, the dataset employed for the analysis of "classic" metrics of accuracy and bias is introduced and the metrics are defined. Afterwards, these metrics are applied to CBL calculations and the results are presented.

A. Dataset

In this paper, the Irish CER smart metering trial dataset [27] has been employed. This dataset contains measurements of around 5000 customers for the course of one and a half year from July 2009 to December 2010. In this paper, the data for 300 customers for the last three months of experiment (92 days) are used. Dec 22nd is selected as an event day due to high electricity consumption.

B. Error Metrics

The hourly accuracy and bias of each baseline is analyzed in the following subsection. Let C be the set of all 300 customers, D be the set of all days in the data set, and T be the set of hourly timeslots in a day. Mean absolute error (MAE) is utilized for measuring baseline accuracy as shown in (5).

$$accuracy = \frac{\sum_{i\in C}\sum_{d\in D}\sum_{t\in T}|b_i(d,t) - l_i(d,t)|}{|C|.|D|.|T|} \tag{5}$$

The lower the MAE, the higher the accuracy. Baseline bias is defined as shown in (4).

$$\mathrm{bias} = \frac{\sum_{i\in C}\sum_{d\in D}\sum_{t\in T}(b_i(d,t) - l_i(d,t))}{|C|.|D|.|T|} \tag{6}$$

It is worth mentioning that the difference between accuracy and bias, as expressed in (5) and (6) is the value of the difference between CBL and the actual consumption, which MAE uses the absolute value, while bias uses the real value. According to (6), baseline methods with positive bias overestimate the customers' actual consumption and vice versa.

C. Signal processing

Before starting to calculate the CBL, first, the consumption load is analyzed by a standard signal processing procedure. The rationale behind this subsection is to see the recurring patterns inside the signal. For this purpose, the load is decomposed to its underlying components by Discrete Fourier Transform (DFT). Then it is divided into two parts: the part that has frequencies within the day (less than 24 hours), and the part that has frequencies beyond one day (more than 24 hours). The former is called high frequency load, and the latter is called low frequency loads. Figures 2 and 3 show these signals for a random customer. The original is normalized for better comparison. By comparing these two figures, it is understood that the high frequency signal is as big as low frequency signal in magnitude. It means that the random and high frequency components of the signal are as significant as the predictable and low frequency components of the signal. It is a sign that it is very hard to calculate the CBL without using any other features from customers' characteristics. For this subsection, an index is defined as randomness level index as in (7).

$$\mathrm{r} = \frac{\sum_{t=1}^{T}\mathrm{abs}(f^{high}(t))}{\sum_{t=1}^{T}\mathrm{abs}(f^{low}(t))} \tag{6}$$

Where r is the randomness level, T is the number of hours in the signal (i.e. 2208 hours), and f^{high} is the high frequency signal, and f^{low} is the low frequency signal. The average of randomness level for all 300 customers is 1.03, which basically means close to 50% of the signal is unpredictable and random. However, it is worth mentioning that this randomness level is defined around one day. There are some other ways to select this benchmark. For example, some researchers believe that 8 hours is a better benchmark, because most of the residential customers follow the cycle of 8 hours work, 8 hours rest, and 8 hours sleep. However, in this paper, one day (24 hours) is selected for simplicity.

D. Analysis

In this part, CBL for all the customers is calculated. In order to observe the details and challenges of CBL calculation, the CBL is calculated for one random customer. Fig. 4 illustrates the actual load and the CBL for the customer. As shown in Fig. 4, although NYISO and regression are two effective CBL calculation methodologies for the industrial sector, they show lukewarm results in the residential sector, and in almost all the hours in the event day, the difference between the estimation and the actual load is significant. This observation will be confirmed by the results of the error analysis. Moreover, in figures 5 and 6, it is illustrated how that particular customer is going to be rewarded at event hours under NYISO and regression methods, respectively. When actual data is less than CBL at event hours (red area), the customer is rewarded for kW difference. However, when CBL is less than actual data at event hours (green area), no action is going to be taken by utility and the customer is still charged with the base price. The yellow area represents non-event hours. The average of accuracy MAE and bias of NYISO and regression methods for event hours for all customers are shown in Tables I. According to the results, adjustment does not improve the outcome of employed CBL

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methods for residential customers. In order to see the financial impact of these accuracy and biases, in the next section, a hypothetical case of a PTR program is offered to the dataset in order to investigate how these metrics translate into financial losses for the utility.

IV. CASE STUDY

For economic analysis of PTR program, the accuracy of CBLs employed for payment settlement must be taken into consideration. In this section, a case of PTR program is introduced and its economic performance is analyzed. This PTR program pays \$0.35/kWh as a reward for load reduction and a base price of \$0.097/kWh as fixed tariff. The event starts from 3:00 P.M. and ends at 9:00 P.M.

TABLE I ACCURACY "MAE" AND BIAS FOR EVENT HOURS

	NYISO	Adjusted NYISO	Regression	Adjusted Regression
Accuracy MAE (kWh/hr)	1.44	1.68	1.40	1.45
Bias (kWh/hr)	+0.12	+0.72	-0.46	-0.14

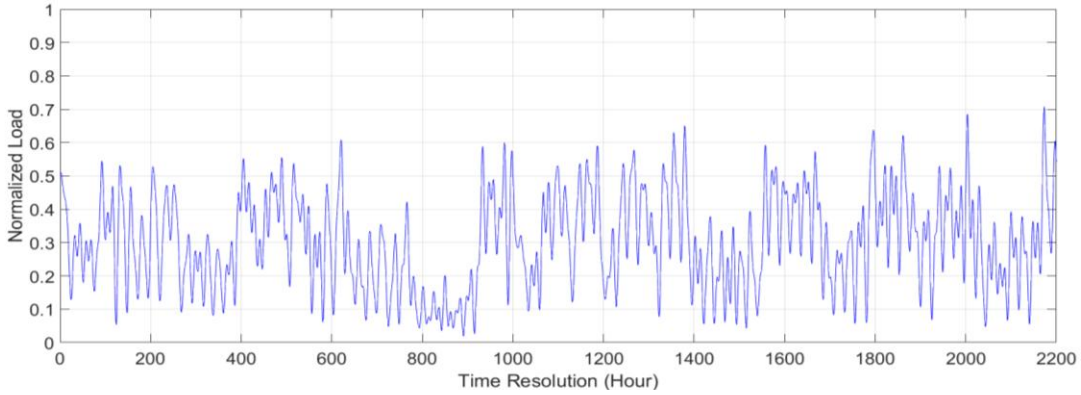

Fig. 2 The low frequency signal of the electricity consumption for one random customer in the dataset.

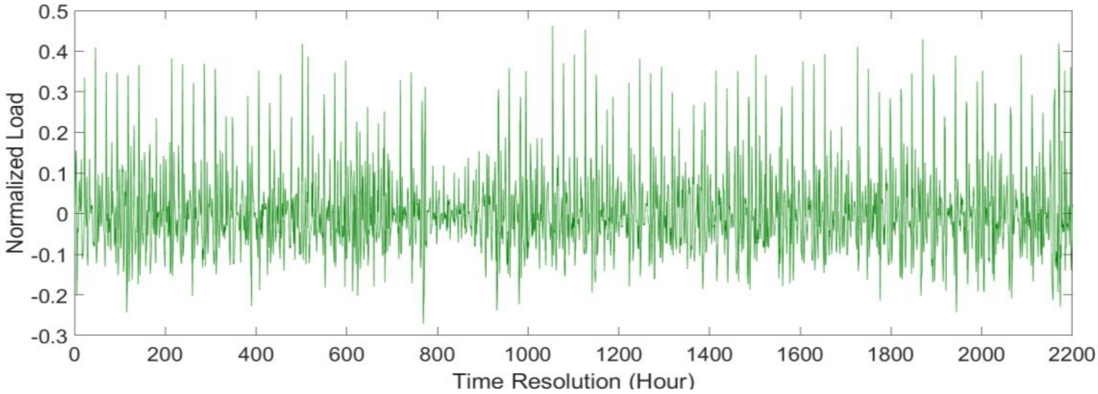

Fig. 3 The high frequency signal of the electricity consumption for one random customer in the dataset.

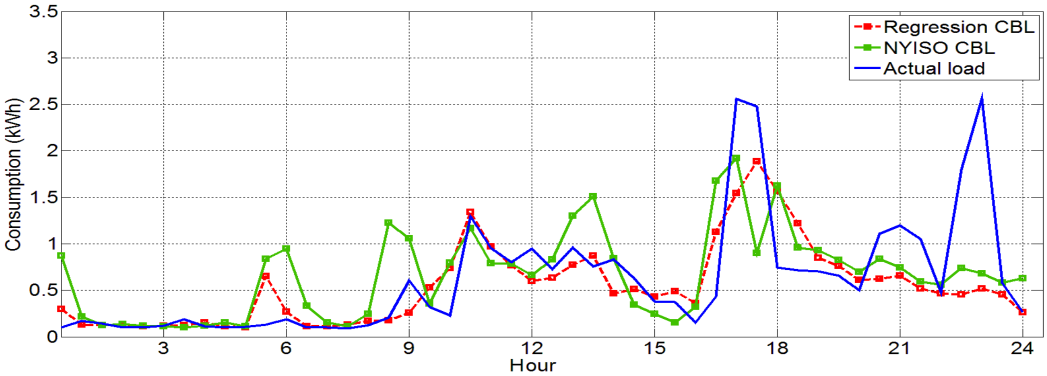

Fig. 4 Actual data vs. CBL for one random customer in the dataset

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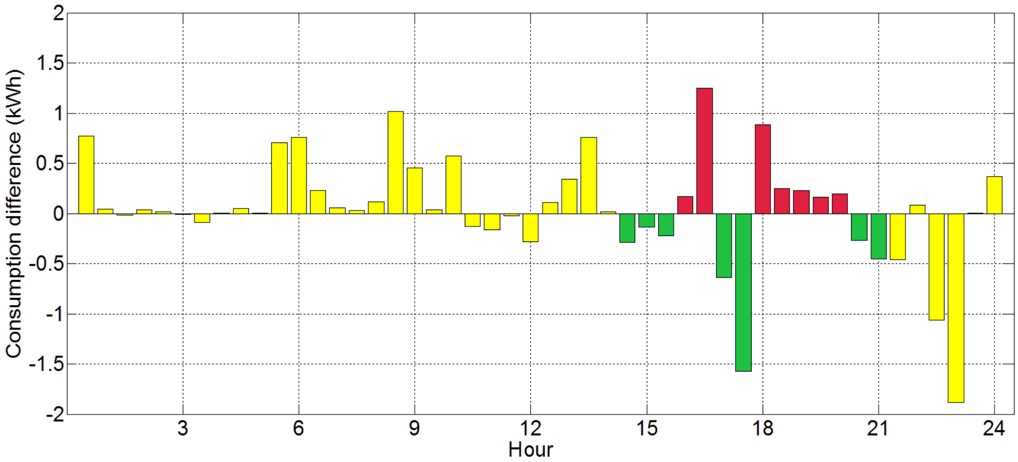

Fig. 5 Difference between NYISO CBL and actual data, red is rebate hours

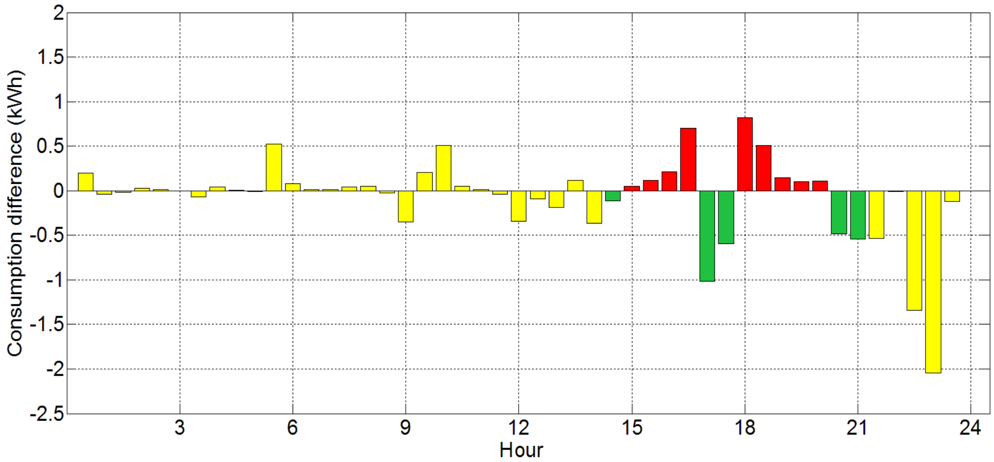

Fig. 6 Difference between Regression CBL and actual data, red is rebate hours

V. RESULTS AND DISCUSSION

In this paper, the data is free from DR event. Therefore, if the CBL is 100% accurate, the load reduction must be zero. On the other hand, if any load reduction is observed, it can be attributed to the inaccuracy of the CBL method. In this dataset and for the case study, the utility revenue from the total of 300 customers on the event day is $1465.5 for selling 1.51 MWh. Table II lists the load reductions under NYISO, adjusted NYISO, regression and adjusted regression CBL methods. It also shows how much rebate this utility must pay to these customers on the event day. For the illustration purpose, the results of this table are shown in Fig. 7.

As discussed earlier, all the rebate money is incurred because of CBL inaccuracy. According to the results, in this PTR program for residential customers, inaccuracy of CBLs costs this hypothetical utility over half of its revenue on the event day. As is shown in this table, the value of the load reduction as a percentage of consumption on event day is always above 14%. In most of DR programs, the intention is to induce customers to reduce their elastic demand during peak time, and since the elastic demand during peak time consists a small portion of the total load of a household demand [28], an error with this magnitude, disables the CBL to distinguish between the real demand reduction and load reduction. It is worth reminding that this load reduction is just an inaccuracy error, and ideally it must be zero. According to the signal processing analysis of the load signal, the high error in this order of magnitude was expected. However, the acceptable performance of CBL calculation methods for customers from different sectors (e.g. large industrial and commercial customers) can be attributed to the different nature of the personal and professional activities. As discussed earlier, according to the findings of multitudes of successful PTR programs offered to industrial customers, adjustment improves the results of CBL methods significantly, but in this case, the adjustment deteriorates the outcome of these methods.

It is worth discussing that the utilities, due to their obligation to serve, must make sure that they have enough electricity to serve in any situation. DR programs can help the utilities in emergency situations. One of these situations is peak time of some special days when electricity in the wholesale market is either very expensive or unavailable. DR

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programs can help to relieve part of this pressure. Utilities, in response to such pressures, might accept any available program that induces customers to lower their peak consumption regardless of its damage to their revenue.

However, the utilities reflect their cost-of-service into their retail rates. Therefore, ultimately the customers are the one who feel most of the aforementioned financial losses. Moreover, this loss of revenue redistributes among the customers randomly. In other words, this program rewards and punishes the customers haphazardly. This random redistribution of the loss cast a shadow on the fairness, and ultimately on the performance of the program.

TABLE II LOAD REDUCTION AND "PTR" PAYMENT SETTLEMENT

	NYISO	Adjusted NYISO	Regression	Adjusted Regression
Load reduction as a percentage of consumption on event day (%)	22.7	43.9	14.4	23.9
Rebate as a percent of utility revenue (%)	81.9	158.7	52.1	86.5

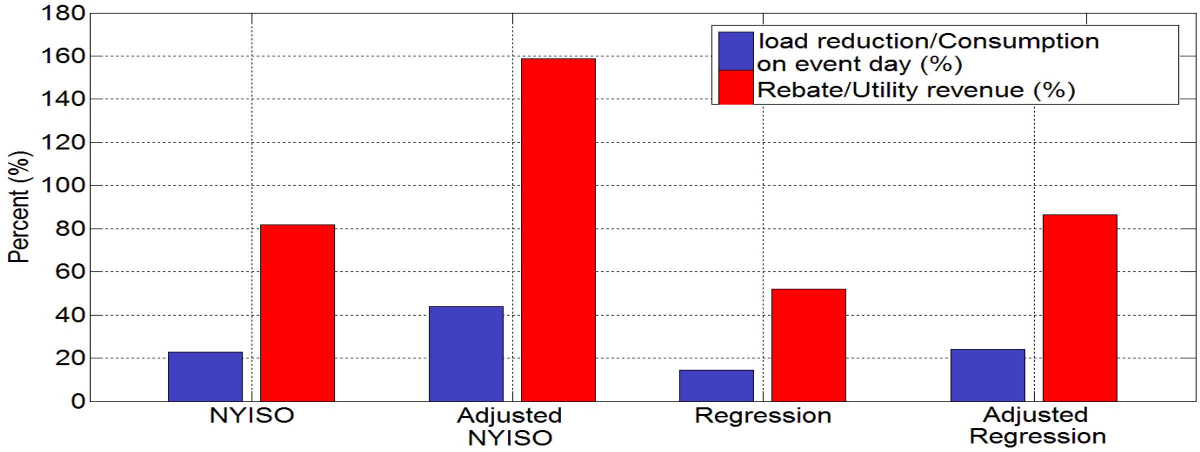

Fig. 7 Load reduction as a percentage of consumption on event day (%) and rebate as a percent of utility revenue (%) for NYISO, regression, and their adjusted form.

VI. CONCLUSION

In this paper, the impact of accuracy of CBL on PTR programs offered to the residential customers was investigated. Previous studies in this area focused on industrial and commercial customers. For the purpose of analysis, High5of10 (NYISO) and regression methods and their adjusted forms are selected to compute the CBL. The calculated baselines are utilized later to examine the economic performance of PTR program.

The key conclusions of this study are:

- From signal processing analysis of the loads, it is understood that the residential customers have a significant high frequency components that are hard to predict.
- The sum of the absolute value of high frequency components of the residential customers' loads are almost equal to the low frequency components (r=1.03).
- For the 300 customers and just on an event day, the utility pays about 81.9% and 52.1% of its revenue as a rebate just because of the inaccuracy of NYISO and regression CBL calculation methods, respectively.
- The additive adjustment did not improve the results in this case study. Conversely, it had a negative impact on the accuracy of each CBL method.
- The PTR program in the absence of an accurate CBL calculation methods can cause a significant loss to the customers and cause unfair redistribution of the utility's revenue.

Based on presented results, it could be concluded that PTR programs may be very inefficient for the residential customers. It is worth emphasizing that the inefficiency stems from the failure of CBL calculation methods to predict residential customers' load profile on event days accurately.

In future work, the authors plan to use a dataset with longer span of time and multiple events in different times of a year to investigate the weakly and seasonal cyclic components of residential customers' electricity consumption. Also, it is intended to study the performance of CBL calculation methods in the presence of a real DR event. Finding the baseline load accurately in the presence of a real DR program is another chief concern in measurement, verification and evaluation of CBL calculation methods.

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