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The impact of Customer Baseline Load (CBL) calculation methods on Peak Time Rebate program offered to residential customers

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ABSTRACT

This paper investigates the impact of CBL's performance on PTR programs offered to the residential customers. For the purpose of analysis, HighXofY (NYISO), exponential moving average (ISONE), regression methods and their adjusted forms are first introduced and then employed to calculate the CBL. Irish Commission for Energy Regulation (CER) smart metering trial dataset is used for this analysis. Furthermore, the metrics of accuracy, bias and Overall Performance Index (OPI) are introduced and then applied to carry out error analysis. Residential customers as opposed to industrial customers show a high degree of unpredictability due to multitudes of non-correlated personal and household activities. Therefore, an approach is also proposed in this paper to harness the randomness of individual customers' consumption. Also, it is necessary to examine how the metrics affect DR programs financially for the sake of reaching a valid conclusion about the overall performance of CBL methods. Consequently, a PTR program for a case of 260 customers is investigated as a case study. Results from this case study as well as their discussion are provided at the end.

1. Introduction

In current wholesale electricity market, the demand response (DR) is completely price-inelastic; hence, it seriously compromise the integrity of the free market as it isolates a portion of the demand from the supply. However, several empirical studies and evaluations of pilot programs at the customer level have demonstrated that the price-elastic demand could improve reliability and economic indices of the electrical grid [1,2]. Nevertheless, due to the prevalence of fixed rate at the retail level, policy makers are disinclined to introduce such groundbreaking changes to the status quo [3].

The isolation of demand side (e.g. residential customers) from the price fluctuations of electricity market is unacceptable from economics points of view as it has plagued this side by many inefficiencies. In the absence of changing prices, the fixed uniform rate deprives the demand side from the price signals. These signals deemed essential as they enable the customers to adjust their consumption to their preferences. Additionally, the fixed uniform rate results in over-consumption during higher wholesale rates and under-consumption during lower wholesale rates leading to welfare losses in both cases [3].

Moreover, many economists regard this isolation as a determining factor in the California energy crisis of 2000 and 2001 which led to significant price spikes and considerable social costs [4]. Such incidence and the following debates in industrial and academic circles have prompted policy makers to take action by initiating the regulation of the demand response at the wholesale level. As a result, the Energy Policy Act of 2005 was proposed to eliminate the unnecessary barriers to demand response participation in energy, capacity and ancillary service markets [5]. However, in practice, there are a host of problems making the implementation of this Act extremely complicated. These problems root in diversity of customers, loads and heterogeneity in types of DR programs [6], which makes policy makers concerned about the way load aggregators financially compensate their customers. Therefore, in 2010, Federal Energy Regulatory Commission's (FERC) in its order No. 745 attempted to address some of the concerns about the implementation of the aforementioned Act and the DR compensation in the organized wholesale energy markets [7]. As a result of such legislative endeavors, utilities were encouraged to open up their energy portfolio to DR programs.

Utilities conventionally offer electricity at a flat rate. This flat rate reflects the average cost-of-service plus a premium that compensates the retailer for the risks associated with buying electricity

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with a volatile price and selling it at a fixed rate [8]. However, DR programs offer an alternative pricing structure in order to influence the customers' decision regarding their consumption. It is essential to detect and measure the change in consumption pattern for evaluating the performance of each DR program [9].

In FERC order No. 745, it has been recommended that each Regional Transmission Organization (RTO) and Independent System Operator (ISO) with a DR program must implement procedures for the Evaluation, Measurement and Verification (EM&V) of DR programs [7]. These procedures include techniques to establish a Customer Baseline Load (CBL) for each customer which could be employed to measure the level of demand response offered to the wholesale market. Moreover, several DR programs need CBL to measure the customers' load reduction and to compensate them financially. CBL is a counterfactual consumption level, i.e. the amount of electricity that customers would have consumed in the absence of DR event. A well-designed CBL calculation method could benefit all stakeholders by aligning their incentives, actions and interests. However, in practice, because of the complicated nature of forecasting and limited availability of the information about customers' future plan and other relevant parameters, designing such CBL is not a simple task [10].

An extensive review of CBL methods is conducted in [11]. By employing the real data from California State, their paper examines empirically numerous methods used by utilities and ISOs within the US. Moreover, the authors utilize the accuracy and bias metrics to assess the performance of CBL methods for large customers. These metrics are utilized in this paper as well and they are elaborated in the future sections. Another study dealing with analysis of methods for CBL estimation is undertaken in [12]. Their study is part of a broader evaluation of California's 2004 DR programs. They target industrial and commercial customers. The methods examined in their work are 3-day, 10-day and prior-day baseline methods. According to the results, 10-day CBL with same day adjustment would be the most accurate approach.

In another attempt, authors in [13,14] evaluate CBL methods' performance on non-residential buildings in California. Their research which is carried out in Lawrence Berkeley National Lab (LBNL) on sample data from 32 sites in California employs a statistical analysis to examine different CBL methods with emphasis on the importance of weather effects. According to the results, applying the morning adjustment could substantially reduce the bias and improve the accuracy of all CBL models.

Although there are various studies on CBL applications on large customers including industrial and commercial customers, due to the lack of granular data, these studies could not examine the performance of CBL methods for residential customers. However, in recent years with high penetration rate of smart meters in residential level, it is possible to collect granular hourly consumption data and expand the aforementioned studies to the residential customers. The research on such customers is in its initial stage and little work has been done so far.

The performance of many DR programs hinges on CBL performance and accuracy. Studies on CBL performance on large customers indicate that CBL methods and morning adjustment are accurate enough to make the associated DR programs feasible. However, this issue is not fully explored for the residential customers yet.

Authors in [15] study the effect of CBL accuracy on residential customers' decisions in DR programs. In their study, different CBL methods are compared and ranked based on their accuracy and biases. Moreover, they explain how CBL will affect customers' decision and participation in a DR event and how it affects both customers and utility's profit.

In this paper, three CBL calculation methods and their adjustment are examined on the real data collected from residential customers. The description of the data is provided in following sections. The accuracy and bias metrics are utilized to examine the CBL calculation. Moreover, a 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 heavily relies on CBL calculation for its efficient performance.

PTR is one of the well-known DR programs in electricity industry. This program is repeatedly employed by utilities for their industrial customers. The performance of this program mainly depends on the performance of CBL. PTR program is extremely appealing from the policy points of view as it requires a minimal revision to status quo and could provide a positive impact if it works correctly. However, it is vulnerable to many implementation deficiencies. Author in [16] reviews some of these practical issues including opportunities for gaming and related problems. Furthermore, authors in [17] study behavioral aspects of customers' involvement in PTR program. In their work, it is shown that the reward mechanism which PTR program employs to incent the customers for load reduction is another source of inefficiency.

As it was mentioned, in this paper the CBL for residential customers are studied. Industrial customers as opposed to residential customers have a high degree of predictability due to their prescheduled loads. Therefore, the authors believe that the findings for industrial customers could not be generalized to residential customers. Also, this paper goes beyond analyzing accuracy and bias metrics of CBLs and explains how these metrics translate into financial losses for utility and customers. To carry out this, an economic performance of a case of PTR for residential customers is investigated. This paper, also, proposes an approach to improve the accuracy and bias of CBL methods for residential customers.

The rest of paper is organized as follows. Section 2 describes the CBL calculation methods and their formulations. Section 3, first, introduces the dataset utilized for CBL calculation. Then, it provides a discussion for calculating the CBLs for each customer in the dataset. Section 4 begins with an introduction to three metrics, accuracy, bias and overall performance index. Afterwards, it continues with applying these metrics to calculated CBLs and presents the results at the end. Section 5 proposes an approach to improve the accuracy and bias and overall performance index. Section 6 provides a case study for an economic analysis of PTR and presents the results of the case study as well as discussions. The conclusions along with recommendations for future work are provided at the end.

2. CBL calculation methods

Several methods are proposed in the literature to calculate the CBL. In this section, three well-established methods, HighXofY, exponential moving average method and regression are outlined mathematically. In addition, the adjustment of these methods is explained. For the purpose of brevity and clarity, the terminology and nomenclature of [15] are used.

2.1. HighXofY method

This method involves several steps. First, it selects Y non-DR days. In the absence of DR event, the days are called non-DR days. Also, weekend are excluded from these non-DR days. Two day types are used in this paper, weekdays (Monday to Friday) and weekend (Saturday and Sunday). Second, X days are chosen from the aforesaid Y days based on the level of consumption. Finally, the baseline is defined as the average load of these X days. If *HighXofY* is defined