An Iterative Bidirectional Gradient Boosting Algorithm for CVR Baseline Estimation

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Abstract—This paper presents a novel iterative, bidirectional, gradient boosting (bidirectional-GB) algorithm for estimating the baseline of the Conservation Voltage Reduction (CVR) program. We define the CVR baseline as the load profile during the CVR period if the substation voltage is not lowered. The proposed algorithm consists of two key steps: selection of similar days and iterative bidirectional-GB training. In the first step, pre- and post-event temperature profiles of the targeted CVR day are used to select similar days from historical non-CVR days. In the second step, the pre-event and post-event similar days are used to train two GBMs iteratively: a forward-GBM and a backward-GBM. After each iteration, the two generated CVR baselines are reconciled and only the first and the last points on the reconciled baseline are kept. The iteration repeats until all CVR baseline points are generated. We tested two gradient boosting methods (i.e., GBM and LightGBM) with two data resolutions (i.e., 15- and 30-minute). The results demonstrate that both the accuracy and performance of the algorithm are satisfactory.

Index Terms—Baseline estimation, bidirectional prediction, Conservation Voltage Reduction (CVR), forecast reconciliation, gradient boosting, load forecasting.

I. INTRODUCTION

Conservation Voltage Reduction (CVR) is a major demand response method used in utilities for peak-shaving and load reduction [1]. During a CVR event, the distribution feeder service voltage is lowered by 2-5% to achieve load reduction. A CVR event can last for a few hours, depending on the expected peak duration. To quantify the CVR performance, it is very important for utility engineers to accurately estimate what the original load profile (i.e., the CVR baseline) during an event would have been if the voltage is not reduced. Once the CVR baseline is available, utilities can calculate the percentage of load reduction with respect to the percentage of voltage change for each CVR event. However, in practice, the CVR performance varies with respect to many factors. For instance, time-of-the-day, load composition, and weather variations can all affect the actual amount of CVR load reduction. Therefore, it is critical for the utility to select the right feeder that can achieve consistent, large load reduction in targeted CVR periods.

In literature, comprehensive studies have been conducted to estimate CVR factors [1]–[3]. Conventionally, the CVR performance is evaluated by the percentage of load reduction per 1% voltage reduction (i.e., CVRf). For several decades, utilities estimate CVRf to range from 0.3 to 1 [4]. However, load composition has changed substantially over the past decade. LED lights that use constant-current or constant-voltage LED drives are rapidly replacing incandescent lights, which are constant-impedance loads. Because a large portion of CVR load reduction is with incandescent lights, the effectiveness of CVR is diminishing [5]. Furthermore, air-conditioning loads have grown rapidly in recent years. Because heating/cooling a building requires a fixed amount of electrical energy injection in a given period of time, lowering instantaneous power consumption will increase air conditioning unit run time, in which case, the synchronous load peak may even exceed the previous load peak. Thus, energy savings need to be considered in addition to the power reduction.

In general, there are four main approaches for CVR baseline estimation: comparison-based, synthesis-based, load modeling-based, and regression-based. Comparison-based methods compare load consumption of the voltage-reduction group (test group) and normal voltage group (control group) [2]. The control groups can be the same feeder on a day without voltage reduction or a different feeder with similar operating conditions. The challenge of the comparison-based method is that there may not be an appropriate control group because there are no two feeders or two days with an exact match of operating conditions. Synthesis-based methods aggregate load-to-voltage (LTV) behaviors to estimate the CVR effects of a circuit [3]. However, it is difficult to collect accurate load share information for a feeder and the LTV response of all existing electrical appliances. Load modeling-based methods represent load consumption as a function of voltages, and calculate CVR factors from the identified LTV sensitivities [6]. However, it cannot represent different load compositions depending on the load model used. Regression-based methods assume a linear model for the load with a linear dependence on impact factors such as temperature, voltage, and other factors [7]. In multivariate regression [8], several impact factors are used as regression variables to formulate the model. The problems with this method are that the margin of error of the regression model may be larger than CVR effect, and most used linear models are unable to accurately capture the characteristics of nonlinear loads. The impact factors for CVR effects and the drawbacks of existing CVR baseline estimation methods are summarized in [4].

Nonlinear regression methods (e.g., support vector regression (SVR) [9]) can be used for approximate nonlinear load estimation.
behaviors but such methods are mathematically complex and computationally expensive [10]. GBM and LightGBM regressors can also approximate any nonlinear functions [11] but with simpler problem formulation that can be solved quickly with less memory requirement [12], [13]. Compared to blackbox machine learning models, GB-based models are interpretable and explainable which is essential for utility engineers to trust the results.

In this paper, we propose a bidirectional gradient boosting algorithm for CVR baseline estimation. Since the CVR factor is a very small number, it can easily fall outside the margin of error of the regression model. Two approaches are proposed to increase the estimation accuracy. First, as the CVR period becomes longer, the prediction accuracy drops toward the end compared to the initial period. Therefore, the estimation error can be lowered by applying bidirectional estimation with iterative forecasting reconciliation instead of using unidirectional prediction. Second, only the set of non-CVR days with similar temperature profiles compared to the CVR days are used to train the bidirectional gradient boosting-based model to further improve the prediction accuracy.

The main contribution of the paper is two-fold. First, for the first time in literature, an iterative, bidirectional, gradient boosting-based baseline estimation method is proposed for estimating the CVR baseline through forecasting reconciliation between the forward-pass and the backward-pass at each iteration. The estimation uses actual data sets recorded by utilities as inputs with estimation errors well within the CVR effect range (between 0.3% and 1%). Second, using the proposed method, we analyzed the CVR efficacy for prolonged CVR range (between 0.3% and 1%).

The estimation performance can be evaluated by mean absolute percentage error (MAPE), normalized root mean squared error (nRMSE), mean percentage error (MPE). The estimation uses actual data sets recorded by utilities estimating the CVR baseline through forecasting reconciliation. The estimation error becomes longer, the prediction accuracy drops toward the end. Therefore, the estimation error can be lowered by applying bidirectional estimation with iterative forecasting reconciliation instead of using unidirectional prediction. Second, only the set of non-CVR days with similar temperature profiles compared to the CVR days are used to train the bidirectional gradient boosting-based model to further improve the prediction accuracy.

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II. METHODOLOGY

This section presents the CVR evaluation criterion and the iterative, bi-directional, gradient boosting (Bidirectional-GB) based CVR baseline estimation algorithm.

A. CVR Performance Evaluation Criterion

As shown in Fig. 1, during a CVR event, when the bus voltage is lowered by $\Delta V\%$ at the distribution substation, we expect the real power consumption to change on average by $\Delta P\%$. Thus, the CVR performance can be evaluated by the CVR factor, $\text{CVR}_t$ as

$$\text{CVR}_t = \frac{\Delta P\%}{\Delta V\%} = \frac{(\bar{P}_{\text{baseline}} - \bar{P}_{\text{CVR}})/\bar{P}_{\text{baseline}}}{(V_{\text{baseline}} - V_{\text{CVR}})/V_{\text{baseline}}} \quad (1)$$

Note that in this paper, we focus on quantifying the real power reduction so the reactive power variations are ignored.

The estimation performance can be evaluated by mean absolute percentage error (MAPE), normalized root mean squared error (nRMSE), mean percentage error (MPE). The definition of MAPE, nRMSE, and MPE can be found in [14]. The energy error, $\epsilon_e$, is defined as

$$\epsilon_e = \frac{\sum_t y_t - \sum_t \hat{y}_t}{\sum_t y_t} \quad (2)$$

where $y_t$ is the actual value at time step $t$, $\hat{y}_t$ is the predicted value at time step $t$.

B. Algorithm Overview

As shown in Fig. 2, there are two key processes in the proposed Bidirectional-GB based CVR baseline estimation methodology: similar day selection and iterative GB training. In the first step, pre-event and post-event temperature profiles of the targeted CVR day are used to select similar days from historical non-CVR days. Then, the pre-event and post-event similar days are used to train two GBMs iteratively: a forward-GBM and a backward-GBM. As shown in Fig. 3, the forward-GBM/backward-GBM generates the CVR baseline using pre-event/post-event load and temperature data as inputs, respectively. After each iteration, the two generated baselines are reconciled into one, where we keep only the first and the last points. Thus, two baseline points can be generated at each iteration. The iteration repeats until all CVR baseline points are generated. We test two gradient boosting methods (i.e., GBM and LightGBM) for two data resolutions (i.e., 15- and 30-minute).

C. Data Preparation

Let $i (i \in \{1, \cdots, N_{\text{CVR}}\})$ and $j (j \in \{1, \cdots, N_{\text{nonCVR}}\})$ be the indices of the CVR and non-CVR days, respectively. Thus, $P_i$ and $T_i$ are the power and temperature profiles for the $i^{th}$ CVR day, respectively; $P_j$ and $T_j$ are the power and temperature profiles for the $j^{th}$ non-CVR day, respectively.

As shown in Fig. 3, we divide a target CVR day into three periods: pre-CVR, CVR, and post-CVR. The CVR period is from $t_{on}$ to $t_{off}$ (the blue shaded area). Thus, $P_t(B_t(t_{on} : t_{off}))$ is the to-be-estimated CVR baseline in the $i^{th}$ CVR day.

Select $N$ data samples immediately before and after the CVR event to be the pre-CVR and post-CVR periods. If the data resolution is $\Delta t$, the pre-CVR period is from $t_{on} - N \times \Delta t$ to $t_{on} - \Delta t$, and the post-CVR period is from $t_{off} + \Delta t$ to $t_{off} + N \times \Delta t$.

D. Similar Day Selection

To increase accuracy, training data should be selected from days with similar load changing patterns as those of the targeted CVR day. Conventional similar day selection [9] is load based instead of weather based (i.e., outdoor temperature).
respectively. Two sets of similar days are selected: the pre-CVR and post-CVR baseline estimation based models, respectively. Train the forward and backward gradient boosting-based mode, respectively. Thus, in this paper, we propose a new temperature-based similar day selection process to account for weather-related load variations.

As illustrated in Fig. 4 (a) and (b), the average Pearson Correlation Coefficient between power and temperature profiles of a real feeder is 0.73, showing very strong correlations in shapewise characteristics. Thus, in this paper, we propose a new temperature-based similar day selection process to train the forward and backward gradient boosting-based mode, respectively. Two sets of similar days are selected: the pre-event similar days (Ω\textsuperscript{pre}) and the post-event similar days (Ω\textsuperscript{post}). Ω\textsuperscript{pre} is selected by matching temperature data in period τ\textsuperscript{pre} (from \(t_{on} - N \times \Delta t\) to \(t_{off}\)). Ω\textsuperscript{post} is selected by matching temperature data in period τ\textsuperscript{post} (from \(t_{on}\) to \(t_{off} + N \times \Delta t\)).

As shown in Fig. 5, two temperature segments in periods τ\textsuperscript{pre} and τ\textsuperscript{post} in the \(k\)th targeted day are used to select similar days from non-CVR days (\(N^{\text{nonCVR}}\)) for training the forward and backward models, respectively. Compare the temperature segments in a non-CVR day in periods τ\textsuperscript{pre} and τ\textsuperscript{post} with those in the targeted day by calculating nRMSE [14]. If nRMSE is smaller than the set threshold (\(\epsilon_{th}\)), then the non-CVR day will be selected as a similar day. In this paper, the length of pre-CVR and post-CVR windows \(N\) is 8 data points (i.e., 2-hour ahead when using 15-minute data) for a 3 hour CVR window with \(\epsilon_{th}\) set at 0.05.

E. Bidirectional, Iterative, GB-based Algorithm

For a CVR event lasting for hours, the baseline prediction accuracy drops sharply towards the end when using unidirectional method. Thus, we develop a bidirectional, iterative prediction process to replace the conventional unidirectional prediction approach.

As shown in Fig. 3, at the beginning of each iteration, the forward-pass input data (orange) is used to generate the first CVR baseline data points (yellow) and the backward-pass input data set (blue) is used to generate the second CVR baseline data points (green). Then, apply forecasting...
reconciliation to merge the two time series data points into one (purple). Keep only the first and the last data points (highlighted by the two red boxes) and use them as input data in the next iteration. Slide both the forward and backward data windows forward by one data point.

1) Forecast Reconciliation: Let $\hat{P}_t^f$ and $\hat{P}_t^b$ be the forward and backward pass forecasted values at time $t$, respectively. Let $\hat{P}_t^{fb}$ be the reconciled value at time $t$.

Let $w_t^f$ and $w_t^b$ be the weighting factors for reconciliation. If linear reconciliation is used, We have

$$\hat{P}_t^{R} = w_t^f \times \hat{P}_t^f + w_t^b \times \hat{P}_t^b$$ (3)

$$P_t^{GT} = \hat{P}_t^{fb} = \hat{P}_t^f + \hat{P}_t^b$$ (4)

Note that $w_t^f$ and $w_t^b$ are hyper parameters and require tuning in the training stage.

In this paper, due to space limit, a fix set of weighting factors are calculated using 160 load profiles in the three summer months in two years by (4). In our follow-up journal paper, we will discuss the forecast reconciliation in detail by comparing the impact of weight selection on baseline prediction accuracy.

2) Gradient boosting Model Selection: In this paper, we compare two types of gradient boosting-based regression models: GBM and LightGBM. GBM and LightGBM are decision tree based method that can approximate any nonlinear functions. GBM splits the tree level-wise with the best fit whereas LightGBM algorithm splits the tree leaf-wise. GBM has proven to be one of the most powerful technique to build predictive models, especially for low-dimensional data [12]. LightGBM is a fast, distributed, high-performance gradient boosting framework for high-dimensional data [13].

Since a tree model have fewer parameters, the Grid Search algorithm is used for their tuning. The parameters of each model are summarized as follows; $GBM$, the number of estimators is 100 and learning rate is 0.1; $LightGBM$, the number of estimators is 100, the maximum depth is -1, the number of leaves is 31, the learning rate is set to 0.1, the bagging fraction is 0.5, and the boosting method is gbdt.

III. SIMULATION RESULTS

This section presents data preparation, impacts of different input data resolutions, and CVR efficacy analysis.

A. Data Preparation

The data set used for conducting this study was collected by a utility on three distribution feeders in North Carolina in 2019 and 2020. The number of CVR and non-CVR days are shown in Table I. By aggregating 15-minute smart meter data on the same feeder together, we obtain the total load profile for that feeder. Thus, the CVR load reduction computed in this paper is the net load reduction on the customer side so that transformer losses and line losses are not included. In our follow-up journal paper, we will present the CVR efficacy study evaluated using the feeder-head data collected by substation meters.

To quantify the algorithm performance, 36 non-CVR days (2 days from each of the three summer months in two years) are selected as virtual CVR days, in which days, we assume that CVR is executed for 3-hour (from 15:00 to 18:00). Thus, for a virtual CVR day, the load profile during the targeted CVR period (i.e., the CVR baseline) is known. After the CVR baseline is estimated by the proposed algorithm, it can be compared with the ground truth profile ($P_{GT}$) to compute for prediction accuracy.

| Feeder No. | CVR | non-CVR | Missing | Total | CVR duration |
|------------|-----|---------|---------|-------|--------------|
| 1          | 24  | 677     | 30      | 731   | 3 h          |
| 2          | 24  | 679     | 28      | 731   | 3 h          |
| 3          | 24  | 679     | 28      | 731   | 3 h          |

B. 1-directional versus 2-directional forecast reconciliation

Figure 6(a) compares the estimation errors (i.e., $\hat{P}_t^f - P_{GT}$, $\hat{P}_t^b - P_{GT}$, and $\hat{P}_t^{fb} - P_{GT}$) during the 3-hour CVR period in the 36 virtual CVR days, where $P_{GT}$ is the ground truth load profile during the CVR period. As expected, the error increases as the time step shifts from 1 to 12 in the forward pass, and from 12 to 1 in the backward pass while the reconciled forecasting baseline shows much lower errors across all 12 points. Figure 6(b) shows the reconciliation weighting factors for the 12 baseline data points for an actual feeder, which are calculated using the method introduced in Section II.E. The simulation results show that baseline forecasting accuracy of the forward pass is higher for the beginning few data points and the accuracy decays slower than that of the backward pass.

![Fig. 6. (a) Estimation accuracy of the uni- and bi-directional approaches, (b) Reconciliation weighting factors calculated by linear regression.](image)

C. Impact for Different Data Resolution

Next, we compare the algorithm performance when using smart meter data with different resolutions. Again, the test is conducted for the 36 virtual CVR days. As shown in Table II, regardless which regression model is used, using 15-minute data for CVR baseline estimation usually outperforms using 30-minute data as inputs on all 3 feeders. In our follow-up journal paper, we will provide comparisons on more data resolution (from 1-minute to 60-minute) for more than 15 feeders using both aggregated smart meter data and feeder-head SCADA data.

D. CVR Performance Estimation

After the algorithm performance is validated for the 36 virtual CVR days. We applied the algorithm on the actual CVR days. The results are shown in Figs. 7 and 8. The CVR factor for each time step is calculated using (1). The hourly average CVR factor is the mean of 4 data samples in an hour.
Fig. 7. Estimated CVR baselines for three actual feeders.

We made the following observations:

- CVR factors are very inconsistent across feeders due to different load compositions. Feeders 1 and 3 show load reduction across all 3 hours but the reduction is more prominent in the first two hours. However, even for the first hour, CVR only leads to about 0.2% hourly load reduction, much lower than literature reported from 0.3% to 1% [4].

- As illustrated in Fig. 7, we observe an interesting step-response-like phenomena during the CVR event. Immediately after a CVR event is executed, the load drops due to the voltage reduction. However, after an hour or so, the load will bounce back, sometimes even higher than the baseline. After that, the load decreases again, making the overall response similar to a step response. We think that this phenomena is caused by air conditioning loads, which require fixed amounts of energy to cool buildings. At lower voltage, air conditioners turn on longer, causing the aggregated load to bounce back after the initial drop.

- Feeder 2 does not show load reduction. Instead, the load increases in hours 2 and 3. We think this is because the proportion of residential load on Feeder 2 is much higher than that of Feeders 1 and 3, which are predominately commercial and industrial loads. As we explained before, because the cooling load requires fixed amount of energy to cool the house in late afternoon hours, reducing instantaneous power consumption will not reduce energy consumption. Because approximately 80% of the residential electricity consumption are cooling loads in a hot summer afternoon, executing CVR may not reduce hourly electricity consumption. Due to increased current and increasing cooling needs in the late afternoon, the energy consumption can even increase slightly compared with the baseline.

IV. CONCLUSION

In this paper, a novel iterative, bidirectional, gradient boosting CVR baseline estimation algorithm is presented to quantify the efficacy of CVR on load reduction. We demonstrate that compared with the unidirectional approach and the power-based similar day selection method, the bidirectional approach and the temperature-based similar day selection method allow us to use both the pre- and post- event power and temperature data as inputs for CVR baseline estimation. This significantly improves the prediction accuracy. By testing the algorithm performance using data sets with different resolutions, we also show that 15-minute is preferred over 30-minute data resolution for CVR baseline estimation. We also discover that the efficacy of CVR diminishes with high-level of weather sensitive loads in a prolonged CVR event. Our follow-up journal paper will compare the algorithm performance on 15 different feeders using both substation and smart meter data with data resolution ranging from 1-minute to 60-minute.

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