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A Methodology to Analyze Conservation Voltage Reduction Performance Using Field Test Data

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***Abstract*—With an ever increasing demand and depleting energy resources, there has been a growing interest in conserving energy, such as the conservation voltage reduction (CVR) program to reduce energy consumption by decreasing feeder voltage. Several utilities are conducting pilot projects on their feeder systems to determine the feasibility and actual CVR payoff. One major challenge in analyzing the CVR field test data lies in the uncertainty of the power system load and a variety of dependent factors encompassing temperature and time. This paper proposes a methodology to facilitate the CVR performance analysis at the utilities by accounting all potentially influential factors. A linear relation to model the system power demand is presented, which allows a sparse linear regression method to obtain its sensitivity parameter to voltage magnitude and accordingly to quantify the CVR payoff. All input factors can also be ranked according to their statistical influence on representing the power demand output. The proposed method is first tested and validated using synthetic CVR data simulated for a 13.8 kV distribution feeder using OpenDss. It is further tested using the field CVR test data provided by a major U.S. Midwest electric utility. Both tests demonstrated the effectiveness of the proposed method as well as the usefulness and validity of the input factor ranking.**

***Index Terms*—Conservation voltage reduction (CVR), energy conservation, energy analytics, sparse regression.**

I. INTRODUCTION

Conservation voltage reduction (CVR) is a technique used by utilities for decades to decrease the peak power demand and yearly energy consumption, by reducing the voltage at the substation level. For constant impedance/current typed of loads, it is clear that a lower voltage magnitude would lead to a decreasing instantaneous power demand. According to the American National Standards Institute (ANSI), the permissible range for service voltage at customers' premises is 120 volts ± 5% [1]. Hence, the service voltage can be reduced using the CVR technique as long as it does not violate the 5% voltage range for the end of the line customers. CVR benefits the electric utilities as well as customers in a variety of ways. First, it directly decreases carbon emissions, and extends transformer lives since the iron losses of the latter would decrease with lower service voltage [2]. Accordingly, utility network maintenance is required less frequently, leading to huge potential maintenance cost savings. Second, it benefits home electric appliances such as incandescent lamps and electric hot water heater elements with an increasing lifespan [3]. Last but not least, it provides improved asset utilization, demand reduction and increased energy efficiency by and large [4]. As society advances and population grows, increased power demand is a certainty. CVR is a simple but practical solution to alleviate these accelerating demands for electricity energy.

CVR has been proposed for the first time around the 1950's, but it is recent advances in metering and communication capabilities within the distribution feeder that have made CVR come to reality [4]. At the same time, field CVR tests has attracted considerate attention in order to quantify the effectiveness of CVR. In 1989, a field test was conducted in Snohomish County public utility districts, on 4 feeder circuits connected to 3 substations that served primarily residential and commercial areas [5]. The test alternated between cycles of nominal and low voltage every 24 hours, and the CVR experiment gained with decreased energy consumption as a result. Many utilities such as Southern California Edison, Northeast Utilities and BC Hydro have reported significant energy savings as a result of voltage reduction implementation. More recently, studies suggest that deploying CVR on all distribution feeders in the US could reduce the national energy consumption by 3.04% annually [6]. Recent trends of distribution feeders under the realm of smart grid greatly facilitate the testing and deployment of CVR at a larger scale. This further motivates to consider an analytical framework for quantifying the pay-off of implementing CVR for any specific feeder system in an efficient and effective fashion.

However, there exist a variety of uncertainties in distribution feeders that may complicate the analysis of CVR pay-off from field test data. The percent of voltage reduction experienced by a particular customer of the feeder and the overall energy reduction effect on the feeder is determined mainly by two factors: 1) the network load composition of the network, and 2) the feeder network topology [2]. With the influx of newer loads like the EVs, LED TVs, smart appliances etc. along with the penetration of renewable resources in the distribution systems, the load composition of the feeder is changing faster than ever before. This has raised a need for a methodology to accurately monitor the CVR performance with such continuously changing circumstances in the feeder. Also, the advent of smart meters has increased the visibility in the distribution systems by providing information and measurements even at the customer level. With the use of such information, CVR performance may be evaluated in the smart grid environments not only at the head of the feeder but also at a customer

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level. Nowadays, the CVR test implementation has been greatly improved and standardized, which usually involves a periodic voltage reduction routine for the test feeder, as well as collecting data for a normally operated reference feeder with similar load/network characteristics. However, it still remains a great necessity to develop a systematic framework to quantify the CVR effectiveness based on only the field test data.

This paper presents a methodology to extract the dependency of the test feeder power demand on the level by accounting for a variety of uncertain factors. Specifically, a linear regression model is proposed to encompass all possible temporal and temperature related variables, as well the voltage and reference feeder power demand. A sparse linear regression approach is further proposed to obtain the voltage dependency parameter, with the additional benefits of providing the ranking of all input variables. The voltage parameter would be directly used to determine the CVR impact by quantifying the so-termed CVR factor. The methodology presented here can efficiently analyze the CVR test data and ultimately facilitate utilities to plan for their future CVR implementation schedules. Synthetic test data using distribution system simulator has been used to validate the proposed method, along with field test data analysis corroborating its effectiveness.

The rest of the paper is organized as follows. The CVR test data and the linear system model are introduced in Section II. This sparse linear regression method with data processing details is the subject of Section III. Synthetic test simulations are used to validate the proposed method (Section IV), and the field test data analysis is presented with interesting discussions (Section V). Finally, the paper is wrapped up with concluding summary and future research directions in Section VI.

Notation: Upper (lower) boldface letters will be used for matrices (column vectors); $\mathbf{1}$ the all-one vector; $\|\cdot\|_p$ the vector $p-$norm for $p \geq 1$; $(\cdot)^\dagger$ the matrix pseudo inverse.

II. Data and Modeling

An analytical framework is presented on how to use the utility field test data to determine the pay-off of CVR, namely, the CVR factor. For any feeder with given loads, its CVR factor is defined as the energy consumption reduction ratio in percentage due to 1% reduction in feeder bus voltage during a period of time, such as a season or a year. The present approach proposes to obtain the CVR factor for any distribution feeders by estimating the dependency of power demand on the feeder voltage magnitude from real CVR test data. The CVR test typically collects data samples at the feeder substation on a periodic basis, e.g., hourly for the one introduced here. As detailed soon, the present framework adopts a linear model of the instantaneous real power consumption based on multiple input variables, either from the real test measurement data, or by capturing certain time-dependent characteristics.

At any time instance t, the real power demand p_t by the feeder of interest is assumed to depend on input variables as listed here:

- c_t: area temperature in Fahrenheit at the test feeder;
- v_t: voltage magnitude measured in volt at the test feeder bus;
- p_t^{ref}: instantaneous real power consumption measured in kW at the reference feeder;
- $\{s_t^i = \mathbb{I}\{SoY(t) = i\}, i = 1, \ldots, 4\}$: variables indicating season-of-year;
- $\{h_t^i = \mathbb{I}\{Hour(t) = i\}, i = 1, \ldots, 24\}$: variables indicating hour-of-day;
- $\{d_t^i = \mathbb{I}\{Day(t) = i\}, i = 1, \ldots, 7\}$: variables indicating day-of-week;
- $f_t = \mathbb{I}\{Holiday(t) = 1\}$: variable indicating it is a federal holiday.

Clearly, the adopted model has 39 input variables in total, related to either real measurements or time-dependent characteristics. In particular, each CVR test feeder has a corresponding reference feeder with similar network/load characteristics. The reference feeder has undergone no CVR testing, and hence its real power consumption could also be used to infer the test feeder power consumption as well.

The data collection lasts for a given period τ where $t \in \{1, ...\tau\}$, which typically corresponds to at least a year. Stack all the p_t into the vector $\mathbf{p}$ of length τ, and similarly for all types of input variables, respectively, to form the matrix $\mathbf{X} = [\mathbf{c}, \mathbf{v}, \mathbf{p^{ref}}, \mathbf{s^1}...\mathbf{s^4}, \mathbf{h^1}...\mathbf{h^{24}}, \mathbf{d^1}...\mathbf{d^7}, \mathbf{f}] \in \mathbb{R}^{\tau \times 39}$. To ensure data uniformity, each input column has been further standardized, which will be detailed later on. With all these notations, the test feeder power consumption $\mathbf{p}$ can be approximated using a linear regression model, as given by

$$\mathbf{p} \approx \mathbf{X}\boldsymbol{\beta} + \beta_0 \mathbf{1} \tag{1}$$

where $\boldsymbol{\beta} \in \mathbb{R}^{39}$ is the parameter vector corresponding to all input variables, and β_0 denotes the intercept parameter. Notice that the linear aggregation model has been used widely in the literature for load prediction/forecasting; see e.g., [7] and references therein. Compared to the existing models, the proposed one in (1) further incorporates the feeder bus voltage and reference feeder power as two additional inputs, both motivated by the CVR tests and analysis considered in the present paper.

The problem now becomes to obtain the parameter β_2, for characterizing the dependency of instantaneous power decrease on the voltage reduction. Once the sensitivity parameter β_2 is given, it can used to estimate the CVR factor and thus determine the effectiveness of CVR for any field test cases.

Remark 1: *(General CVR factors).* There exist other similar CVR factors to characterize peak power reduction or reactive power/energy savings. While the present paper discusses only the linear model for power demand and the CVR factor for determining the yearly real energy saving effect, it is clear that the proposed analytical framework can be easily extended to investigate more general CVR effects, with additional measurement data on reactive power becoming available. This points out an interesting direction to pursue more CVR field tests and investigate more broader CVR effects.

III. Sparse Linear Regression Based CVR Analysis

The linear regression model (1) is overdetermined since the number of samples $\tau \gg 39$. Hence, the parameter estimation problem could be easily solved using the ordinary least-squares (OLS), as given by

$$\left[\beta_0^{\mathrm{OLS}};\ \boldsymbol{\beta}^{\mathrm{OLS}}\right] := \arg\min_{[\beta_0;\ \boldsymbol{\beta}]} \|\mathbf{p} - [\mathbf{1}\ \mathbf{X}]\,[\beta_0;\ \boldsymbol{\beta}]\|_2^2 = [\mathbf{1}\ \mathbf{X}]^{\dagger}\,\mathbf{p} \quad (2)$$

where † denotes the matrix pseudo-inverse operator. However, since the OLS criterion is solely based on the fitting error norm, the solution (2) is typically non-zero in all entries. It has been pointed out that such solution tends out to experience lack of accuracy when extended to additional data samples. This is generally the data over-fitting issue in statistics.

To tackle this, the principle of parsimony is usually adopted to regularize the complexity of the data fitting model. For the groups of variables in (1), notice that several of them may be highly related when used to estimate $\mathbf{p}$. For example, since the load curves are highly similar for weekdays, $\mathbf{p}$ may not be dependent on which specific weekday it is. As a result, it is preferred to have 0 values for those parameters corresponding to the weekday variables. Motivated by this, a sparse linear regression approach is used to develop a more robust estimate of $\boldsymbol{\beta}$. Specifically, the so-termed Lasso method [8] aims to promote a parsimonious solution by penalizing the squared error norm with an additional norm-1 term of the unknowns, as given by

$$\min_{\boldsymbol{\beta},\beta_0} \|\mathbf{p} - \mathbf{X}\boldsymbol{\beta} - \mathbf{1}\beta_0\|_2^2 + \lambda\|\boldsymbol{\beta}\|_1 \quad (3)$$

where $\lambda \geq 0$ controls the level of sparsity in the estimated solution. The OLS solution in (2) corresponds to the estimate in (3) when $\lambda = 0$, while the Lasso solution is all-zero for every parameter when $\lambda \to \infty$. By varying the value λ from ∞ down to 0, a Lasso solution path can be obtained with an increasing number of non-zero entries [8]. Hence, one additional benefit of the proposed framework is to rank the input variables in determining the output power demand. For example, the most influential variables would first appear to be non-zero along the solution path. This would also become used to analyze the load data later on.

To choose the regularization parameter λ, the popular K-fold cross validation (CV) approach will be adopted to estimate a suitable λ from the data; see e.g., [9]. Specifically, the full dataset is first partitioned into K subsets, with a typical choice of K from 5 to 10. Second, one subset will be chosen as the training set to perform the Lasso, while the solution path for a varying λ will be used to calculate a specific CV error based on all other testing subsets. Once an appropriate λ is chosen, a subset of active input variables corresponding to non-zero parameters can be selected. The OLS estimation can be further performed on the active variables to increase the accuracy in computing the CVR factor.

A. Input data pre-processing

In order to balance the various scales of the input variables, it is necessary to standardize the column of matrix $\mathbf{X}$. This way, it is more fair to judge their statistical influence on the output $\mathbf{p}$. Note that input variables can be categorized into two groups based on whether they are real-valued measurements or binary indicators. The first group includes the columns $\{\mathbf{x}_i\}_{i=1}^3$, for which a mean subtraction and norm scaling are performed successively to the corresponding pre-processed vector $\mathbf{x}'_i$, as given by

$$\mathbf{x}_i = \frac{\mathbf{x}'_i - \mu_i\mathbf{1}}{c_i}, \quad i = 1, 2, 3 \quad (4)$$

where the mean $\mu_i := (\sum_{t=1}^{\tau} x'_{it})/\tau$ and the scaling factor $c_i := \|\mathbf{x}'_i - \mu_i\mathbf{1}\|_2$. The second group contains the rest of columns $\mathbf{x}_i$ with $i \in [4, 39]$. The corresponding pre-processed binary vector $\mathbf{x}'_i$ is first transformed using the mapping from $\{0, 1\}$ to $\{-1, 1\}$ with further normalization, as given by

$$\mathbf{x}_i = \frac{2\mathbf{x}'_i - \mathbf{1}}{c_i}, \quad \mathrm{i} = 4, 5, ..., 39 \quad (5)$$

where again the scaling factor $c_i := \|2\mathbf{x}'_i - \mathbf{1}\|_2$. After this pre-processing step for the input data, all the standardized vectors $\{\mathbf{x}_i\}$ will be used to construct $\mathbf{X}$ for the aforementioned regression analysis in (3).

B. Computing the CVR factor

Once the parameter β_2 is obtained, it can be used to compute the CVR factor metric. Specifically, a virtual 1% voltage reduction test is assumed for the test feeder based on its voltage and power measurement data. The virtual test voltage vector is smaller than the test voltage $\mathbf{v}$ by $\Delta\mathbf{v} := 0.01\mathbf{v}$, which would lead to the instantaneous power demand reduction $\Delta\mathbf{p} = (\beta_2/c_2)\Delta\mathbf{v}$, based on the linear model in (1) and the scaling factor in (4). Hence, the CVR factor as the ratio in percentage between the energy reduction and the energy consumption becomes

$$CVRf = \frac{\sum_{t=1}^{\tau} \triangle p_t \times 100}{\sum_{t=1}^{\tau} p_t}. \quad (6)$$

This completes the step for computing the CVR factor under the proposed data-driven framework.

IV. Numerical Validation using Synthetic Data

With the analytical method presented, the ensuing step is to demonstrate its capability and accuracy in determining the CVR factor through numerical tests. For this purpose, a set of synthetic measurements are generated for a realistic 13.8 kV (7.96 kV line to ground) feeder circuit located in central Illinois. This is performed using the yearly load flow toolbox in the distribution system analysis software OpenDSS [10]. This procedure involves three steps. In the first step, all the loads in the feeder system are categorized into three distinct types, namely, Residential, Commercial, and Industrial loads, based on their peak power consumption. A recently developed ZIP load model presented in [11] is used for modeling each load according to its predetermined type. The second step is to generate an hourly load flow for an entire year (January to December), which will be simulated without any reduction in voltage with real power and voltage measured at the head of the feeder. This corresponds to the base scenario with no reduction for the study. In the third step, the voltage is regulated at the head of the feeder, by reducing one percent of its magnitude using load tap changing transformer techniques. Again, the full year hourly load flow is simulated, with the corresponding measurements of voltage and real power obtained at feeder bus forming the CVR test case data.

The synthetic tests could greatly facilitate obtaining the test feeder's CVR factor. Since the load shape used in both no-reduction and reduced simulated cases are exactly same, comparing the difference of the measured power consumptions for the two tests would easily yield the actual impact of voltage reduction. The CVR factor can be hence determined and found to be 0.71. This data set will now be used to determine the CVR factor using the proposed method.

Specifically, the dataset contains the test feeder hourly power demand, and time-stamped measurements of single-phase voltage and temperature. Since there is no reference feeder available in this synthetic test, it is necessary to pick selected ranges of power demand data to prelude the possibility that low voltage scenarios arise due to high feeder loading stress. The input dataset is pre-processed to generate the matrix $\mathbf{X}$. For each range of power data, the Lasso regression analysis is performed with 10^{th}-fold cross validation. The corresponding CVR factors obtained using (6) are listed in Table I, all of which are fairly close to the projected value 0.71. Therefore, this demonstrates that our proposed method can estimate the CVR factor with high accuracy. For the demand range of 2680 - 2700 kW, Fig. 1 plots the residual terms obtained from the linear analysis versus time, confirming an approximate zero sample mean. The autocorrelation for this time series is further illustrated in Fig. 2, showing the shape close to the Dirac's delta function. Both plots confirm that the proposed linear regression model is very accurate in representing the power demand data. Table II lists the selected ranking of input variables provided by Lasso. The voltage input is ranked first by the Lasso, and shows much higher dependency compared to all the rest variables. Interestingly, the other temporal variables as identified in Table II exactly correspond to the hours associated with that specific power demand range. This again confirms the capability of the proposed method in identifying more influential input variables to overcome over-fitting.

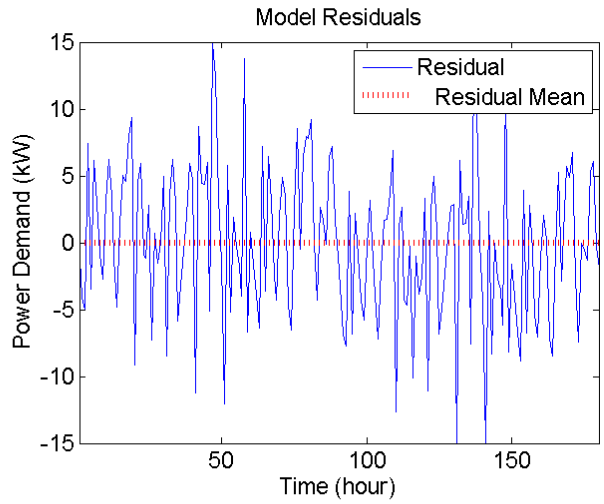

Figure 1. The power demand estimation residue versus time for synthetic dataset

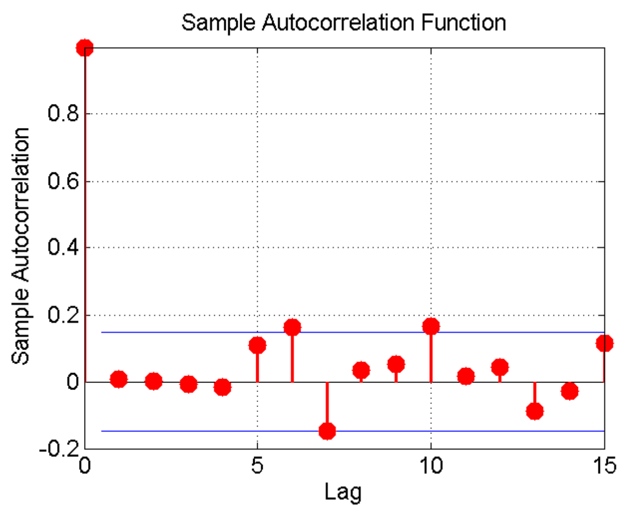

Figure 2. The sample autocorrelation coefficients of the residue series for up to 15 lags

V. CVR Analysis for Field Test Data

The proposed method will be further validated using the field CVR feeder test data, which is provided by an electric utility company at the U.S. Midwest region. The data is collected at a 13.8 kV feeder system from May 2012 to May 2013. The field CVR test was performed by periodically setting the feeder bus voltage at one of the following three

Table I
Estimated CVR factors using different power demand ranges

Power Demand Range (kW)	CVRf
2600 - 2620	0.6688
2620 - 2640	0.6967
2640 - 2680	0.6916
2680 - 2700	0.696
3000 - 3020	0.676

Table II
Ranking of the variables from synthetic dataset

Var.	Coef.	Rank	Var.	Coef.	Rank
v	132.39	1	Wednesday	14.04	6
Hour9	16.95	2	Hour15	13.72	7
Hour4	22.7	3	Hour18	-15.76	8
Hour8	21.49	4	Hour20	-13.61	9
Hour0	-9.02	5	Hour2	-6.37	10

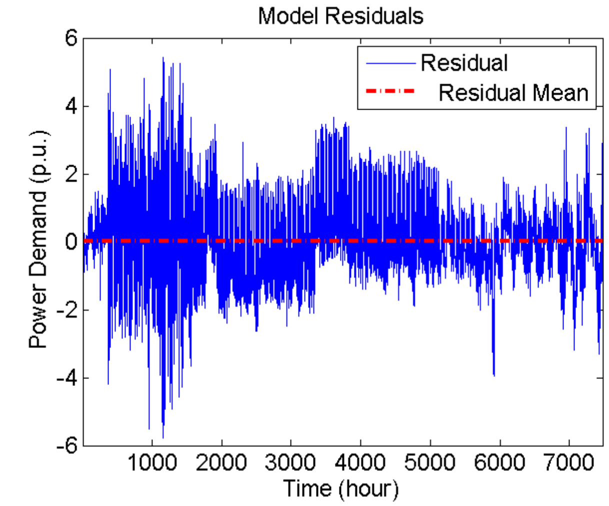

Figure 3. The power demand estimation residue versus time for test dataset

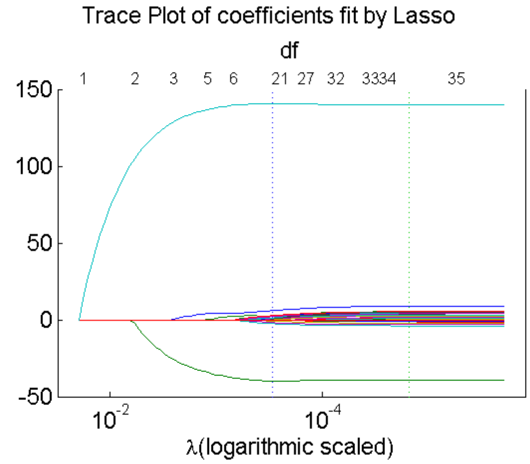

Figure 5. The Lasso solution path with a varying λ

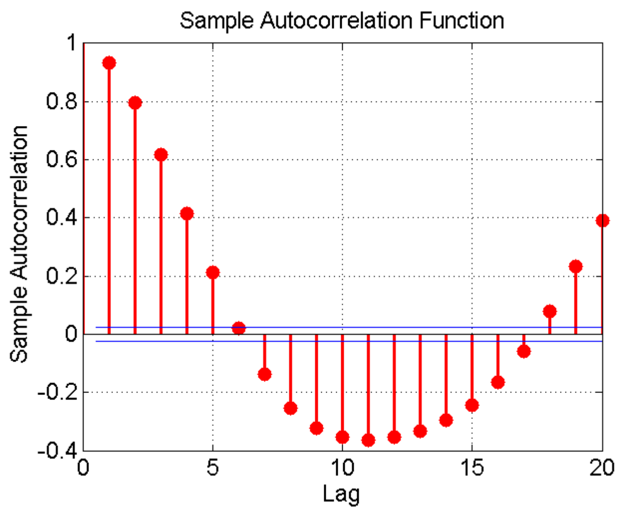

Figure 4. The sample autocorrelation coefficients of the residue series for up to 20 lags

Table III
RANKING OF THE VARIABLES

Var.	Coef.	Rank	Var.	Coef.	Rank
p_{ref}	140.22	1	Hour22	4.4	12
Fall	-39.17	2	v	2.71	13
Summer	8.73	3	Hour18	3.66	14
Hour12	-0.02	4	Saturday	3.36	15
c	5.05	5	Hour10	-2.39	16
Hour8	-4.19	6	Hour23	2.88	17
Hour20	5.26	7	Winter	5.34	18
Hour21	5.23	8	Hour7	-1.54	19
Hour9	-3.41	9	Hour17	2.31	20
Hour19	4.84	10	Hour11	-1.34	21
Sunday	4.35	11			

levels:

- 0% reduction: $v_t \geq 7.843kV$
- 2% reduction: $7.716kV \leq v_t \leq 7.843kV$
- 4% reduction: $7.589kV \leq v_t \leq 7.716kV$

Compared to the earlier synthetic test, the field CVR test also collects the power demand data at a reference substation with topology and load modeling characteristics similar to the test feeder. Similar to the synthetic data validation, the field test data is pre-processed and analyzed using the Lasso with 10^{th}-fold cross validation. The estimation residual term and its autocorrelation are depicted in Fig. 3 and Fig. 4, respectively. Both figures again confirm the validity of the linear relation to model the power demand data.

The Lasso solution path with varying λ is shown in Fig. 5. The voltage related parameter β_2, and with other significant parameters are ranked in Tab. III. The CVR factor for this feeder system can thus be determined as the following:

$$CVRf = \frac{\sum_{t=1}^{\mathcal{T}} \frac{2.711}{8.142}(0.01) \cdot v_t}{\sum_{t=1}^{\mathcal{T}} p_t} = 0.43$$

The CVR factor value in this case lies in an expected range and shows that the voltage has a direct impact over the power demand. It also suggests that reduction in voltage will decrease power demand in turn of saving energy.

As shown in Tab. III, the test feeder power demand is most significantly dependent on that of the reference feeder. This is expected since the behavior of the test feeder is in practice extremely similar to the test feeder, based on the test feeder selection criterion. The ensuing parameters in the ranking list are related to the season and temperature. The season/temperature are among the top factors that dictate the changing load composition of the feeder, such as turning on or off of fans, air conditioners, and heaters etc. It is expected that the season and temperature variables are ranked highly in the list, since the test feeder here is a residential feeder. This might not be true for other feeders, such as highly industrial loads with constant power load characteristics. Since the hour and day variable are represented in the model as indicator variables the ranking of these variables can be understood in terms of periodic load composition change during the course of a day or a week. The impact of voltage on the load consumption is ranked in the medium range, below several temperature and time related variables. This corroborates our proposed linear regression model in incorporating as many dependent variables as possible in order to achieve a more accurate sensitivity to the voltage variable.

VI. Conclusion and Future Works

We have proposed a linear model of the distribution feeder power model based on several factors, including the voltage magnitude at the substation bus. This analytical model is used to computer the CVR factor based on field test data, in order to quantify the effectiveness of CVR at specific feeders. A sparse linear regression framework is used to solve the linear model with the capability of ranking the input factors. The proposed model and method are validated using synthetic simulation data using OpenDSS, as well as tested on the utility CVR field test data. The CVR factor value exhibits a good estimation accuracy based on the synthetic tests, while the field CVR factor also lies in an expected range. Moreover, the factor ranking results are useful and coincides with earlier experiences in dealing with load curve data.

This work opens up several future research directions including the extension to more general CVR factor analysis. A finer power demand model is also of interest, in order to account for the dependency of each individual variable, i.e., among season, temperature and hour-of-day.

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