CVR Assessment Methodologies & Field Results

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Overview

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- Methodologies for CVR factor evaluation
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  - Load-modeling-based methods
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- Case studies
  - Data set description & Simulation setup
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Background & Motivation

Background and Motivation

- Definition: Conservation Voltage Reduction (CVR) is an energy efficiency measure that reduces energy consumption through feeder-level voltage reduction.
- Motivation: A major benefit of CVR is its non-intrusive nature, i.e., energy consumption at the customer end reduces automatically without negatively impacting equipment operation or customer comfort.
- Measure: The CVR impacts can be measured by CVR factor (CVR_f) for energy, which is defined as

$$CVR_f = \frac{\Delta E\ (\%)}{\Delta V(\%)}$$

Methodologies for CVR factor evaluation

Methodology

Comparison-Based Methods

There are two basic approaches of comparison-based methods for measuring CVR effects.

- Select two similar feeders in the same performance period (similar configurations, topologies, loading conditions). Voltage reduction is applied to only one feeder.

- Perform a CVR test on a feeder and apply normal voltage to the same feeder but during another time period with similar loading conditions.

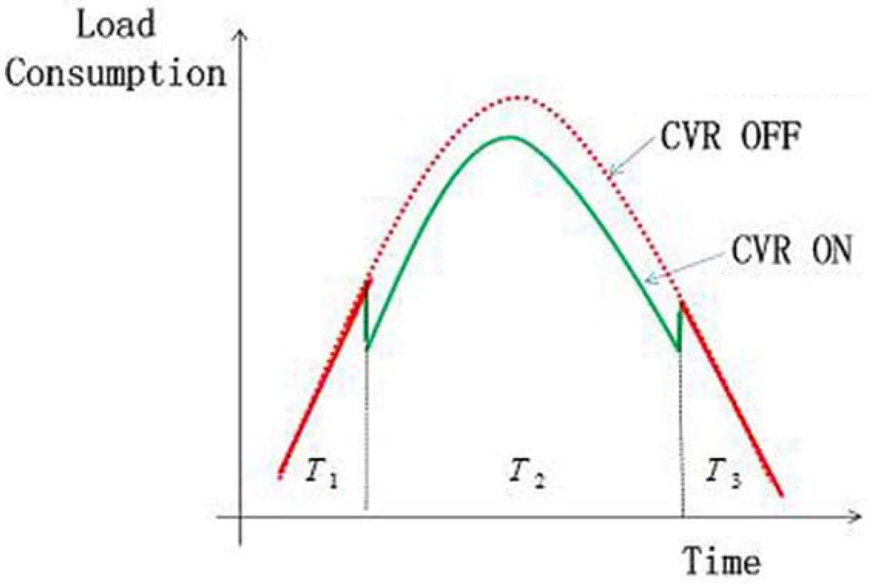

Fig. 1. Demonstration of comparison-based method for evaluating CVR factor.

Methodology

Regression-Based Methods

- In regression-based methods, loads are modeled as a function of some impact factors, e.g., temperature.
- Models for the normal-voltage load process are identified using linear regression, and their outputs are compared with the measured reduced-voltage load to calculate the CVR factor.

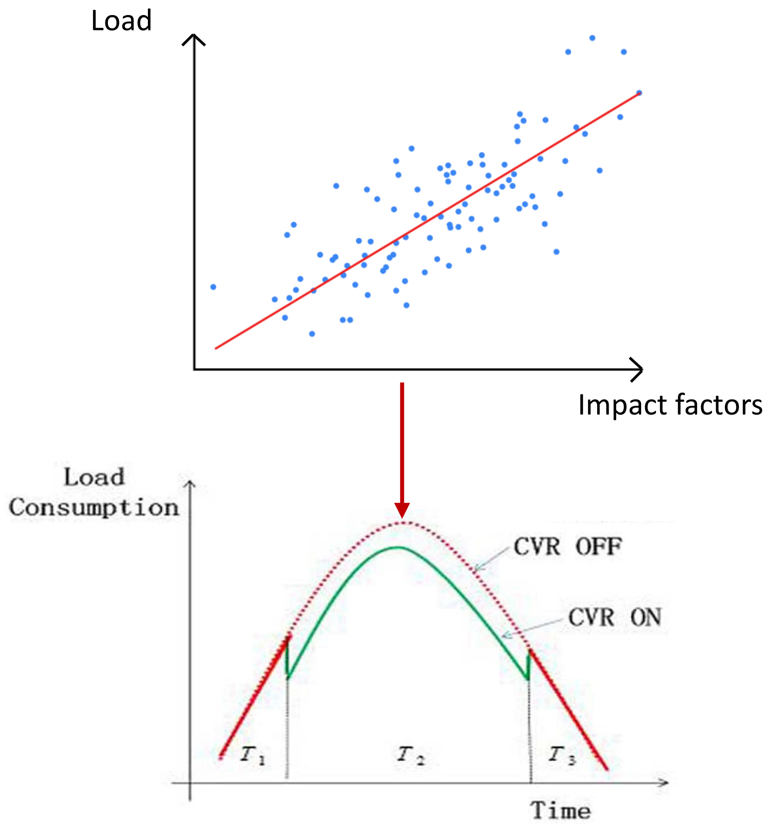

Fig. 2. Demonstration of regeression-based method for evaluating CVR factor.

Methodology

Load Modeling-Based Methods

- The nature of CVR is that load is sensitive to voltage. Whether voltage reduction is applied or not, loads are always sensitive to voltage and the sensitivities vary with time due to the ever-changing load compositions.
- In the load modeling-based method, a function of voltages and other exogenous factors is established to represent the load consumption. This function can be used to capture the load-to-voltage sensitivities by identifying the model parameters in real time.

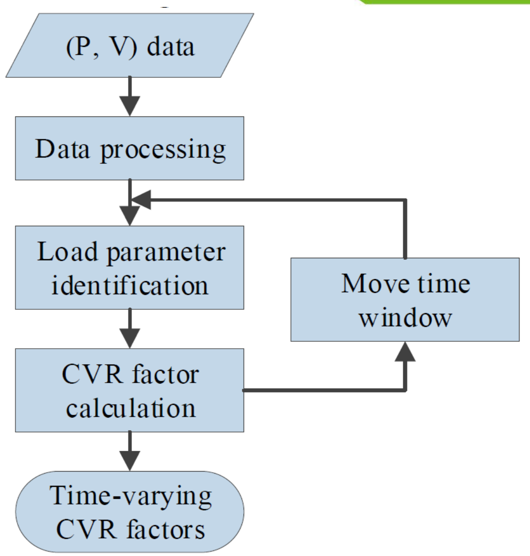

Fig. 3. Flowchart of load modeling-based method for evaluating CVR factor.

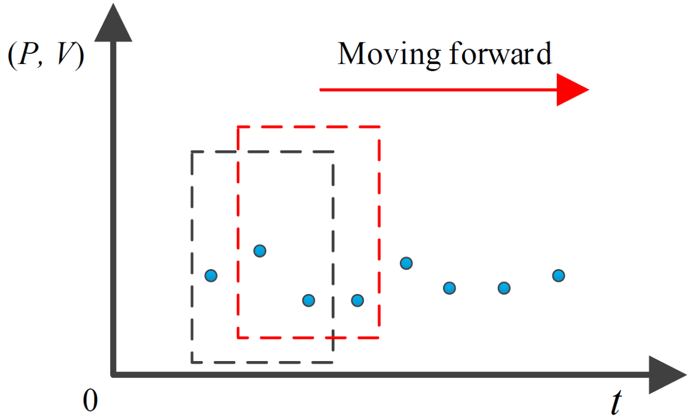

Fig. 4. Demonstration of moving time window.

Methodology

Load Modeling-Based Methods

<u>Step 1</u>: Select a mathematical representation of the load model, e.g., the ZIP load model

$$\frac{P_{ZIP}}{P_0} = \alpha_P \left(\frac{V}{V_0}\right)^2 + \beta_P \frac{V}{V_0} + \gamma_P$$

where P_{ZIP} (Watt) is the active power of the load of ZIP model; P_0 (Watt) is the nominal power of the feeder/bus of the load; α_P is the active power-related coefficient of the load's constant impedance component; V (Volt) is the voltage magnitude measurement; V_0 (Volt) is the nominal voltage; β_P is the active power-related coefficient of the load's constant voltage component; γ_P is the active power-related coefficient of the load's constant power component.

We choose the ZIP load model because the voltage-insensitive components can be reflected into the constant power term.

Methodology

Load Modeling-Based Methods

<u>Step 2</u>: In real-world engineering, the load composition, customer behavior and operation condition are changing over time. To identify the time-varying load model parameters $\alpha_{P,i}$, $\beta_{P,i}$, and $\gamma_{P,i}$, a general optimization problem is formulated as follows.

$$\min_{\alpha_{P,i},\beta_{P,i},\gamma_{P,i}} J = \sum_{i=1}^{n} \left(\alpha_{P,i} \left(\frac{V_i}{V_0} \right)^2 + \beta_{P,i} \frac{V_i}{V_0} + \gamma_{P,i} - \frac{P_i}{P_0} \right)^2$$

$$\text{s.t.,} \quad \alpha_{P,i} + \beta_{P,i} + \gamma_{P,i} = 1$$

$$0 < \alpha_{P,i}, \beta_{P,i}, \gamma_{P,i} < 1$$

where J is the accumulative squared error, i is the ith time interval, and n is the total number of time intervals. The lengths of time intervals depend on the time resolution of the measurement data. V_i and P_i are field voltage and power measurements.

This optimization problem can be solved by various kinds of methods, such as least-square-type algorithms.

Methodology

Load Modeling-Based Methods

Step 3: Compute estimated voltage reduction $\Delta V(\%)$ for the *i*th time interval from the measurement data:

$$\Delta V(\%) = \frac{V_{\text{average}}^{off} - V_{\text{average}}^{on}}{V_{\text{average}}^{off}} \times 100\%$$

$$V_{\text{average}}^{off} = \frac{\left(\sum_{i=1}^{n_{off}} V_i^{off}\right)}{n_{off}}, \qquad V_{\text{average}}^{off} = \frac{\left(\sum_{i=1}^{n_{on}} V_i^{on}\right)}{n_{on}}$$

where V_{average}^{off} and V_{average}^{on} are averaged voltages when CVR is on and off, respectively; V_i^{off} and V_i^{on} are voltages for CVR-off and CVR-on respectively; n_{on} and n_{off} are the total numbers of measurements for CVR is on and CVR is off, respectively.

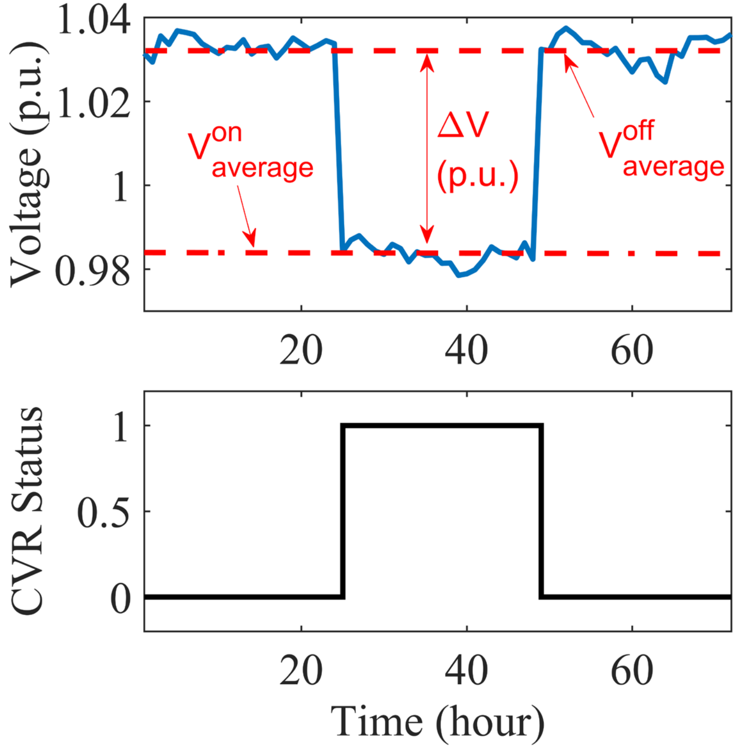

Fig. 5. Demonstration of average voltages and voltage reduction.

Methodology

Load Modeling-Based Methods

<u>**Step 4**</u>**:** By substituting the obtained load model into the definition of CVR factor, the time-varying CVR factor can be explicitly derived as a function of load model parameters, estimated voltage reduction and normalized voltage measurement:

$$CVR_{f_i} = \frac{\Delta E_i\ (\%)}{\Delta V_i\ (\%)} = \frac{\frac{e_i^{off} - e_i^{on}}{e_i^{off}}}{\frac{V_i^{off} - V_i^{on}}{V_i^{off}}} = \frac{\frac{P_i^{off} - P_i^{on}}{P_i^{off}}}{\frac{V_i^{off} - V_i^{on}}{V_i^{off}}} = \frac{\left(2\alpha_{P,i} - \alpha_{P,i}\Delta V_i\ (\%)\right)(\bar{V}_i^{on})^2 + \beta_{P,i}\bar{V}_i^{on}(1 - \Delta V_i\ (\%))}{\alpha_{P,i}\left(\bar{V}_i^{on}\right)^2 + \beta_{P,i}\bar{V}_i^{on}(1 - \Delta V_i\ (\%)) + \gamma_{P,i}(1 - \Delta V_i\ (\%))^2}$$

where $\bar{V}_i^{on} = V_i^{on}/V_0$ is the normalized voltage when CVR is off; $\Delta V_i\ (\%)$ can be approximated by $\Delta V(\%)$.

Note that this CVR_{f_i} is the CVR factor at the *i*th time interval, i.e., the load-modeling-based methods can identify instantaneous CVR factors.

Methodology

Load Modeling-Based Methods

<u>Step 5</u>: At a time period that CVR is on, we can use time-varying CVR factor, estimated voltage reduction and measurement data P_i^{on} to estimate the power consumption if CVR was off during the same period, $P_{i,\text{estimate}}^{off}$:

$$P_{i,\text{estimate}}^{off} \approx \frac{P_i^{on}}{1 - \Delta V(\%) \times CVR_{f\,i}}$$

The energy baseline $E^{baseline}$ is the total energy consumed if CVR was off:

$$E^{baseline} = E^{on,baseline} + E^{off,baseline} = \sum_{i=1}^{n_{on}} P_{i,\text{estimate}}^{off} \Delta t + \sum_{j=1}^{n_{off}} P_i^{off} \Delta t$$

where $E^{on,baseline}$ and $E^{off,baseline}$ are energy baselines for the CVR-on and CVR-off periods, respectively.

Methodology

Load Modeling-Based Methods

Step 6: The energy savings during the periods when CVR is on can be computed as

$$E^{save} = E^{on,baseline} - E^{on} = \sum_{i=1}^{n_{on}} \left(P_{i,\text{estimate}}^{off} - P_i^{on}\right)\Delta t$$

where E^{on} is the energy consumed during the CVR-on period.

Step 7: Calculate the estimated energy reduction ΔE (%) by

$$\Delta E\ (\%) = \frac{E^{save}}{E^{on,baseline}} \times 100\%$$

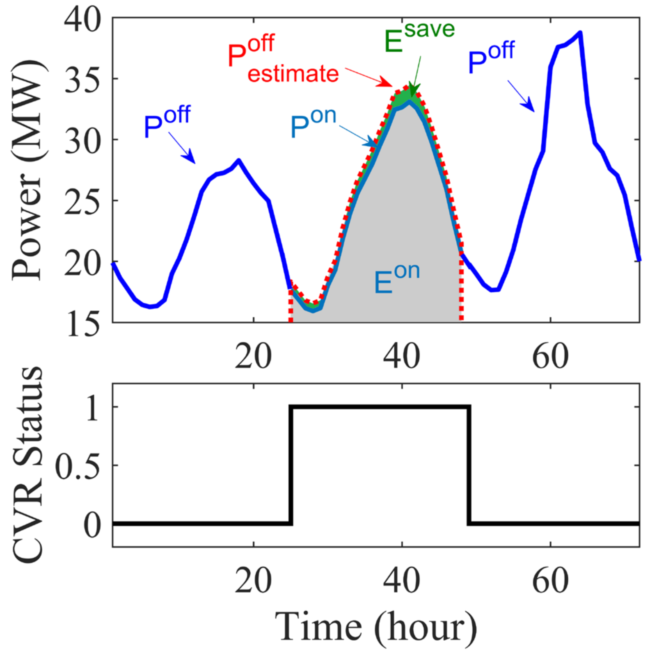

Fig. 6. Relationship among variables.

Step 8: The CVR factors computed in Step 4 are a series of "instantaneous" values at different time intervals. To integrate this series of CVR factors into one single value, the overall scalar-valued CVR factor can be computed as

$$CVR_f = \frac{\Delta E\ (\%)}{\Delta V(\%)}$$

Methodology

Load Modeling-Based Methods

Step 9: In case of missing data, scaling coefficients are needed to calculate baseline energy and energy savings:

$$E^{on,baseline} = \alpha^{on} \sum_{i=1}^{n_{on}} P_{i,\text{estimate}}^{off} \Delta t$$

$$E^{save} = E^{on,baseline} - \alpha^{on} E^{on} = \alpha^{on} \sum_{i=1}^{n_{on}} \left(P_{i,\text{estimate}}^{off} - P_i^{on}\right) \Delta t$$

The baseline energy, $E^{baseline}$, can accordingly be calculated as follows:

$$E^{baseline} = E^{on,baseline} + \alpha^{off} E^{off} = \alpha^{on} E^{on} + \alpha^{off} E^{off} + E^{save}$$

where α^{on} and α^{off} are scaling coefficients to take the missing data in CVR-on and CVR-off periods into account, respectively.

$$\alpha^{on/off} = \frac{\#\ of\ CVR^{on/off}\ datapoints}{\#\ of\ CVR^{on/off}\ datapoints - \#\ of\ missing\ CVR^{on/off}\ datapoints}$$

Methodology

Pros and Cons of the three methods

Types	Pros	Cons
Comparison-based methods	1) It is the most simple and straightforward method to understand.	1) A good control group may not exist. 2) It is vulnerable to noises (such as weather impacts, and natural load variation).
Regression-based methods	1) It is easy to implement. 2) It has a clear physical meaning easy to understand. 3) It is capable of forecasting the CVR effects.	1) It is subject to regression error. 2) It typically assumes a linear relationship between the load and the factors, which may not be valid. 3) It needs to collect a sufficient amount of data for accurate regression analysis.
Load modeling-based methods	1) It can estimate time-varying CVR factors. 2) It is robust to outliers and disturbances in raw data. 3) It can provide the energy saving potential of a feeder without running voltage reduction experiments.	1) Appropriate selection of the load model (e.g., exponential model, ZIP model or others) is desired for a practical feeder. 2) It needs empirical voltage reduction which may not be always exact due to several operational issues.

Review of CVR factor Range

A comprehensive study was conducted to review the values of reported CVR factors in utilities.

Utility	Value of CVR Factor	Methodology
Clark Public Utilities	0.3	
Douglas PUD	2.07-2.17	
Snohomish County Public Utility	0.74	Comparison-based
New York State Electric & Gas	0.6	
Central Florida Electric Cooperative	0.5-0.75	
Clay Electric Cooperative	1.0	
Progress Energy-Florida	1.0	
Georgia Power	0.5-1.7	
Cobb EMC	0.75	
Progress Energy	0.4	
Kansas City Power and Light	0.7	Comparison-based
Clatskanie PUD	1.4	
Inland power & light	0.93	
Seattle city light	0.13	
BC Hydro	0.6-0.77	Regression-based
Hydro-Québec	0.06-0.97	
Bonneville Power Administration	0.41-0.99	
AEP	0.35-0.89	Regression-based
Korea Electric Power Corporation	0.681-0.939	
San Diego Gas & Electric	0.08-1.14	
City-of-Lethbridge-Electric-Utility	0.83-0.9	
Central Lincoln People's Utility District	0.43- 1.05	Comparison-based
Ameren Illinois	0.148 - 1.48	Regression-based
ComEd	0.8	Regression-based/Constant CVR factor
Idaho Power Company	0.41-5.75	Constant CVR factor/ Comparison-based
West Penn Power Company	0.86	Regression-based
Indianapolis Power & Light	0.75	Comparison-based
PECO Energy	1.08	Regression-based
Duke Energy Ohio	0.50-0.79	Constant CVR factor
Xcel Energy	0.8	Simulation-based method/Statistical analysis
PG&E	0.6-0.8	Regression-based
Southern California Edison	1.56	Regression-based
Puget Sound Energy	0.475	Regression-based
Dominion Energy	0.92	Comparison-based
Indiana Michigan Power	-0.43-4.48	Regression-based
NRECA	1.04	Comparison-based
NEEA	0.17-1.12	Comparison-based
Avista Corp	0.84	Regression-based/Simulation based

Case Studies

Field measurement validation

Case Studies

Description of Data Set

- The case studies are conducted on two data sets (named as D2_2016 and D3_2016) from two different sources during 01/01/2016~12/31/2016.
- The data sets have five different time resolutions (5, 10, 15, 30, 60 min).
- Both data sets contain CVR-on and CVR-off tests. In D2, the CVR is applied during 08/30/2016 ~ 09/06/2016 and 09/27/2016 ~ 10/04/2016. In D3, the CVR is applied every other day during 05/28/2016 ~ 08/14/2016.

Simulation Setup

Three case studies are carried out.

- Case 0 (Base case): Clean data is prepared by averaging raw values over 30-min intervals.
- Case 1 (Analyzing resolution impact): Clean data is prepared by averaging raw values from over 5, 10, 15 and 60-min intervals.
- Case 2 (Analyzing outlier impact): 30-min frequency data with 5%, 10%, 20%, 30% and 50% outliers included.

Case Studies

Case 0: Simulations based on no data anomalies

	Comparison-Based				
Name	Ebaseline (MWh)	Estimated Voltage Reduction (%)	Estimated Energy Reduction (%)	Esavings (MWh)	CVR Factor
D2_2016	178,314.14	2.70	-0.90	-58.38	-0.33
D3_2016	202,501.17	4.83	4.73	1,050.97	0.98

	Regression-Based				
Name	Ebaseline (MWh)	Estimated Voltage Reduction (%)	Estimated Energy Reduction (%)	Esavings (MWh)	CVR Factor
D2_2016	178,160.16	2.83	-3.36	-212.36	-1.19
D3_2016	202,320.66	4.85	3.95	870.45	0.81

	Load-Modeling-Based				
Name	Ebaseline (MWh)	Estimated Voltage Reduction (%)	Estimated Energy Reduction (%)	Esavings (MWh)	CVR Factor
D2_2016	181335.39	2.78	2.21	136.92	0.79
D3_2016	203989.32	4.85	3.96	845.47	0.82

Case Studies

Case 1: Simulations based on data resolution (D2_2016)

	Comparison-Based				
Resolution	Ebaseline (MWh)	Estimated Voltage Reduction (%)	Estimated Energy Reduction (%)	Esavings (MWh)	CVR Factor
5 min	180,309.13	2.76	-0.27	-17.90	-0.10
10 min	179,575.50	2.70	-2.41	-153.92	-0.89
15 min	179,461.11	2.75	2.41	161.55	0.88
60 min	177,677.06	2.77	1.11	73.59	0.40
	Regression-Based				
Resolution	Ebaseline (MWh)	Estimated Voltage Reduction (%)	Estimated Energy Reduction (%)	Esavings (MWh)	CVR Factor
5 min	180,119.32	2.87	-3.29	-207.71	-1.14
10 min	179,521.45	2.85	-3.29	-207.97	-1.15
15 min	179,512.00	2.76	3.15	212.44	1.14
60 min	177,388.95	2.82	-3.40	-214.52	-1.20
	Load-Modeling-Based				
Resolution	Ebaseline (MWh)	Estimated Voltage Reduction (%)	Estimated Energy Reduction (%)	Esavings (MWh)	CVR Factor
5 min	185003.03	2.81	1.72	98.23	0.61
10 min	183733.89	2.79	1.82	108.05	0.65
15 min	182879.53	2.79	2.00	121.02	0.72
60 min	179922.31	2.78	2.28	141.61	0.82

Case Studies

Case 1: Simulations based on data resolution (D3_2016)

	Comparison-Based				
Resolution	Ebaseline (MWh)	Estimated Voltage Reduction (%)	Estimated Energy Reduction (%)	Esavings (MWh)	CVR Factor
5 min	204,484.61	4.85	4.47	1,001.76	0.92
10 min	203,770.01	4.86	4.28	954.72	0.88
15 min	203,191.69	4.85	3.75	828.95	0.77
60 min	201,867.62	4.83	4.33	956.15	0.90
	Regression-Based				
Resolution	Ebaseline (MWh)	Estimated Voltage Reduction (%)	Estimated Energy Reduction (%)	Esavings (MWh)	CVR Factor
5 min	204,344.16	4.85	3.87	861.31	0.80
10 min	203,679.13	4.85	3.89	863.84	0.80
15 min	203,164.22	4.85	3.63	801.49	0.75
60 min	201,781.88	4.85	3.96	870.41	0.82
	Load-Modeling-Based				
Resolution	Ebaseline (MWh)	Estimated Voltage Reduction (%)	Estimated Energy Reduction (%)	Esavings (MWh)	CVR Factor
5 min	211604.87	4.85	3.55	673.35	0.73
10 min	208659.75	4.85	3.55	709.09	0.73
15 min	206744.77	4.85	3.72	763.99	0.77
60 min	202459.54	4.84	3.83	831.58	0.79

Case Studies

Case 2: Simulations based on additional missing data (D2_2016)

	Comparison-Based				
Outlier	Ebaseline (MWh)	Estimated Voltage Reduction (%)	Estimated Energy Reduction (%)	Esavings (MWh)	CVR Factor
5%	178,384.99	2.63	-0.66	-43.10	-0.25
10%	178,194.29	2.62	-2.65	-168.75	-1.01
20%	178,703.04	2.74	1.00	65.60	0.36
30%	178,707.13	2.59	0.20	13.01	0.08
	Regression-Based				
Outlier	Ebaseline (MWh)	Estimated Voltage Reduction (%)	Estimated Energy Reduction (%)	Esavings (MWh)	CVR Factor
5%	178,201.16	2.82	-3.59	-226.94	-1.27
10%	178,155.16	2.81	-3.28	-207.88	-1.17
20%	178,440.51	2.81	-3.11	-196.94	-1.11
30%	178,506.81	2.83	-2.97	-187.30	-1.05
	Load-Modeling-Based				
Outlier	Ebaseline (MWh)	Estimated Voltage Reduction (%)	Estimated Energy Reduction (%)	Esavings (MWh)	CVR Factor
5%	181394.49	2.77	2.21	130.51	0.80
10%	181357.72	2.77	2.21	121.09	0.80
20%	181566.75	2.76	2.20	109.29	0.80
30%	181807.29	2.78	2.21	95.76	0.79

Case Studies

Case 2: Simulations based on additional missing data (D3_2016)

	Comparison-Based				
Outlier	Ebaseline (MWh)	Estimated Voltage Reduction (%)	Estimated Energy Reduction (%)	Esavings (MWh)	CVR Factor
5%	202,271.96	4.86	4.37	966.51	0.90
10%	202,715.66	4.86	4.86	1081.35	1.00
20%	202,777.20	4.87	4.38	966.38	0.90
30%	202,701.06	4.85	4.57	1017.19	0.94
	Regression-Based				
Outlier	Ebaseline (MWh)	Estimated Voltage Reduction (%)	Estimated Energy Reduction (%)	Esavings (MWh)	CVR Factor
5%	202,191.88	4.85	4.02	886.43	0.83
10%	202,503.18	4.85	3.94	868.88	0.81
20%	202,670.72	4.85	3.92	859.90	0.81
30%	202,511.22	4.85	3.75	827.34	0.77
	Load-Modeling-Based				
Outlier	Ebaseline (MWh)	Estimated Voltage Reduction (%)	Estimated Energy Reduction (%)	Esavings (MWh)	CVR Factor
5%	203779.76	4.84	3.96	808.64	0.82
10%	204180.31	4.85	3.95	780.15	0.81
20%	204392.96	4.85	3.99	702.53	0.82
30%	204252.29	4.85	3.85	628.77	0.79

Conclusions

- There can be differences in the results of different methods, sometimes even when the same data is used. This is because methods may have different mechanisms and consider different factors.
- Different methods require different data. For example, the comparison-based methods require the CVR-on and CVR-off data of the similar days/hours at similar weather. Appropriate methods must be adopted based on the availability of data.
- Resolution of data may be an impact factor for the methods. Usually, the high-resolution data leads to better accuracy.
- The noise can influence the accuracy of different methods as well. For the comparison-based methods, the accuracy may be greatly impacted by the noise in the measurement data. The regression-based methods and load-modeling-based methods may be more robust to the measurement noises.

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Thank you!

Q&A

Backup slides

Steps for comparison-based method

Methodology

Comparison-Based Methods

Using the *second approach* as an example, the typical steps to calculate the CVR factor are explained as follows:

Step 1: Calculate the CVR factor for each time interval by dividing the percentage of energy reduction by percentage of voltage reduction:

$$CVR_{f_i} = \frac{\Delta E_i\ (\%)}{\Delta V_i\ (\%)},$$

$$\Delta E_i\ (\%) = \frac{e_j^{off} - e_i^{on}}{e_j^{off}} \times 100, \Delta V_i\ (\%) = \frac{V_j^{off} - V_i^{on}}{V_j^{off}} \times 100$$

where e_i^{on} and e_j^{off} refer to the measured energy of paired i^{th} CVR-on and j^{th} CVR-off time intervals, V_i^{on} and V_j^{off} refer to the measured voltage of paired i^{th} CVR-on and j^{th} CVR-off time intervals

Methodology

Comparison-Based Methods

<u>Step 2</u>: Calculate the feeder's CVR factor and voltage reduction by averaging over all time interval specific values:

$$CVR_f = Avg(CVR_{f_i}), \Delta V = Avg(\Delta V_i)$$

<u>Step 3</u>: Calculate the feeder energy savings and baseline energy:

$$E^{on,baseline} = \frac{E^{on}}{1 - CVR_f \times \Delta V}$$

$$E^{save} = E^{on,baseline} - E^{on} = E^{on}\left(\frac{CVR_f \times \Delta V}{1 - CVR_f \times \Delta V}\right)$$

where E^{on} is the total energy in CVR-on time periods. $E^{on,baseline}$ is the total energy in CVR-on periods before CVR was applied. The baseline energy, $E^{baseline}$, can accordingly be calculated as follows:

$$E^{baseline} = E^{on,baseline} + E^{off} = E^{on} + E^{off} + E^{save}$$

Methodology

Comparison-Based Methods

<u>Step 4</u>: In case of missing data, scaling coefficients are needed to calculate baseline energy and energy savings:

$$E^{on,baseline} = \alpha^{on} \frac{E^{on}}{1 - CVR_f \times \Delta V}$$

$$E^{save} = E^{on,baseline} - \alpha^{on} E^{on} = \alpha^{on} E^{on} \left(\frac{CVR_f \times \Delta V}{1 - CVR_f \times \Delta V} \right)$$

The baseline energy, $E^{baseline}$, can accordingly be calculated as follows:

$$E^{baseline} = E^{on,baseline} + \alpha^{off} E^{off} = \alpha^{on} E^{on} + \alpha^{off} E^{off} + E^{save}$$

where α^{on} and α^{off} are scaling coefficients to take the missing data in CVR-on and CVR-off periods into account, respectively.

$$\alpha^{on/off} = \frac{\#\ of\ CVR^{on/off}\ datapoints}{\#\ of\ CVR^{on/off}\ datapoints - \#\ of\ missing\ CVR^{on/off}\ datapoints}$$

Backup slides

Steps for regression-based method

Methodology

Regression-Based Methods

Step 1: Model parameters estimation

$$\mathbf{E} = \beta_0 \mathbf{1} + \beta_1 \left[T_{fh} \mathbf{1} - \mathbf{T}\right] + \beta_2 \left[T_{fc} \mathbf{1} - \mathbf{T}\right] + \boldsymbol{\varepsilon}$$

- $\mathbf{E}$ and $\mathbf{T}$ are training data for the model, $\mathbf{E}$ represents the vector of measured normal-voltage load data, **T** is the vector of recorded ambient temperature, the resolution of $\mathbf{E}$ and $\mathbf{T}$ depends on measurement devices and user preferences.
- T_{fh} is the heating reference temperature, T_{fc} is the cooling reference temperature (e.g., in [1], T_{fh} and , T_{fc} are set to be 60F and 70F, respectively).
- β_0, $\beta_1$and β_2 are parameters that need to be calculated using linear regression, $\boldsymbol{\varepsilon}$ represents the errors.

[1] Z. Wang and J. Wang, "Review on Implementation and Assessment of Conservation Voltage Reduction," IEEE Trans. on Power Systems, vol. 29, no. 3, pp. 1306-1315, May 2014.

Methodology

Regression-Based Methods

Step 2: The parameters β_0, β_1 and β_2 can be estimated by minimizing the errors. For an ordinary least squares method, the parameters can be calculated as follows:

$$\widehat{\boldsymbol{\beta}} = (\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{E}$$

$$\mathbf{X} = [\mathbf{1} \quad T_{fh}\mathbf{1} - \mathbf{T} \quad T_{fc}\mathbf{1} - \mathbf{T}]$$

where $\widehat{\boldsymbol{\beta}} = [\hat{\beta}_0\ \hat{\beta}_1\ \hat{\beta}_2]^T$ represents the estimated parameters, and X represents the vector of problem variables in the regression model.

Step 3: Calculate the estimated load consumption for the CVR-on days if CVR is not implemented. With a new vector of temperature $\mathbf{T}^*$ on those CVR-on days, the load consumption if without CVR on those days can be calculated as follows:

$$\mathbf{E}^{off,*} = \hat{\beta}_0\mathbf{1} + \hat{\beta}_1\left[T_{fh}\mathbf{1} - \mathbf{T}^*\right] + \hat{\beta}_2\left[T_{fc}\mathbf{1} - \mathbf{T}^*\right]$$

where $\mathbf{E}^{off,*}$ is the estimated load if CVR is not implemented.

Methodology

Regression-Based Methods

Step 4: Calculate the CVR factor for each time interval. With the measured load on test days with CVR on, denoted as $\mathbf{E}^{on}$, and the $\mathbf{E}^{off,*}$ calculated from step 3, the Energy and voltage reductions are first determined as below. In these equations, e_i^{on} and e_i^{off} refer to the i^{th} time interval elements of $\mathbf{E}^{on}$ and $\mathbf{E}^{off,*}$, respectively. Similar fashion is applied to the voltage terms.

$$\Delta E_i\ (\%) = \frac{e_i^{off} - e_i^{on}}{e_i^{off}} \times 100$$

$$\Delta V_i\ (\%) = \frac{V_i^{off} - V_i^{on}}{V_i^{off}} \times 100$$

The remaining procedure follows the same steps (Step 1 to 4) as in the **comparison-based** method.

Backup slides

Soft-constrained gradient analysis method

Problem formulation of load modeling

To identify the time-varying load model parameters $\alpha_{P,i}$, $\beta_{P,i}$, and $\gamma_{P,i}$, a general optimization problem is formulated as follows.

$$\min_{\alpha_{P,i},\beta_{P,i},\gamma_{P,i}} J = \sum_{i=1}^{n} \left(\alpha_{P,i} \left(\frac{V_i}{V_0}\right)^2 + \beta_{P,i} \frac{V_i}{V_0} + \gamma_{P,i} - \frac{P_i}{P_0} \right)^2$$

$$\text{s.t., } 0 < \alpha_{P,i}, \beta_{P,i}, \gamma_{P,i} < 1$$

where J is the accumulative squared error, *i* is the *i*th time interval, and *n* is the total number of time intervals, V_i and P_i are field voltage and power measurements.

Note that we delete the constraint $\alpha_{P,i} + \beta_{P,i} + \gamma_{P,i} = 1$, because it can lead to negative load model parameters, thus resulting in negative CVR factors.

Time-Varying Load Parameter Identification

Since the above objective function is convex with respect to coefficients, without considering the constraints, the optimum can be calculated by letting the first-order gradient with respect to each of the coefficients $\alpha_{P,t}, \beta_{P,t}, \gamma_{P,t}$ be zero:

$$\frac{\partial J}{\partial \alpha_{P,i}} = \sum_{i=1}^{L} 2(V_i')^2\left(\alpha_{P,i}(V_i')^2 + \beta_{P,i}V_i' + \gamma_{P,i} - P_i'\right) = 0$$

$$\frac{\partial J}{\partial \beta_{P,i}} = \sum_{i=1}^{L} 2V_i'\left(\alpha_{P,i}(V_i')^2 + \beta_{P,i}V_i' + \gamma_{P,i} - P_i'\right) = 0$$

$$\frac{\partial J}{\partial \gamma_{P,i}} = \sum_{i=1}^{L} 2\left(\alpha_{P,i}(V_i')^2 + \beta_{P,i}V_i' + \gamma_{P,i} - P_i'\right) = 0$$

where we denote $\frac{V_i}{V_0} = V_i'$ and $\frac{P_i}{P_0} = P_i'$ for conciseness.

Time-Varying Parameter Identification

- The above problem is not solvable because it has nine variables but only three equations.
- A sliding window approach is applied to calculate the time-varying parameters $\alpha_{P,i}$, $\beta_{P,i}$ and $\gamma_{P,i}$, as depicted in the right figure.
- For a set of data in a time window, it is assumed that the time-varying parameters are *constant* in each time window with length long at a time with overlaps.
- The calculated parameters within each window are considered as the result of the last sample point of the window.
- Then, denoting $i' = i - n + 1$, the above equations can be expressed in a matrix form as

$$\begin{bmatrix} \sum_{i=t'}^{n} {V_i'}^4 & \sum_{i=i'}^{n} {V_i'}^3 & \sum_{i=i'}^{n} {V_i'}^2 \\ \sum_{i=i'}^{n} {V_i'}^3 & \sum_{t=i'}^{n} {V_i'}^2 & \sum_{i=i'}^{n} V_i' \\ \sum_{i=i'}^{n} {V_i'}^2 & \sum_{i=i'}^{n} V_i' & n \end{bmatrix} \times \begin{bmatrix} \alpha_{P,i} \\ \beta_{P,i} \\ \gamma_{P,i} \end{bmatrix} = \begin{bmatrix} \sum_{i=i'}^{n} P_i' {V_i'}^2 \\ \sum_{i=i'}^{n} P_i' V_i' \\ \sum_{i=i'}^{n} P_i' \end{bmatrix}$$

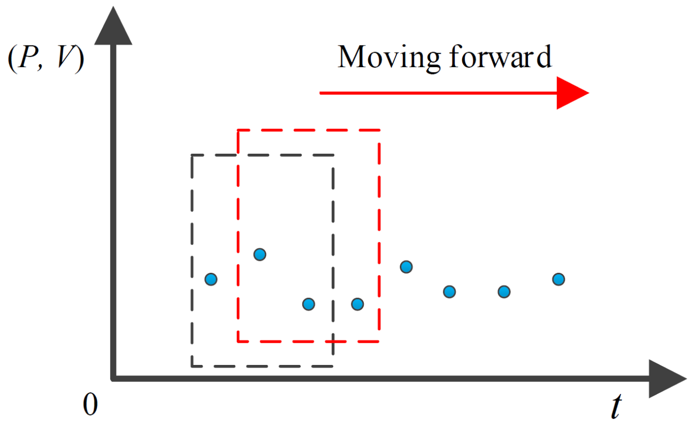

Fig. 4. Demonstration of moving time window.

Time-Varying Parameter Identification

To deal with the constraint, improve the robustness and capture the temporal correlation of loads, we propose a method using over-determinant least squares optimization with soft constraints as follows

$$\begin{bmatrix} \sum_{i=t'}^{n} {V_i'}^4 & \sum_{i=i'}^{n} {V_i'}^3 & \sum_{i=i'}^{n} {V_i'}^2 \\ \sum_{i=i'}^{n} {V_i'}^3 & \sum_{t=i'}^{n} {V_i'}^2 & \sum_{i=i'}^{n} V_i' \\ \sum_{t=i'}^{n} {V_i'}^2 & \sum_{i=i'}^{n} V_i' & n \\ \varepsilon_1 + \varepsilon_2 & 0 & 0 \\ 0 & \varepsilon_1 + \varepsilon_2 & 0 \\ 0 & 0 & \varepsilon_1 + \varepsilon_2 \end{bmatrix} \times \begin{bmatrix} \alpha_{P,i} \\ \beta_{P,i} \\ \gamma_{P,i} \end{bmatrix} = \begin{bmatrix} \sum_{i=i'}^{n} P_i' {V_i'}^2 \\ \sum_{i=i'}^{n} P_i' V_i' \\ \sum_{i=i'}^{n} P_i' \\ \varepsilon_1 \alpha_{P,i}^{o} + \varepsilon_2 \alpha_{P,i-1} \\ \varepsilon_1 \beta_{P,i}^{o} + \varepsilon_2 \beta_{P,i-1} \\ \varepsilon_1 \gamma_{P,i}^{o} + \varepsilon_2 \gamma_{P,i-1} \end{bmatrix}$$

Solved by least square method

- The lower three rows in over-determinant problem softly constrain the values of $\alpha_{P,i}$, $\beta_{P,i}$ and $\gamma_{P,i}$ by guiding them towards a near optimal initial estimation that is in the normal range.
- The initial estimation is a weighted average of two components: 1) solution of current time window $\alpha_{P,i}^{o}$, $\beta_{P,i}^{o}$ and $\gamma_{P,i}^{o}$ obtained by solving the original optimization problem with interior point method; 2) the solution from the last time window, $\alpha_{P,i-1}$, $\beta_{P,i-1}$ and $\gamma_{P,i-1}$.
- To ensure meaningful CVR factor, $\alpha_{P,0}$, $\beta_{P,0}$ and $\gamma_{P,0}$ must be selected within the normal range.