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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

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

**Step 1:** 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; \(\alpha_P\) 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; \(\beta_P\) is the active power-related coefficient of the load’s constant voltage component; \(\gamma_P\) 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

**Step 2:** 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.

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

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

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

where $J$ is the accumulative squared error, $i$ is the $i$th 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:

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

where $V_{\text{average}}^{\text{average}}$ and $V_{\text{average}}^{\text{off}}$ are averaged voltages when CVR is on and off, respectively; $V_{i}^{\text{off}}$ and $V_{i}^{\text{on}}$ 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

**Step 4:** 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:

\[
CVR_{f_i} = \frac{\Delta E_i \,(\%)}{\Delta V_i \,(\%)} = \frac{e_i^{\text{off}} - e_i^{\text{on}}}{e_i^{\text{off}} e_i^{\text{on}}} = \frac{p_i^{\text{off}} - p_i^{\text{on}}}{p_i^{\text{off}} p_i^{\text{on}}} = \frac{(2\alpha_{P,i} - \alpha_{P,i}\Delta V_i \,(\%)) (\bar{V}_i^{\text{on}})^2 + \beta_{P,i}\bar{V}_i^{\text{on}} (1 - \Delta V_i \,(\%))}{\alpha_{P,i}(\bar{V}_i^{\text{on}})^2 + \beta_{P,i}\bar{V}_i^{\text{on}} (1 - \Delta V_i \,(\%)) + \gamma_{P,i}(1 - \Delta V_i \,(\%))^2}
\]

where \(\bar{V}_i^{\text{on}} = V_i^{\text{on}} / V_0\) 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

**Step 5:** 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 $E_{\text{baseline}}$ is the total energy consumed if CVR was off:

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

where $E_{\text{on,baseline}}$ and $E_{\text{off,baseline}}$ 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

\[ E_{\text{save}} = E_{\text{on,baseline}} - E_{\text{on}} = \sum_{i=1}^{n_{\text{on}}} (P_{i,\text{estimate}} - P_{i}^{\text{on}}) \Delta t \]

where \( E_{\text{on}} \) is the energy consumed during the CVR-on period.

**Step 7**: Calculate the estimated energy reduction \( \Delta E \) (%) by

\[ \Delta E \text{ (%) } = \frac{E_{\text{save}}}{E_{\text{on,baseline}}} \times 100\% \]

**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

\[ CVR_f = \frac{\Delta E \text{ (%)}}{\Delta V \text{ (%)}} \]
Methodology

Load Modeling-Based Methods

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

\[
E_{\text{on,baseline}} = \alpha_{\text{on}} \sum_{i=1}^{n_{\text{on}}} p_{i,\text{estimate}}^{\text{off}} \Delta t
\]

\[
E_{\text{save}} = E_{\text{on,baseline}} - \alpha_{\text{on}} E_{\text{on}} = \alpha_{\text{on}} \sum_{i=1}^{n_{\text{on}}} (p_{i,\text{estimate}}^{\text{off}} - p_{i}^{\text{on}}) \Delta t
\]

The baseline energy, \(E_{\text{baseline}}\), can accordingly be calculated as follows:

\[
E_{\text{baseline}} = E_{\text{on,baseline}} + \alpha_{\text{off}} E_{\text{off}} = \alpha_{\text{on}} E_{\text{on}} + \alpha_{\text{off}} E_{\text{off}} + E_{\text{save}}
\]

where \(\alpha_{\text{on}}\) and \(\alpha_{\text{off}}\) are scaling coefficients to take the missing data in CVR-on and CVR-off periods into account, respectively.

\[
\alpha_{\text{on/off}} = \frac{\# \text{ of CVR}_{\text{on/off}} \text{ datapoints}}{\# \text{ of CVR}_{\text{on/off}} \text{ datapoints} - \# \text{ of missing CVR}_{\text{on/off}} \text{ datapoints}}
\]
Methodology

Pros and Cons of the three methods

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

<table>
<thead>
<tr>
<th>Utility</th>
<th>Value of CVR Factor</th>
<th>Methodology</th>
<th>Utility</th>
<th>Value of CVR Factor</th>
<th>Methodology</th>
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<td>Clark Public Utilities</td>
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<td>Central Lincoln People's Utility</td>
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<td>Idaho Power Company</td>
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<td>PECO Energy</td>
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<td>Duke Energy Ohio</td>
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<td>Progress Energy</td>
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<tr>
<td>Clatskanie PUD</td>
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<td>PG&amp;E</td>
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<td>Puget Sound Energy</td>
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<td>Dominion Energy</td>
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<td>Indiana Michigan Power</td>
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<td>NRECA</td>
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<tr>
<td>AEP</td>
<td>0.35-0.89</td>
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<td>NEEA</td>
<td>0.17-1.12</td>
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<td>Korea Electric Power Corporation</td>
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<td>Avista Corp</td>
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</table>
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

<table>
<thead>
<tr>
<th>Name</th>
<th>Ebaseline (MWh)</th>
<th>Estimated Voltage Reduction (%)</th>
<th>Estimated Energy Reduction (%)</th>
<th>Esavings (MWh)</th>
<th>CVR Factor</th>
</tr>
</thead>
<tbody>
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<td>D2_2016</td>
<td>178,314.14</td>
<td>2.70</td>
<td>-0.90</td>
<td>-58.38</td>
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<tr>
<td>D3_2016</td>
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<td>4.73</td>
<td>1,050.97</td>
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### Regression-Based

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<th>Name</th>
<th>Ebaseline (MWh)</th>
<th>Estimated Voltage Reduction (%)</th>
<th>Estimated Energy Reduction (%)</th>
<th>Esavings (MWh)</th>
<th>CVR Factor</th>
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<tr>
<td>D2_2016</td>
<td>178,160.16</td>
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<td>D3_2016</td>
<td>202,320.66</td>
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### Load-Modeling-Based

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<th>Name</th>
<th>Ebaseline (MWh)</th>
<th>Estimated Voltage Reduction (%)</th>
<th>Estimated Energy Reduction (%)</th>
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<tr>
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## Case Studies

### Case 1: Simulations based on data resolution (D2_2016)

<table>
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<tr>
<th>Resolution</th>
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<th>Regression-Based</th>
<th>Load-Modeling-Based</th>
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<tr>
<td></td>
<td>Ebaseline (MWh)</td>
<td>Estimated Voltage Reduction (%)</td>
<td>Estimated Energy Reduction (%)</td>
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<td>5 min</td>
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<td>10 min</td>
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### Case Studies

**Case 1: Simulations based on data resolution (D3_2016)**

<table>
<thead>
<tr>
<th>Resolution</th>
<th>Ebaseline (MWh)</th>
<th>Estimated Voltage Reduction (%)</th>
<th>Estimated Energy Reduction (%)</th>
<th>Esavings (MWh)</th>
<th>CVR Factor</th>
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<tr>
<td><strong>Comparison-Based</strong></td>
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<tr>
<td>5 min</td>
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<td>4.47</td>
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<td><strong>Load-Modeling-Based</strong></td>
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## Case Studies

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

<table>
<thead>
<tr>
<th>Outlier</th>
<th>Ebaseline (MWh)</th>
<th>Estimated Voltage Reduction (%)</th>
<th>Estimated Energy Reduction (%)</th>
<th>Esavings (MWh)</th>
<th>CVR Factor</th>
</tr>
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<tbody>
<tr>
<td><strong>Comparison-Based</strong></td>
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Case Studies

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

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<th>Outlier</th>
<th>Ebaseline (MWh)</th>
<th>Estimated Voltage Reduction (%)</th>
<th>Estimated Energy Reduction (%)</th>
<th>Esavings (MWh)</th>
<th>CVR Factor</th>
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<table>
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<th>Outlier</th>
<th>Ebaseline (MWh)</th>
<th>Estimated Voltage Reduction (%)</th>
<th>Estimated Energy Reduction (%)</th>
<th>Esavings (MWh)</th>
<th>CVR Factor</th>
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<td>0.77</td>
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<table>
<thead>
<tr>
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<th>Ebaseline (MWh)</th>
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<th>Estimated Energy Reduction (%)</th>
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<th>CVR Factor</th>
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<tbody>
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<td>3.85</td>
<td>628.77</td>
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</table>
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.
References

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:

\[
\text{CVR}_{f_i} = \frac{\Delta E_i \, (\%)}{\Delta V_i \, (\%)}
\]

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

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

Comparison-Based Methods

**Step 2:** Calculate the feeder’s CVR factor and voltage reduction by averaging over all time interval specific values:

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

**Step 3:** 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

**Step 4:** 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 \( \alpha^{on} \) and \( \alpha^{off} \) 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

\[ \mathbf{E} = \beta_0 \mathbf{1} + \beta_1 [T_{fh} \mathbf{1} - \mathbf{T}] + \beta_2 [T_{fc} \mathbf{1} - \mathbf{T}] + \mathbf{\epsilon} \]

- \( \mathbf{E} \) and \( \mathbf{T} \) are training data for the model, \( \mathbf{E} \) represents the vector of measured normal-voltage load data, and \( \mathbf{T} \) 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).

- \( \beta_0, \beta_1 \) and \( \beta_2 \) are parameters that need to be calculated using linear regression, \( \mathbf{\epsilon} \) represents the errors.

Methodology

Regression-Based Methods

**Step 2:** The parameters $\beta_0$, $\beta_1$ and $\beta_2$ can be estimated by minimizing the errors. For an ordinary least squares method, the parameters can be calculated as follows:

$$\hat{\beta} = (X^TX)^{-1}X^TE$$

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

where $\hat{\beta} = [\hat{\beta}_0 \ \hat{\beta}_1 \ \hat{\beta}_2]^T$ 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 $T^*$ on those CVR-on days, the load consumption if without CVR on those days can be calculated as follows:

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

where $E_{off,*}$ 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 $E^{on}$, and the $E^{off,*}$ 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 $E^{on}$ and $E^{off,*}$, 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.

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

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:

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

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

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

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 $\alpha_{Z,i}$, $\beta_{Z,i}$, and $\gamma_{Z,i}$, 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

\[
\begin{bmatrix}
\sum_{i=i'}^{n} V_i'^4 \\
\sum_{i=i'}^{n} V_i'^3 \\
\sum_{i=i'}^{n} V_i'^2 \\
\sum_{i=i'}^{n} V_i' \\
n
\end{bmatrix}
\begin{bmatrix}
\sum_{i=i'}^{n} P_i' V_i'^2 \\
\sum_{i=i'}^{n} P_i' V_i' \\
\sum_{i=i'}^{n} P_i' \\
n
\end{bmatrix} = 
\begin{bmatrix}
\alpha_{P,i} \\
\beta_{P,i} \\
\gamma_{P,i}
\end{bmatrix}.
\]

Fig. 4. Demonstration of moving time window.
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:

\[
\begin{bmatrix}
\sum_{i=t}^{n} V_i^4 \\
\sum_{i=t}^{n} V_i^3 \\
\sum_{i=t}^{n} V_i^2 \\
\varepsilon_1 + \varepsilon_2 \\
0 \\
0
\end{bmatrix}
\begin{bmatrix}
\alpha_{p,i} \\
\beta_{p,i} \\
\gamma_{p,i}
\end{bmatrix}
= 
\begin{bmatrix}
\sum_{i=t}^{n} P_i' V_i^2 \\
\sum_{i=t}^{n} P_i' V_i' \\
\varepsilon_1 \alpha_{p,i}^0 + \varepsilon_2 \alpha_{p,i-1} \\
\varepsilon_1 \beta_{p,i}^0 + \varepsilon_2 \beta_{p,i-1} \\
\varepsilon_1 \gamma_{p,i}^0 + \varepsilon_2 \gamma_{p,i-1}
\end{bmatrix}
\]

• 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 \(\alpha_{p,i}^0\), \(\beta_{p,i}^0\) and \(\gamma_{p,i}^0\) 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.