Recovering Behind-the-Meter Power Factor Control Settings

of Solar PV Inverters from Net Load Data

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Power Factor Control

Description of Power Factor Control

1. Power factor control is the most common **reactive power control** method for inverter-based resources (IBRs).
2. A **unity power factor control setting** is the default of the IEEE 1547-2018 standard on the interconnection and interoperability of IBRs [1].

Graphical Depiction of Power Factor Control

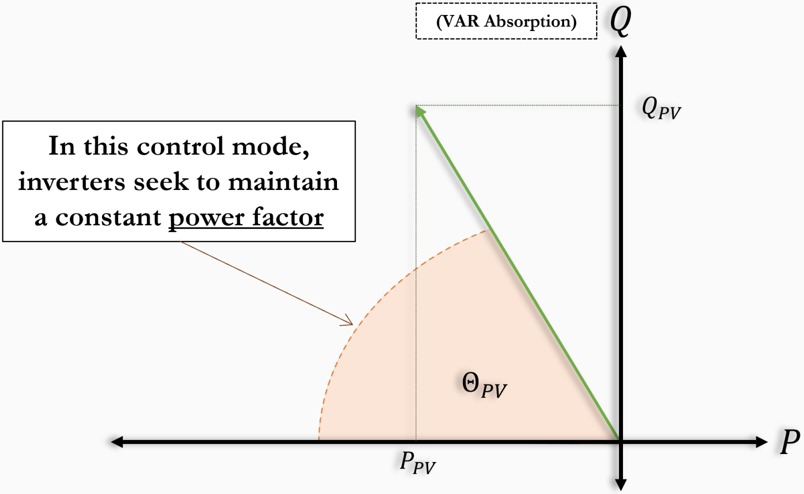

Figure 1: Graphical description of inverter power factor control

Graphical Depiction of Power Factor Control

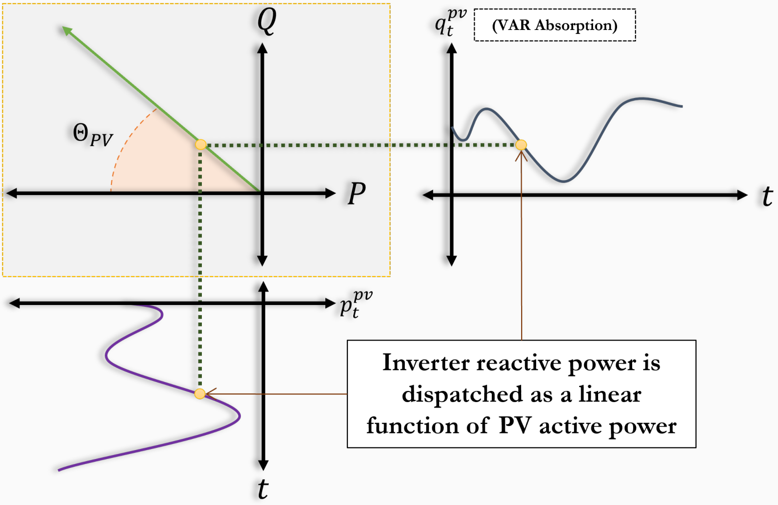

Figure 2: Real-time inverter power factor control action shot

The Problems We Are Solving

Problem 1:

1. The power factor control settings of a *behind-the-meter* inverter **may be unknown or may change over time.**
2. This creates unobservable distribution network impacts.

The Problems We Are Solving

Problem 2:

1. An engineer's **model** for a BTM IBR may be inaccurate.
2. It is often difficult to update this model.

The Problems We Are Solving

Problem 3:

1. Distribution engineers often only observe **net load** smart meter data at the BTM IBR interconnection, containing information about **both the IBR generation and the user's demand**,
2. It isn't obvious what the BTM power factor setting is.

Parameterized Fixed Power Factor Control

The reactive power injection of an inverter with power factor control is determined by a line in the complex plane:

$$q_t^{pv} = \phi_\Theta(p_t^{pv}) = \frac{\Delta q}{\Delta p} p_t^{pv} \quad (1)$$

The slope of this line is the "sensitivity" of the IBR reactive power injections to real power injections.

Parameterized Fixed Power Factor Control

Use trigonometry to relate the line slope to the power factor setting:

$$\mathrm{pf} = \cos(\phi_V - \phi_I) \implies \mathrm{pf} = \cos\left(\mathrm{atan2}\left(\frac{\Delta q}{\Delta p}\right)\right), \qquad (2)$$

where ϕ_V, ϕ_I is the phase angle of the voltage and current, respectively.

Estimating Behind-the-Meter Power Factor Control Settings

Distribution engineers often only have access to smart meter data:

$$\mathcal{D}_l = \{\mathsf{X}_t\}_{t=1}^{M} = \{(v_t^{pcc}, p_t^{net}, q_t^{net})\}_{t=1}^{M}, \quad (3)$$

where:

$$\begin{aligned} p_t^{net} &= p_t^{pv} + p_t^{native} \\ q_t^{net} &= q_t^{pv} + q_t^{native} \end{aligned} \quad (4)$$

Note:

If we had a separate meter for the IBR, determining power factor control setting would be trivial.

Question:

From this **net load** data, can we determine the power factor control setting of the BTM inverter?

An Intuitive Solution

Lagging power factor settings:

$$\mathrm{atan2}\left(\frac{\Delta q}{\Delta p}\right) < 0, \tag{5}$$

are typically used to **prevent overvoltages** from PV systems [4].

Net Load Percentile Filter

Hypothesis:

1. We can expose the behind-the-meter power factor control curve by taking the subset of the smart meter data that have "δth percentile" extreme voltages:

$$\mathcal{D}_l^{\delta} = \{\mathsf{X}_t \in \mathcal{D}_l : v_t^{pcc} > V_{\delta}\}, \tag{6}$$

2. If the **voltage is high**, the local PV generation must be **high** and the load **low**, so the majority of the net measurement must be from PV.

Real Data: Non-Unity Power Factor Control

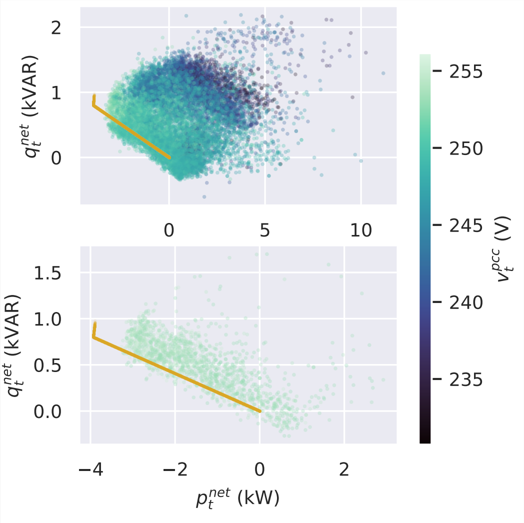

Figure 3: Non-unity power factor control: 99th percentile voltage filter

Real Data: Unity Power Factor Control

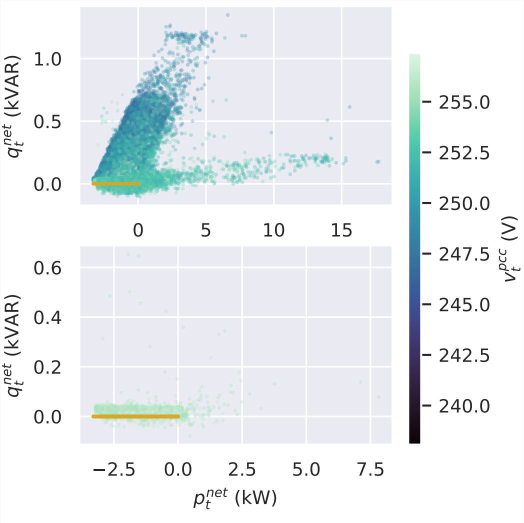

Figure 4: Unity power factor control: 99th percentile voltage filter

Regression

Perform ordinary least squares regression on the filtered active and reactive power time series vectors ($\tilde{\mathsf{p}}$ and $\tilde{\mathsf{q}}$):

$$\hat{\Theta} = (\mathsf{A}^T\mathsf{A})^{-1}\mathsf{A}^T\tilde{\mathsf{q}} \tag{7}$$

where[1]:

$$\Theta = \begin{bmatrix} \frac{\Delta q}{\Delta p} & b \end{bmatrix}^T, \text{ and } \mathsf{A} = \begin{bmatrix} \vdots & \vdots \\ \tilde{\mathsf{p}} & 1 \\ \vdots & \vdots \end{bmatrix}. \tag{8}$$

We can now estimate the power factor from net load data.

[1] Usually we have $b = 0$.

Recovering the Power Factor Setting

Power Factor Estimation

Use trigonometry to recover the power factor setting with the regression slope:

$$\boxed{\hat{\mathrm{pf}} = \cos\left(\mathrm{atan2}\left(\frac{\widehat{\Delta q}}{\Delta p}\right)\right),} \tag{9}$$

where ϕ_V, ϕ_I is the phase angle of the voltage and current, respectively.

Making the Estimator More Robust

Huber Loss

A common way to build robustness to noise is to solve:

$$\underset{\Theta}{\text{minimize}} \, ||\tilde{\mathbf{q}} - \mathbf{A}\Theta||_1, \tag{10}$$

where the loss function in (10) is the sum of the absolute value of the residuals:

$$||\tilde{\mathbf{q}} - \mathbf{A}\Theta||_{\ell_1} = \sum_{t=1}^{M'} |\tilde{q}_t - a_t^T \Theta|. \tag{11}$$

Huber Loss Function

Alternatively, trade off bias and variance with the Huber Loss Function [3, 2]:

$$l_\epsilon = \begin{cases} ||\tilde{\mathsf{q}} - \mathsf{A}\Theta||_2^2 & ||\tilde{\mathsf{q}} - \mathsf{A}\Theta||_2 \leq \epsilon \\ \epsilon(||\tilde{\mathsf{q}} - \mathsf{A}\Theta||_{\ell_1} - \frac{1}{2}\epsilon) & \text{otherwise} \end{cases} \tag{12}$$

Summary and Results

Performance Summary

Table 1: Performance evaluations (MAE) of power factor estimation for 50 real BTM PV systems

PF Control Type	ℓ_1	Huber, $\epsilon = 7 \times 10^{-2}$
Unity	0.0000571	0.00343
Non-unity	0.0104	0.0103

Results:

We can estimate **unity and non unity** PF control settings from net load data with high accuracy.

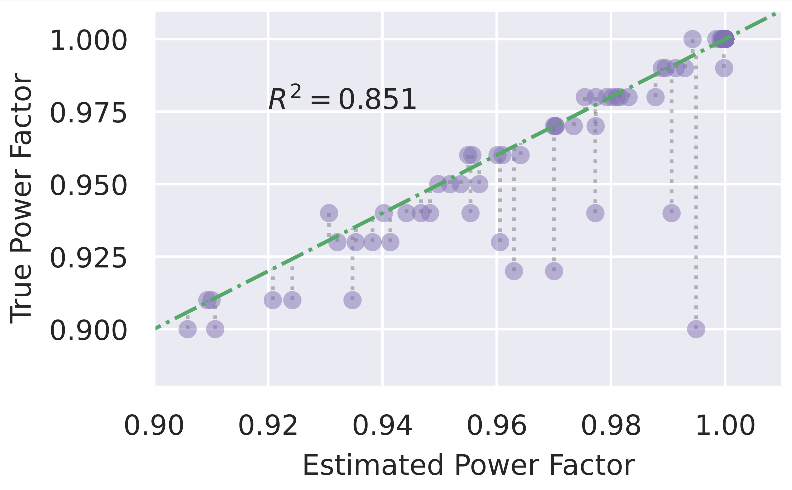

Figure 5: Scatter plot of estimated power factor vs. true power factor for all datasets studied

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