

# Complex power inverse problems

ACM SIGENERGY Graduate Student Seminar Series

---

Samuel Talkington

August 30, 2023

School of Electrical and Computer Engineering  
Georgia Institute of Technology



Georgia Tech College of Engineering  
School of Electrical  
and Computer Engineering

# Table of contents

1. Motivation and Background
2. Reactive power inverse problems
3. Phaseless inverse problems
4. Computational Results
5. Outlook

# Acknowledgement

Thanks to my collaborators:

1. Daniel Turizo (Georgia Tech)
2. Santiago Grijalva (Georgia Tech)
3. Daniel Molzahn (Georgia Tech)
4. Matthew Reno (Sandia)
5. Joseph Azzolini (Sandia)

This material is based upon work supported by the National Science Foundation Graduate Research Fellowship Program under Grant No. DGE-1650044. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

# Motivation and Background

---

## Inverse problem

Causal system or process

$$F: \mathcal{X} \mapsto \mathcal{Y}.$$

True causation  $\mathbf{x}^*$ , indirect output measurements  $\mathbf{y}$ , noise  $\boldsymbol{\eta} \sim \mathcal{D}$

$$\mathbf{y} = F(\mathbf{x}^*) + \boldsymbol{\eta}$$

Can we recover the causation  $\mathbf{x}^*$  of our measurements?

# Complex power physics

# Electric power is complex (literally)

An electric power network is an undirected graph

$$\mathcal{G} = (\mathcal{N}, \mathcal{V}).$$

Every node  $i \in \mathcal{N}$  has a complex **voltage phasor** and **power injection**:

$$v_i \angle \theta_i \in \mathbb{C}, \quad p_i + jq_i \in \mathbb{C}.$$

# Power factor and the power triangle

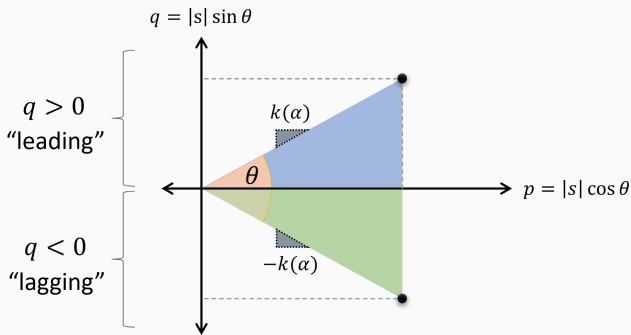


Figure 1: The power triangle relates complex power to the power angle



# Power factor and the power triangle

The *power factor*  $\alpha_i \in (0, 1] \subset \mathbb{R}$  at nodes  $i \in \mathcal{N}$ :

Ratio of the real part (active power) of the complex power injection at  $i \in \mathcal{N}$  to its magnitude:

$$\alpha_i = \cos(\text{atan2}(q_i, p_i)), \quad i \in \mathcal{N}, \quad (1)$$

where  $\text{atan2}(\cdot, \cdot)$  is the two-argument arc tangent.

## Motivation 1: Missing measurements

## The case of the missing voltage phasor

Every node  $i \in \mathcal{N}$  has a complex **voltage phasor** and **power injection**:

$$v_i \angle \theta_i \in \mathbb{C}, \quad p_i + jq_i \in \mathbb{C}.$$

It's hard to find the **voltage phase angles** in the real world.

# The case of the missing voltage phasor

Example: PJM, circa 2022

1. 400 PMUs throughout PJM territory<sup>1</sup>
2. Only required on substations

---

<sup>1</sup>PJM, “Synchrophasor Technology Roadmap”, 2022.

# The case of the missing voltage phasor

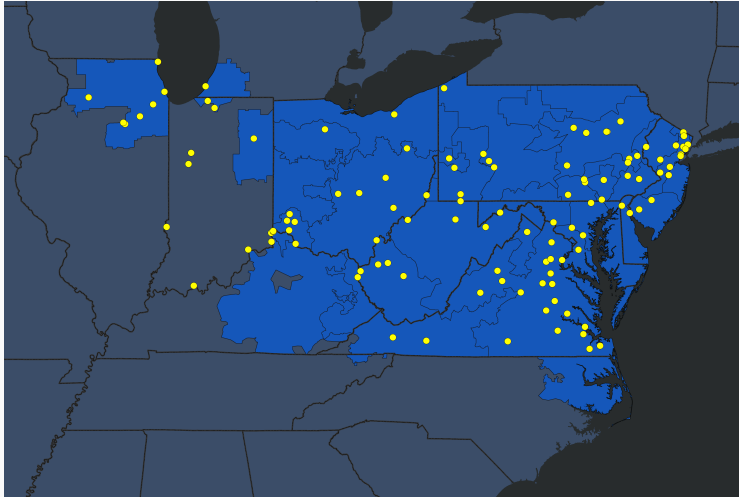


Figure 2: circa 2022 PMU deployment in PJM<sup>2</sup>

<sup>2</sup>Credit PJM, "Synchrophasor Technology Roadmap", 2022. Source: <https://www.pjm.com/markets-and-operations/ops-analysis/synchrophasor-technology>

# The case of the missing voltage phasor

≈ 3000 phasor measurement units (PMUs) in North America [1].

Rare in:

1. Distribution systems
2. Transmission system boundaries
3. Rural transmission systems
4. Underserved areas

## Motivation 2: Missing models

# The case of the missing model

**Challenge:** realistic physical models in electric power systems.

Two types of models are often **unknown**:

1. **Network model:** Network topology parameters.
2. **Reactive power model:** Control law parameters.



# The case of the missing model

The network topology is encoded in the *admittance* matrix:

$$Y = G + jB \in \mathbb{C}^{n \times n}.$$

These parameters are **difficult to come by** in the real world.

# The case of the missing model

The non-linear power flow equations govern the power injections at every node  $i \in \mathcal{N}$ :

$$p_i = v_i \sum_{k=1}^n v_k (G_{ik} \cos \theta_{ik} + B_{ik} \sin \theta_{ik}), \quad (2a)$$

$$q_i = v_i \sum_{k=1}^n v_k (G_{ik} \sin \theta_{ik} - B_{ik} \cos \theta_{ik}). \quad (2b)$$

They are functions of the network topology.

# The case of the missing model

The causal factors for the reactive power injections:

$$q = f(\cdot | \theta),$$

are the *control law parameters*  $\theta \in \Theta$ . These are often unknown, or can change over time.

It's pretty hard to be a power engineer without  
this information!

What do we actually know?

# What do we actually know?

What do we **actually** know in practice?

Commonly, we receive measurements of the form [2]

$$v_i \in \mathbb{R}, \quad p_i + jq_i \in \mathbb{C}.$$

1.  $v_i$  —voltage *magnitude*
2.  $p_i$  —active (real) power
3.  $q_i$  —reactive (imaginary) power<sup>3</sup>

**No network model, either!**

---

<sup>3</sup>e.g., from a historical or chosen power factor [2]

# Reactive power inverse problems

---

# Problem 1: reactive power system identification

## Inverse problem: reactive power system identification

What is the causation (**control law parameters**) of our reactive power measurements?

$$q = F(\theta^*) + \eta$$

There are several reactive power control frameworks:

1. **Power factor control:** control the relationship between  $p, q$ .
2. **Volt-VAR control:** control the relationship between  $q, v$ .



# Graphical Depiction of Power Factor Control

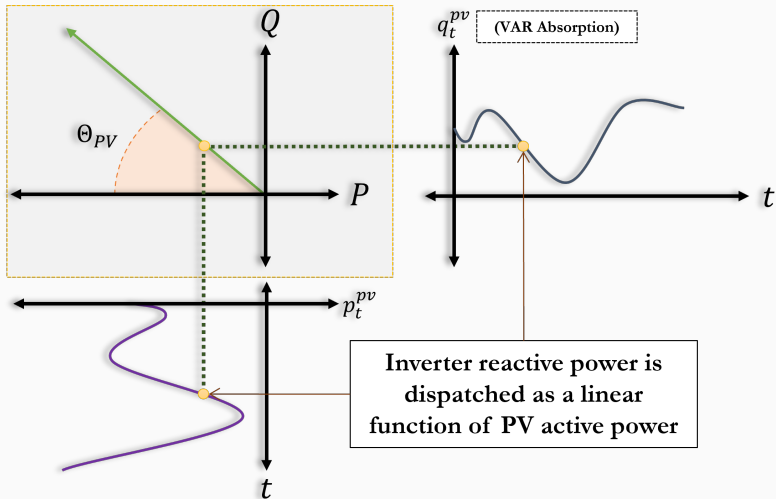


Figure 3: Illustration of real-time inverter power factor control [3].

# Graphical Depiction of Volt-VAR Control

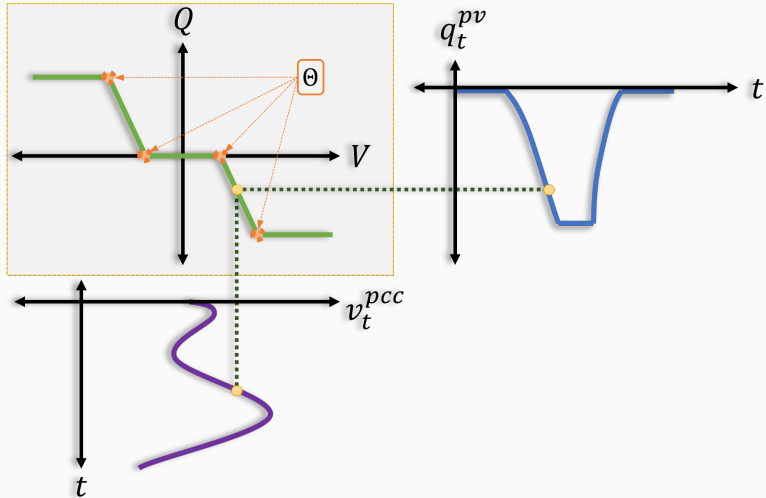


Figure 4: Illustration of real-time inverter volt-VAR control [3].

# 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:

$$q = \phi_{\Theta}(p) = \frac{\Delta q}{\Delta p} p \quad (3)$$

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:

$$\text{pf} = \cos(\phi_V - \phi_I) \implies \text{pf} = \cos\left(\text{atan2}\left(\frac{\Delta q}{\Delta p}\right)\right), \quad (4)$$

where  $\phi_V, \phi_I$  is the phase angle of the voltage and current, respectively.

# Parameterized Volt Var Control

For the response of a Volt-VAR control law, a general representation of the reactive power response is given by a parameterized function of PCC voltage  $v_t^{pcc}$ ,

$$\phi_{\Theta}(v_t^{pcc}) := \begin{cases} Q_1 & v_t^{pcc} \leq V_1, \\ v_t^{pcc} \frac{Q_2 - Q_1}{V_2 - V_1} + b_1 & V_1 < v_t^{pcc} < V_2, \\ 0 & V_2 \leq v_t^{pcc} \leq V_3, \\ v_t^{pcc} \frac{Q_4 - Q_3}{V_4 - V_3} + b_2 & V_3 \leq v_t^{pcc} \leq V_4, \\ Q_4 & v_t^{pcc} > V_4. \end{cases} \quad (5)$$

where  $b_1 = Q_1 - V_1 \frac{Q_2 - Q_1}{V_2 - V_1}$  and  $b_2 = Q_3 - V_3 \frac{Q_4 - Q_3}{V_4 - V_3}$ , and  $\theta_i := [P_i, Q_i]^T$ ,  $i = 1, \dots, N$ .

## Estimating reactive power parameters

$$\underset{\theta}{\text{minimize}} \ell(\mathbf{P}, \mathbf{Q}, \mathbf{V}|\theta) \quad \text{subject to } \theta \in \Theta, \quad (6)$$

where  $\Theta$  is the set of feasible parameters for the control mode.

Several possible loss functions can be used, such as MLE and regularized norm approximation losses.

# Fixed power factor system identification result summary

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

PF Control Type	$\ell_1$	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.



# Performance Summary

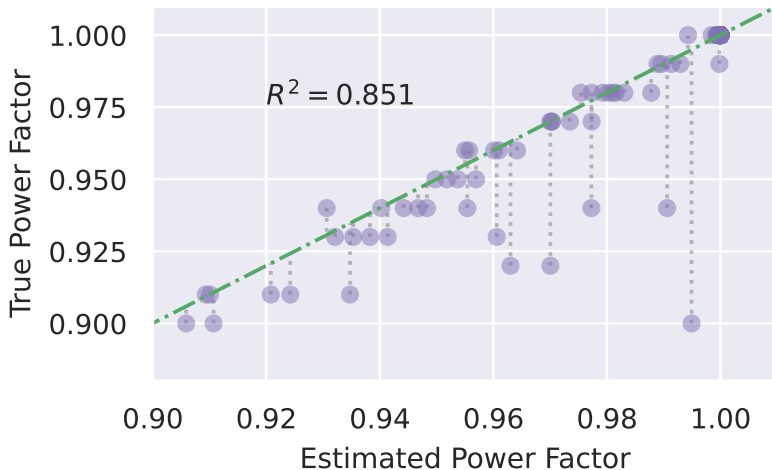


Figure 5: Scatter plot of estimated power factor vs. true power factor for all datasets studied

## Volt-VAR system identification result summary

# Performance summary

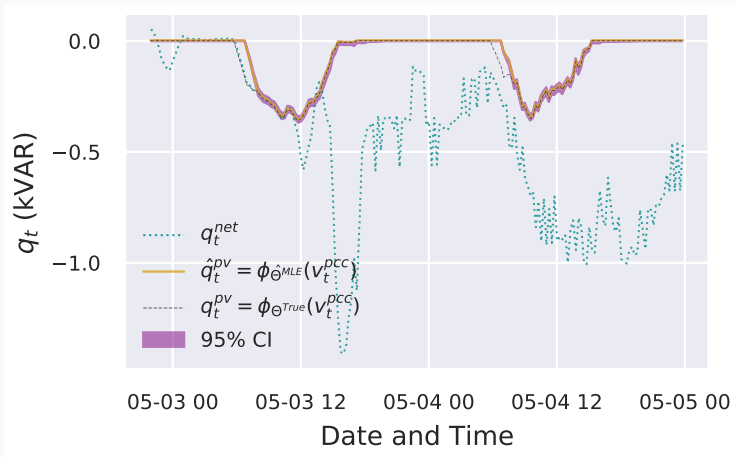


Figure 6: Reconstruction of VVC reactive power time series with estimated control law.

S. Talkington, S. Grijalva, M. J. Reno, J. A. Azzolini, “Solar PV Inverter Reactive Power Disaggregation and Control Setting Estimation”, IEEE Transactions on Power Systems, 2022

# Phaseless inverse problems

---

## Inverse problem: voltage phase retrieval

What are the causal factors (power-phase angle sensitivity matrices) of our complex power measurements?

$$p + jq = F \left( \frac{\partial p^*}{\partial \theta}, \frac{\partial q^*}{\partial \theta} \right) + \eta$$

*Corollary:* what are the voltage phase angles?

## Case study: Newton-Raphson Power Flow model

How to solve the non-linear power flow equations?

Classic approach: *Newton-Raphson power flow*.

Iteratively solve a linear system of equations of the form

$$\begin{bmatrix} \Delta p \\ \Delta q \end{bmatrix} = \begin{bmatrix} \frac{\partial p}{\partial \theta}(\mathbf{x}) & \frac{\partial p}{\partial \mathbf{v}}(\mathbf{x}) \\ \frac{\partial q}{\partial \theta}(\mathbf{x}) & \frac{\partial q}{\partial \mathbf{v}}(\mathbf{x}) \end{bmatrix} \begin{bmatrix} \Delta \theta \\ \Delta \mathbf{v} \end{bmatrix} = J(\mathbf{x})\Delta \mathbf{x}. \quad (7)$$

1.  $\Delta p, \Delta q \in \mathbb{R}^n$  are small perturbations in the active and reactive power injections
2.  $\Delta \theta, \Delta \mathbf{v} \in \mathbb{R}^n$  are small perturbations in the voltage phase angles and magnitudes

## Case study: Newton-Raphson Power Flow model

$$\begin{bmatrix} \Delta p \\ \Delta q \end{bmatrix} = \underbrace{\begin{bmatrix} \frac{\partial p}{\partial \theta}(x) & \frac{\partial p}{\partial v}(x) \\ \frac{\partial q}{\partial \theta}(x) & \frac{\partial q}{\partial v}(x) \end{bmatrix}}_{:=J(x)} \begin{bmatrix} \Delta \theta \\ \Delta v \end{bmatrix} = J(x)\Delta x, \quad (8)$$

1. The matrix  $J(x) \in \mathbb{R}^{2n \times 2n}$  is the **power flow Jacobian matrix**.
2. Derivatives of the power flow equations (2) with respect to the voltage magnitudes  $\mathbf{v}$  and phase angles  $\boldsymbol{\theta}$ .



## Case study: Newton-Raphson Power Flow model

$$\begin{bmatrix} \Delta p \\ \Delta q \end{bmatrix} = \underbrace{\begin{bmatrix} \frac{\partial p}{\partial \theta}(x) & \frac{\partial p}{\partial v}(x) \\ \frac{\partial q}{\partial \theta}(x) & \frac{\partial q}{\partial v}(x) \end{bmatrix}}_{:=J(x)} \begin{bmatrix} \Delta \theta \\ \Delta v \end{bmatrix} = J(x)\Delta x, \quad (9)$$

1. Can we learn **this matrix** as a proxy model?
2. Can we exploit the **structure of this matrix**?

# What is the problem?

1. How can we recover voltage phasors from their magnitudes?
2. How can we recover a *phaseless model* of the voltage phasors?
3. How can we do this provably?

# Solution overview

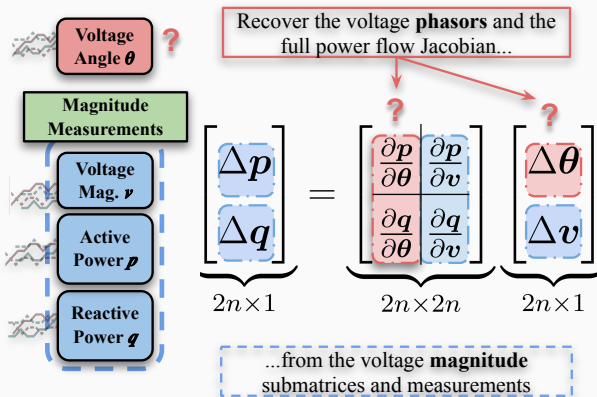


Figure 7: Voltage phasor recovery via power flow Jacobian recovery

# New characterization of Power Flow Jacobian structure

## Lemma 1: Phaseless power flow Jacobian structure

We can write the partial derivatives of power injections with respect to phase angles without the phase angles and without the grid model.

$$\frac{\partial p_i}{\partial \theta_k} = \begin{cases} v_k \frac{\partial q_i}{\partial v_k} & i \neq k \\ v_i \frac{\partial q_i}{\partial v_i} - 2q_i & i = k, \end{cases} \quad (10a)$$

$$\frac{\partial q_i}{\partial \theta_k} = \begin{cases} -v_k \frac{\partial p_i}{\partial v_k} & i \neq k \\ -v_i \frac{\partial p_i}{\partial v_i} + 2p_i & i = k. \end{cases} \quad (10b)$$

These are functions of the **power injection measurements!**

# New characterization of the structure of the Power Flow Jacobian

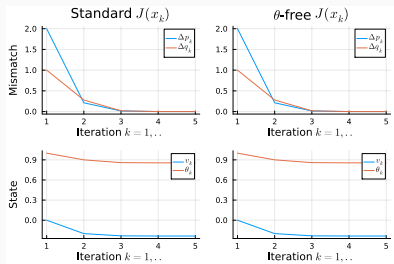
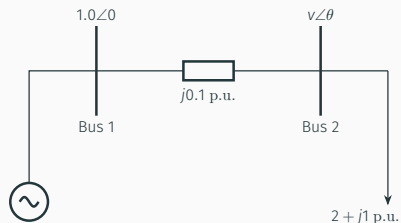
The power-voltage phase angle sensitivity matrices can be expressed as functions  $\frac{\partial p}{\partial \theta}, \frac{\partial q}{\partial \theta} : \mathbb{R}^n \times \mathbb{R}^n \mapsto \mathbb{R}^{n \times n}$  of the form

$$\frac{\partial p}{\partial \theta}(\mathbf{v}, \mathbf{q}) = \text{diag}(\mathbf{v}) \frac{\partial \mathbf{q}}{\partial \mathbf{v}} - 2 \text{diag}(\mathbf{q}), \quad (11a)$$

$$\frac{\partial \mathbf{q}}{\partial \theta}(\mathbf{v}, \mathbf{p}) = -\text{diag}(\mathbf{v}) \frac{\partial \mathbf{p}}{\partial \mathbf{v}} + 2 \text{diag}(\mathbf{p}), \quad (11b)$$

which are implicitly parameterized by  $\frac{\partial \mathbf{q}}{\partial \mathbf{v}}$  and  $\frac{\partial \mathbf{p}}{\partial \mathbf{v}}$ .

# New characterization of the structure of the Power Flow Jacobian



**Figure 8:** Equivalence of the Newton-Raphson iterations using the  $\theta$ -free expressions and standard expressions for  $\frac{\partial p}{\partial \theta}$ ,  $\frac{\partial q}{\partial \theta}$  (right) for a simple two bus test case (left).

# Phase retrieval by the power flow Jacobian

Apply a classic phase retrieval algorithm [4] to solve the power flow equations using **learned** voltage magnitude blocks

$$\underset{\Delta\theta_t}{\text{minimize}} \quad \left\| \begin{bmatrix} \Delta p_t \\ \Delta q_t \end{bmatrix} - \begin{bmatrix} (?) & \frac{\partial p}{\partial v} \\ (?) & \frac{\partial q}{\partial v} \end{bmatrix} \begin{bmatrix} \Delta\theta_t \\ \Delta v_t \end{bmatrix} \right\|_2^2$$

Learning the Jacobian blocks is well studied [5].

# Phase retrieval by the power flow Jacobian

The phase retrieval program for samples  $t = 1, \dots$ , can then be written as

$$\begin{aligned} & \underset{\Delta \theta_t, \frac{\partial p}{\partial \theta}, \frac{\partial q}{\partial \theta}}{\text{minimize}} \quad \left\| \begin{bmatrix} \Delta p_t \\ \Delta q_t \end{bmatrix} - \begin{bmatrix} \frac{\partial p}{\partial \theta}(\mathbf{v}_t, \mathbf{q}_t) & \frac{\partial p}{\partial \mathbf{v}} \\ \frac{\partial q}{\partial \theta}(\mathbf{v}_t, \mathbf{p}_t) & \frac{\partial q}{\partial \mathbf{v}} \end{bmatrix} \begin{bmatrix} \Delta \theta_t \\ \Delta \mathbf{v}_t \end{bmatrix} \right\|_2^2 \\ & \text{subject to: } \quad \text{power flow Jacobian structure!} \end{aligned}$$



Use the power flow Jacobian structure to  
guarantee voltage phase retrieval

## Long story short:

1. Use the Jacobian structure to show when the voltage phase can be uniquely recovered.
2. Use spectral theory to bound the eigenvalues of the full Jacobian using the phaseless expressions

# Guaranteed phase retrieval via spectral theory

## Theorem (Phase retrieval from active power injections)

For a set of buses in a network  $\mathcal{B} \subset \{1, \dots, n\}$ , if for every bus  $i \in \mathcal{B}$ , the reactive power differential inequality

$$|q_i| > \frac{1}{2}v_i \left( \sum_{k \in \mathcal{B} \setminus \{i\}} \left| \frac{\partial q_k}{\partial v_i} \right| - \left| \frac{\partial q_i}{\partial v_i} \right| \right) \quad (12a)$$

$$\text{or } |q_i| > \frac{1}{2} \left( \sum_{k \in \mathcal{B} \setminus \{i\}} v_k \left| \frac{\partial q_i}{\partial v_k} \right| - v_i \left| \frac{\partial q_i}{\partial v_i} \right| \right), \quad (12b)$$

holds, then the voltage phase angles can be uniquely recovered from solely the active power (real) injections  $\mathbf{p}$ .

# Guaranteed phase retrieval via spectral theory

## Theorem (Phase retrieval from reactive power injections)

Analogously, if for every bus  $i \in \mathcal{B}$ , the active power differential inequality

$$|p_i| > \frac{1}{2} v_i \left( \sum_{k \in \mathcal{B} \setminus \{i\}} \left| \frac{\partial p_k}{\partial v_i} \right| - \left| \frac{\partial p_i}{\partial v_i} \right| \right) \quad (13a)$$

$$\text{or } |p_i| > \frac{1}{2} \left( \sum_{k \in \mathcal{B} \setminus \{i\}} v_k \left| \frac{\partial p_i}{\partial v_k} \right| - v_i \left| \frac{\partial p_i}{\partial v_i} \right| \right), \quad (13b)$$

holds, then the voltage phase angles can be uniquely recovered from solely the reactive power (imaginary) injections  $\mathbf{q}$ .

# Jacobian invertibility guarantees

Side note: can also guarantee Jacobian invertibility

Jacobian invertibility  $\iff$  No voltage collapse  $\implies$  Phase retrieval

Take a look at the paper for more details

# Computational Results

---

1. RTS-GMLC network model [6]
2. Open-source
3. Real-world data

How does this compare to classical  
model-based state estimation?



# Comparison with classical state estimation

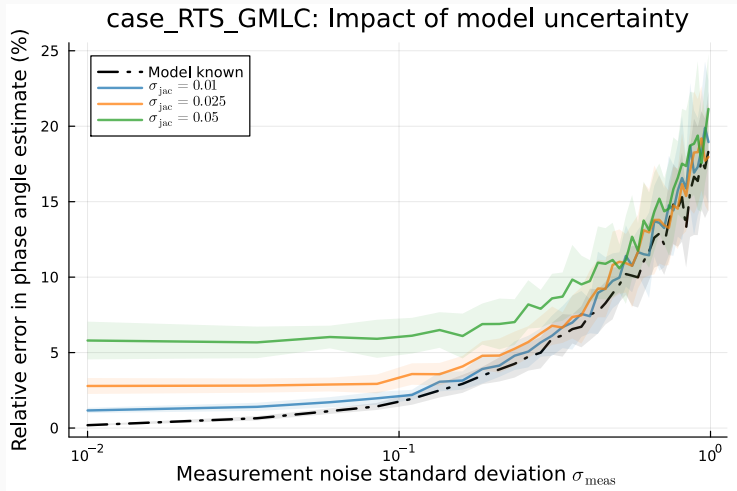


Figure 9: Impact of (*RTS\_GMLC*) model uncertainty on recovered phase angle relative error vs. measurement noise level. Shaded regions indicate  $\pm 1$  standard deviation of the relative errors computed over 20 bootstraps.

Voltage phasor recovery performance

# Voltage phasor recovery performance

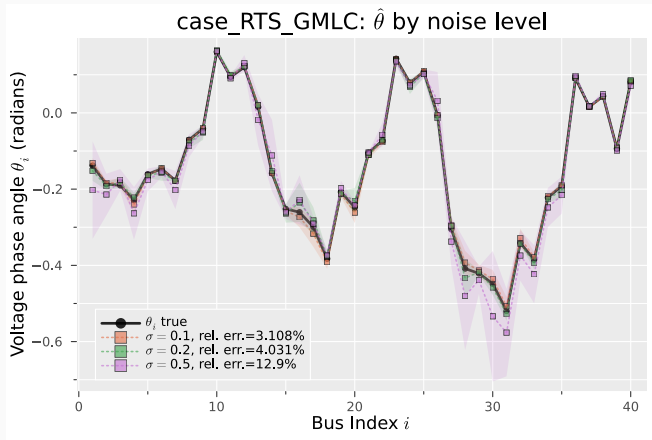


Figure 10: Voltage phasor recovery by measurement noise level.

How about the matrices?

# Power flow Jacobian recovery

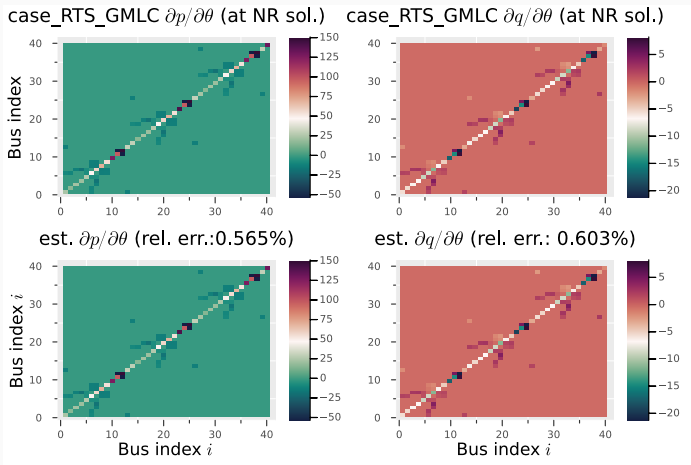
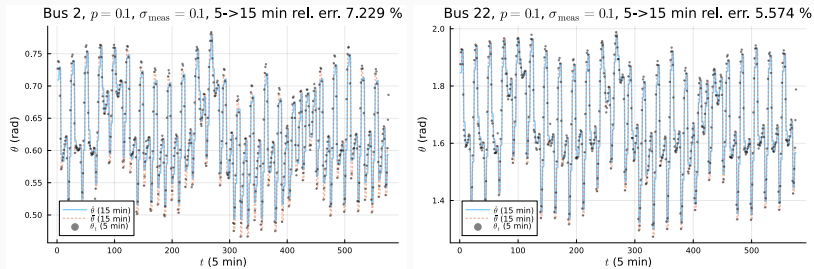


Figure 11: Recovery of the power-phase angle submatrices  $\frac{\partial p}{\partial \theta}$ ,  $\frac{\partial q}{\partial \theta}$  of the power flow Jacobian for the *RTS\_GMLC* network via the phase retrieval program.

How about real-time performance?

# Real-time voltage phasor recovery performance



**Figure 12:** Ground truth (blue) and estimated (orange dashed) voltage phase angles at 15 min. granularity, juxtaposed with ground truth 5 min. granularity voltage phase angles (black dots).

## Inverse problem: voltage magnitude sensitivity matrix recovery

What is the causation (voltage magnitude-complex power sensitivity matrices) of our voltage magnitude measurements?

$$\mathbf{v} = F \left( \frac{\partial \mathbf{v}^*}{\partial \mathbf{p}}, \frac{\partial \mathbf{v}^*}{\partial \mathbf{q}} \right) + \boldsymbol{\eta}$$



# Voltage magnitude Taylor series expansion.

Construct an **underdetermined** linearization of the voltage magnitudes via Taylor Series:

**Definition: Voltage magnitude linearization**

$$\underbrace{\Delta \mathbf{v}}_{(|\mathcal{N}|\times 1)} = \underbrace{\begin{bmatrix} \frac{\partial v}{\partial p} & \frac{\partial v}{\partial q} \end{bmatrix}}_{(|\mathcal{N}|\times 2|\mathcal{N}|)} \underbrace{\begin{bmatrix} \Delta p \\ \Delta q \end{bmatrix}}_{(2|\mathcal{N}|\times 1)} = \underbrace{|\mathbf{Sx}|}_{(|\mathcal{N}|\times 1)}. \quad (14)$$

# Representing reactive power as an equivalent active power

Given power factors  $\boldsymbol{\alpha} = [\alpha_1, \dots, \alpha_n]^T \in (0, 1]^n$  of the net complex power injections at each bus, there exists a matrix function  $K(\boldsymbol{\alpha}) : (0, 1]^n \mapsto \mathbb{R}^{n \times n}$  of the form

$$K(\boldsymbol{\alpha}) = \begin{bmatrix} \pm \frac{1}{\alpha_1} \sqrt{1 - \alpha_1^2} & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \pm \frac{1}{\alpha_n} \sqrt{1 - \alpha_n^2} \end{bmatrix}, \quad (15)$$

such that the reactive power can be written as a parameterized function of the active power [7]

$q$  as a function of  $p$  given  $\alpha$

$$q(p|\alpha) = K(\alpha)p. \quad (16)$$

# Graphical Example

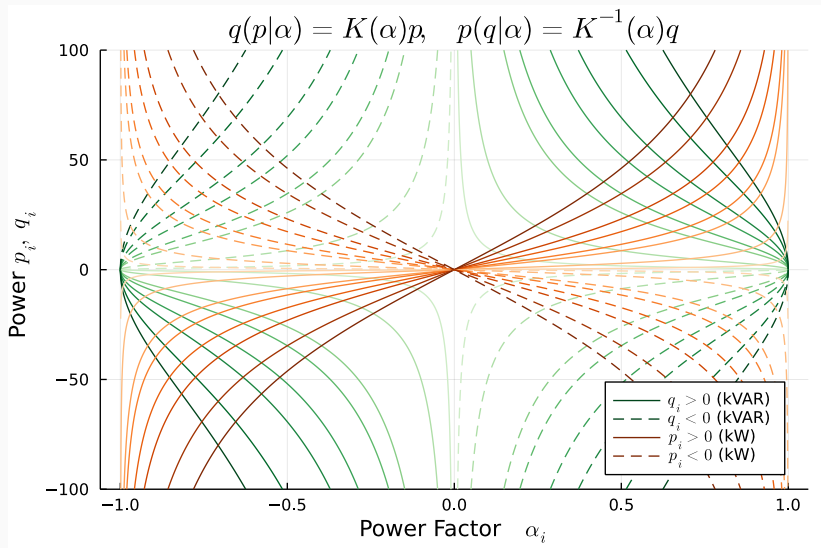


Figure 13: Representing  $q$  and  $p$  as parameterized function of  $\alpha$

# Phaseless sensitivity operator

Use  $K$  to construct an equivalent square system.

**Definition: phaseless voltage sensitivity operator**

$$\begin{aligned}\underbrace{\Delta v}_{(|\mathcal{N}|\times 1)} &= \underbrace{\begin{bmatrix} \frac{\partial v}{\partial p} & \frac{\partial v}{\partial q} \end{bmatrix}}_{(|\mathcal{N}|\times 2|\mathcal{N}|)} \underbrace{\begin{bmatrix} \Delta p \\ \Delta q \end{bmatrix}}_{(2|\mathcal{N}|\times 1)} = \underbrace{|\mathbf{Sx}|}_{(|\mathcal{N}|\times 1)} \\ &= \underbrace{\left( \frac{\partial v}{\partial p} + \frac{\partial v}{\partial q} K(\alpha) \right)}_{|\mathcal{N}|\times |\mathcal{N}|} \underbrace{\Delta p}_{|\mathcal{N}|} \\ &\triangleq S(\alpha)\Delta p.\end{aligned}$$

Solution: show when  $S(\alpha)$  is invertible

# Invertibility of phaseless sensitivity operator

## Theorem: phaseless observability

Let  $\Delta\mathbf{K} := \max_{i \in \mathcal{N}} K_{i,i} - \mathbf{I}$ . Then the complex power injections can be estimated from the voltage magnitudes if

$$\left\| \mathbf{M}^{-1} \Delta\mathbf{K} \frac{\partial \mathbf{p}}{\partial \boldsymbol{\theta}} \right\|_2 < 1, \quad (17)$$

where  $\|\cdot\|_2$  is the largest singular value—the spectral norm or operator norm—of the argument.

# Theorem characterization

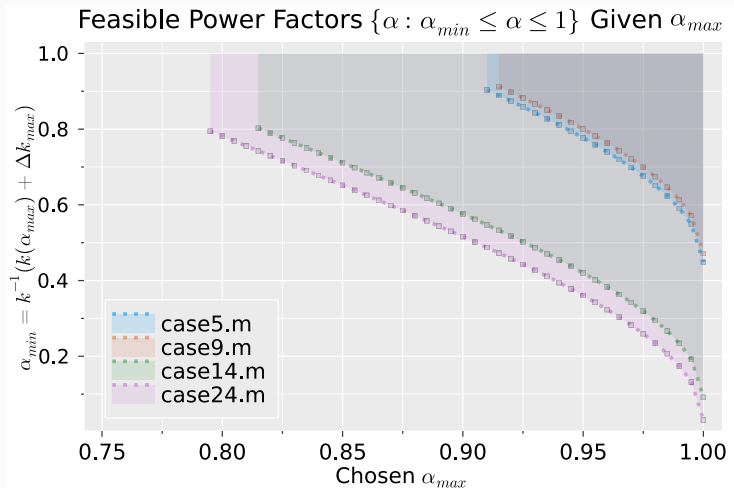


Figure 14: Feasible power factors such that the phaseless observability Theorem holds for several popular test cases.

# Outlook

---



# What do we have?

We have shown that we can:

1. Recover voltage phasors from their magnitudes
2. Recover complex power injections from voltage magnitudes
3. Recover models of voltage phase angles from their magnitudes
4. Recover the power flow Jacobian blocks and the blocks of its inverse

This can save a lot of money<sup>4</sup>

---

<sup>4</sup>A PMU installation costs \$40,000-\$180,000 each.

“Factors affecting PMU installation costs”, US Department of Energy, 2014.




# What are the limitations?




1. Bottle necked by measurement frequency (PMUs, milliseconds, other devices, minutes-hours)
2. Bottle necked by measurement type (Reactive power assumptions needed)
3. Needs further incorporation of the non-linearities of the AC power flow equations.

# Acknowledgement

This material is based upon work supported by the National Science Foundation Graduate Research Fellowship Program under Grant No. DGE-1650044. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

Thanks for listening

-  M. Kezunovic, “Panel session VII: PMU testing and synchrophasor system life-cycle management,” in *International Conference on Smart Grid Synchronized Measurements and Analytics (SGSMA)*. Split, Croatia: IEEE Power and Energy Society and IEEE Instrumentation and Measurement Society, May 2022.
-  J. Peppanen, M. Hernandez, J. Deboever, M. Rylander, and M. J. Reno, “Distribution Load Modeling - Survey of the Industry State, Current Practices and Future Needs,” in *2021 North American Power Symposium (NAPS)*, Nov. 2021, pp. 1–5.
-  S. Talkington, S. Grijalva, M. J. Reno, and J. A. Azzolini, “Solar PV Inverter Reactive Power Disaggregation and Control Setting Estimation,” *IEEE Transactions on Power Systems*, vol. 37, no. 6, pp. 4773–4784, Nov. 2022.

-  I. Waldspurger, A. d'Aspremont, and S. Mallat, “Phase recovery, MaxCut and complex semidefinite programming,” *Math. Program.*, 2015.
-  Y. C. Chen, J. Wang, A. D. Domínguez-García, and P. W. Sauer, “Measurement-Based Estimation of the Power Flow Jacobian Matrix,” *IEEE Transactions on Smart Grid*, vol. 7, no. 5, pp. 2507–2515, Sep. 2016.
-  C. Barrows, A. Bloom, A. Ehlen, J. Ikaheimo, J. Jorgenson, D. Krishnamurthy, J. Lau, B. McBennett, M. O’Connell, E. Preston, A. Staid, G. Stephen, and J.-P. Watson, “The IEEE Reliability Test System: A Proposed 2019 Update,” *IEEE Transactions on Power Systems*, vol. 35, no. 1, Jul. 2019, institution: National Renewable Energy Lab. (NREL), Golden, CO (United States) Number:

NREL/JA-6A20-71958 Publisher: IEEE. [Online]. Available:  
<https://www.osti.gov/pages/biblio/1545004>



S. Talkington, S. Grijalva, and D. K. Molzahn, “Conditions for Estimation of Sensitivities of Voltage Magnitudes to Complex Power Injections,” *submitted to IEEE Transactions on Power Systems*, May 2022.

Backup slides

---



# Background: Gershgorin Circle Theorem

## Where are the eigenvalues of a square matrix?

For any matrix  $\mathbf{A} \in \mathbb{C}^{n \times n}$ , by the *Gershgorin Circle Theorem* the eigenvalues of  $\mathbf{A}$  are guaranteed to lie in the union of the  $i = 1, \dots, n$  Gershgorin discs  $\mathcal{G}_i(\mathbf{A})$  of the matrix, i.e.,

$$\lambda_i(\mathbf{A}) \in \bigcup_{i=1}^n \mathcal{G}_i(\mathbf{A}), \quad i = 1, \dots, n, \quad (18)$$

where

$$\mathcal{G}_i(\mathbf{A}) \triangleq \{w \in \mathbb{C} : |w - A_{ii}| \leq \sum_{k:k \neq i} |A_{ik}|\} \subseteq \mathbb{C}. \quad (19)$$

# Classical phase retrieval

Given:  $|Ax| = b$ ,  $\boxed{b \in \mathbb{R}^m}$ , what is  $x \in \mathbb{C}^n$ ?

Classical phase retrieval problem:

$$\min_{x \in \mathbb{C}^n, y \in \mathbb{C}^m} \|Ax - y\|_2^2 \quad \text{s.t.} \quad |y| = b, \quad (20a)$$

$$\iff \min_{x \in \mathbb{C}^n, u \in \mathbb{C}^m} \|Ax - \text{diag}(b)u\| \quad \text{s.t.} \quad |u| = \mathbb{1}, \quad (20b)$$

$$\iff \min_{u \in \mathbb{C}^m: |u_i|=1 \forall i \in [1, m]} u^* M u, \quad \text{s.t.} \quad M = \text{diag}(b - AA^\dagger) \succ 0. \quad (20c)$$

for any candidate phase  $u'$ , note that

$$\boxed{\hat{x} = A^\dagger \text{diag}(b)u' = (A^*A)^{-1}A^* \text{diag}(b)u'}, \quad (21)$$

## Theorem accuracy

Case	# PQ Buses	% Satisfying Thm. 1	$r_{\text{worst}}$
14	9	100.0%	—
24_ieee_rts	13	100.0%	—
ieee30	24	95.83%	$1.4 \times 10^{-14}$
RTS_GMLC	40	100.0%	—
118	64	100.0%	—
89pegase	77	94.81%	8.32
ACTIVSg200	162	96.91%	0.088
ACTIVSg500	444	94.37%	3.014
ACTIVSg2000	1608	84.83%	28.31

Table 2: Analysis of Theorem 1 for PQ buses of various test cases

## Theorem accuracy

Case	# PQ Buses	% Satisfying Thm. ??	$\sigma_{\max}$
14	9	100.0%	0.876
24_ieee_rts	13	100.0%	0.401
ieee30	24	95.83%	1.437
RTS_GMLC	40	100.0%	0.444
118	64	100.0%	0.473
89pegase	77	100%	0.954
ACTIVSg200	162	100%	0.698
ACTIVSg500	444	99.77%	1.090
ACTIVSg2000	1608	99.69%	1.180

Table 3: Analysis of Theorem ?? for PQ buses of various test cases

Quantity	Value
$\left. \frac{\partial p}{\partial \theta} - \frac{\partial p}{\partial \theta}(\mathbf{v}, \mathbf{q}) \right _F / \left. \frac{\partial p}{\partial \theta} \right _F$	$2.510 \times 10^{-8}$
$\left. \frac{\partial q}{\partial \theta} - \frac{\partial q}{\partial \theta}(\mathbf{v}, \mathbf{p}) \right _F / \left. \frac{\partial q}{\partial \theta} \right _F$	$1.725 \times 10^{-7}$

**Table 4:** Verification that the structure expressions of the Lemma hold for multiphase unbalanced networks.