

# Semidefinite Programming for Power System State Estimation

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## Motivation

- Based on real-time measurements, Static State Estimation serves as the foundation for monitoring and controlling the power grid.

❖ *Classical method:* For AC power system, state estimation is usually formalized mathematically as a Weighted Least Square or Weighted Least Absolute Value problem, and solved by Newton's method.

❖ *Problem:* Highly sensitive to the initial point, as it is essentially a local search algorithm.

❖ *New approach:* Employ Semidefinite Programming (SDP) to effectively obtain a good initial state.

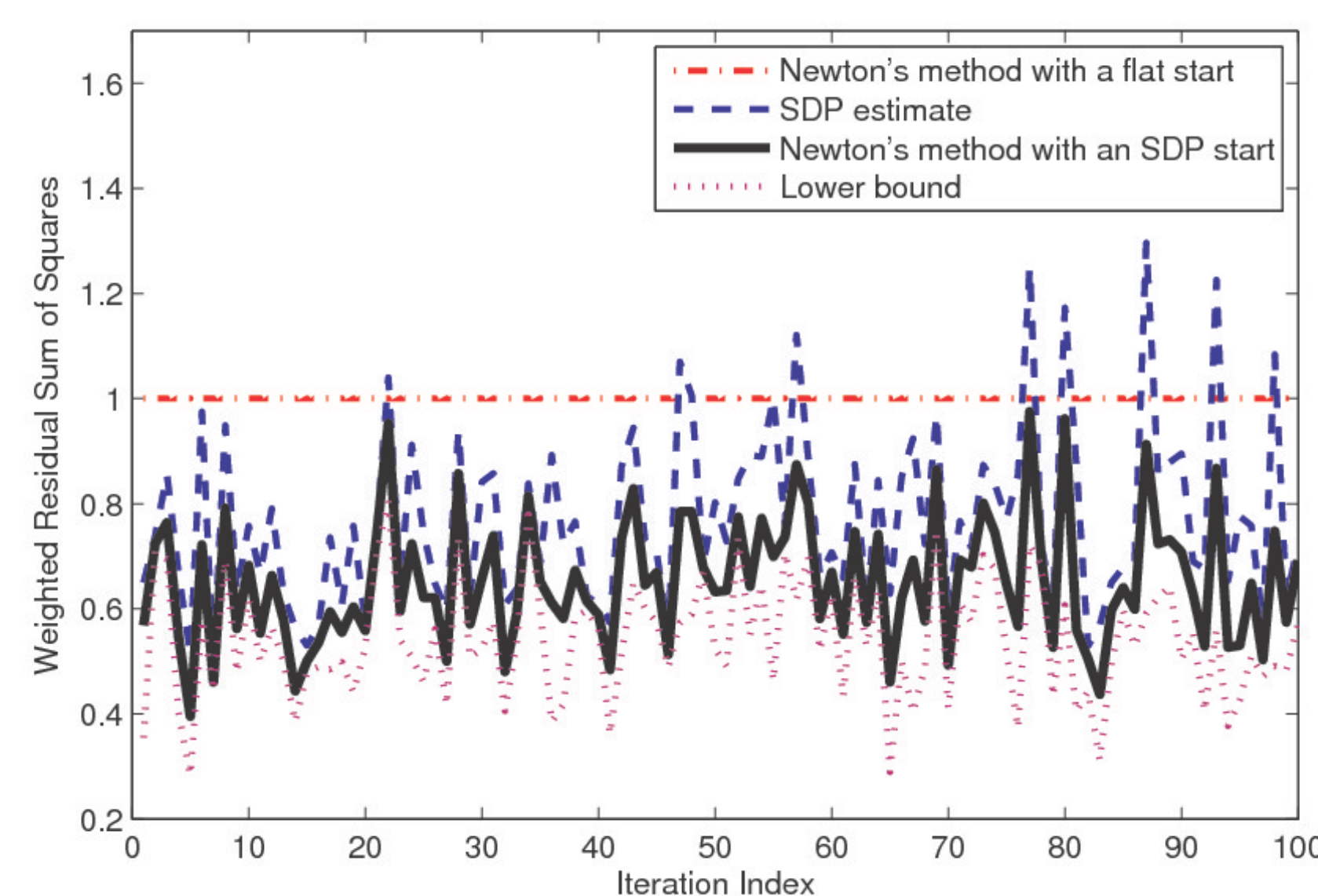
## Numerical Result

- Simulation for IEEE 14 bus (SDP initial guess v.s. Flat start)

- The state: 14 voltage magnitudes and 14 phase angles
- The measurements:
  - Voltage magnitudes
  - Active and reactive power flow on the lines
  - Active and reactive power injection at buses
- 100 random sample sets

- Objective Comparison

$$\text{WRSS} = \sum_{i=1}^m \left( \frac{z_i - \text{tr}(A_i W)}{\sigma_i} \right)^2$$

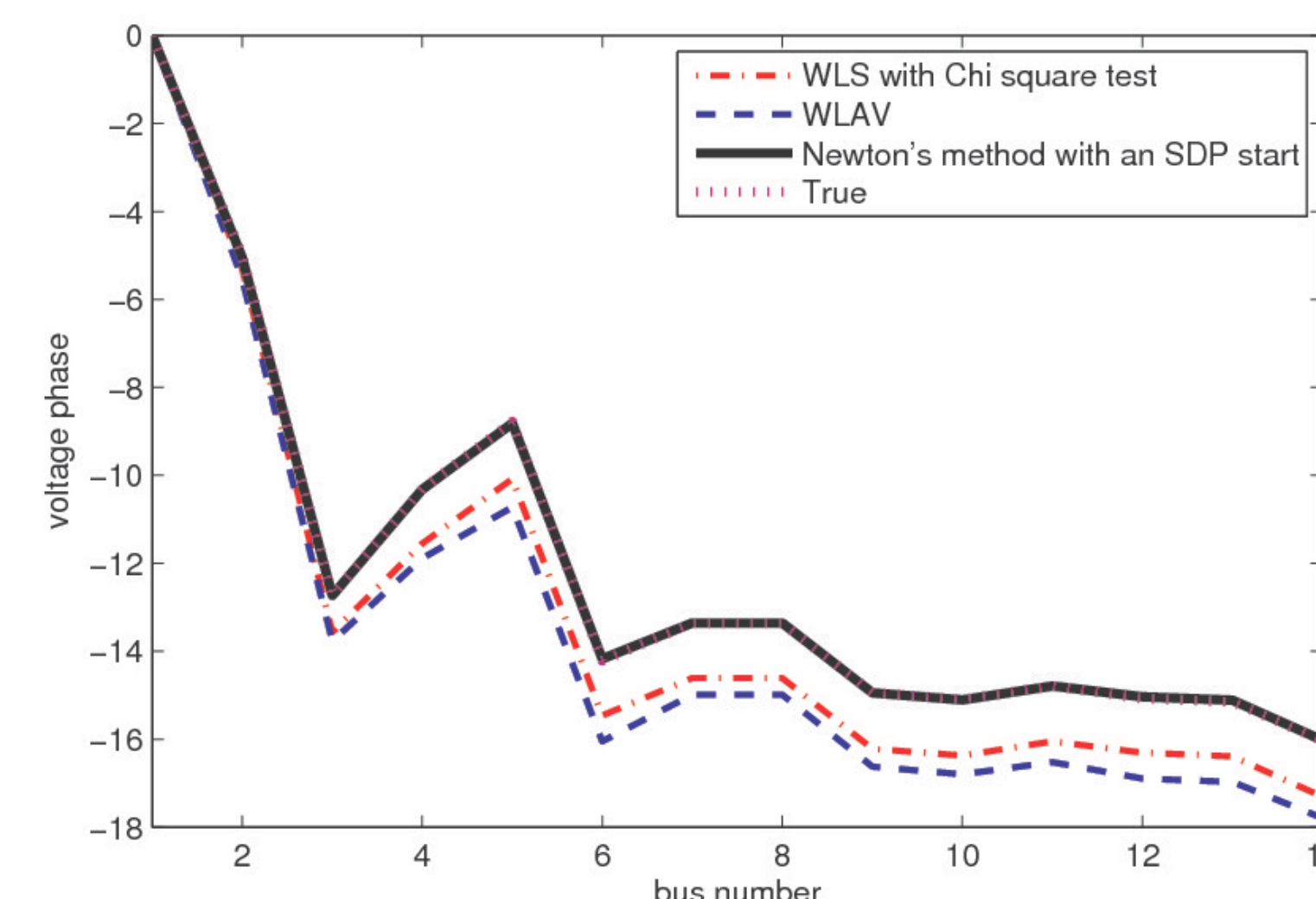


- Figure. Performance comparison for the 14 bus case.

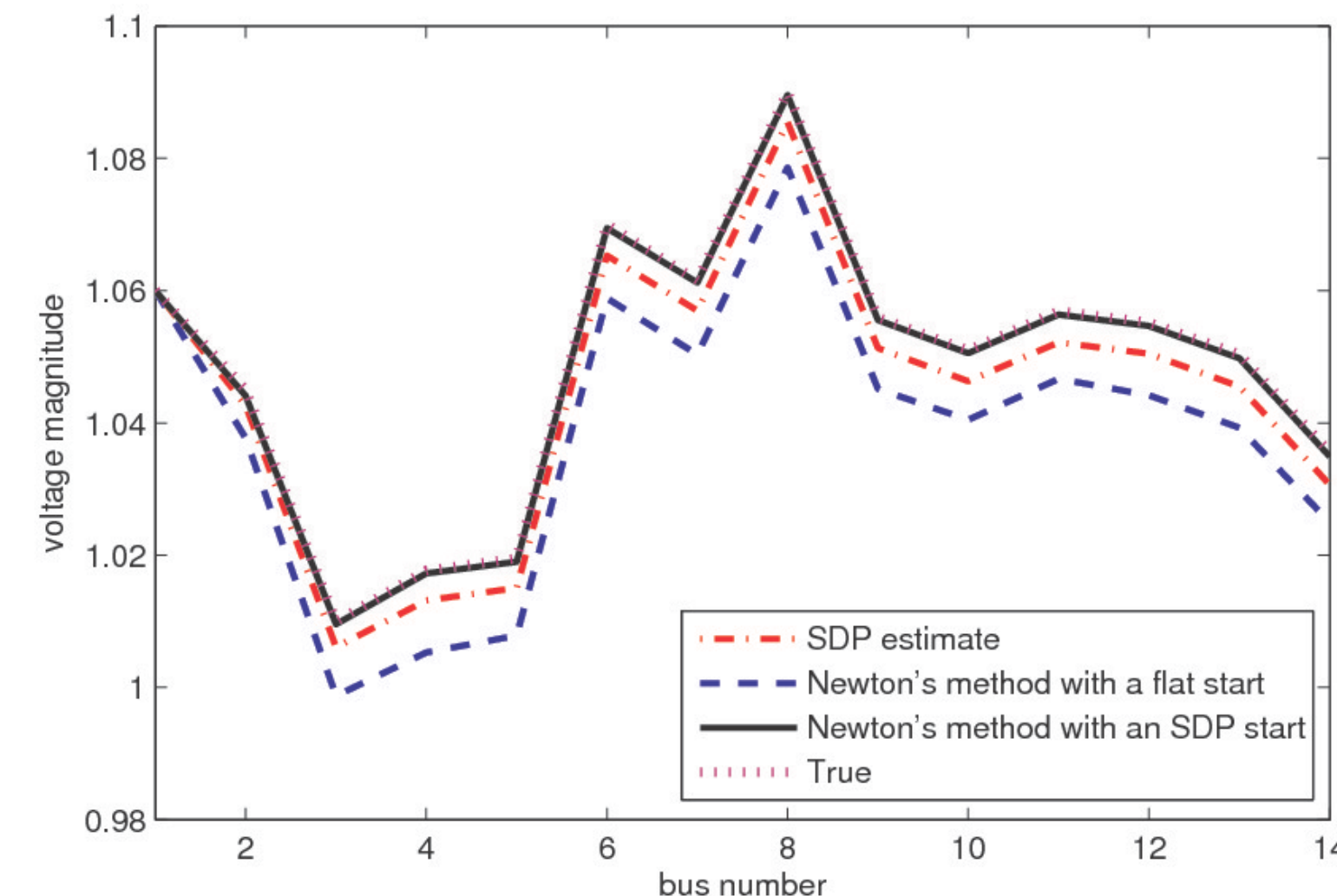
(A lower bound is also computed from relaxed problem's objective)

- State Comparison

- Gaussian Noise



- Bad data



## Preliminaries of State Estimation

- Goal:

- To determine the most likely state of the system based on the quantities that are measured. [1]

- Model:  $z = h(x) + u$

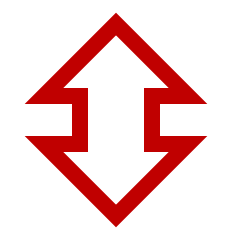
- $h$ : Nonlinear functions, relating state and measurements
- State(x): Voltage magnitudes and phase angles
- Measurements (z) and noise (u)

- Optimization:

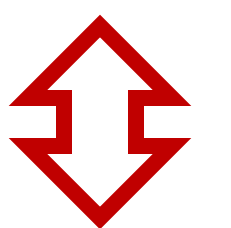
$$\text{minimize}_{\mathbf{x}} J_p(\mathbf{x})$$

subject to

$$\begin{aligned} P' &= P(\mathbf{x}) + \mathbf{u}_p & Q' &= Q(\mathbf{x}) + \mathbf{u}_q \\ P'_f &= P_f(\mathbf{x}) + \mathbf{u}_{pf} & Q'_f &= Q_f(\mathbf{x}) + \mathbf{u}_{qf} \\ P'_t &= P_t(\mathbf{x}) + \mathbf{u}_{pt} & Q'_t &= Q_t(\mathbf{x}) + \mathbf{u}_{qt} \\ |V_k|' &= |V_k| + \mathbf{u}_v \end{aligned}$$



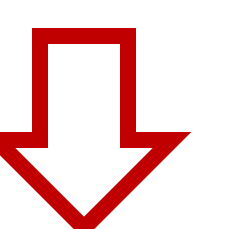
$$\min_{\mathbf{x}} J_p(\mathbf{x}) = \left( \sum_{i=1}^m \left| \frac{z_i - h_i(\mathbf{x})}{\sigma_i} \right|^p \right)^{\frac{1}{p}}$$



$$\begin{aligned} \min_W J_p(W) &= \left( \sum_{i=1}^m \left| \frac{z_i - \text{tr}(A_i W)}{\sigma_i} \right|^p \right)^{\frac{1}{p}} \\ \text{subject to} & \quad W \succeq 0, \quad \text{rank}(W) = 1. \end{aligned}$$

- Constraint relaxation:

$$\begin{aligned} \min_W J_p(W) &= \left( \sum_{i=1}^m \left| \frac{z_i - \text{tr}(A_i W)}{\sigma_i} \right|^p \right)^{\frac{1}{p}} \\ \text{subject to} & \quad W \succeq 0. \end{aligned}$$



$$\hat{W} = \sum_{i=1}^p \lambda_i g_i g_i^T$$

- State Recovery:

$$\hat{\mathbf{x}} = \hat{U}_{1:n} + j\hat{U}_{n+1:2n}$$

- Use it as initial guess for Newton's method

## New Approach

- Reformulate the state in another form. [3]
- Relax the non-convex constraint to convexify the problem.
- Use the "relaxed" estimate as a new initial guess for Newton's method

$$\begin{aligned} U &= (\text{Re}(\mathbf{x})^T, \text{Im}(\mathbf{x})^T)^T & P_k &= \text{Re}\{V_k^H I_k\} \\ & & &= \text{Re}\{V^H e_k e_k^T Y V\} \\ & & &\triangleq \text{Re}\{V^H Y_k V\} \\ \tilde{Y}_k &= \frac{1}{2} \begin{pmatrix} \text{Re}(Y_k + Y_k^T) & \text{Im}(Y_k^T - Y_k) \\ \text{Im}(Y_k - Y_k^T) & \text{Re}(Y_k^T + Y_k) \end{pmatrix} & &= U^T \tilde{Y}_k U \\ & & &= \text{tr}(\tilde{Y}_k U U^T) \\ W &= U U^T & &= \text{tr}(\tilde{Y}_k W) \end{aligned}$$

- Reference

- [1] A. Abur and A. G. Exposito, "Power System State Estimation: Theory and Implementation." Marcel Dekker Inc, 2004.
- [2] A. Monticelli, State Estimation in Electric Power Systems, A Generalized Approach., 1999.
- [3] J. Lavaei and S. H. Low, "Zero duality gap in optimal power flow problem," Technical Report, California Institute of Technology, vol. PWRD-1, no. 3, pp. 355-360, Aug. 2010.

- Acknowledgment

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